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Natural language processing and communication models in chosen crisis situations

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Łukasz Wilkoń Sosnowiec, dn. 14.04.2023 r.

Streszczenie

Modele komunikacji oraz przetwarzanie języka naturalnego w wybranych sytuacjach kryzysowych

Celem niniejszej rozprawy jest zbadanie, czym negocjacje kryzysowe różnią się od tekstów pokrewnych, takich jak negocjacje biznesowe czy przesłuchania policyjne. Kolejny cel stanowi analiza predykcyjna danych pochodzących z negocjacji. Pozwala ona ustalić, które zadania z zakresu przetwarzania języka naturalnego mogą uzupełniać analizę językową negocjacji kryzysowych. Główny korpus danych do badań składa się z zapisu negocjacji policyjnych z Grantem Sattaurem.

Rozdział pierwszy omawia główne taktyki negocjacyjne stosowane przez policję, rozdział drugi opisuje metody przesłuchań. W rozdziale trzecim przedstawiono zagadnienie emocji we współczesnej psychologii. Przedmiotem rozdziału czwartego są akty mowy, tropy stylistyczne oraz inne aspekty komunikacji kryzysowej. Rozdział piąty zawiera automatyczną klasyfikację danych pochodzących z negocjacji kryzysowych, przeprowadzoną na poziomie zdań z użyciem sztucznej inteligencji, a także eksploracyjną analizę danych. Za pomocą sześciu modeli uczenia maszynowego wykonano dziesięć zadań z zakresu przetwarzania języka naturalnego. Zastosowano metody ilościowe, gdyż podejścia oparte na uczeniu maszynowym zasadniczo mają naturę ilościową. Do analizy wskaźników ilościowych omawianych w niniejszej rozprawie wykorzystano metodę statystyczną.

Eksploracyjna analiza danych umożliwiła zrozumienie głównych cech tekstu oraz zastosowanie odpowiednich parametrów w modelach uczenia maszynowego. Zbudowano dwie własne bazy danych w języku angielskim: zbiór danych niezbędny do wykrycia tendencji samobójczych oraz zbiór danych potrzebny do wykrycia mowy nienawiści i obraźliwego języka. Wykorzystano procesowanie języka naturalnego oraz data mining, aby pozyskać informacje ze źródeł w obszarze mediów społecznościowych.

Model głębokiego uczenia XLNet, wykorzystujący wykrywanie emocji, ujawnił przewagę klasy emocji „smutek” oraz dużą liczbę zdań zawierających potencjalne tendencje samobójcze/depresyjne w zapisie negocjacji policyjnych z Grantem Sattaurem. W ten sposób wykryto w nim również liczne zdania zawierające nieuprzejmy język.

Analizę automatyczną uzupełniła analiza jakościowa. Jej celem było zbadanie przejawów emocji i innych elementów leksykalnych w tekście. Każde zdanie z zapisu negocjacji z Grantem Sattaurem oznaczono zgodnie z modelem komunikacji kryzysowej Roda Fowlera. Większość zdań przypisano do kategorii: „uspokajanie”, „budowanie zaufania”, „zbieranie informacji” oraz „zręczna taktyka”. Tekst zawiera jednak wiele prób stłumienia rozmówcy, w których negocjator stosuje reprymendy, wdaje się w sprzeczki czy traci porozumienie z rozmówcą. Analiza lingwistyczna wykazuje, że zapis negocjacji policyjnych z Grantem Sattaurem stanowi mieszankę twardych i miękkich strategii negocjacyjnych z przewagą drugiego z wymienionych rodzajów.

Słowa kluczowe: data mining, głębokie uczenie, procesowanie języka naturalnego, klasyfikacja danych, modele komunikacji kryzysowych, tropy językowej komunikacji, wyrażanie emocji

Abbreviations

AIDA	Action-implicature discourse analysis
BERT	Bidirectional Encoder Representation from Transformer
BCSM	Behavioural Change Stairway Model
BISM	The Behavioral Influence Stairway Model
BOW	Bag-of-words
CA	Conversation analysis
CDA	Critical discourse analysis
CNN	Convolutional Neural Network
DD	Dysthymic disorder
DID	Dissociative identity disorders
DP	Discoursive psychology
FI	Frustration intolerance
HPD	Histrionic Personality Disorder
LFT	Low frustration tolerance
LSTM	Long short-term memory network
MDD	Major depressive disorder
MPD	Multiple personality disorders
NB	Naïve Bayes
NLP	Natural language processing
PAD	Pleasure, Arousal and Dominance
PANA	Positive Activation - Negative Activation
P.E.A.C.E.	Planning and Preparation, Engage and Explain, Account, Closure, and E-Evaluate.
PTSD	Post-traumatic stress disorder
RNN	Recurrent Neural Network
S.A.E.B.	Symptoms Automatic Thoughts Emotions Behavior
S.A.F.E.	Substantive demands, attunement, face, emotion framework
SIER	Sensing, Interpreting, Evaluating and Responding
STEPS	Structured Tactical Engagement Process model
SVM	Support Vector Machine
TF–IDF	Term frequency – Inverse document frequency

0. INTRODUCTION

A crisis is any non-routine disruptive event that threatens the security and integrity of an individual. Crisis communication entails special procedures and tactics to restore the situation to normality where the individual's life is not threatened (Korzeniowski 2016; Gierszewski 2017). Crisis communication encompasses communication that can occur during a disaster communication (Waymer and Heath 2007, Kivikuru et al. 2009), organizational crises (Coombs 2010, 2014; Christen 2005), epidemics (Lee 2009), hostage negotiations, and others. The presented work focuses on crisis or hostage negotiations. Recently the term hostage negotiation has been superseded by crisis negotiation, as negotiators deal with people in crisis. During such events, certain lexical items and expressions are likely to occur as a response to stress. Moreover, a particular language is expected from the negotiation team as part of those procedures and tactics. Therefore, from the linguistic perspective, this work aims to determine how crisis negotiations differ from other types of text, such as business negotiations or police interviews. It also highlights the differences between various types of crisis negotiations with real-life examples.

An important linguistic aspect of the research is to find out what emotions and communication tropes occur during negotiations and how they are expressed via lexical features. The main problem, however, is the time required to conduct a linguistic analysis. While natural language processing is not intended to substitute that analysis, it plays a complementary role and provides valuable insights that help understand text better. The longer the text is, the more relevant natural language processing appears. Automatic text classification has gained increasing interest in both research and commercial applications due to its potential to determine individuals' affective states. Emotions play a central role of emotion in crisis negotiations (Hammer 2007: 96–97).

The term natural language processing (NLP) describes the function of analyzing or synthesizing spoken or written language (Jackson and Moulinier 2002: 2–3). The adjective "natural" refers to human speech and writing, which are different from formal languages (Jackson and Moulinier 2002: 3). Natural language processing enables humans to interact with the computer and refers to the automatic computational processing of human language. The text must be human- and machine-readable, which can be accomplished through preprocessing.

Natural language processing, which makes automatic text classification possible, can facilitate the work of law enforcement agents and linguists during the evaluation phase of the negotiation and beyond. Moreover, natural language processing helps identify the nature of the text, enabling one to answer, for example, the following questions: "does rude language dominate the text?," "is the subject potentially depressed?," "does religious language prevail in the text?." Determining the type of subject helps establish the proper tactics to be used by the negotiation team. The consequences of applying incorrect tactics are discussed in chapter one and four.

From the machine learning perspective, the main goal is to determine which artificial intelligence model and dataset are adequate for recognizing the key language features and emotions of crisis negotiation within and would thus be useful for linguistic analysis without sacrificing too much time and resources. Therefore, I focus on small to medium datasets between 9000 to 200 000 sentences; and for model training, I utilize the low-cost Google Cloud Colaboratory Pro plan. The textual data is in English. The collection, assembly, and transformation of proper datasets would only be possible with linguistic knowledge, which also applies to the language of crisis communication. Furthermore, the categorization and tagging of sentences would only be improved with a linguistic description of the emotions represented by each sentence or lexical item. By combining linguistic and machine learning, one can determine what went wrong during a crisis negotiation.

As far as literature is concerned, crisis communication and natural language processing have become a large interdisciplinary field. The main components of crisis negotiation theory are psychology, securitology, behavioral science, linguistics, and law. The main securitology concerns are risk reduction and communication flow optimization to ensure safety of groups and individuals (Korzeniowski 2016). As law enforcement agents often deal with subjects affected by mental disorders, medical domains also overlap with the crisis negotiation literature. Over 1000 sources were utilized to write this dissertation; therefore, only the main works used are presented in the introduction. In Poland, the topic of crisis communication during high-risk moments has been studied, among many, by Jadwiga Stawnicka (2014; 2016), Dariusz Biel (2012), Robert Poklek (2021), Magdalena Chojnacka (2021), Jacek Kamiński (2003; 2006) and Dariusz Piotrowicz (2010). The concept of security was studied in the works of Leszek Korzeniowski (2006; 2016), Józef Żółtaszek (1931), Stanisław Kozdrowski (2011), Ryszard Zięba (2012) and Sławomir Zalewski (2009).

Worldwide, Timothy Coombs (2010, 2014) and Kathleen Fearn-Banks (2016) provided techniques applicable to organizations in times of crisis. Roger Fisher and William Ury's (1981) work influence mediation and crisis negotiation theory. The role of emotions that arise during any negotiating process was studied by world-renowned negotiator Roger Fisher and psychologist Daniel Shapiro (2005). Although I focus on crisis negotiations and many works on business negotiations have been omitted, a few worth mentioning are Piotr Mamet (2004; 2009) and Joan Mulholland (1991).

Authors who published significant works specific to crisis negotiations are, among many, Philip Gulliver (1979), William Donohue (1991), William Ury (1993), Michael McMains (1996), Wayman Mullins (1996), Mitchell Hammer (1997), Randall Rogan (1997), Rod Fowler (2001), Ellen Giebels (2002), Paul Taylor (2002; 2008), Gregory Vecchi (2005; 2009), Carol Ireland (2007), Gregory Vecchi (2006; 2007; 2009), Brad Kellin (2007), Meghan McMurtry (2007), Sally Thomas (2008), Arthur Slatkin (2009), Demetrius Madrigal (2009), Daniel Bowman (2009), Bryan McClain (2009), Gary Noesner (2010), Jeff Thompson (2014), Hugh McGowan (2014), and Christopher Voss (2017).

The work *Crisis Negotiations: Managing Critical Incidents and Hostage Situations in Law Enforcement and Corrections* (McMains, Mullins, and Young 2021) can be considered one of the primary sources of information for crisis negotiation professionals as it encompasses most crisis-relevant aspects with a focus on techniques and language. The latest (sixth) edition is the most informative (the original work was written in 1996) because it includes insights from Andrew Young that expand the content, for instance, in the field of managing difficult subjects affected by depression. Individuals suffering from mental illnesses respond differently to negotiation tactics; the same applies to religious groups and terrorist organizations.

In crisis negotiation models, the role of emotions, personality type, the mental health of an individual, and behavioral patterns are all taken into account. Therefore, the involvement of psychologists specializing in various fields, who act as advisors and provide information in the negotiation process, is crucial.

An exploratory mixed analysis of crisis negotiations that encompasses fields of psychology and negotiation theory has been conducted predominantly by Amy Rose Grubb (2010; 2019; 2020). From the linguistic point of view, an important book on how emotions are expressed in texts is the multi-author monograph *Wyrażanie emocji*, edited by Kazimierz Michalewski (2006). The psychological aspect of crisis (hostage) negotiations has been analyzed mainly by Thomas Strentz (1983; 1992; 2011; 2013) and, concerning police work, by Daniel Rudofossi (2017a; 2017b). The chief sources of information regarding various mental disorders important from the perspective of negotiations are, among many, "Aggression and Violent Behavior" (a bimonthly peer-reviewed journal), "Journal of Affective Disorders", "American Psychological Association (APA) Dictionary of Psychology", and "The Diagnostic and Statistical Manual of Mental Disorders".

An interesting analysis of the influence of traumatic events and other disorders on the human psyche is provided by Marek Jarema (2016) and on depression by Marek Jarema (2017). Moreover, Jeffrey Michael and Grady Bray (1990) elaborated stress management techniques for law enforcement, such as "defusing" and "debriefing." Like crisis negotiations, interviews can be considered out-of-ordinary situations; therefore, their language is worth studying. The main authors of police interrogation techniques include John Reid (1974), Stan Walters (2003), Vivian Lord (2010), Allen Cowan (2010), John Schafer (2004), and Joe Navarro (2004). Studies of interrogation techniques are generally based on: 1) tape recordings of real-life police interrogations or 2) laboratory-based experiments (Hartwig, Granhag and Vrij 2005).

Machine learning (Samuel 1959) and natural language processing (NLP) are rapidly evolving fields. The field of natural language processing originated in the 1940s to create a machine that could perform translation automatically. The work of Noam Chomsky (1965) helped identify critical issues in automatic translation. The invention of the Internet and personal computers gave new impetus to the development of natural language processing which became more accessible to the public. Natural language processing started to focus on statistical and probabilistic methods and text manipulation and extraction so that consumer-level applications and tools would proliferate. Steven Bird and Edward Loper at the University of Pennsylvania created the Natural Language Toolkit in 2001 (Loper and Bird 2002), whereas Christopher Manning, along with colleagues, created CoreNLP at Stanford University in 2010 (Manning et al. 2014).

One of the most widely referenced works on natural language processing was written by James Allen (1994), Hinrich Schütze (1999; 2008), Christopher Manning (1999; 2008), Daniel Jurafsky (2022), James Martin (2022), Taku Kudo (2018), John

Richardson (2018), Prabhakar Raghavan (2008), Mike Schuster (2012), Kaisuke Nakajima (2012), Peter Jackson (2007), and Isabelle Moulinier (2007). Tomas Mikolov et al. (2013a) presented a revolutionary technique to learn word embeddings using a shallow neural network called Word2Vec. From Polish authors, we should also mention, among many, Wojciech Abramowicz (2002), Jakub Piskorski (2003), Piotr Potiopa (2011), Wiesław Babik (2013), Przemysław Sołdacki (2018), Maciej Piasecki (2018), Michał Karwatowski (Karwatowski et al. 2021), and Adrian Trzoss (2021). Noteworthy are Tadeusz Piotrowski's (2001) lexicography works and NLP's Wordnet to Wordnet Mapping (Rudnicka et al. 2018).

Regarding newly developed artificial intelligence models, the developments that come from Google Brain – a deep learning artificial intelligence research team, are worthy of note[1]. The invention of the Transformer encoder and decoder blocks (Vasvani et al. 2017), which did not utilize recurrence or convolution (Vasvani et al. 2017), was revolutionary. The Bidirectional Encoder Representations from Transformers (BERT; Devlin et al. 2018) constitute an important improvement in contextual understanding of text data. The epithet "bidirectional" comes from the fact that BERT can see the context of a text both in forward and backward directions. A BERT encoder is used to receive a representation system of a language in combination with the Transformer architecture.

XLNet (Yang et al. 2019), which is based on the Transformer architecture, was introduced in 2019 and outperforms[2] BERT on the problem of multi-label emotion analysis (Kebe, Matuszek, Ferraro 2019: 1) and on a set of twenty NLP tasks, including sentiment analysis (Arslan et al. 2021: 263; Yang et al. 2019). The XLNet model[3] was chosen in this work due to its improvements over BERT. Significant developments also come from Elon Musk's co-founded artificial intelligence projects, such as the OpenAI Generative Pre-trained Transformer (GPT) model.

In predictive analytics, various techniques, such as statistical inference, machine learning, data mining, and information visualization, are applied to forecast, model, and understand a system's future behavior based on historical data (Kumar, Kumar and Tawhid 2021: 2). Text classification means auto-categorizing textual data (Maiya 2022: 2). "Text classification is the most vital area in natural language

[1] Microsoft, IBM Watson, Facebook, Amazon, Intel or Cylance also drive innovation in artificial intelligence.
[2] In terms of precision, recall and F1-score results.
[3] Most of the commented results are based on the XLNet model predictions.

processing in which text data is automatically sorted into a predefined set of classes" (Hassad, Ahmad and Ahmad 2022: 238).

Classifying short sequences of text, however, is still relatively uncommon. Apart from 1) Mondher Bouazizi and Tomoaki Ohtsuki (2017), 2) Timothy Liu, Tong Hui Kang, Chia Yew Ken (2017), 3) Jakub Nowak, Ahmet Taspinar and Rafał Scherer (2017), few researchers describe the effectiveness of short sentence predictions on text. Therefore, I performed automatic text classification using older and newer models on real crisis negotiation transcripts with the help of natural language processing, representing an original topic of research. Previously, Douglas Twitchell et al. (2013) built a method to detect the negotiation outcome (positive versus negative outcome) by mining dialogue speech acts such as "code to comply," "integrate," "question of fact," "statement of fact," "statement of demand," "avoidance," "reject other's demand," and "threat to take action." However, the negotiations studied by Douglas Twitchell (2013) do not represent crisis negotiations.

Another original (at the time of writing) topic of research is represented by religious sentence detection in English based on the "20 Newsgroups" dataset (Mitchell et al. at 1999; Lang 1995) utilized for model training. Religious text classification in English was studied in relation to rude language (toxicity) detection (Abbasi et al. 2022).

The present work is composed of five chapters. Chapter one describes the communication processes that occur during crises. It presents the strategies and techniques invented by negotiation experts and deployed during crisis interventions, focusing on language. Furthermore, it includes a comparison of negotiation and mediation since those terms are frequently used interchangeably, which needs to be corrected.

Chapter two discusses interrogation methods as a special, albeit unequal, kind of negotiation between the interrogator and the other side during crisis situations. One of the goals at this stage is to determine what questions should be asked and which ones should be avoided during that process.

In chapter three, the negotiation process is analyzed from the perspective of emotions. This part shows how emotions shape negotiations, presents the main emotion theories, and studies how emotions are expressed in textual data. Particular emphasis is put on categorical emotional models in modern psychology, where the works of Paul Ekman are the most influential. Anger, fear, joy, and sadness are all frequently experienced during crisis negotiations. Anger is an example of a discrete emotion that is more likely to occur during crises. Sadness, in turn, is typically one of the most studied emotions because of the associated problem of depression that can influence the negotiation outcome.

Chapter four presents the main linguistic theories with a focus on dialogue, discussing selected methods of language analysis in crisis communication. Speech acts crucial to negotiations are also identified, including confirmation, denial, questioning, apology, request, compliment, proposal, thanking, expressing compassion, and instilling confidence. In situations where the goal of communication is considered to be the exchange of information, dialogue and speech acts provide a pragmatic angle on crisis communication forms and functions. On the other hand, the politeness theory focuses on appealing to a person's positive or negative face via speech acts. The theory was introduced by Penelope Brown and Stephen Levinson (1978) and is based on Erving Goffmann's concept of "face" (1955, 1967), which is centered on who backs down in conflict situations and what backing down means. Different strategies exist to enhance one's face, including directive speech acts. Face-threatening acts can be used as well to make a person lose face.

This part of the work also includes a separate analysis of hate speech and offensive language based on the concept of face, as it can influence the subject's self-esteem. Hate speech (cyberhate) is the focus of Łukasz Grabowski (Kopytowska, Woźniak and Grabowski 2017a; 2017b; 2017c). The chapters partly focus on lexical issues, such as the mechanism of figurative language and specialized terminology. Concerning metaphor, the prominent authors analyzed are George Lakoff (1979, 2003) and Mark Johnson (2003). The concepts of hyperbole, sarcasm and jocularity, often present in crisis situations, were also studied.

Chapter five presents nine automated classification tasks performed using six machine learning models: Naïve Bayes – Support Vector Machines (NB-SVM; Wang and Manning 2012), Logistic Regression, FastText (Joulin et al. 2016), Bidirectional Gated Recurrent Unit (BiGRU; Rana 2016), Bidirectional Encoder Representations from Transformers (BERT; Vasvani et al. 2017), and XLNet (Yang et al. 2019). The models' metrics, such as precision, F1-score, recall, macro average, and weighted average, were calculated too. Several popular machine learning text collections (datasets or corpora) exist for model training and testing. Therefore, I adopted the following public datasets for the automated classification of sentences described in chapter five:

1) For sentiment analysis, I used the Internet Movie Database (IMDb; Maas et al. 2011), which was complemented by a Google Natural Language pre-trained API analysis.

2) For emotion detection, I adopted a concatenated dataset which contains data pulled from the "DailyDialog" (Li et al. 2017), "Emotion-Stimulus" (Ghazi, Inkpen and Szpakowicz 2015), and "ISEAR" (Scherer and Wallbott 1994) datasets and was used to classify five emotions.

3) For the detection of rude behavior (toxicity) in sentences, I retrieved the Google's Toxic Comment Classification dataset from Kaggle.com website.

4) For rude question detection (toxicity), I utilized the "Quora Insincere Questions Classification" (Mungekar et al. 2019) dataset.

5) For automated sarcasm detection, I utilized the "Sarcasm in News Headlines" dataset (Misra and Arora 2019).

6) For metaphor detection, I used the "Language Computer Corporation" dataset (LCC; Mohler et al. 2016).

7) For persuasion detection, I used the publicly available "Multilingual Persuasion Detection Dataset" (Pöyhönen, Hämäläinen and Alnajjar 2022).

8) For the detection of religious text, I utilized the public "20 Newsgroups" dataset (Mitchell et al. 1999; Lang 1995).

9) I incorporated a dataset created by Thomas Davidson et al. (2017) for hate speech and offensive language detection. I balanced the dataset so that each class contains 7000 sentences by mining sentences gathered from social media platforms.

10) For so-called suicidal ideation detection, I created a custom-built dataset of 110 989 sentences by mining social media platforms and forums dedicated to depression, which was reduced in size after cleaning.

After the machine learning model has learned from text data, it can predict and categorize new sentences based on past knowledge fed to it. This behavior is helpful to linguists. Therefore, I sought to verify how these models perform in real-life scenarios. The real negotiation dataset used for testing was the Oceanside Police negotiation with Grant Sattaur, whereas the Waco Siege transcript was utilized for comparison purposes. However, before going any further, it is necessary to provide information on the studied negotiations first.

The Waco Siege took place at Mount Carmel in Waco, Texas, between February 28 and April 19, 1993, and represented a negotiation with a religious sect. The Grant Sattaur negotiation took place in 2007 in San Diego and represents a negotiation with a subject (Grant Sattaur) who threatened self-harm. Both presented cases are controversial and are still under debate by experts.

Retrieving the audio tapes of the Oceanside Police negotiation was impossible because incidents over ten years old are purged according to the City Retention Policy, as stated by Cathy Osgan, the Police Records Manager of the Oceanside Police (Osgan 2021). Retrieving the tape would help assess the rude language utilized, as certain rude expressions are removed and tagged as "explicit language" in the publicly available transcripts.

The Waco custom dataset consists of 208 934 sentences, 1 828 648 words, and 23 249 unique words. I used the following tape transcripts downloaded from the Internet: "0," "1–3," "4–9," "10A," "11A," "11B," "12A," "12B," "13–26," "29–31," "33," "36–48," "50–51," "53–142," "45," "149–155," "157–196," "198–219," "221–222," and "223–247." Tape "0" represents the February 28 raid before the fifty-one-day siege that followed.

The Grant Sattaur negotiation consists of 1429 sentences, 15 755 words, and 1028 unique words. Thus, due to its size and the fact that it is a complete, uninterrupted crisis negotiation, this transcript is better suited for a linguistic analysis of results produced by automated approaches. In contrast, the Waco Siege was utilized for comparison purposes regarding selected aspects of the negotiation.

Both transcripts were downloaded from the Internet and cleaned manually, following automated text normalization. The Waco Siege transcripts tapes were cleaned and organized using the Python programming language, regular expressions, and optical character recognition (OCR). Some of the tapes had to be discarded due to bad quality. Then, both negotiation transcripts were split into sentences; a column was assigned to the interlocutors' names and another one to their uttered sentences. After the text was organized and indexed, the machine learning model predicted and tagged (classified or predicted) each sentence with an appropriate category or tag describing its characteristics. Finally, all ten classification tasks mentioned were performed. I formulated the following hypotheses:

1) Enhancing the suspect's positive face is essential to a positive negotiation outcome. In addition, the suspect needs to maintain self-respect and integrity for a positive outcome.

2) Disruptions of the conversation flow lead to negotiation failure.

3) The suspect needs to feel secure in order to establish good communication flow and to prevent him from adopting defensive strategies.

4) The analyzed machine learning models and datasets are adequate to conduct an informative analysis of a crisis negotiation in order to determine key emotions and communication tropes.

5) Religious sentence detection allows to predict potentially religious text sentences. A significant number of sentences referring to this particular use of language may indicate that the person behind the text is a member of a sect or a religious person. By merging categories from the "20 Newsgroups" dataset, it is possible to train a model capable of predicting key features of a text that make such identification possible.

6) The customized dataset for suicidal ideations detection allows to determine if the suspect is potentially affected by a Borderline personality disorder and depressive mood disorder or that the topic of discussion concerns suicidal ideation or depression.

I performed automatic classification using artificial intelligence at the sentence level and exploratory data analysis. Therefore, quantitative methods were applied, as machine learning approaches are essentially quantitative. That was complemented by a qualitative analysis of how specific emotions and other lexical items appear in the text and how they are invoked by the parties involved. The quantitative indicators discussed in this work were analyzed using a statistical method. The exploratory data analysis helped me understand the main features of the text as well as apply proper parameters to the model. Data mining methods and tools were also used to retrieve information from social media sources.

As mentioned, to determine the types of information to collect, knowledge of linguistic methods and tools was essential. The bibliographic method enabled the separation and elaboration of sources, followed by an analysis and criticism of the current literature. To further understand crisis negotiation texts, I performed a linguistic analysis in chapter one, where each sentence of the Grant Sattaur negotiation was manually annotated based on the Verbal Interactional Analysis crisis communication model (Fowler and Devivo 2001). The model includes the following components: "insertion," "tranquilizing," "trust building," "intelligence seeking," "finessing," "squelching," "perpetrator resists," "perpetrator acquiesces," "perpetrator initiates," and "silence and chaos." In addition, I introduced a new category called "casual conversation," which can help indicate that there is an exchange of information in place, the conversation flow is not interrupted, and the subject is, to a certain extent, ready to cooperate and comply.

CHAPTER 1
CRISIS COMMUNICATION MODELS

1. Security, securitology and crisis communication

Securitology was conceived to help measure the level of threats and defense potential with the following formula:

$$\mathbf{S} = f\ (Z_1, Z_2, \ldots, Z_n)\ Po, \tag{1}$$

where **S** stands for state of security, *f* is the function of measuring the level of threats, Z_1 , Z_2 , … Z_n – represents threat 1, threat 2, (…) threat n , and Po – the defense potential (Korzeniowski 2016: 112).

Only the lack of threats to human interests enables the proper functioning of individuals in society (Korzeniowski 2016). Janusz Gierszewski (2017: 249, see annex, Figure 1) argues that humans require seven layers of security to guarantee lasting and sustained development, dignity and freedom from fear and social needs. The notion of safety stems from both subjective and objective observations. For instance, an event can represent real danger given a particular situation, though highly fearful individuals often overestimate the risk. Therefore, the "state" of security is unmeasurable and can be defined as a state and a process (Korzeniowski 2016).

Thus, as an objective state, security can also be perceived subjectively (Korzeniowski 2016). As Tom Cockroft said (2021: 8), we live in an age of increased insecurity and uncertainty, in which public perceptions of crime and insecurity are becoming essential. Moreover, perceptions of crime and insecurity strongly impact social life and public policies to the extent that societies are governed by their perceptions of crime and insecurity (Cockcroft 2021: 8).

For authorities, what is often crucial is the perception of security by society. For that, authorities can look for an illusion of due diligence, and successfully prosecuting some criminal acts reinforces that illusion. Securitology, on the other hand, represents a specialized branch of security or else a sub-discipline of the science of security. Securitology focuses on verbal, para-verbal, and non-verbal cues occurring during a crisis. It includes the tone of voice and body language, which may sometimes take precedence over the words used. Each human being perceives security differently. There are at least four examples of different perceptions of security:

1) insecurity: when the threat is real and the perception of this threat is accurate,
2) obsession: when a slight threat is perceived as significant,
3) false security: when the threat is serious but perceived as insignificant,
4) security: when the external threat is insignificant and the perception of security is accurate (Frei 1977; Korzeniowski 2005: 203; Zięba 2012: 11).

The concept of crisis associated with security comes from the Greek word κρίσις, which can be translated as: settling, deciding, choosing or judging, but also to face something, to argue or to fight (Gawor 2015: 11). A crisis can be defined as a "dramatic, unanticipated threat, with widespread and wholly negative impact" (Sellnow and Seeger 2007: 5). Charles Hermann (1963) identified three characteristics components of a crisis: 1) a crisis represents an unexpected and unwanted event, 2) a crisis poses a serious threat to human life and organizations, and 3) it entails limited time to respond and act. Communicating means sharing knowledge and information between communicating units, such as individuals, organizations, nations, social classes, groups, countries and regions (Rosengren 2000: 14).

Crisis communication, on the other hand, can be defined as an "ongoing process of creating shared meaning among and between groups, communities, individuals and agencies" within the context of a crisis for the purpose of "preparing for and reducing, limiting and responding to threats and harm" (Sellnow and Seeger 2007: 13). Functions of crisis communication are: 1) monitoring potential crisis events, 2) response (planning and managing a crisis), 3) resolution (re-establishing the situation back to normality which requires proper communication procedures), and 4) learning (emerging from a crisis with enhanced knowledge; compare Sellnow and Seeger 2007: 14).

As we saw, crisis negotiations include all conversations taking place in crisis situations, not only by the police or other uniformed services but also by all other individuals endeavoring to communicate with those involved in crisis negotiations or rescue operations. Crisis communication models provide methods of peaceful conflict resolution. We can distinguish two types of security objects. Protection (security) of "whom," which refers to an individual (man) or group of citizens (a small group, society, mankind), or protection (security) of "what"? (Korzeniowski 2016). Linguistic aspects of information that occur during a crisis include:

1) information shared between the security services engaged in actions to solve crisis situations and the victims or perpetrators of crime (two-way communication, see annex, Figure 2), and

2) information coming from the people concerned during a crisis period (one-way communication, see annex, Figure 3).

Contrary to one-way communication, a two-way communication process moves in both directions between sender and receiver. The flow of communication can be improved dynamically through various methods like feedback or information sharing. Crisis negotiations involve two-way communication. As a result, I will go over the negotiator's behavior and tactics. Before analyzing hostage negotiations (I use the terms "hostage" and "crisis" negotiation interchangeably), it is important to define conflict, mediation, and negotiation terms.

2. Communication, conflict and peace

Conflict comes from Latin *conflictus*, which means to clash, to collide, to contend, to fight, to combat, to be in conflict, to be at war argue, or to disagree (Frączek 2018; Latin Dictionary 2023a). Conflict can be considered an escalation of a disagreement between parties that can lead to violence and chaos. Conflict, however, does not always involve fighting (Heitler 1993). Conflict occurs when "conscious, though not necessarily rational, beings, such as individuals or groups, wish to carry out mutually inconsistent acts concerning their wants, needs, or obligations" (Nicholson 1992: 11).

Contrary to functionalists such as Émile Durkheim, conflict theorists such as Karl Marx, Niccolò Machiavelli, Max Weber, Thomas Hobbes and Georg Simmel believe that conflict is an integral part of society and that it is challenging to reconcile after a conflict. For Émile Durkheim, society exists independently of the individuals who create it, so conflict is not an integral part of society.

Interesting points emerge from the field of conflict sociology. Conflict and competition permeate "all areas of social life as a result of people's ongoing struggles to improve their position in terms of material resources, status, and power" (Johnson 2008: 368). Randall Collins concludes that the major division in society is between order-givers and order-takers (Collins 2004). This division represents the basis of society and diversification but is also the primary source of conflicts.

Conflict "constitutes evidence of emotional tension and disturbance between individuals and groups" (Blake 1964: 29). In communication theories, four levels of conflict exist depending on who can is involved in a conflict (Islam 2016: 1): 1) intrapersonal conflict, 2) interpersonal conflict, 3) intragroup conflict, and 4) intergroup conflict[1]. We can divide conflict into "content conflict," where people disagree over an issue, and "relational conflict," where people disagree about one another (Jowett 2007: 34). Relational conflicts lead to negative outcomes more often. Furthermore, we can differentiate conflict according to different styles.

The Conflict Mode Instrument (TKI) is a tool created to measure an individual's response to conflict based on two dimensions: assertiveness and cooperativeness (Thomas and Kilman 2016). Assertiveness can be understood as how much the subject emphasizes his own needs, and cooperativeness as how much the subject cares for and responds to the other side's needs. Competing represents a win–lose approach where the subject focuses on personal goals. Competition is characterized by high assertiveness and low cooperativeness (Shetach 2009: 91). Compromising is the opposite of competing in that it represents a lose–lose scenario where neither party is fully satisfied. Therefore, it requires a moderate level of assertiveness and cooperation (Shetach 2009: 91).

An avoidance tactic is deployed when the subject knows the risk of losing is high. Avoidance is a state in which the subject does not pursue his own goals but, at the same time, does not pursue the other side's goals. It is characterized by a low level of assertiveness and a low level of cooperativeness (Shetach 2009: 91). Accommodation represents the opposite behavior: a high degree of cooperation at the expense of personal needs. It tends to foster long-term relationships with the opposing

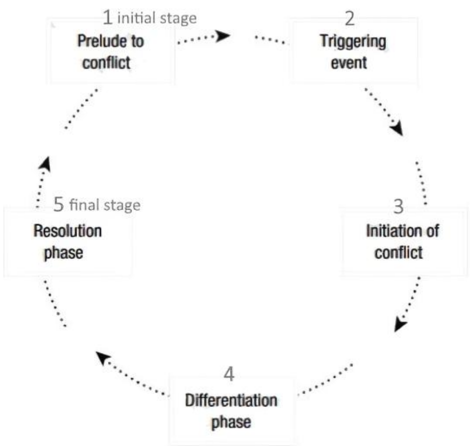
[1] Interpersonal conflict occurs within the person's mind. Interpersonal conflict happens between two individuals. Intragroup conflict is a conflict among individuals within a group. Intergroup conflict is a conflict that occurs between different groups that compete with one another. Further differentiation can be on the object of the dispute that causes conflict.

party. Accommodation entails a low level of assertiveness and a high level of cooperativeness (Shetach 2009: 91).

Subjects may react differently to conflicting interests. Each subject has a different degree of assertiveness and cooperativeness. The competing approach represents the fastest method of conflict resolution, while the collaborating approach is time-consuming and requires a higher degree of trust. Collaboration is a difficult approach to achieve while compromising requires less effort.

A successfully resolved conflict (Cahn and Abigail 2014: 11–13) should move through five recognizable stages, each affecting the next (see Figure 1). These stages are: 1) prelude to conflict, 2) triggering event or conflict stimulus, 3) initiation phase or response, 4) differentiation phase or ongoing interaction pattern, and 5) resolution phase or outcome. The prelude phase has four variables: the type of participants in the conflict situation, their relationship, bystanders, and the social environment (Cahn and Abigail 2014). The triggering event is defined by the parties as the issue, cause, or focal point of the disagreement (Cahn and Abigail 2014).

Figure 1. Five stages of conflict (Cahn and Abigail 2014: 12)



The initiation phase or response happens when at least one person involved makes the other aware that a conflict exists (Cahn and Abigail 2014). The differentiation phase occurs when the people involved use constructive or destructive methods and tactics, going back and forth in the negotiation, presenting both sides of the story, and escalating and de-escalating the conflict (Cahn and Abigail 2014). Finally, the resolution phase occurs when parties accept some outcome of the conflict and finally compromise on some points of the dispute (Cahn and Abigail 2014). Parties typically take a position, argue for it, and make concessions to reach a compromise (Ury and Fisher 1991).

Sometimes third-party intervention is essential to conflict resolution. For example, in arbitration, both parties agree to have the dispute resolved by an arbitrator and commit to the arbitration procedure. Establishing rapport with feuding parties, listening attentively to all sides, and making a decision by acting impartially are all strategies a third party must use to resolve conflict. In addition, a good knowledge of cultural differences and parties' needs is essential. Poor communication transforms latent conflict into violence, while dialogue is the first step toward a positive conflict outcome.

3. The mediation process

Before delving into the main principles of mediation, it is important to define key terms like "mediation," "alternative dispute resolution" (ADR)," "legal basis for mediation," and "mediator." We can derive the following meaning from the Latin language:

1) *mediatio* – intercession, mediation or intervention (Latin Dictionary 2023b),

2) mediate – to settle a dispute through mediation.

Mediation means "neutral," "not belonging to any party," or "intermediary." Medium means "middle," like something that is between or in the middle, whereas *mediare* means "to be in the middle" or "halve, divide in the middle" (Latin Dictionary 2023c). Mediation is an alternative method of conflict resolution where a third party, impartial and neutral, helps the conflicted parties reach an agreement satisfactory to both. Key mediation concepts are:

- "Alternative Dispute Resolution (ADR)" represents alternative dispute resolution methods. This term was coined in the United States in the late 1970s (Frączek 2020).

- "Legal basis for mediation" is a mediation contract or an order of the court directing the parties to a mediation process. It contains a description of the legal rights and obligations of the parties (Frączek 2020).
- The "mediator" is a natural person trained in the mediation process having full capacity for acts of law and enjoying full civil rights (Frączek 2020). Such a person is tasked with conducting the mediation process while remaining impartial and competent, regardless of their profession (Frączek 2020).

A mediator does not try to steer the conversation or manipulate the subjects. Contrary to (crisis) negotiation, mediation is a form of "assisted negotiation" where parties agree to appoint a trained, neutral and impartial mediator to assist them in resolving their dispute (Mediation guide - the basics 2016). Mediation is the resolution of a conflict between two parties with the participation of a third party, i.e., the mediator, whereas negotiation is the resolution of a conflict solely between the parties.

Another difference is that mediation is legally regulated, while (crisis) negotiation is often not. More differences can be found in judicial proceedings. In judicial proceedings, one party always wins, and the other party always loses. This may also be true for hostage negotiations and police interview proceedings. It should also be stressed that mediation proceedings are aimed at dispute resolution, while the goal of judicial proceedings is dispute settlement. In most juridical systems, a mediator is not legally responsible for the outcome of the dispute, while a hostage negotiator might be held accountable for the outcome (Frączek 2020). The main principles of mediation are:

1. Voluntariness – the parties participate in the mediation voluntarily, without being forced to reach an agreement (Douglas H. Y. 1999: 275),
2. Impartiality – the mediator is obliged to conduct the mediation impartially (Douglas H. Y. 1999: 277) without discrimination between the parties. "In the context of dispute settlement, the concept of impartiality is most commonly understood as acting neutrally, without superstitions and prejudices, without any impact on or discrimination between the parties to the dispute" (Tobor and Pietrzykowski 2003: 57),

3. Neutrality – the mediator must remain neutral and ensure that the agreement is reached voluntarily; the mediator cannot force the parties to accept any solutions. A mediator has "no power to impose an outcome on disputing parties" (Douglas H. Yarn 1999: 276),
4. Confidentiality – mediation is confidential, and the mediator cannot disclose any information obtained in the course of the mediation process (Frączek 2020). Criminal offenses are an exception, e.g., under Article 240 of the Polish Criminal Code (Frączek 2020).

Main mediation techniques and guidelines are presented as follows:

1. Going to the balcony – becoming a spectator, watching how the situation develops from a distance, and responding to it with a delay. Going to the balcony allows distancing from emotions and not acting impulsively (Ury 1993: 33).
2. Paraphrasing – the use of one's own words to describe the contribution of the interlocutor (Ury 1993: 47); it is aimed at checking or affirming the belief that the parties understand their words in the same manner.
3. Reflecting feelings – this means that the listening party puts into words the emotions expressed by the speaking party.
4. Appreciation – the goal of this technique is to appreciate the ideas and actions aimed at resolving a conflict; when summing up, one should appreciate an action, not a person, as this would be a violation of the principle of impartiality (Frączek 2020).
5. Focus on small victories– break the conflict down into building blocks. It is easier to reach an agreement, if the conflict is broken down into smaller disputes. Agreements made on smaller issues, if combined, can lead to a general agreement (Priscoli 2003: 50).
7. Golden Bridge – entails drawing the other side in the direction you want them to move by proposing an alternative path to conflict (Ury 1993: 86–87).

The Golden Bridge can be considered one of the most challenging techniques to implement. Here, a settlement agreement should be reached in such a manner as to ensure that both parties maintain their dignity. A mediator should allow the parties to feel satisfied. The parties must feel important, satisfied and appreciated and think they are the authors of the adopted solutions (Jakubiak-Mirończuk 2023: 21). Satisfaction translates into accepting the conflict-solving procedures and the perception that they are fair (Jakubiak-Mirończuk 2023: 21).

In mediation proceedings, once a settlement agreement is reached, both parties have a "sense of victory," because the parties themselves actively decide what the settlement agreement will finally contain. (Frączek 2020). Negotiations arguably provide more successful and practical tools than conflict management or mediation when resolving crisis situations and international disputes (compare Jackson 2000: 324).

4. Negotiation strategies and scenarios

Negotiation is a linguistic process that "entails the communication of propositions between participants" (Gibbons 1992: 156). These propositions represent the relationship between agency and action expressed through language (Gibbons 1992: 156). Most of the studies focus on the outcome of negotiations and non-verbal interactions. Negotiators are trained to learn and read non-verbal communication, like the tone of voice, posture, gestures, facial expressions, and eye movements. As Charles Walcott, Terrence Hopmann and Timothy King have stated (1977: 203):

> "Though negotiation is essentially verbal interaction, the bulk of the empirical literature concerning it does not deal directly with words. Much of the work on bargaining behavior has dealt with non-verbal interaction".

The term "negotiation" comes from the Latin word *negotium*, meaning business, work, activity, or job (Latin Dictionary 2023d). It was borrowed from the trading vocabulary. "Negocjacje," according to the PWN Polish dictionary, are talks or discussions held by authorized representatives of two or more countries, institutions, organizations, or other entities (Encyklopedia PWN 2021). According to the Cambridge University Press dictionary, negotiations are "the process of discussing something with someone in order to reach an agreement with them, or the discussions themselves" (Cambridge 2021). Negotiating entails continuous discussions, deliberations, and the exchange of views and opinions on a particular topic. The negotiator is responsible for the direction of the negotiations.

The negotiator can choose different negotiation strategies, "soft" or "hard" negotiations. The soft negotiator: "wants to avoid personal conflict and so makes concessions readily in order to reach an agreement. He wants an amicable resolution, yet he often ends up exploited and feeling bitter" (Fisher and Ury 1991: 6)[2]. The hard negotiator

"views any situation as a battle of wills in which the side that takes the more extreme positions and holds out the longest fared better. He "wants to win; yet he often ends up producing an equally hard response that exhausts him and his resources and harms his relationship with the other side" (Fisher and Ury 1991: 6).

We can further distinguish principled, cooperative and competitive negotiations (Cahn and Abigail 2014: 231). Principled negotiations are based on principles and standards. Both parties draw on "objective criteria to settle differences of opinion" (Shonk 2021); thus, they do not feel exploited and are likely to cooperate again. In competitive or distributive negotiations, the competitive negotiator sees almost everything as a constant struggle between winning and losing (Cohen 2005: 114). The competitive negotiator gathers as much information as possible about the other side without revealing much information about his plans (Cahn and Abigail 2014). The competitive negotiator does not exhibit weaknesses or make premature concessions (Cahn and Abigail 2014).

Competitive negotiations are characterized by an aggressive first offer, i.e., a high offer. The negotiator is firm in his decisions, but he gradually concedes and exaggerates the worth of his concessions. Furthermore, he conceals facts, argues forcefully, and outwaits the opponent (Cahn and Abigail 2014: 231). The motives of one's actions are not disclosed and are based on bluff and manipulation, just like in poker (Carr 1968: 148–149). In competitive or distributive negotiations, parties adopt a win-lose approach. They aim to reach their own goals, often at the other side's expense.

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2 There is also a distinction between low-power and high-power negotiators (compare Sinaceur et al. 2015: 1851).

During cooperative negotiations, parties aim to reach a common goal or outcome so that both sides can win (Dawson 1999: 298). This strategy involves sharing information and resources. This integrative approach is based on clarity and the absence of manipulation. The motives and assumptions of the parties are known from the beginning. In this case, however, the agreement will likely not satisfy all parties. Realistically we may define three types of scenarios: "win-win" and "win-lose" scenarios mentioned above and the "lose-lose" scenario (Winch and Winch 2010). During a longer negotiation process composed of stages, these scenarios may occur alternately (Winch and Winch 2010: 52).

5. Negotiation characteristics

A negotiation is characterized by the following: at least two parties are in conflict, and there are common interests and conflict issues (Chmielecki 2020: 14–15). Without common interests, there is nothing to negotiate for; without conflict, there is nothing to negotiate about (Chmielecki 2020: 15). Usually, parties enter into negotiations knowingly and willingly. Negotiation is used, e.g., when no dispute resolution rules have been established. At the start of negotiations, each party has its demands, but in the course of the negotiations, compromises are made, and the parties are willing to make concessions. Therefore, negotiations require deep motivation, which might enable parties to reach a satisfactory resolution (Zohar 2015: 541). In crisis negotiations, one party may not enter the negotiation process willingly and may not be motivated to solve the conflict. In addition, one party may not pursue rational goals. Crisis negotiations represent acute stress situations that require flexibility and psychological resilience.

6. Active listening in relationship development

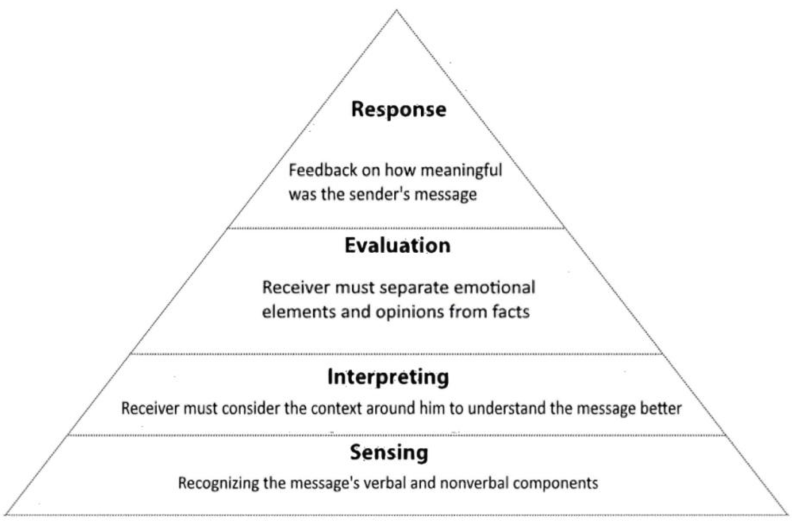
The first wave of negotiation theories revolved around bargaining (mainly in the 80s). Later, more effective methods based on empathy and active listening were developed. As active listening represents one of the key negotiation elements, a more detailed insight into active listening is necessary. Active listening originated from the patient-centered work of Carl Rogers and Richard Farson (Rogers and Farson 1957/2021) following World War II (Strentz 2013: 14).

The Sensing, Interpreting, Evaluating and Responding (SIER) hierarchy of active listening developed in 1982 is represented by a hierarchy of categories with a pyramidal shape. SIER analyzes the active listening processes and can be presented in the form of a pyramid (Steil, Barker and Watson 1982). At the bottom of the pyramid, we find the sensing category. Not only what we utter is important but how we utter something, e.g., "How do we sound when we speak?," "Is our tone of voice convincing?."

Sight is essential for non-verbal communication, accompanied by less important senses such as smelling or tasting, see Figure 2. Another stage of listening in the hierarchy is interpreting; we may interpret a message differently based on past experiences or culture. We may often be under the illusion that a common understanding has been achieved (Steil, Barker and Watson 1982: 21).

"Evaluating" means judging and processing a message. "Sensing," "interpreting," and "evaluating" are internal acts, whereas with "response," we provide feedback to the sender about their message, which helps evaluate the success of the listening act (Steil, Barker and Watson 1982: 22).

Figure 2. Four phases of active listening (based on: Steil, Barker and Watson 1982: 21)



7. Hostage negotiation theory

7.1. The origin of crisis negotiations

Hostage negotiation strategies began flourishing a year after the Munich Olympics incident in 1972. Introducing a field psychologist in 1973 and creating the first NYPD Hostage Negotiation Team represent crucial steps. The legal foundation for hostage negotiations was established in the Downs versus the United States suit following an incident of air piracy on October 4, 1971 (McMains, Mullins and Young 2021: 43; Justia US Law 1974).

In the 1960s, tactical intervention and assault were most commonly used in hostage situations (compare Hancerli 2005: 16). As a result, both hostages and hostage takers were killed during an incident (Hancerli 2005: 16). Although most hostage negotiation theories began to thrive since 1973 (Vecchi et al. 2005), law enforcement agents and hostage negotiation experts, including psychologists, did not necessarily cooperate. Progressively, the number of casualties during crisis negotiations decreased[3] due to improved methods of communication (McClain et al. 2006; Vecchi et al. 2005; Ireland and Vecchi 2009; Vecchi 2009).

7.2. A brief history of recent crisis incidents

Crisis situations between the 1960s and 2010 involved many hijacked airliners, mainly for political reasons (Busch 2016: 23, Aviation Safety Network 2021). This type of incident was gradually reduced due to improved security measures (Busch 2016: 24). From 2004, mainly due to the war in Afghanistan, the abduction of aid workers soared and continues to rise today (Busch 2016: 26; Aid Worker Security 2021). The aid worker incident typically involves kidnap and extortion and happens thirteen times more often worldwide than the barricaded suspect situation (Global Terrorism Database 2021: bar chart).

According to the Global Terrorism Database (2021), from 2010 to 2015, we can observe another peak in "bombing and explosion" and "armed assault," the most common crisis incidents worldwide. Police negotiators are deployed for diverse types of crisis incidents, varying from sieges, natural disasters, kidnappings, extortions,

[3] Tactical interventions in the context of crisis negotiations gradually become rare. After the Munich Olympics, police assaults involving chlorobenzylidene malononitrile (CS) were common. The use of gas was deemed an acceptable form of pacification for close-quarter situations. A large quantity of tear-gas canisters was used during the Branch Davidian Standoff in Waco, Texas, in 1993. Although adults can withstand exposure by wearing gas masks, the Branch Davidian compound had no masks that would fit children (Bunting 1995). CS gas is potentially hazardous when applied in confined spaces (Bunting 1995), which is also proven by an episode of unrest in a Hong Kong Refugees" Detention Centre where police applied CS gas, causing 96 cases of acute burn injury (see Zerki, King and Taylor 1995). The Carandiru prison massacre occurred in 1992 after military police intervention.

suicide attempts, barricaded persons, prison riots, or problems in the domestic sphere[4].

7.3. Crisis negotiation characteristics

Many hostage negotiations revolve around unplanned conflict escalations. For example, 70 percent of home incidents are unplanned (Roush 2002). Around 20 percent of police interventions involve hostage situations (Miller 2021: 278). Crisis negotiation situations are unstable and chaotic during the initial stage. The duration of this stage is usually between 15 to 45 minutes and might involve panic (Miller 2021: 278). The second stage involves either the surrender of the hostage-taker or conflict escalation (Miller 2021: 278). During the second stage, emotions run very high, while rationality is very low on the part of crime perpetrators (Lanceley 1999/2003). Finally, the last stage is the tactical intervention stage, which is necessary if the negotiation fails (Miller 2021: 278).

Typically, the most experienced negotiator will take over after an initial ad hoc negotiator or dispatch unit has established contact. After that, the subject typically negotiates with one person, the primary negotiator. The whole negotiating team, however, is usually composed of a team leader, primary and secondary negotiators, an intelligence and think tank group, a messenger, a guard or tactical team, a chronographer, a radio operator, a tactical liaison, a mental health consultant, and an interpreter (see more Slatkin 2009: 18–20). Most negotiations are complex and involve a wide range of techniques and tactics. They allow little margin for error, and the negotiator must stay concentrated all the time. Hostage negotiators carefully observe if there is a "good vibe" between the negotiator and the other party.

Nowadays, tactical interventions are adopted in situations of "overtly dangerous or assaultive behavior directed toward officers or citizens" and for "suspects wanted on serious crimes" (IACP 2011: 8). Crisis communication models were invented to prevent the last stage from occurring. Tactical interventions are risky and should only be used as a last resort. The most basic goal in crisis methodology is minimizing risks and casualties. Negotiating led to more peaceful resolutions and placed a smaller risk on victims than using direct coercive measures.

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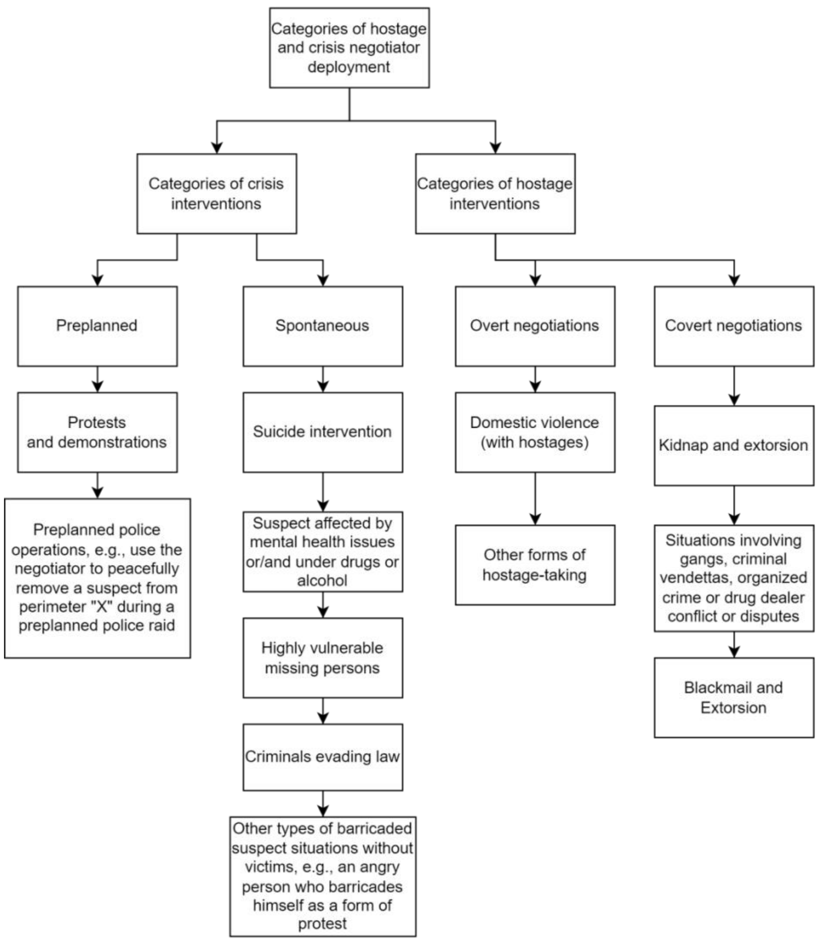
[4] For worldwide statistics on crisis incidents, see annex, Chart 1 and Tables 2–4.

7.4. Crisis negotiation classification

Hostage-taking is the act of holding a person "against his or her own will to be used as collateral in securing certain desired goals" (Richardson 1983; compare Álvarez 2014: 118–119). One of the first classifications divided hostage-takers into: suicidal personalities, vengeance seekers, cornered perpetrators, aggrieved inmates, extortionists, social protesters, ideological zealots, religious fanatics, and terrorists (Goldaber 1979).

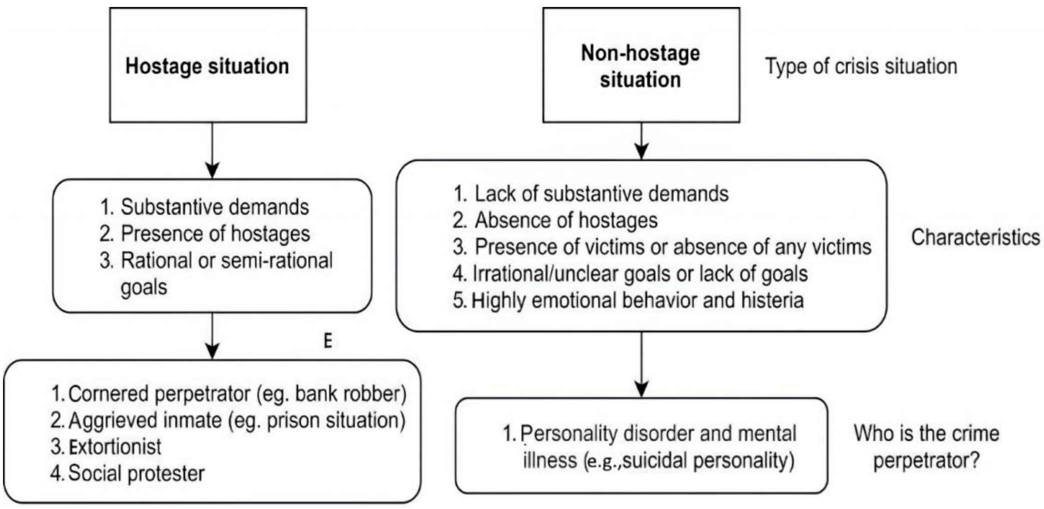
A newer classification divides hostage-takers into: political extremists, fleeing criminals, institutionalized or incarcerated persons, estranged persons, wronged persons, religious fanatics, and mentally disturbed persons (Cooper 1981). A broader definition includes three categories of hostage-takers: the emotionally disturbed, the criminal, and the ideologically motivated hostage-taker (Giebels, Noelanders and Vervaeke 2005: 242). A recent description of categories of negotiator deployment was provided by Amy Grub et al. (2018: 10), compare Figure 3.

Figure 3. Categories of hostage and crisis negotiator deployment (based on: Grub et al. 2018: 10)



Although Amy Grub et al. (2018: 10) distinguish between crisis and hostage negotiations, I prefer the hostage vs. non-hostage crisis negotiation distinction, compare Figure 4. Crisis negotiation should encompass hostage and non-hostage terms as the negotiator interacts with people in crisis. Crisis situations depend on the demands made or the absence of demands (Noesner and Webster 1997).

Figure 4. Hostage and non-hostage situations



Within the hostage negotiation domain, we can distinguish between two types of subject behavior: expressive behavior that can lead to A) expressive crisis situations and instrumental behavior that can lead to B) instrumental bargaining situations (Álvarez 2014). The difference between expressive and instrumental situations lies in the number of parties involved, their behavior, and the presence or absence of substantive demands.

Instrumental behavior is defined as "substantial demands and clearly recognizable objectives that, if met, will benefit the subject" (Noesner and Webster 1997). The absence of substantial demands and objectives characterizes expressive behavior. Thus, expressive, non-hostage situations are situations where the suspect has barricaded himself without hostages and, apart from the demand to be left alone, no substantive demands are made (Álvarez 2014: 119).

Sometimes the subject has some goals and demands, but these goals and demands are unclear or irrational, so they do not qualify as substantive. "If there is no substantive demand, by definition, there is no hostage situation" (Lanceley and Crandall 2005: 5). A vengeance seeker can be "extremely deranged," stalking both real and imagined enemies (Goldaber 1979). Moreover, mentally deranged persons may fire a weapon indiscriminately at other people nearby, who become victims (Di Rito 1992: 2). In this case, the person being held is a victim rather than a hostage (Royce 2005: 6). Table 1 shows the main[5] negotiation techniques that aim to solve hostage and non-hostage situations peacefully that are also presented from section 7.5 onwards.

Table 1. Chosen hostage negotiation models and relevant works

Creator/Creators, Author/Authors:	**Model or major work name on which the model is based:**	**Year:**
Philip Hugh Gulliver	"Gulliver's Phase Model"	1979
William A. Donohue and colleagues	"The Crisis Bargaining Model"	1991
Roger Fisher and William Ury	"Getting to Yes: Negotiating Agreement Without Giving In"	1981
William Ury	"Getting Past No"	1991
Michael McMains and Wayman Mullins (Andrew Young participated in the third edition)	"Crisis Negotiations. Managing Critical Incidents and Hostage Situations in Law Enforcement and Corrections"	1996
Mitchell Hammer	"SAFE. framework"	2001; 2007
Rod Fowler and Paul Devivo	"Analyzing police hostage negotiations: The Verbal Interactional Analysis"	2001
Ellen Giebels	"Table of Ten"	2002
Paul J. Taylor	"The Cylindrical Model of Communications Behavior"	2002
FBI's Crisis Negotiation Unit; (Vecchi, Van Hasselt and Romano 2005)	"Behavioural Change Stairway Model (BCSM)"	1997–2005
Carol A. Ireland, Gregory M. Vecchi	"The Behavioral Influence Stairway Model (BISM)"	2007
Brad Kellin and Meghan McMurtry	"Structured Tactical Engagement Process model (STEPS)"	2007
Paul J. Taylor, Sally Thomas	"Linguistic style matching and negotiation outcome"	2008
Arthur A. Slatkin	"Training Strategies for Crisis and Hostage Negotiations: Scenario Writing and Creative Variations for Role Play"	2009
Gary Noesner	"Stalling for time"	2010
Jeff Thompson, Hugh McGowan	"Talk To Me: What It Takes To Be An NYPD Hostage Negotiator"	2014
Christopher Voss	"Never Split the Difference. Negotiating as if Your Life Depended on It"	2017

7.5. Philip Gulliver's Phase Model

Crisis communication models have been developed to help police effectively respond to crisis situations. These models provide a structured approach to crisis

[5] Arguably, Table 1 shows the most original, influential and established crisis negotiation strategies.

communication and help law enforcement agents manage the flow of information during a crisis. One of the first crisis communication models was elaborated by Philip Gulliver. Philip Gulliver's Phase Model, developed in 1979, mentions a series of important steps:

1) searching for the right place, means and experts,
2) examining the scope of the problem and gathering information (number of hostages, setting),
3) exploring possibilities for cooperation, problem clarification and relationship development, problem simplification, and
4) problem-solving and resolution.

These steps are to be considered an ordered sequence of events or phases. During the first phase, the main concern is finding the right negotiators. During the second phase, negotiators try to understand the nature of the dispute and the initial demands. Negotiators gather information (number of hostages, setting), formulate an agenda based on the motives for the hostage-taking, and identify issues to be negotiated. In the third stage, negotiators try to simplify the agenda. They discard unsolvable and minor issues to focus on significant issues. In the last stage, negotiators try to determine a viable range of acceptable outcomes for both parties. Making concessions is followed by executing one of the demands, like releasing hostages.

7.6. The Crisis Bargaining Model

The Crisis Bargaining Model (Donohue, Ramesh, and Borchgrevink 1991: 1–9) distinguishes between from crisis bargaining to more normative incident management. During negotiations, the model integrates the notion of relationship and substantive issues. Crisis negotiation focuses on solving relational problems rather than focusing only on substantive issues. The focus of spontaneous hostage negotiations should be on relational development (Donohue 2015: 7). Negotiators build positive relationships and establish trust to avoid a deadlock (see Donohue 2016). To gain more autonomy and control, the hostage taker may attempt to detach from both the hostages and his own life (Donohue 2015: 7). The hostage taker may say, "You better do what I ask, or I am going to kill that woman," or "I would rather die than go back to prison." To solve substantive problems, the negotiator should establish communication using particular language: 1) small talk and humor; and 2) expressions of support (Donohue 2015: 7).

7.7. William Ury's negotiation strategies

Although Roger Fisher and William Ury do not focus only on crisis negotiations, their work is highly influential in crisis negotiation strategies. According to Roger Fisher and William Ury (1981), negotiations ought to be based on the following tenets:

(a) do not bargain over positions,
(b) separate people from the problem,
(c) focus on interests, not positions,
(d) invent options for mutual gain,
(e) insist on using objective criteria, and
(f) identifying basic needs.

Setting a position over the object of the dispute is useful as it provides the other side with anchors on which the negotiation is based. However, locking ourselves behind a position and arguing for a position is dangerous because our ego becomes identified with our position, and new interests arise, like "saving face" (a). We thus end up digging in our heels (Fisher and Ury 1981). "Separate people from the problem" means that we should understand that there are real people behind the problem and not just "the other side" (Fisher and Ury 1981) (b). Three basic categories: perception, emotion, and communication, help circumvent these problems:

> "Where perceptions are inaccurate, you can look for ways to educate. If emotions run high, you can find ways for each person involved to let off steam. Where misunderstanding exists, you can work to improve communication" (Fisher and Ury 1981: 55).

The tenet "focus on interests, not positions" means that we should reconcile interests rather than a compromise between positions to find shared interests (Fisher and Ury 1981) (c). We wrongly assume that the other side wants to attack us, and we become defensive. After we focus on shared interests, we discover a mutually beneficial ground. As many negotiators fail to reach an agreement when they might have, or the agreement they do reach could have been better for each side, they should focus on inventing options for mutual gain (Fisher and Ury 1981) (d).

If we negotiate based on "will," negotiating becomes very difficult, and we end up following the maxim "either we back down, or they do." The solution is to negotiate on some basis independent of the will, such as, for instance, on the basis of objective criteria (Fisher and Ury 1981: 116) (e). The negotiator should focus on the basic needs that motivate all people: security, economic well-being, a sense of belonging, recognition, identity (face), or control over one's life (Fisher and Ury 1981) (f). The more people involved in the negotiation, the more difficult it is to satisfy everyone's needs. Ideally, we want to negotiate with one person. William Ury (1993) also presented the following influential tactics:

(1a) stay calm and concentrated,

(1b) use few seconds pause,

(1c) recognize the other side's game,

(1d) take sides with the enemy,

(1e) build a bridge,

(1f) inculcate thoughts,

(1g) summarize,

(1h) apply pressure tactics when necessary,

(1i) think about rewards, and

(1j) prepare.

Negotiators concentrate their efforts on getting the subject to say "yes," which opens possibilities and helps avoid an impasse. The negotiator should focus on the intention in a particular situation. The negotiator should think about the desired outcome and goal once the negotiation is over. As a result, before beginning the negotiation, the negotiator should spend a few minutes alone to remain calm and focused on the goal (Ury 1993) (1a). Allowing a few seconds pause during a negotiation before responding to the subject will help silence one's internal voice and aid more effective listening (Ury 1993) (1b).

The negotiator should suspend natural reactions when responding to the subject's attacks. Instead of responding with counter-attacks, the negotiator should "name the game" and go to "the balcony" to distance himself from the situation and neutralize impulses and emotions (Ury 1993) (1c). "Naming the game" means identifying the underlying strategy being employed by the other side. The negotiator can step back from their emotional reactions and better understand the other person's motives and goals.

Thus, the negotiator should focus on interests and not emotions and on the "Best Alternative to a Negotiated Agreement" (BATNA)[6]. BATNA represents the best option available when we cannot agree with the other side. The negotiator should avoid getting even with the other side but rather pursue his goal. The negotiator should think about the reward to prevent being overwhelmed by negative emotions (Ury 1993) (1i).

The negotiator should take sides and agree with the perpetrator on crucial topics. This tactic is successful because it is relatively difficult to attack someone we agree with (Ury 1993) (1d). The negotiator should establish common ground by not considering the enemy as irrational but as a capable dialogue partner (Ury 1993) (1e). Finally, the negotiator should inculcate thoughts and ideas (Ury 1993) (1f). In doing so, the other side will think he invented them on his own, which makes agreement possible. Summarization helps identify areas of agreement, as well as areas where there may be differences or misunderstandings (Ury 1993) (1g).

Other interesting options are provided by re-framing, which deserves further study. Re-framing helps parties find mutually beneficial solutions. The negotiator should steer attention toward the challenge of meeting each side's interests by re-framing what was said. Re-framing means developing a new way of interpreting a situation (Agne 2007). Negotiators try to make the subject's problem a common problem, so for instance, negotiators use "us" or "we" instead of "you." The negotiator may say: "let us solve this situation together," or "we have a common problem we are trying to resolve" instead of "you have a problem." Each word evokes the so-called "frame picture" in our minds. The negotiator should briefly summarize a fragment of the other party's statement and re-frame it in a more positive fashion.

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[6] The BATNA concept was developed as part of the Harvard Negotiation Project by authors Roger Fisher and William Ury in late 1970s and presented in 1981 in *Getting to Yes*.

However, sometimes re-framing is not enough, and using pressure tactics is necessary. The negotiator can put the other side in a situation where the subject is forced to choose. The negotiator creates a situation where the subject is left with only few options. The negotiator uses these options to educate the subject (Ury 1993) (1h). The negotiator can ask questions and let the other side understand the consequences of not reaching an agreement. The negotiator thus warns the subjects of the consequences instead of threatening the other side. One of the indispensable strategies is preparation (Ury 1993) (1j). Even if there is no time, the negotiators must always find at least a few minutes to prepare and evaluate the situation, goals, and outcomes. Negotiations in which the negotiator is not prepared are characterized by failure.

7.8. The substantive demands, attunement, face, emotion (SAFE) framework

Michael Hammer and Randall Rogan (1996) developed a communication approach combining the bargaining and expressive approaches. Bargaining in this context means the clarification of demands and terms for the exchange of resources. For each concession given, the negotiator would obtain something in return. The expressive approach focuses on emotions and is composed of three elements that the negotiator should be aware of:

a) the presence of hostages that act as tools in the hands of the offender to demonstrate his ability to control others,

b) the fact that the goals of the offender and the negotiator share similar goals as they both want to avoid injury and death, and

c) the fact that hostage negotiations result in increased negative emotions and stress (Lord and Cowan 2010: 251–252).

This communication approach gave birth to the Substantive Demands, Attunement, Face, and Emotion framework (SAFE; Hammer 2001; 2007; Lord and Cowan 2010: 250). SAFE is useful for detecting, measuring, and reporting indicators of a worsening crisis situation (Hammer 2001; 2007). Therefore, negotiators should pay close attention to four dimensions that, if ignored, can lead to conflict escalation:

the substantive frame, the attunement frame, the face frame, and the emotional frame (Hammer 2001; 2007).

The substantive frame represents the instrumental demands of the parties involved. The attunement frame represents the mutual harmonization of interests. The face frame represents the subject's level of identity integrity; the self-image that can be threatened or honored. SAFE responds to the "why" question, e.g., why the subject shifts from one behavior to another. The main strategies of SAFE are: 1) identify the dimensional aspect (frame) that is important to the subject, 2) be flexible and adapt to the respective frame, and if some progress is made, 3) shift to another frame (Hammer 2001; 2007). Shifting to another frame represents changing communicative behaviors.

7.9. Verbal Interactional Analysis

According to Rod Fowler and Paul Devivo, a negotiation can be decomposed into the following elements (Fowler and Devivo 2001: 91):

(a1) insertion,
(a2) tranquilizing,
(a3) trust building,
(a4) intelligence seeking,
(a5) finessing,
(a6) squelching,
(a7) perpetrator resists,
(a8) perpetrator acquiesces,
(a9) perpetrator initiates, and
(a10) other: silence and chaos.

In the introductory phase, the negotiator becomes acquainted with the perpetrator (a1). Next, the negotiator introduces himself and explains the rules. The negotiator might try to calm down the perpetrator (a2). He slowly builds trust and makes cooperation possible (a3). During reconnaissance, the negotiator asks probing questions, gathers information, and examines the situation (a4). Finessing is part of the negotiator's process where the subject is being maneuvered by the negotiator (a5). It is the art of "skillfully maneuvering the perpetrator," which "includes the use of artifice" (Fowler and Devivo 2001: 91). While the use of lies and deceit is allowed, the subject should never feel deceived. Deception is used in negotiations to accomplish two objectives 1) use lies to achieve a goal (e.g., misleading the other side about a wounded person's condition), 2) use lies to deal with a deceitful subject (see more: Rogan, Hammer and Van Zandt 1997: 98–99).

Another situation to avoid is silencing. Silencing represents an undesired negotiator's modus operandi. The negotiator might use reprimands, argue, or lose contact with the subject (a6). Resistance can be encountered during various negotiation stages due to the deterioration of communication between the negotiator and the subject, which often happens due to the negotiator's mistakes. Resistance can manifest itself through demand formulation, taking control of the situation, or behaving erratically due to mental illness or the influence of alcohol or drugs (a7).

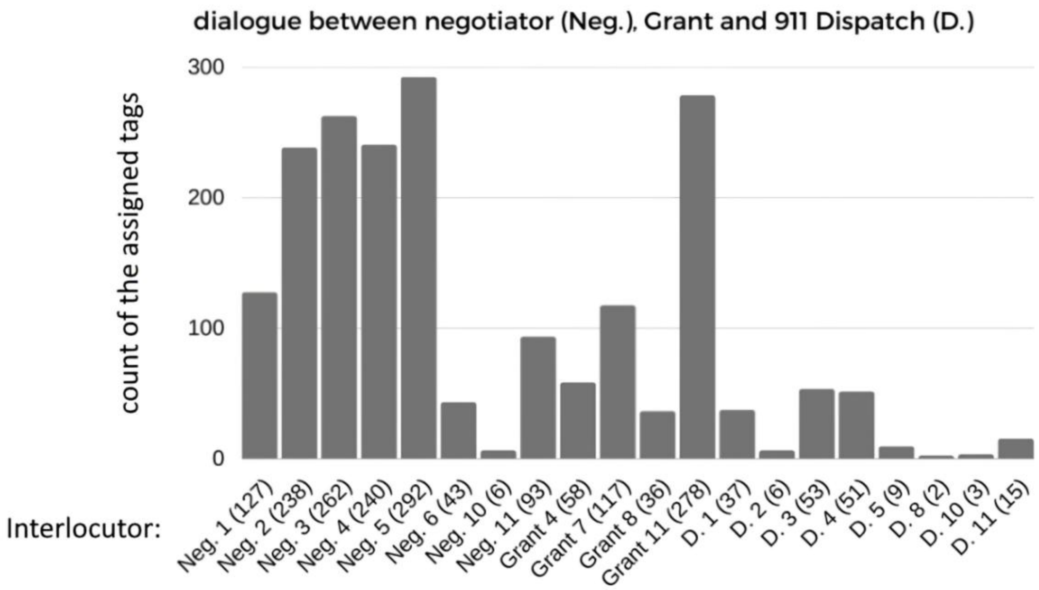
Conversely, an agreement is a desired outcome in which the subject tries to cooperate with the negotiator (a8). Similarly to resistance, silence and chaos (a10) should be avoided. Silence is a state in which nothing productive transpires, at least not on the surface. The perpetrator might also take the initiative at various stages of the negotiation to find a positive outcome through cooperation (a9).

We can summarize the Verbal Interactional Analysis model by diving into the negotiator and perpetrator categories. The negotiator tries to defuse the situation using verbal techniques to: "(1) introduce and structure his/her role in the situation; (2) defuse the perpetrator; (3) establish trust; (4) gather information; and (5) manipulate the perpetrator into a safe resolution of the situation". The perpetrator, on the other hand, might "(7) resist, (8) acquiesce, or (9) help resolve the situation" (Fowler and Devivo 2001: 90–91).

The Verbal Interactional Analysis model makes identifying and tagging sentences in a transcript possible. This method calculates the prevalence of different types of behavior and identifies the negotiator and perpetrator types. In Figure 4, insertion is tagged as N1, tranquilizing as N2, trust building as N3, intelligence seeking as N4, finessing as N5, squelching as N6, perpetrator resists as Grant 7, perpetrator acquiesces as Grant 8, perpetrator initiates as Grant 9, and silence and chaos as N10 or D10. Tags are not mutually exclusive, and a sentence can have multiple tags. I added the category "casual conversation," which is tagged as D11 for 911 dispatch, N11 for the negotiator, and Grant 11 for Grant Sattaur (the suspect). It can take place, for instance, when the perpetrator provides information that indicates that some form of positive attitude or cooperation is taking place, which is better than "chaos," "silence," or "resistance."

Most sentences are tagged as tranquilizing, trust-building, intelligence-seeking, and finessing. Grant Sattaur mainly resisted persuasive attempts but responded to the negotiator and 911 dispatch unit questions. The suspect adopted a defensive stance and refused to comply 117 times. However, 43 squelching attempts were also made by the negotiator by reprimanding, arguing, or losing contact with the subject. Figure 4 shows the results of the Verbal Interactional Analysis model applied to each sentence of the Oceanside Police negotiation with Grant Sattaur.

Figure 4. Tagging the Grant Sattaur negotiation with the Verbal Interactional Analysis model



Legend: 1: insertion, 2: tranquilizing, 3: trust building, 4: intelligence seeking, 5: finessing, 6: squelching, 7: perpetrator resists, 8: perpetrator acquiesces, 9: perpetrator initiates, 10: silence and chaos, 11: casual conversation or small talk. The count of how many times the text was tagged with one of the predefined categories is shown in parenthesis.

7.10. Ellen Giebels" "Table of Ten"

Ellen Giebels analyzed interpersonal influence behavior in crisis situations called the "Table of Ten" (2002). The Table of Ten contains the following tactics:

1) being kind,
2) being equal,

3) being credible,
4) emotional appeal,
5) intimidation,
6) imposing a restriction,
7) direct pressure,
8) legitimizing,
9) exchanging, and
10) rational persuasion (Giebels 2002).

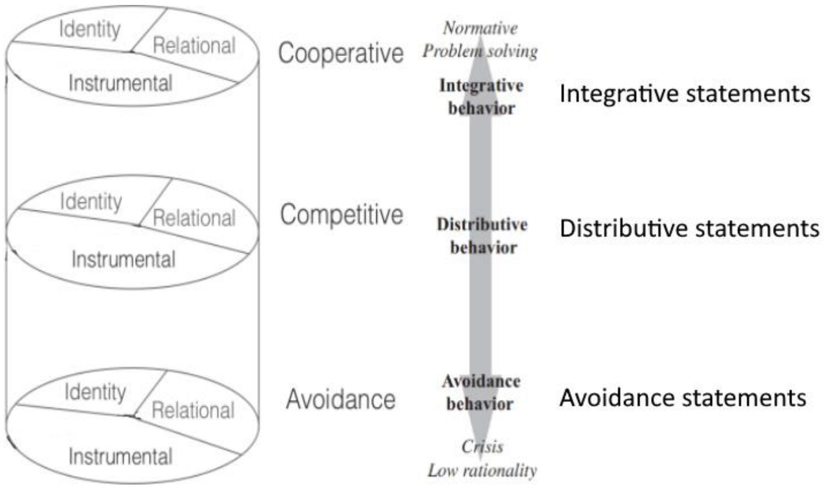
"Being kind" represents friendly and helpful behavior. "Being equal" refers to statements aimed at something parties have in common. "Being credible" means that the negotiator must show expertise or be reliable. With "emotional appeal," the negotiator plays upon the emotions of the other. "Intimidation" means threatening with punishment or accusing the other personally. "Imposing a restriction" means delaying a behavior or making something available in a limited way. "Direct pressure" signifies exerting pressure by being firm and neutral at the same time. "Legitimizing" refers to what has been agreed upon in society or with others. "Exchanging" can refer to a give-and-take behavior, while "rational persuasion" refers to persuasive arguments and logic.

7.11. The Cylindrical Model of Communications Behavior

Paul Taylor (2002: 17) developed the Cylindrical Model of Communications Behavior, which provides interesting insights into the crisis negotiation process. The theory stems from early conceptions of negotiation focused on the dichotomy of integrative (cooperative) and distributive (antagonistic) behavior and incorporates the additional level of interaction of avoidance or withdrawal (Taylor 2002: 9). Negotiations are presented as an interrelated communication component. The complex nature of negotiations is represented through levels of interaction, motivational emphases, and behavioral intensity between participants (Taylor 2002). Negotiation behavior can be graphically represented as a cylinder representing the relationships between these levels, see Figure 5.

Subjects either adopt an avoidant, competitive, or cooperative orientation to interaction and pursue identity, instrumental, or relational goals with different intensity levels (Holtgraves 2014). During different time frames, the dialogue may shift between different cylinder areas and focus on various facets of language. Taylor distinguished between avoidance, distributive, and integrative statements, see annex, Table 10. A lack of trust and engagement is reflected in avoidance statements, which could lead to a withdrawal from the negotiation. Distributive statements aim to take a hard stance by attempting to gain the upper hand in the negotiation. Finally, integrative statements emphasize the importance of finding a mutually beneficial solution and are characterized by a higher level of engagement.

Figure 5. Cylindrical Model of Communications Behavior (Taylor 2002: 17)



7.12. Jeff Thompson, Hugh McGowan, Gary Noesner and Mike Webster's skills and requirements list

Jeff Thompson, Hugh McGowan, Gary Noesner and Mike Webster emphasize seven crisis negotiation skills and eight requirements that, in my opinion, work best with subjects affected by personality disorders (Noesner and Webster 1997: 13–18; Thompson and Mcgowan n.d.). The negotiators should focus on the following elements and mottoes:

(1a) listen more/talk less,

(1b) patience,

(1c) active listening,

(1d) respect,
(1e) calm,
(1f) self-awareness, and
(1g) adaptability (Noesner and Webster 1997; Thompson and Mcgowan n.d.).

Talking less and listening more represents the foundation of a negotiation. The negotiator can use expressions such as "talk to me," which serves the purpose of building rapport and trust and of displaying empathy (1a) (Noesner and Webster 1997: 13–18). Empathy is a core element of negotiations. It is considered essential for social communication, predicting the behavior of subjects, and identifying emotional cues (see Keysers 2012). Empathy is also seen as the "natural" capacity to "share, understand, and respond with care to the affective states of others" (Decety 2012). The negotiator should slow down the communication flow as overwhelming emotions influence the rational thought process (Noesner and Webster 1997: 13–18) (1b).

"Active listening" combines affective and effective skills, where affect is used to build rapport and effect is used to retrieve information (1c). The negotiator should be able to move to empathic listening, which is the practice of being attentive and responsive to others' input during a conversation. This technique is often referred to as the "80/20 rule," as the negotiator should spend 80% of the negotiation time listening and the remaining 20% talking (Hammer 2007).

The negotiator should avoid judging his counterpart and use an appropriate tone and words. He should demonstrate that he cares by being friendly and assertive (1d). As our behavior influences the behavior of our counterpart, being calm is one of the key skills to practice (1e) for two reasons: 1) being calm is a display of confidence, and 2) being calm will make the other side calm as well.

As long as the subject perceives the atmosphere as threatening, no meaningful communication can take place (Noesner and Webster 1997: 13–18). As the negotiator must establish a relationship with a stranger, they must know when it is time to talk, taking into account verbal and non-verbal elements (1f). The negotiator adapts to emotional shifts and topics discussed (1g). Negotiators fixated on negotiation plans tend to ignore alternate paths to a successful outcome. Instead, negotiators should remain vigilant for opportunities (Noesner and Webster 1997: 13–18). Substantive demands are addressed with "strategies of bargaining or problem solving" (Noesner and Webster 1997). Furthermore, negotiators must observe the following communication flow requirements:

(2a) paraphrasing,
(2b) reflecting/mirroring,
(2c) "I" messages,
(2d) minimal encourages,
(2e) emotion labeling,
(2f) summarization,
(2g) open-ended questions, and
(2h) silence/effective pauses (Noesner and Webster 1997; Thompson and Mcgowan n.d.).

Paraphrasing communicates to the other person that you are trying to understand their situation (2a). This negotiation method also helps interpret the situation, slowing the conversation speed and reducing emotional tension. With paraphrasing, we say what we hear in different words with the same meaning. Paraphrasing can be initiated with the use of the sentences below (Seven Active Listening Skills 2018):

"I wonder if (...)."
"It seems like (...)."
"As I hear it (...)."
"Could it be that (...)."
"I gather that (...)."
"You appear to be (...)."
"It sounds like (...)."
"Is it correct to say (...)."
"I guess that (...)."

With mirroring, negotiators repeat the last words or the main idea of the subject's message, which is particularly helpful during the first stages of a crisis situation (2b). This technique is applied to demonstrate interest. The negotiator becomes the subject's partner. Instead of interrogating the subject, which blocks building rapport, the negotiator establishes a non-confrontational presence (2b). Negotiators communicate their feelings in reaction to what the subject said by using "I" messages.

"I" messages help "communicate concerns, feelings, and needs without blaming others or sounding threatening" (see Montemurro 2011). These messages show the negotiator's perspective, which can be leveraged to reduce blame, anger, resentment, accusations and defensiveness (see Montemurro 2011). "I" messages can be used to promote constructive conversations in place of defensive communication. Defensive communication takes place when the subject feels attacked, accused or insulted (see Montemurro 2011).

Through "minimal encourages," negotiators want to demonstrate that they are focused on the subject's words, which can be conveyed via body language or brief verbal replies such as "yes," "Okay," "I understand," or "I can see" (Royce 2005: 10).

In so doing, negotiators slowly take control and maintain a desired conversation flow. Negotiators should avoid words that impede the flow. Negotiators must learn to adapt to dynamic situations, e.g., recognizing the counterpart's shifts from instrumental needs ("I need a car") to expressive ones ("I am so sad"). Thus they include emotional labeling (2e) in order to acknowledge their emotions. Negotiators can state the emotions that are heard during the negotiation:

"You seem upset."
"You sound angry."
"I hear loneliness."
"You sound betrayed."
"You sound anxious."
"I can hear anger in your voice, and it appears like you were also hurt by this situation."

Labeling stems from the idea that people want to have others understand how they feel. Negotiators should focus on capturing the emotions that the other person is feeling and name them accordingly (Noesner and Webster 1997; Thompson and Mcgowan n.d.) (2e). It helps defuse negative emotions or to combat adverse reactions, such as:

"I did not say you were sad. I said you sound sad."

Negotiators should also summarize concluded discussion points. Throughout the negotiation process, negotiators should summarize to ensure that the subject has the same understanding of what has been agreed to so far (2f). Negotiators should try to use open-ended questions and avoid asking "why" questions, which could imply interrogation (2g). Instead, negotiators stimulate the subject to talk through questions such as "Can you tell me more about that?" (Noesner and Webster 1997: 13–18). Negotiators can adopt strategic pauses at suitable times. Subjects tend to fill the gaps in a discussion. Long pauses force the subject to speak to provide more information that may assist negotiators in reaching an agreement (Noesner and Webster 1997; Thompson and Mcgowan n.d.) (2h). Thus, silence is used to provoke a reaction[7].

7.13. Paul Taylor and Sally Thomas mirroring techniques

Paul Taylor and Sally Thomas (2008) found that we can achieve a better negotiation outcome by mirroring the subject's linguistic style and use of words. Their work is one of the first that focuses on linguistic aspects of crisis negotiations. Social distancing is reduced by convergence, which involves becoming the other side by using the same gestures, idioms, and behavioral strategies (Taylor and Thomas 2008: 264). To further increase chances of agreement, we should focus on linguistic matching with the other side, as words reflect the global perception of a situation and "explicit concerns and goals at any moment in time" (Taylor and Thomas 2008: 264). Showing similarities between oneself and the other side can be used to reinforce trust (Ashkanasy 2006).

7.14. Arthur Slatking's list of wants and needs and the key desirable negotiator traits

Arthur Slatking (2009) distinguishes between the subject's wants and needs and the key desirable traits of a crisis negotiator. The subject mainly wants to: 1) feel good about himself; 2) think of himself as a good person; 3) meet his needs without giving up his integrity during and after the crisis; 4) avoid feeling trapped; 5) avoid

[7] An experimental study of prolonged teacher silence demonstrated what happened when the teacher "froze," remaining still and silent for at least one minute. After a few seconds, the class appeared to notice it because the typical routine was disrupted. Next, the students became quiet and still, mirroring the teacher's behavior. After a few more seconds, many students began to react physically by moving in their seats or leaning forward in an attempt to capture the teacher's sounds. During prolonged silence, students became anxious and started to laugh and whisper (Hammer 1976: 73).

responsibility, blame, and consequences of his actions; 6) feel that he matters, that he is liked and that he is in control; 7) be heard, understood and acknowledged, 8) be treated in a fair manner and with respect; 9) put the present situation and pain aside, and 10) be told the truth and understand the situation (Slatking 2009: 3).

Conversely, the negotiator should display self-confidence or assurance (Slatking 2009: 5). He cannot display shock or dismay, especially when facing a demanding situation (Slatking 2009: 5). His nerves and temper should not fray. He should not show his personal feelings unless it is necessary (Slatking 2009: 5). He should be able to communicate thoughts with words fluently (Slatking 2009: 4). He should feel comfortable with himself and display a sincere desire to help (Slatking 2009: 4–5). The negotiator's language should be unscripted, unstilted, and plain (Slatking 2009: 5). The negotiator should be flexible, spontaneous and able to adapt to a volatile situation (Slatking 2009: 5). He should possess a non-judgmental and tolerant view of others as his main goal is to establish a connection (Slatking 2009: 4). He should also be patient and persistent in listening (Slatking 2009: 4).

As far as negotiation strategies are concerned, the negotiator should furthermore: 1) act quickly if the situation demands it and control the environment; 2) make verbal contact with the suspect; 3) slow down the negotiation process; 4) gather intel about the suspect, e.g., learn about the suspect's cultural diversity; 5) learn the other side's language, speech patterns, values, keywords, touchpoints and triggers; 6) draw an initial plan of the negotiation; 7) make the other side understand the reason for the crisis by connecting it to precipitating life events; 8) help the other side achieve small goals first and foster realistic hope; 9) avoid propositions and ultimatums; 10) ignore all set deadlines; 11) help the suspect save face during and after the negotiation; and 12) present positive outcome possibilities (Slatking 2009: 8).

7.15. "Stalling for Time" book insights on hostage negotiations

Gary Noesner's (2010) book "Stalling for Time" provides commented real life examples from which we can extract the following tactics:

1) self-control,
2) project sincerity,
3) do not give a hostage taker anything without getting something in return,

4) minimize casualties and potential charges against the hostage taker,
1) apply the Behavioral Influence Stairway (BISM) model, and
2) stall for time.

Self-control is a critical negotiator skill and represents the "ability to help those around you to keep their cool" (Noesner 2010). Untrained police officers might overreact to words such as "I will kill this kid..." without considering the context or the second part of the sentence, for example, "...if you do not back off" (Noesner 2010). Project sincerity means to make the other side believe that "what you are saying is honest and aboveboard" (Noesner 2010).

The subject needs to address their primal safety and security needs, which can be achieved by establishing a bond. Lies are acceptable, but the negotiator needs to establish trust. For instance, the negotiator might lie that the subject's request will be fulfilled in order to calm the subject. The negotiator should only empower the hostage-takers by making concessions to them after getting something in return. For example, the negotiator might only give the perpetrator something tangible in exchange for releasing a hostage. Concessions can be made depending on the situation's gravity or the suspect's history. The negotiator aims to minimize the consequences the perpetrator will face once the negotiation ends. The subject must be reassured that they will not be hurt if they surrender and be informed that harming someone only aggravates their situation.

A hostage negotiator must avoid unnecessarily confrontational approaches, arrogantly asserting his authority as an FBI agent (Noesner 2010). Instead, the negotiator should apply the Behavioral Influence Stairway (BISM) model principles of empathy, rapport and influence. Most importantly, the negotiator must stall for time, slow down the negotiation process and avoid any rushed decisions. Stalling for time was a key strategy adopted by Gary Noesner when negotiating with Branch Davidians during the Waco Siege negotiation in 1993.

7.16. Christopher Voss FBI tactics

Christopher Voss FBI tactics (Voss and Raz 2017) present some interesting points:

1) show the other side that you are negotiating in good faith,
2) be genuinely interested in what drives the other side,
3) take emotions into consideration,
4) build trust-based influence through the use of tactical empathy,
5) work to deactivate negative feelings,
6) aim to magnify positive emotions, and
7) keep an eye out for "black swans.

Similarly to the previously mentioned tactics, one of the key techniques is to be empathetic, which can be manifested by letting your counterpart know you understand the situation from their side. This puts the negotiator in a better position. The negotiator should avoid thinking that the other side is "crazy." Chris Voss points out that the so-called tactical empathy will influence the amygdala, where fear, suspicion, anger, aggression and distrust reside. The negotiator should focus on trust, comfort or rapport to defuse negative emotions and to be more effective. As the human brain is programmed to be overly negative, being in a so-called good mood reinforces brain activity. It activates internal sources of ideas and makes the other party more inclined to make concessions and be more rational and creative (Voss and Raz 2017).

Furthermore, Christopher Voss recommends always showing respect to your counterpart. Contrary to other negotiation techniques, the aim of the negotiator should not only be to make the other side say "yes" (agreeing on small matters helps with agreeing on bigger ones) but also to say "no," making the counterpart drop their defenses. To achieve this, the following question is asked: "do you want me to fail?" which should force the subject to say: "no, I do not want you to fail." The goal of making the other side say "no" is to provide a different reaction. Last but not least, the negotiator aims to find the so-called black swans or unknown unknowns, which are described as pieces of information that can change the negotiation outcome (Voss and Raz 2017). Being open-minded and discovering the unknown unknowns allows the negotiator to benefit from a wider spectrum of opportunities.

Chris Voss further splits the negotiator type into three categories: 1) aggressive and assertive, 2) analyst (conflict avoidant who often tries to run away, also called the "flight type"), and 3) accommodator (relationship-oriented) who tries to reconcile and be friendly (Voss and Raz 2017), which I believe to be similar to the mentioned

Conflict Mode Instrument (TKI; Thomas and Kilman 2016) styles: competing, avoiding, accommodating, compromising, and collaborating.

7.17. Stairway models of crisis negotiation

Models based on so-called stairways or steps can be analyzed separately. The Behavioral Change Stairway Model (BCSM), developed by the FBI's Crisis Negotiation Unit, is a relationship-oriented process that culminates in a peaceful settlement. Most hostage negotiation techniques stem from BCSM or any influenced by BCSM. The BCSM model comprises five stages: active listening, empathy, rapport, influence, and behavioral change. BCSM responds to "how" and "what" questions, e.g., what the negotiator can do to convince someone or how he can trigger behavioral change.

Active listening" is described in terms of the uses of "emotional labeling," "paraphrasing," "mirroring," "summarizing," "effective pauses," "minimal encouragers," and "open-ended questions" (Royce 2005). Progression through these stages occurs sequentially and cumulatively (Vecchi, Van Hasselt and Romano 2005: 541) and requires time. The negotiation progresses up to the last step, the suspect's behavioral change, see Figure 6.

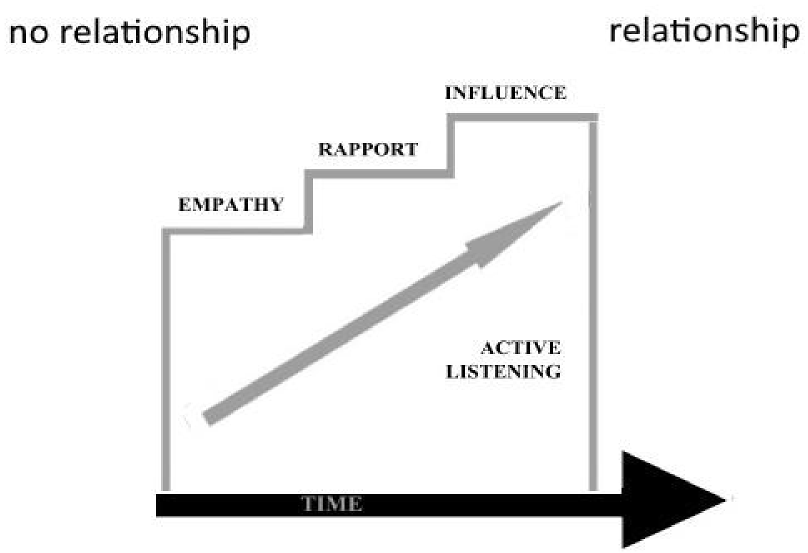
Figure 6. Behavioral Change Stairway Model (BCSM; Vecchi, Hasselt and Romano 2005: 542)

A four-phase model was also created on the basis of BCSM and contained only four steps (Madrigal, Bowman, and McClain 2009). The 1) first phase entails establishing a dialogue with the suspect and takes the suspect's hostility into account, the 2) second phase focuses on building rapport and personal relationship, the 3) third phase focuses on influencing (making suggestions, making promises, or re-framing the situation to de-emphasize negative outcomes of surrender), the 4) fourth phase is dedicated to ensuring that the surrender of the suspect is conducted safely (Madrigal, Bowman, McClain 2009: 129–130).

The Behavioral Influence Stairway Model (BISM) represents a slight variation of the BCSM model (Vecchi, Van Hasselt and Romano 2005; Vecchi 2009; Van Hasselt, Romano and Vecchi 2008). It also focuses on influencing behaviors through a behavioral staircase. BISM, according to Gary Noesner (2010), is composed of the following systematic and intertwined elements:

1) listen to show interest,
2) respond empathetically to slowly build rapport, and
3) use your influence to show alternatives to violence. It does not accrue automatically, but it must be slowly earned through listening and building rapport.

Figure 7. Behavioral Influence Stairway Model (BISM; McDonald 2014)



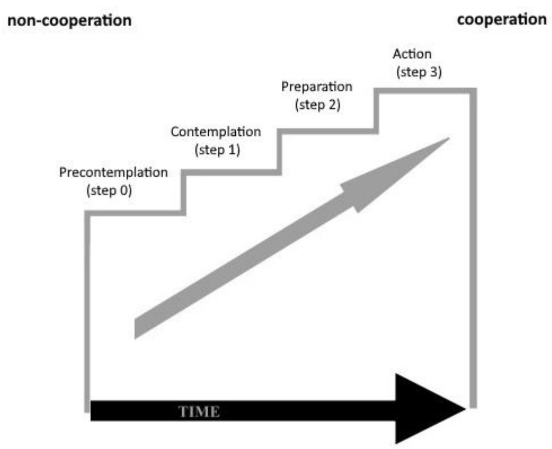
Contrary to BCSM, BISM is composed of only empathy, rapport, and influence steps, during which active listening must be practiced (Ireland and Vecchi 2009: 206–207), see Figure 7. It is a process focused on building a positive and trusting relationship between the negotiator and the other side (Ireland and Vecchi 2009: 206–207). This relationship should culminate in a peaceful settlement. Less importance is placed on problem-solving, which can lead the perpetrator to a rushed resolution (Ireland and Vecchi 2009: 206–207).

During the last stage, reached only if the conditions of the other stages are met, the other side changes behavior from non-cooperative, with no relationship between the negotiator and the other side, to cooperative, characterized by a developed relationship between the negotiator and the subject (compare Figure 7).

A similar stairway strategy can be found in the works of Brad Kellin and Meghan McMurtry (2007), who conceptualized the Structured Tactical Engagement Process (STEPS). To reach a satisfactory outcome during a crisis scenario, you must adopt step-specific strategies (see Figure 8):

1) pre-contemplation (step 0),
2) contemplation (step 1),
3) preparation (step 2), and
4) action (step 3).

Figure 8. Structured Tactical Engagement Process model (STEPS; Brad Kellin and Meghan McMurtry 2007)



Step 0 is characterized by reluctance, hostility, or anger towards the negotiator. The subject is unable to resolve the situation peacefully. The anger and defensiveness of the subject in step 0 can shift towards mounting anxiety and concern, and the subject becomes more talkative. In step 1, the subject might provide explanations and apologize to the negotiator. The subject realizes he must change his behavior but lacks the means or courage to do so alone. In step 2, the negotiator gives the subject hope and confidence that together they can resolve the situation by cooperating and formulating a plan in step 3. Finally, the subject should follow the agreed-upon plan for a peaceful surrender in step 4. To reach the last stage, culminating in behavioral change and a positive outcome, we must first advance through all the previous steps, which require psychological and behavioral commitment.

8. Common reasons of negotiation failure

Aggression, compliance, and inadequate preparation can all lead to negotiation failure (Opresnik 2013). Exerting pressure and lacking flexibility lead to similar results (Opresnik 2013). Pressure produces counter-pressure, which can lead to undesired results. Exerting too much pressure can, for instance, lead to an escalation of conflict. Pressure exerted through aggressive tactics can lead to conflict escalation or an impasse (Allred 1997: 178). On the other hand, defensive and submissive negotiators can also make concessions that are too generous (McCarthy n.d.). The most important indicators of aggression are (see Stawnicka 2014; 2016):

1) raising the voice or shouting,
2) accelerating the speech rate,
3) interrupting the interlocutor,
4) sharp (poisonous, commanding) tone,
5) irony, combined with laughter,
6) prolonged silence (the subject does not speak at all),
7) mocking and distorting words,
8) negative evaluation of the person conducting the negotiation, and
9) the use of face-threatening acts (FTA).

Another mistake negotiators make is seeing their own side as "more intelligent, skilled, reasonable, and moral" than the other side, making it difficult to build relationships (PON Harvard Staff 2022). In interpersonal conflicts, negotiators tend to devalue the interests of their counterparts (Mejer et al. 2021). Given the different situations he faces, a negotiator will often make mistakes. Jochen Reb (Reb et al. 2006) investigates various responses to reconcile with the other side after a mistake, such as providing an explanation or monetary compensation and apologizing.

Since trust is a core component of relationship development along with active listening, the consequences of distrust are: 1) withdrawal from cooperative behavior called defensive non-cooperation and 2) intense adverse reactions individuals experience when they believe they will be treated unfairly (Liu and Wang 2010). As the crisis negotiation is a dynamic process, parties that lack flexibility will find it challenging to adapt to changing circumstances. Much depends on the negotiator traits[8] and the other side's traits. An inadequate personality is "likely to begin negotiating by making excessive demands" (Strentz 1983). Knowing the subject, planning, preparing, rehearsing, role-playing (Van Hassel, Romano and Vecchi 2005: 545–547), and setting achievable goals helps crisis negotiations become less chaotic.

9. Negotiating with difficult subjects and groups

9.1. Negotiating with borderline subjects

Difficult, out-of-the ordinary negotiation subjects require particular tactics, strategies, and language to be observed. Some hostage negotiations represent out-of-the-ordinary situations. Hostage negotiations that deal with personality disorders or mentally ill subjects, as well as religious groups or terrorists, represent more difficult encounters that require specialized procedures mentioned earlier.

Emotionally Unstable Personality Disorder (EUPD) or Borderline Personality Disorder (BPD) are very common types of personality disorders[9]. Borderline personality disorder (BPD) frequently co-occurs with depressive mood disorders (Bateman and Fonagy 2015: 792). Borderline subjects exhibit poor control over their emotions and impulses, and they often engage in potentially self-damaging high-risk activities throughout the negotiation process (Borum and Strentz 1992: 9).

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8 A key element of successful negotiations is the negotiator's emotional intelligence (EI). Research shows that personality, decision-making style, emotion regulation and emotional intelligence are intertwined (Grubb and Brown 2012: 5). Emotional intelligence (EI), a key negotiator feature, can be decomposed into: 1) self-awareness, 2) self-management, 3) self-motivation, 4) empathy, and 5) social skills (Goleman 1995; 2000; Goleman and Boyatzis 2002). Negotiator employment history often represents a predictor of successful versus unsuccessful negotiations (Herndon 2009: 265).

9 The American Psychiatric Association (APA) describes a personality disorder as a collection of long-term character traits that significantly interfere with an individual's ability to relate to others or function in a job (APA Dictionary of Psychology 2021). These traits generally cause considerable personal discomfort and anxiety. Personality disorders are "a group of disorders involving pervasive patterns of perceiving, relating to, and thinking about the environment," and the self that interferes with the "long-term functioning of the individual and are not limited to isolated episodes" (APA Dictionary of Psychology 2021). There are ten types of specific personality disorders organized within three clusters: 1) Cluster A that includes paranoid, schizoid, and schizotypal, 2) Cluster B that includes antisocial, borderline, histrionic, and narcissistic, 3) Cluster C includes avoidant, dependent, and obsessive-compulsive (APA Dictionary of Psychology 2021).

The borderline individual "must be kept as calm as possible, and excess activity around the scene must be eliminated" (Borum and Strentz 1992: 9). Particular emphasis should be placed on empathy and rapport-building strategies. Borderline subject may be affected by drugs and repeat the same phrase over and over that include swear words and acts of threat, e.g.:

"Fuck off! Do not come close or I jump" (Young 2020)

If the law enforcement agent is patient despite the aggressive language, the drugs will wear off, and the subject may want to get a reward for complying. We also buy time to let reason replace emotions (Strentz 2011: 142). We often feel the urgency to do something, but the best option is to wait and be patient (Young 2020). Subjects will likely resist what the negotiator says at the beginning, as they intend to harm themselves (Cleveland, Kevoe-Feldman and Stokoe 2022). For example, a borderline suicidal subject will often exhibit destructive, non-cooperative behavior by saying:

"Leave me alone."
"I want to be alone."
"Go away."
"do not come any closer" (Young 2020).

In that case, the negotiator should respond:

"I have never been in your situation before, but I imagine you must be feeling
very depressed and lonely" (Vecchi, Hasselt and Romano 2005: 539).

In this example, the negotiator named the emotions and moods the subject experiences. During the initial phase, we wait or, if possible, establish contact to keep the subject busy. It is unlikely that the subject will kill himself while engaged in a conversation. "Why" questions are productive for getting people in crisis to talk (Cleveland, Kevoe-Feldman and Stokoe 2022: 115). In the beginning, we should ask the subject directly about his intent:

"Are you thinking about killing yourself?"

The subject might say:

"No, I was not, but hearing you say it makes it sound like a good idea" (Strentz 2011: 140).

Although this answer does not sound comfortable, it is better than a "no" answer. This answer means that the "subject trusts the negotiator enough with his or her emotions" and is honest with the negotiator (Strentz 2011: 140). It is also advisable to listen to all the problems the subject has. At the end of this narrative, the negotiator might conclude the story by saying:

"Oh my God, if I were you, I would kill myself !" (Strentz 2011: 142).

The role of the negotiator is to instill doubt and suggest an alternative to what the borderline subject was set to do. The subject does not agree to come down but intends to do so. It turns out that negotiators can use this intent productively to shift the subject's intentions towards a more positive outcome (Cleveland, Kevoe-Feldman and Stokoe 2022: 3). The negotiator may productively get a person in crisis, at least momentarily, to choose safety over harm, by challenging the subject's terms of resistance (Cleveland, Kevoe-Feldman and Stokoe 2022: 203). The negotiator can provide moral reasons to choose life and return to safety that the subject cannot refute, e.g., by saying: "Okay. But don't you think that the baby is a good enough reason not to jump off that bridge?" (Cleveland, Kevoe-Feldman and Stokoe 2022: 118).

9.2. Negotiating with terrorists

A terrorist might formulate substantive demands and take hostages, or his only intent might be to harm and punish accidental victims. When dealing with subjects such as terrorists, many times, the role of the negotiator is to gather information leading to an assault rather than to solve a conflict. Terrorism can be defined as "acts of violence intentionally perpetrated on civilian non-combatants with the goal of furthering some ideological, religious, or political objective" (Borum 2021). Negotiating with terrorists is difficult because their demands are often too broad or extreme. "Total terrorists" do not think beyond their immediate goals and are, therefore, willing to die. Similarly, "conditional terrorists" make the negotiation difficult because their demands are beyond the possibilities of the negotiator (IIASA Policy Brief 2009).

"Conditional terrorists" want to achieve a goal without necessarily sacrificing their lives. In such a scenario, the negotiator's task is to identify the correct type of terrorist ("total" versus "conditional") and, when the "conditional terrorist" is identified, reduce the demands to achievable goals or change the terms. There is also a third type of "contingent terrorists" (IIASA Policy Brief 2009). A key difference exists between "contingent terrorists" and other types of terrorists. "Contingent terrorists," such as kidnappers, usually do not have idealistic goals. "Contingent terrorists" are similar to "conditional terrorists" because we can negotiate with them and find a positive outcome.

9.3. Negotiating with ideological zealots and religious fanatics

When negotiating with so-called firm believers or religious fanatics, the best strategy is to avoid arguing on issues regarding their system of beliefs. Negotiators know how to solve conflicts over material goods; if the "divide the pie" approach does not work, they try to "expand the pie" by extending the negotiations to other areas, such as the social world, to reach a social agreement (Docherty 2001: 30–31). While most people, including negotiators, are able to recognize material and social facts, they tend to ignore symbolic facts. Jayne Docherty says that "human symbol-creating and symbol-using activities are deeply embedded in the acquisition and use of language. Because their native language is acquired developmentally, most people rarely recognize the impact of symbolic reality on human interactions" (Docherty 2001: 32).

Negotiating in the symbolic world is thus counterproductive. Negotiators can only negotiate in matters of the "material" and "social" worlds but not the "symbolic" world (Docherty 2001: 32). Arguably, similar difficulties may arise with subjects that represent different cultures. Gary Noesner's (2010) strategy in the Waco standoff negotiation with the Branch Davidians was to look only for similarities and areas where connections could be made and try to exploit them (Safier 2020).

CHAPTER 2

INTERROGATION AND INVESTIGATIVE INTERVIEWING COMMUNICATION METHODS

1. Interrogation and interview models

Examining some of the interviewing and interrogation strategies and tactics as information-gathering techniques is helpful as these methods have aspects in common with negotiations. Interrogation is "merely a special kind of negotiation, albeit an unequal one where the interrogators – who wield great power over the process and the interrogatee - are trying to negotiate the release of information from the interrogatee (...)" (Sharma 2019). The P.E.A.C.E. model, an acronym for P- Planning and Preparation, E-Engage and Explain, A-Account, C-Closure, and E-Evaluate, provides valuable insights into investigation and interview process. In an investigation, In an investigation, interviews acquire information by asking open-ended questions and allowing the witness to provide the evidence (Investigative Interviewing a practical guide for using the P.E.A.C.E. model 2020: 3).

Interrogations, on the other hand, are designed to extract a confession, sometimes in the absence of any other corroborating evidence (Investigative Interviewing a practical guide for using the P.E.A.C.E. model 2020: 3). Interrogation is the process of systematically questioning the other side to elicit helpful information related to a suspected crime. Another difference between interrogation and an interview relates to the type of questioned person. We typically interrogate suspects, while an interview encompasses a broader spectrum of persons such as witnesses and victims. In addition, interrogating victims requires additional skills and experience, as mistakes interrupt the interview process (see more Acquaviva et al. 2013: 645).

An interview can be considered a non-accusatory initial stage that can lead to an interrogation. Agents conduct interviews when they still need to learn the answers to the questions they are asking. Moreover, the interviewing stage requires patience and time. It should be remembered that giving testimony often has irreversible consequences for the interviewee. Therefore, it is not advisable to rush the interviewing or the following interrogation stage, which may result in failure. Interrogation requires good knowledge of psychology but also excellent preparation of the evidence. The interrogator must be able to operate with facts well and look for testimonial inconsistencies. The better the interviewer is prepared, the greater his advantage over the interrogatee is. Unfortunately, the elicited information is not always accurate. Two main factors have been linked to the false confession problem: personal or psychological vulnerabilities of the individual and the use of accusatory interrogative methods based on psychology (Meissner et al. 2012: 1–53).

Investigative interviewing was created to symbolize police interrogation, moving away from a confession-oriented strategy toward evidence collection. A 2009 study found that "innocent people are sometimes induced to confess to crimes they did not commit as a function of certain dispositional vulnerabilities or the use of overly persuasive interrogation tactics" (Kassin, Appleby and Perillo 2010: 1). In North America, for instance, 631 police investigators surveyed acknowledged that about 4.78% of innocent people confessed during interrogation (Kassin et al. 2007).

Old interviewing techniques used unacceptably high levels of close-ended questions, while new techniques focused on open-ended questions. Open-ended questions gather preliminary information and ascertain the other side's involvement in a crime. Utterances in open-ended questions can start with an adverb, functioning as an adjunct in clause structure: "what?," "who?," "where?," "when?," "how?," "which," and "why?." Closed-ended questions lead to short responses, which the interrogator tries to avoid during the initial stage. Closed-ended questions provide less information than open-ended questions because possible responses are pre-set. Typical verbs that lead to an open-ended response are "tell," "explain," "elaborate," "say," "talk," or "describe."

One of the most controversial questions asked during interrogation is the so-called misleading bait question or hypothetical question about the evidence. "Such questions can distort peoples' memory for what evidence exists in a case" (Crozier, Luke and Strange 2019). They are formulated in such a way to suggest the existence of evidence that may not exist. These questions aim to provoke the suspect. Although the impact of the presence versus the absence of misleading bait questions is difficult to asses, subjects exposed to misleading bait questions exhibited a higher rate of guilty verdicts (Crozier, Luke, and Strange 2019: 3). Misleading bait questions also caused jurors to commit memory errors about the evidence regardless of race or age (Ascheri 2018). Interrogations represent a stressful process for both the interviewer and the interviewee. Three groups of defense strategies suspects use to cope with this stressful situation:

1) rational strategy,

2) emotional strategy, and

3) irrational strategy (Matysiak 1978: 23–29).

By following the rational strategy, the suspect denies all allegations without hesitation. He is confident and, at the same time, has a well-prepared defense plan and alibis. His strategy is to wait through the interrogation. The emotional strategy is characterized by the aggressive and expressive behavior of the suspect who negates all allegations or refuses to provide information. The suspect sometimes pretends to be mentally ill in order to avoid liability. The third irrational strategy is characterized by the fact that the suspect firmly denies all allegations, but these denials are accompanied by emotional instability and memory loss. Interrogations and interviews represent two-way communication between the investigator and the suspect. Below, I present a selection of investigative interviewing models ordered by date (see Table 1).

Table 1. A selection of interview and interrogation techniques

Creator/Creators:	Model or major work name on which the model is based:	**Year:**
Central Intelligence Agency	"KUBARK Counterintelligence Interrogation Manual"	1963
John E. Reid and Associates	"J.E. Reid's Nine Steps of Interrogation" (Reid)	1974
Collaborative effort between law enforcement and psychologists	"P.E.A.C.E. Model of Investigative Interviewing"	early 90's
Stan Walters and Associates	"The Kinesic Interview method"	2003
John Schafer, Joe Navarro	"Advanced Interviewing Techniques: Proven Strategies for Law Enforcement, Military, and Security Personnel"	2004

1.1. The KUBARK manual

The KUBARK manual[1], declassified in 1997, contains coercive elements that are not applicable by today's standards. One of this technique's critical elements was

[1] The KUBARK manual was issued by the US Central Intelligence Agency (CIA) in 1963. The CIA used the cryptonym KUBARK for this manual or "KUBARK Counterintelligence Interrogation Manual".

maximizing helplessness by inducing high levels of stress and maximum mental and physical discomfort. It was discredited as having "offensive and objectionable material" (Reyes and Basoğlu 2017). KUBARK is based on psychology: the interrogator first identifies a victim's sense of self and then destroys it through torture and pressure tactics. CIA's harsh techniques that authorize torture are still practiced, as there is evidence of "questionable confessions and the death of a detainee since the techniques were first authorized in mid-March 2002" (Ross and Esposito 2008). Nevertheless, some of the insights of KUBARK are applicable today.

KUBARK postulates, for instance, that "interrogation is defined both by its intensely interpersonal nature and intractably shaped by the unique personalities of the interrogator and the source" and that "each interrogation is unique and therefore one must be cautious about trying to apply a strategic template that would prove effective in each case" (Kleinman 2016: 139). Every interrogation thus is an "intensely interpersonal process" (The Central Intelligence Agency 1963). As interrogation represents a complex process, practitioners of interrogation must undergo extensive training and supervised experience (Kleinman 2016: 139). Furthermore, non-verbal communication is emphasized.

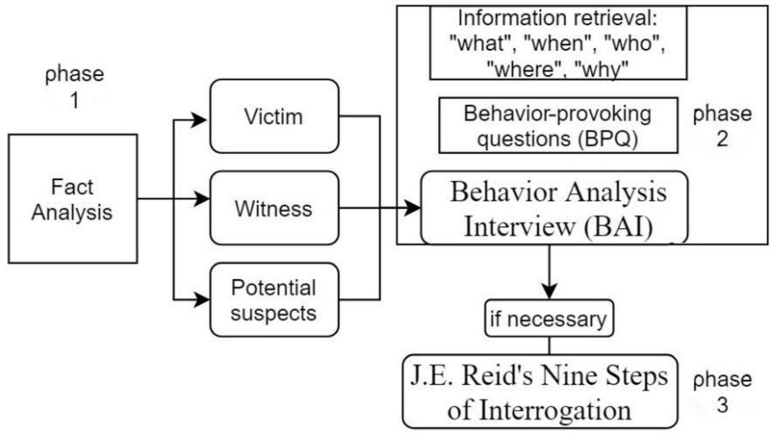
1.2. John Reid's Nine Steps of Interrogation

Apart from KUBARK, another technique considered controversial, albeit to a lesser extent, is Reid's Nine Steps of Interrogation (Reid). Reid, a common technique in the US and Canada, was created by John Reid and associates. It involves three phases (see Orlando 2014):

1) factual analysis,
2) interviewing, and
3) interrogation.

During the factual analysis, we determine who should be interviewed (see Figure 1). It can be the victim, a witness, or a suspect. The factual analysis relies on crime scene analysis and the information learned about each suspect. During this phase, the suspect, as well as physical and circumstantial evidence, is evaluated.

Figure 1 - J.E. Reid's three phases of interrogation



As we can observe from the graph, Reid is more than an interrogation. The factual analysis seeks to verify the suspect's: 1) bio-social status, 2) opportunity and access to commit the crime, 3) behavior before and after the crime, and 4) motivations and propensity to commit the crime (see Orlando 2014). Interviewing consists of a non-accusatory question-and-answer session. It is described as Behavior Analysis Interview (BAI). During BAI, personal information is first collected. "What," "when," "who," "where," and "why" are clarified. After information retrieval, the investigator asks questions intended to provoke verbal and non-verbal responses.

Typical behavior of both truthful and deceptive subjects is reticence, nervousness, impertinence, anger, despair, and resignation. We should often look for the intensity of felt emotions as the "guilty subject will display greater and more reliable symptoms when questioned about a rape than when questioned about a petty theft" (Inbau et al. 2015: 170). A difficult behavioral reaction to evaluate is anger. Investigators should be aware that a guilty person's "anger" is more easily appeased than the persistent anger of an innocent person (Inbau et al. 2015: 169). Behavior-provoking questions (BPQ) allow for distinguishing between truthful and deceptive suspects. Fourth, the interrogator presents facts and evidence to increase discomfort.

Contrary to the last step, BAI represents a non-accusatory and non-confrontational process designed to find objective facts and investigative information. We proceed to interrogation only if necessary, BAI thus acts as a filter. The interrogation will occur if the investigator is confident of the suspect's involvement in a crime. Interrogators should proceed to the "Nine Steps" immediately since a suspect is most vulnerable to interrogation following the interview because he is worried that the investigator detected his deception (Inbau et al. 2015). "J.E. Reid's Nine Steps of Interrogation" are deployed gradually during interrogation (see Orlando 2014):

(a1) positive confrontation,
(a2) theme development,
(a3) handling denials,
(a4) overcoming objections,
(a5) procurement and retention of suspect's attention,
(a6) handling the suspect's passive mood,
(a7) presenting an alternative question,
(a8) having the suspect orally relate various details of the offense, and
(a9) converting an oral confession to a written confession (documenting).

With positive confrontation, the investigator informs the suspect that the evidence proves his guilt (Orlando 2014) (a1). The declaration should be made unambiguously if the evidence against the suspect is strong. Then, in a monologue, the interrogator blames the crime on external circumstances or other persons. The technique starts with a confrontation, and after an evaluation of the suspect's response and behavior, the interrogator proceeds to explain the importance of telling the truth (Lord and Cowan 2010: 228). The interviewee's reactions are observed from a close distance using several seconds of pauses. If the person does not promptly deny the accusation, avoids eye contact, or behaves passively - this behavior is treated as a potential indication of the perpetrator's guilt. There is also a greater suspicion of deceit when there are too many denials (compare Vrij 2004). This assumption can lead to false accusations (Vrij 2004).

The next step introduces theme development. During this step, the investigator helps the suspect develop a theme (Orlando 2014) (a2), which helps shift the blame away from him (Black and Fennelly 2021). We also observe to which theme the suspect is responsive (Black and Fennelly 2021). Criminals try to diminish the consequences of their behavior, e.g., "I hit him, but it was not a strong blow," "I did not take all the money." or "I did not leave him to die, I called the police." These strategies can be decomposed into the following elements:

1. denial of responsibility: blame alcohol, drugs, stress, financial problems,

2. denial of injury: "the victim was not really hurt"; "the company will not go bankrupt,"
3. denial of victim: "he deserved to be robbed"; "she wanted to have sex," "he was a bad person anyway,"
4. condemnation of the condemner: "everyone else steals," "I am not the only one,"
5. appealing to higher loyalties: the suspect did not do it for himself (Reid 2021).

If the suspect provides a reason why he could not commit the crime, that can be used to assess what the suspect did (Black and Fennelly 2021). The investigator can leverage five neutralization techniques to reduce the suspect's hesitation to confess. Storytelling provides valuable assistance. Initially, the investigator offers an explanation or excuse for why the suspect committed the crime taking his side. Next, three dignity-driven and face-saving theme development strategies are used: rationalization, projection, and minimization. Rationalization is the "act of re-describing what a person does in such a way as to avoid responsibility for the consequences of their behavior" (Reid 2021). The investigator suggests, for instance, that anyone in the suspect's place would feel stressed that the other party broke specific rules, which could cause understandable aggression. Projection involves an individual "shifting the blame for their thoughts or actions onto another person, place or thing" (Reid 2021).

We can also minimize the "moral seriousness of the behavior or the psychological consequences of the behavior" (Reid 2021). The investigator can convince the suspect that the criminal justice system will handle his case more favorably if he confesses (Hirsch 2014: 824). The investigator might point to the provocative or careless behavior of the victim, who created an "opportunity" for the criminal act. For example, a person may dress provocatively or leave valuables in plain view.

Words such as "mistake," "accident," "miscalculation," "misjudgment," or "oversight," or sentences such as "not your fault" are all intended to lower the importance of the crime and the severity of potential punishment, thereby reducing the perpetrator's resistance to persuasion. Rationalization, projection, and minimization will not bring the expected results if misused. It is not advisable to apply too much pressure or to list all arguments simultaneously. Exposing the brain to the right emotional stimuli and convincing arguments are essential aspects of persuasion (Gruza 2009: 111). Successful persuasion attempts are typically associated with vocal tones denoting focus, low stress, or stable emotions (Wang et al. 2021).

Handling denials (Orlando 2014) consists of denying permission to speak and interrupting all attempts at denial to keep the suspect's confidence low (Orlando 2014) (a3). It was observed that innocent suspects would promptly dismiss the accusation. A subject who is honest in his answers feels more secure than a dishonest one. Honest suspects utilize broader denials and informative language (Inbau et al. 2015: 134).

Truthful subjects directly respond to questions, while deceptive subjects may answer evasively. Truthful subjects directly respond to questions, while deceptive subjects may answer evasively. Truthful subjects would employ the following expressions with conviction more frequently during spontaneous interview situations when claiming innocence:

"I am absolutely sure."
"There is no way."
"I am a hundred percent positive."
"I would never do that in my life."
"There is no other explanation."
"For the love of God, no!."
"There is no other possibility."
"I did not have anything to do with that."
"I told you the truth."

The guilty subjects' denials will slowly weaken during the interrogation, while the truthful subjects will express their claim of innocence with greater strength. Truthful subjects will not allow themselves to be interrupted and will stick to their version of the story. An attempt to pressure the subject will meet with firmer denials until the subject refuses to listen (Hess 2010: 73). Deceptive subjects are not easily insulted (Hess 2010: 73). If the guilty suspect realizes the pointlessness of his denials, he will present various reasons why he could not have committed the crime, e.g., "I do not know why you are accusing me of stealing it because I cannot even reach it" (compare Hess 2010: 73).

A guilty suspect would typically raise objections to support a claim of innocence (Orlando 2014) (a4). The interrogator should address the suspect's concerns truthfully instead of arguing with the suspect. The interviewer focuses on getting the subject to confess and persuading him by adopting his words and phrases and following his reasoning. Arguing with the suspect at this stage would likely provoke an unwanted defensive reaction and increase the suspect's resilience to questioning (Orlando 2014). This technique is adopted to gain information that can be used against the suspect. An example of "raising objections" by the suspect can be:

"I would never do that because I love my wife."

The investigator might respond:

"that's good, you would never do that to a woman, you said that you love your wife, it was just a mistake."

The interviewer's task is to keep the conversation flowing, provide appropriate rationalization to the subject's actions, and return to the theme of the interview if necessary. Procurement and retention of the suspect's attention consist of keeping the suspect's attention on the theme discussed rather than on crime punishment (Orlando 2014). This can be achieved with verbal and non-verbal techniques such as closing the distance with the subject or calling the subject's name (Orlando 2014) (a5).

The suspect's frustration level should increase and can often result in a strong emotional response. Handling the suspect's passive mood, the investigator should pressure the suspect to disclose the truth (Orlando 2014) (a6). He should be empathetic and offer a psychological justification of the crime, so the suspect feels supported and comforted by the investigator (Orlando 2014).

Reinforcing sincerity helps verify if the suspect is receptive, which may be indicated by the suspect becoming quiet (Black and Fennelly 2021). The investigator can provide his version of the situation and offer alternatives to resolve the suspect's issues (Black and Fennelly 2021). If the suspect cries, we should infer guilt (Black and Fennelly 2021). The investigator should rationalize criminal behavior by presenting an alternative justification (Orlando 2014) (a7). It can be presented in the form of an alternative question. For example, the investigator could ask two parallel and possibly close-ended questions representing equally incriminating motives (Orlando 2014). One is morally justifiable, while the other is not. An example includes:

1) "did you plan to do this on your own or did somebody influence you?" (an answer to this question is morally justifiable),

"you planned to kill for the money, right?" (a positive answer to this question puts the suspect in a bad light and cannot be justified from a moral standpoint).

2) "You are not a killer; you are a smart guy who made a mistake" (morally justifiable),

"You planned to kill somebody?" (not morally justifiable).

3) "You accidentally fired a gun, that is, it was an accident?" (morally justifiable),

"Otherwise, I am going to think that you are a cold-blooded killer" (not morally justifiable).

The interrogator opens the possibility of two reasons of a crime, which should provoke the suspect to tell his version of the story or start confessing. The negotiator allows the suspect to "save face." His confession is motivated by fear of being judged as morally reprehensible. The "good people" have nothing to hide and always confess.

Having the suspect orally relate various details of the offense consists of having the suspect verbally describe various aspects of the crime (Orlando 2014) (a8). The investigator should quickly respond to affirm the suspect's admission of guilt. At this stage, the interrogator gathers all the missing information. An admission of guilt requires a witness and corroborating information to establish the validity of the confession (Black and Fennelly 2021). The investigator should request a brief oral summary of the events and convert an oral confession to a recorded or written confession (Orlando 2014) (a9). This stage should provoke the suspect's intense emotional reaction. The suspect might raise an objection to the interview being recorded. The investigator has several tactics he may use to convince the suspect otherwise. He might say:

"Even without recording the interview, I will be free to make any notes of the interview. It is in your own interests for the interview to be recorded, as it will provide a clear and undisputed record of what is said. In any case, you do not have to say anything if you do not wish to" (Interviewing suspects 2020: 29).

1.3. The P.E.A.C.E. Model

While the Reid technique entails keeping the suspect's focus by being close to him or asking hypothetical questions, the P.E.A.C.E. Model entails persuasion to seek cooperation which helps retrieve information. It represents a less confrontational and more transparent interrogation method introduced in the U.K. in 1980 (see Williamson 2006). Both Reid and P.E.A.C.E. models are popular because they are effective at obtaining confessions, but the main issue with Reid is the high false confession ratio (see Villeneuve 2017). It must be noted, though, that according to Reid and Associates company (2020), there are several tenets we need to observe to reduce the number of false confessions:

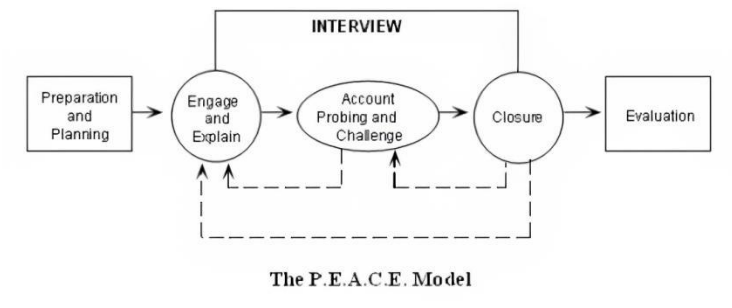
1) "always conduct interrogations in accordance with the guidelines established by the courts",
2) "do not make any promises of leniency,"
3) "do not threaten the subject with any physical harm or inevitable consequences",
4) "do not conduct interrogations for an excessively long period of time,"
5) "do not deny the subject any of the rights,"
6) "do not deny the subject the opportunity to satisfy their physical needs,"
7) "always withhold information about the details of the crime to corroborate the authenticity of the subject's confession",
8) "exercise special caution when questioning juveniles or individuals with mental or psychological impairments", and
9) "always treat the subject with dignity and respect".

Reid can be considered a harsh interrogation method based, to some extent, on psychological manipulation, coercion, and evaluation. Police lead suspects to believe that the "evidence against them is overwhelming, that they will be convicted regardless of their confession, and that they will benefit from confessing" (Hritz 2017: 504). Rather than eliciting confessions through persuasion tactics, which often lead to false confessions, the P.E.A.C.E. Model focuses on soft methods in search of truth and fact-finding. P.E.A.C.E. is also focused on a better understanding of the psychological processes involved during the interrogation proces (Marques and St-Yves 2022). Newer models, including P.E.A.C.E., represent a more investigative interviewing approach created to acquire accurate and reliable information from subjects. As per the acronym, the main components of the P.E.A.C.E. methods are:

(a) P - planning and preparation,
(b) E - engage and explain,
(c) A - account, probing and challenge,
(d) C - closure,
(e) E - evaluation (Jay 2018).

The P.E.A.C.E. model is composed of stages. The only pieces that constitute an interview are 1) engage and explain, 2) account, probing (clarification), and challenge, and 3) closure (see Figure 2). Contrary to Reid, the P.E.A.C.E. model "is no more combative or confrontational whether the subject is a victim or a perpetrator," and it is applied to "witnesses, victims and suspects alike" (Trainum 2016).

Figure 2 - P.E.A.C.E. interview model (Investigative Interviewing a practical guide for using the P.E.A.C.E. model 2021)



The P.E.A.C.E. model is not composed of fixed stages but allows moving between stages within the interview area. Before the interview begins, the investigator should prepare to include evidence and witness statements (Jay 2018) (a). During the preparation stage, we should review statements, look at documentary records, or consult with other investigators. The pre-interrogation stage represents a unique opportunity to gather facts that help discover new information during live interrogation. If we do not prepare, we will also fail to follow the lines of inquiry essential in the evaluation phase (Jay 2018). Specific hints are easy to miss without proper situation knowledge and factual analysis.

However, knowing too much can cause bias since we seek confirmation of what we already know. Planning includes looking for the best place to conduct the interview, time, content, and duration. Defining aims and goals is vital to recognize if the interview is complete. An interview plan must be created to establish what questions will be asked and what information will be disclosed or withheld (Jay 2018). Legal context should also be taken into account. The other side should be informed of his rights and entitlements. Points to prove need also to be set. Points to prove are facts related to the allegation that needs to be demonstrated (Jay 2018).

The agent should establish rapport with the other side and explain the methods that will be used and the reasons for the interview, revealing some questions that will be asked (b) (Jay 2018). The subject must believe that he can trust the interrogator. Engaging and explaining sets a positive atmosphere and helps the interviewee understand what will happen next. The agent should ask for consent to record the interview. The agent might begin the interview by saying:

"During this interview I will ask you about (…)",

"I will tell you why you are here, who I am and what I need of you".

During the interrogation, the other side should not be treated as a suspect and be allowed to provide a complete account of what happened without interruption (Jay 2018) (c). Officers trained in the PEACE model avoid leading questions that prompt the subject towards providing a predetermined answer. Instead, the agent selects a topic for probing, engages in probing, then seeks clarification and challenges the person's responses (Hutchison 2020). In the closure stage, the investigator must review the aims and objectives and explain what will be discussed next (Jay 2018) (d).

The investigator provides a summary but, at the same time, allows for information to be added. After the suspect has provided all the information about the case, the investigator should analyze contradictions or inconsistencies (Jay 2018) (e). During this stage, the investigator performs self-evaluation and incorporates the gathered information. This represents an often overlooked step, but it allows us to assess the performance of the investigator and verify if he acted within or outside of the law. This stage also allows for reviewing objectives and goals.

1.4. Stan Walters' Kinesic Interview method

Stan Walters' Kinesic Interview method consists primarily of deception detection and non-verbal communication. His 2002 book defines different interrogation strategies that should be used for different personality types; one technique applied to one archetype, such as introverts, might not work on another person, like on extroverts. Different techniques are also adopted for witnesses and suspects. Stan Walters (2002) describes four fundamental stages of the interview:

(a) orientation,
(b) narration,
(c) cross-examination, and
(d) resolution.

During the first orientation stage, it is important to establish the purpose, topic, and goals of an interview (a). Like in the P.E.A.C.E. model, the other side must be informed about his legal rights and the purpose of the interview. Before proceeding with an interview, the interrogator must gain essential background information. In order to maintain a good and uninterrupted communication flow, a successful interrogator should develop empathy and conversational skills. These skills are developed through extensive training, practice, and experience.

Empathy serves the purpose of building rapport, which is helpful in determining deceit. Admiration and respect must be earned and not demanded. The more the subject admires and respects the interrogator, the stronger the emotional response will be to lying, which increases the chances of deception detection. A good communicative flow can be achieved by drawing the subject into a general conversation, like, for example, sport, that does not represent a threat to the other side. The goal is establishing rapport through "common interests or backgrounds" (Walters 2002: 45).

The primary purpose of narration is to focus on listening to the subject's narration (Walters 2002) (b). This narration should not be interrupted and must be maintained through simple and brief questions that differ between witnesses and suspects. For witnesses, we adopt the following questions:

"What do you know about…?"
"Can you tell me what happened?."
"Can you tell me what you have heard?."
"Can you tell me what you saw?."
"Where were you when it happened?" (Walters 2002).

These questions allow the subject to feel that he is in charge of the situation. To obtain more information and maintain a good communication flow we should ask:

"(...) and then what happened?."
"What did you do then?" (Walters 2002).

When dealing with a suspect, the goals and the questions change. We leave the suspect the liberty to tell the truth or engage in deception, which is essential for behavioral analysis and can inform the interrogator about which strategies to adopt later. This information may be crucial at future points to force the subject to acknowledge his responsibility or personal involvement in the crime. An interrogator should not immediately confront the subject at the first sign of deception. It should be reserved for the cross-examination phase instead. Examples of questions asked of suspects include:

"Where were you when it happened?."
"What do you think happened?."
"How would you explain what went on?."
"What have you heard about…?" (Walters 2002).

Narration must be verified with cross-examination, which consists of verifying facts and inconsistencies (c). Accusatory approaches should be abandoned, as they increase the chance of generating false confessions and can lead to false accusations. All the gaps of gathered information must be thus filled.

We also analyze what the subject said and what was at the center of his attention. Lying subjects tend to gloss over incriminating issues and focus on unrelated facts. The interrogator must keep the suspect focused on these issues to "force the evasive subject to address the information" (Walters 2002). Thus, like in the P.E.A.C.E. model, interrogation is considered a process during which we move back and forth through various stages to finally come to a resolution. The goal of the resolution phase is to get the subject to accept the established truths and to gather evidence of deception, as well as ownership of uttered words and accountability of actions (d).

A central element of the interview is the confrontation of the suspect's negative-response emotional states. Anxiety-filled situations that generate negative responses are:

(a) anger,
(b) depression,
(c) denial,
(d) bargaining, and
(e) acknowledgment (Walters 2002: 66–96).

These responses are organized from strongest (anger, depression, and denial) to weakest (bargaining and acknowledgment). Anger, depression, denial, and bargaining represent a general rejection of the situation or event, while acknowledgment is a state during which we gather relevant information. Anger is an attempt to dominate or maintain control through aggression. Anger represents the most destructive state, in which the person becomes close-minded, focused on himself, and unwilling to cooperate (a). These effects are similar to depression (b), with the main difference being the element of emotional resignation which can be misinterpreted as acknowledgment (Walters 2002).

We are unable to elicit complete and truthful confessions from a depressive subject (Walters 2002). Denial represents a state in which the subject will bend reality and opinions about a crime (Walters 2002) (c). He will try to convince or manipulate the interrogator. Continuing denial by subjects who lie to themselves and others build the most significant barrier preventing the interviewer from gaining a subject's confession. Bargaining is the weakest of all the adverse reactions and is when the subject jockeys for the best position for himself (Walters 2002) (d). An interrogator should be careful not to "accept any portion of the subject's flawed view of himself and the crime" (Walters 2002: 40). A complete and truthful confession can be educed only during the acknowledgment state (Walters 2002) (e). During the acknowledgment state, the subject becomes submissive to requests and questions, an opportunity that the interrogator must recognize and seize.

1.5. Joe Navarro FBI tactics

Joe Navarro presents strategies and tactics adopted by the FBI and distances himself from the Reid or Kinesic methods concerning deception detection. Similarly to the Kinesic method, he considers verbal communication crucial. Some of the characteristics of this technique are:

(a) making the other side feel comfortable,
(b) avoid stress,
(c) looking for signs of discomfort and distress,
(d) clarify the reasons for discomfort and distress,
(e) calm the suspect,
(f) ask simple questions,
(g) do not pressurize the other side,
(h) look for non-verbal communication signs, and
(i) focus on communication flow (Navarro 2021; Schafer and Navarro 2017).

By making the other side feel comfortable, the law enforcement agent offers psychological comfort, which can be achieved, for instance, by placing the suspect next to the door (a). Violating someone's space causes discomfort. According to this theory, signs of deception do not exist. Aggression and the use of threats should be avoided. When we create stress, we affect memory, which can cause the other side to forget case-related facts or provide misleading information (b). The Pinocchio effect, where nervous suspects touch body parts like the nose, neck, forehead, and ears, carries no significant meaning and depends on the context and situation.

Furthermore, there is no single behavior indicative of deception. Misleading indications of deceit are rubbing and touching areas of the face, sniffing, asking for a glass of water, avoiding eye contact, looking nervously at different places, laughing, etc. These body behaviors do not immediately mean that the suspect is lying.

According to Joe Navarro, deceit can not be proven, and deception theory is not supported with scientific evidence (Navarro 2021). We should be looking at signs of discomfort and distress instead (c). However, studying body language can sometimes be helpful as an indicator of deceit — an indicator that specific actions or statements should be analyzed more thoroughly to find gaps and inconsistencies. At the same time, the interrogator should be aware of the reasons for the subject's discomfort and distress, which might be unrelated to the case. The agent should ask why the other side is exhibiting unusual behavior (Navarro 2021; Schafer and Navarro 2017) (d). Interviews and interrogations represent a stressful process, so calming the other side is of the utmost importance (Navarro 2021; Schafer and Navarro 2017) (e).

The negotiator should: 1) slow down the communication process, 2) lower his tone of voice, 3) present himself and explain the reasons for the other side being called upon in relation to the case, 4) decrease the tactic of using intimidating eye-contact, 5) do loud exhales so the other side would subconsciously mirror this behavior according to the homeostasis rule (Navarro 2021). Asking simple questions about the past or family is meant to further relax the other side (Navarro 2021) (f). Escalating a situation does not produce good results for the suspect, so psychological pressure should be avoided (Navarro 2021; Schafer and Navarro 2017) (g). Psychological pressure can lead to frustration and an inability to think clearly because of negative emotions like anger and fatigue that negatively affect both sides. Psychological pressure is tiresome for law enforcement agents. Pressure produces counter-pressure or may lead the other side to repeat his version of the story consistently. It can happen when the story is true or when dealing with someone prepared or trained to resist interrogation. A trained person can lie effectively and be fluid in his answers.

The interrogator should try to normalize homeostasis and behavior while at the same time concentrating (Navarro 2021; Schafer and Navarro 2017). By leveraging homeostasis, we mimic what the other side is doing. Therefore, if the interrogator regulates his emotions and avoids explosive behavior, there is a chance that the subject will exhibit similar behavior. Keeping a calm mind impacts communication flow, memory, and cognitive processes. It increases the chance that the educed information will be accurate. It is not enough to urge the subject to stay calm with words; we must also stay calm.

Although it does not represent evidence admissible in court, the interrogator should learn to recognize body behavior (h). For example, a subject who feels guilt or remorse or engages in deception can sometimes adopt a defensive stance by lowering his chin and looking down. It can happen when he is confronted with facts or images he recognizes, like a murder weapon or images of his victims. Similarly, when asked about facts, a guilty or lying subject might encounter difficulties. Simple questions should provoke simple answers. When the subject is lying, asking specific questions causes cognitive load that can disrupt communication flow (i), e.g.:

Police Interrogator: "What time did you land at the airport?"
Suspect: "4 o'clock"
Police Interrogator: "Where did you stay upon arrival?"
Suspect: "eee.. I stopped at Hilton… eee… no… it was Sheraton".

This disruption of communication flow can be an indication of deceit. However, it is more likely to happen during spontaneous interrogations. "Cognitive load associated with lying is believed to stem largely from the need to maintain a coherent account while monitoring the interviewer's reaction" (Van Der Zee et al. 2021). How an interrogator's questions affect a lying subject represents an interesting topic that deserves further study. However, studies of human deception and non-verbal behavior typically focus on "the acts of interviewees who are tasked with lying or telling the truth, or interviewers who are tasked with determining the veracity of the account. Few consider the joint nature of conversation" (Van Der Zee et al. 2021).

1.6. Interrogation and interviewing domains

Christopher Kelly et al. (2013: 169) identified six domains that encompass most interrogation techniques and strategies . These six main domains are:

(a) rapport and relationship building,
(b) context manipulation,
(c) emotion provocation,
(d) confrontation and competition,
(e) collaboration, and
(f) presentation of evidence (Kelly et al. 2013).

Rapport and relationship-building interrogation techniques concentrate on identifying common ground, shared experiences, and needs of the subject (a). According to this technique, the investigator must be patient and slowly build a bond by mirroring the subject's behavior and views. Similar language, like slang, should be adopted. Context manipulation consists of manipulating physical space by adopting specific colors, placing furniture or wearing particular clothing to influence the subject's psyche (Kelly et al. 2013) (b). The prisoner's dilemma strategy is also adopted. Prisoner's dilemma is a game theory by Merrill Flood and Melvin Dresher, that was later formalized and named by Princeton mathematician Albert William Tucker.

According to this theory, two players acting in their interest will make decisions that result in a suboptimal choice for both through 1) manipulation, e.g., isolating subjects from each other, and 2) deceit, e.g., providing information that the subject has been given up to the police by his partner in crime. The emotional provocation technique appeals to self-interest, negative feelings, conscience, and religion (Kelly et al. 2013) (c). The emotional provocation technique focuses on instilling fear and hopelessness on the other side to capitalize on stress and shock (Kelly et al. 2013).

Confrontation and competition techniques focus on adopting an unfriendly confrontational stance by constantly staring and showing feelings of impatience, frustration, or anger (Kelly et al. 2013) (d). According to the Reid method, the interrogator should exhibit authority and expertise. Confrontation and competition techniques allow the investigator to use deception and insults and keep the source uninformed about his fate (Kelly et al. 2013). Questions would be repeated quickly and without allowing the other side to fully respond. Subject denials are prohibited, and the subject is threatened with consequences for non-cooperation. The subject is interrupted at each attempt at denial. Following the Reid technique, the interrogator often acts that he does not need to listen to denials because he already knows what happened. He only needs a confession.

Collaboration techniques focus, on the other hand, on convincing the subject to cooperate through rewards (Kelly et al. 2013). The interrogator would offer a scenario where the subject's innocence would be defended and the subject would be allowed to regain control and freedom (Kelly et al. 2013) (e). Presentation of evidence techniques focused on confrontation through fabricated or tangible evidence of involvement (Kelly et al. 2013) (f). Following this technique, the interrogator tries to educe more information by presenting evidence. The interrogator acts as if he knows more than what can be deduced from the evidence. He would bait the other side with evidence or demonstrate that no more useful information is needed to solve the case to provoke a reaction. Using this technique, the interrogator would identify contradictions within the subject's story.

1.7. Factual versus indirect approaches to police interrogation

Another classification of interrogation and interviewing methods is presented by Vivian Lord and Allen D. Cowan (2010: 224–230), who separate factual from indirect approaches. These approaches are used depending on the situation. If the subject has provided an alibi and if he is a first-time offender, we should use an objective approach. A first-time offender is likely to have strong emotions such as passion, anger, or jealousy that the interrogator should use to his advantage. With the factual approach, we cause the subject to become defensive. We use open-ended questions and questions regarding minor details to retrieve information and destroy the subject's alibi credibility. As liars rely partially on their imagination and partially on real facts, they tend to keep the main facts of their story consistent but fall short on "small peripheral detail" (Lord and Cowan 2010: 226). With the indirect approach, we observe if the suspect listens to the interviewer. The interviewer dominates the conversation and begins by describing his responsibilities, experience, and training (Lord and Cowan 2010: 227). The longer the subject listens, the higher the chance of eliciting a confession (Lord and Cowan 2010: 227).

1.8. Main police interrogation routines

Police interrogation routines, such as the "good cop, bad cop" routine, leverage human behavior. The subject wants to please the other side, be treated well, and be understood. Therefore, the interrogator gives two choices; one has pleasant consequences, and the other has painful consequences. "Most people enjoy having choices because it gives them the feeling of being in control" (Hess 2010: 75). The subject prefers to receive rewards or experience pleasure rather than experience punishment and pain. This negotiation routine triggers three mechanisms: 1) subjects may comply to escape interaction with the bad cop, in other words, they escape from anxiety and fear, 2) subject will reciprocate the perceived kindness and liking of the good cop, 3) subject will perceive cooperation with the good cop to be in their best interest (see Rafaeli and Sutton 1991: 749 and 765). Five different variations of the good cop, bad cop strategies exist:

1) sequential good cop: "two people play good cop and bad cop in sequence, interacting separately with the target, after each other,"

2) simultaneous good cop: "two people play good cop and bad cop simultaneously, both interacting with the target together in the same room,"

3) "a single individual plays both roles by switching behavior between role,"

4) "a single individual plays good cop, and makes reference to a hypothetical bad cop, who is attributed with bad cop behavior,"

5) "a single individual plays good cop in contrast to a stereotype expectation of a bad cop: the good cop acts only as a good cop, but the expectation of the target is that this individual should exhibit bad cop behavior" (see Fili 2015: 7, Rafaeli and Sutton 1991: 758).

The first two strategies present positive and negative emotions to the subject (Rafaeli and Sutton 1991: 761). Positive and negative emotions can be presented simultaneously or sequentially. Juxtaposing two kinds of emotions can change a target person's perceptions of both emotions (Rafaeli and Sutton 1991: 750). What changes is the magnitude of perceived emotions. An alternative to what the "bad cop" has to offer would also seem much worse to the "good cop" offer than it is in reality.

The carrot and stick approach involves creating a carrot, or reward, and a stick, or consequence, to force or motivate the subject to perform an action or activity. An example of this technique involves making the subject susceptible to the carrot: financial advances, work, or money, but only if he declares honestly about his criminal past (Eidam, Lindemann and Ransiek 2020: 92). If he does not cooperate, the organization adopts the stick: breaks the contact or threatens the subject (Eidam, Lindemann and Ransiek 2020: 92). If the subject cooperates the interrogator starts to behave in a friendly manner and is sympathetic to the subject's motives, e.g., "I know how difficult it is raising children on a single income".

Another known routine is represented by a negative incentive/positive incentive narrative. With negative incentives, the interrogator overcomes the subject's resistance and defensive strategies, lowers the subject's self-confidence, and induces feelings of "resignation, distress, despair, fear, and powerlessness" (Leo 2008: 134). This strategy is adopted until the suspect is emotionally disrupted and left with limited choices, possibilities, and outcomes. Positive incentives motivate the suspect to comply and confess before it is too late (Leo 2008: 134). The subject wants to end this painful interrogation process and adopts an exit strategy elucidated in the positive incentive narrative that benefits the interrogator (Leo 2008: 134). Interesting insights on interrogations also come from the semantic analysis of deception. As deception is one of the core elements investigated during an interview, we should define it and verify how it manifests on a semantic and emotional level.

2. Semantic and emotional indicators of deception

Deception constitutes a specific type of communication, where "the speaker intends the hearer to form thoughts which the speaker believes to be false" (Grondahl and Asokan 2019: 3). Suspects are recalcitrant confessing to crimes (Walsh and Bull 2010: 307). The main reason a person chooses to lie is for some perceived personal benefit or to avoid punishment. The term deception comprises omission, distortion, half-truths, blatant lies, lies of necessity, and white lies. We can find three types of deception in textual data: 1) deception of authority, deception of intention, and deception of literal content (Grondahl and Asokan 2019: 4). Deception of authority occurs when the deceiver pretends to have authority over an issue he does not possess. Deception of intention occurs when the deceiver has a hidden motive.

Most studies, however, focus on uncovering the deception of literal content. With the deception of literal content, we analyze the semantic content of the text that is deceptive. There are several methods to discover clues that deception has occurred on a semantic level. Subjects tend to behave similarly; they are to some extent, predictable and follow a specific style. Any noticeable shift in behavior, style, or pattern may indicate deceit. For example, specific individuals use long sentences, while others use short sentences. The interviewee can suddenly change this sentence length pattern when he is lying. Such pattern shifts can be calculated with the mean length of utterance (MLU):

Total number of words/Total number of sentences = MLU

A sudden change in MLU should draw attention. Roger Shuy (1998: 106) argues that lying subjects often produce a quantitative imbalance between parts of narration such as the prologue, main event, and epilogue. Between these parts of narration, we can often observe a reduced mean length of utterance (MLU) in relation to one another. Liars also exhibit reduced lexical diversity, which is "the number of different words in a statement divided by the total number of words used in that statement" (Meibauer 2018: 362). Further analysis can be performed on words that reveal uncertainty:

"about," "kind of," "I guess," "sort of," "more or less," "mainly," "pretty much," "I do not know," "not really," "I suppose," "almost," "perhaps," "maybe," "it may be that," "it could be," "somewhat."

The use of allusions and general statements, depersonalization, and present verb tense for past events should also be probed further (Lord and Cowan 2010: 135). For example, truthful people usually describe past events in the past tense. On the other hand, deceptive subjects allude to actions without saying they performed them. Examples of general statements that lack detail include:

"we messed around,"
"got my stuff together,"
"it was a mess,"
"we talked for a little bit,"
"we went some place for a drink,"
"I vaguely remember."

These sentences are characterized by abstractness and lack of specificity. A key characteristic of truthful subjects is the ability to tell a story in vivid details that are remembered after some time in successive interviews. Deceptive subjects tend to change the description and details of the story or forget what was said in a previous interview or time period. Two interviews regarding the same theme tend to differ in deceptive subjects. Deceptive subjects often use oaths to make their statements sound more convincing (Clikeman 2012) such as:

"I swear,"
"on my honor,"
"as God is my witness,"
"cross my heart,"
"I swear on my children's life,"
"I swear by Almighty God" (Christians),
"I swear by Allah" (Muslims).

Another characteristic element is the use of euphemism: "missing" instead of "stolen," "borrowed" instead of "took," "bumped" instead of "hit," and "warned" instead of "threatened" (Clikeman 2012). Deceptive subjects often use weak verbal substitutes. Lack of conviction can thus be evinced if the subject starts modifying or equivocating terms (Rabon 1994: 48). The use of passive voice as a way to reduce self-references leads to depersonalization which represents another indicator (Clikeman 2012). The subject would also avoid using first person or reflex pronouns like "I," "me," "myself," or "mine," placing himself behind someone or something that provides an alibi in order not to be seen, noticed, or interacted with.

A tactic often adopted by companies or corporations during business conversations with a client is to use "we" or "us" to dilute personal responsibility, e.g., "our company policy is to (...)," or "We will verify the situation and come back to you." During an interview, the subject may also move away from personal responsibility. At each successive statement, the subject may progressively change the way he communicates about certain actions or events:

"I always lock the the door."
"We always lock the door."
"They always lock the door."
"The door is always locked."

It must be noted that in case of psychological distancing first person pronouns are often used and accompanied by an increase in negations, e.g., "no", "not," and "never" (Toma and Hancock 2012). Psychological distancing is the liar’s efforts to manage symptoms such as shame, guilt, anxiety, worry, intense stress, fear or sadness. Emotional cues can be studied from facial expressions and so-called microexpressions.

It must be remembered that although deception may elicit negative feelings, it can also cause positive emotions such as relief, satisfaction, pleasure, and what's known as duping delight — pleasure at succeeding in one's lies and getting away with it (Ekman and Friesen 1969). Deceptive subjects exhibit less contempt and more intense smiles than innocent respondents as found during a Concealed Information Test (CIT) (Pentland et al. 2015).

How liars answer questions is also important. A lack of response, partial response or answering the question with a question can represent an important indicator. Especially when, as mentioned previously, the question is unexpected and the answer is not rehearsed. A lying subject is trying to figure out how to respond (see Girod 2015: 143). Deceptive subjects encounter problems when handling denials which can be grouped into three types (see Girod 2015: 143):

1) absence of an explicit denial of wrongdoing,
2) non-specific denial, and
3) isolated delivery of denial.

The absence of an explicit denial of wrongdoing happens when the subject does not deny accusation, changes topic or remains silent. Non-specific expression of denial is a lack of specific answer. The subject use weak substitutes such as "I would never do something like that," "I did not do anything" (Girod 2015: 143). Suspicious behavior can be identified if there is a large number of answers such as:

"I don't know if I was there,"
"I am not sure,"
"I don't remember,"
"maybe,"
"I don't know him/her."

With isolated delivery of denial, the "no" answer is not delivered immediately after an accusation but is buried within the answer. In court, refusal to answer the question or lying is only successful if the evidence is weak and insufficient (Rzeszutko-Iwan 2019: 42). In case of weak and insufficient evidence, each suspect's credibility plays a significant role in determining crime perpetrators. On the emotional level, deception can cause a higher stress level due to the lying process or an attempt to perform emotional persuasion on the audience (see Grondahl and Asokan 2019: 4–5). Thus deception carries a high emotional load. The best way to conceal strong emotions is by wearing a mask (Ekman 1992: 33).

Since it is difficult not to show emotion, the lying subject can choose another strong emotion, e.g., to hide anger, he can simulate sadness. Beyond semantic content, the focus of the deception study can also be discovering the intention of hiding the author's identity or writing style obfuscation. Although it represents an interesting area of study, deception studies might not provide sufficient evidence in court as there are no unequivocal signals of lying (Memon, Vrij and Bull 2003: 157–159). Moreover, we can also argue that many external and internal factors can impact the subject's response, e.g., culture or religion. Similarly, emotion detection during deceit is not always convincing. For example, concealed Information Test (CIT) results show that it is challenging to recognize liars by facial expression and microexpression analysis (Pentland et al. 2015).

As an alternative, analysis of the subject's immobility (behavioral inhibition) can produce better results as lying subjects are affected by distressful emotions (e.g., fear, anxiety, or shame), grave consequences (e.g., physical pain, financial loss, or imprisonment) and cognitive load (see Burgoon 2018). As far as interrogation techniques are concerned, when dealing with the deceitful subject, the interrogator's focus should not be on getting a subject to confess but rather persuade him that "admitting to the truth is far more acceptable and advantageous for them than sticking to their deception" (Walters n.d.).

3. Interviewing particular subjects

3.1. Interviewing distinct ethnic groups

At times, particular behavior needs to be observed when questioning Arabs and Muslims, and African Americans. When speaking to Arabs and Muslims, the conversation should start with a question about their health and the health of their families (Schafer and Navarro 2017: 52). An inquisitive question about the subject's wife should be avoided (Schafer and Navarro 2017: 52). Discussing cultural differences serve the purpose of building relations.

It must be remembered that most human beings tend to favor people who remind them of themselves. Therefore, the law enforcement agent should show respect and display polite behavior during the relationship building process. To maintain good communication flow, we can compare past experiences of the subject in his country of origin versus experience in a foreign country (Schafer and Navarro 2017). Another generic but useful topic is sport. "Arabs or Muslims" tend to be "visual types" of people (Schafer and Navarro 2017: 53).

Consequently, instead of asking to describe a person, the law enforcement agent should ask concrete questions about the person's appearance, e.g., hair color, outfit or make-up. While "Westerners" generally relate facts chronologically, some Arabs or Muslims associate concepts or events (Schafer and Navarro 2017: 53). Topical questions should be asked along with specific questions that close chronological gaps. Similarly, some Indo-Americans have a different measure of time, which often is calculated by taking into account particular events or ceremonies (Schafer and Navarro 2017: 51). African Americans, especially the older generation, are taught to show respect by looking down or away, which can be misinterpreted as deceit (Schafer and Navarro 2017: 53–54).

3.2. Questioning subjects affected by personality disorders or mental illness

Apart from cultural differences, a law enforcement agent should be aware of personality disorders and mental illnesses. Similarly to juveniles, subjects affected by personality disorders or mental illness might lose patience faster, especially during lengthy interrogations, and are easier to manipulate. People with mental health problems display heightened "suggestibility, compliance, and acquiescence levels compared to those without a mental disorder" (Ferrugia 2019: 157).

Individuals affected by depressive disorders are also more vulnerable in police interrogations and can be easily manipulated, leading to a false confession or self-harm. Although depression lacking psychosis may not induce a false confession, it is worth noting that according to the Independent Police Complaints Commission, roughly 66% of those who committed suicide after being arrested by the police in 2013–2014 had mental health issues (Teers 2014). In addition, various studies suggest that police officers have difficulty detecting suspects vulnerable to false confessions, e.g., suffering from mental disorders or intellectual disabilities (Gudjonsson 2010; Kassin 2012; Young, Goodwin and Gudjonsson 2013).

John Schafer and Joe Navarro (2017) provide valuable insights on how to deal with subjects affected by personality disorders and mental illnesses like narcissists, people with schizophrenia, psychopaths, and people affected by paranoid personality disorder (PPD; Schafer and Navarro 2017: 54–57)[2]. A difficult encounter is represented by psychopaths who are manipulative, deceptive, and calm during an interrogation[3].

[2] Investigators must avoid criticizing narcissists as they consider criticism a personal attack on their self-esteem and image (Schafer and Navarro 2017). Therefore, they are likely to establish relationships with people that can enhance that self-esteem and image (Schafer and Navarro 2017). When confronted with facts, they become less detached from reality (Schafer and Navarro 2017). Narcissists' sense of entitlement can be used against them to reveal more facts about their deeds (Schafer and Navarro 2017). Schizophrenics' thoughts are disordered, and their evidence is easy to discredit. They mix reality with fantasy. A person with schizophrenia may present objective evidence, but it can be contaminated with the product of his imagination. Only a few percent of people with schizophrenia are dangerous, and those that are dangerous usually suffer from co-existing mental illnesses. When dealing with people with schizophrenia, interviewers should avoid asking suggestive questions and be patient (Schafer and Navarro 2017). When questioning paranoid people, interrogators should always tell the truth (Schafer and Navarro 2017: 58). The interrogator should ask the person affected by PPD to give concrete examples confirming his suspicions. Interviewers should avoid getting into an argument. The interviewer should guide the conversation so the subject focuses on relevant topics (Schafer and Navarro 2017). During an interview, a paranoid person might provide too much information. The interviewer must also learn to distinguish between relevant and irrelevant information (Schafer and Navarro 2017). As far as psychopaths are concerned, the interviewer should keep the subject's attention on the question asked. If the discussion is derailed by the subject, which often happens with this type of personality disorder, the law enforcement agent should focus on what is essential. It can be achieved by saying, "that is interesting," and formulating the question again (Schafer and Navarro 2017: 56). The interviewer should not proceed until that question is answered (Schafer and Navarro 2017: 56). As psychopaths rarely admit guilt, the interviewer should offer few choices to the subject, as he will likely opt for the ones he believes serve his interest. Psychopathic subjects are confident and relaxed when questioned (Schafer and Navarro 2017: 56).

[3] Psychopaths also exhibit narcissistic traits (Durvasula 2019).

CHAPTER 3

EMOTION THEORIES: A LINGUISTIC PERSPECTIVE

1. Defining emotions

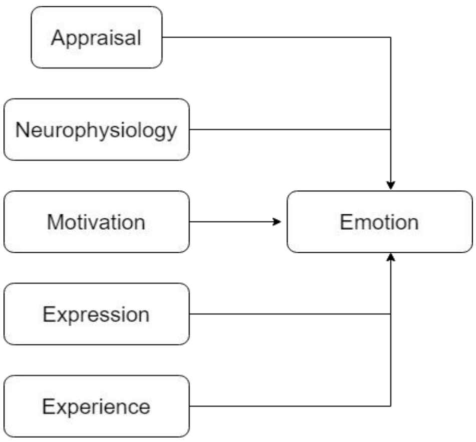
Before categorizing emotions, a definition of a commonly understood emotion term is necessary. According to the Cambridge University Press (n.d.), emotions represent "a strong feeling such as love or anger, or strong feelings in general." The Free Dictionary by Farlex (2021) describes emotions as a "mental state that arises spontaneously rather than through conscious effort and is often accompanied by physiological changes." Thus, emotions are in contrast with reason (The Free Dictionary by Farlex 2021). According to the PWN dictionary, "emocja," from the Latin *emovere*, means "to stir." Emotions are generally elicited by stimulus events (Scherer 2016: 700). Emotions can be defined as "current states of individuals, differing in terms of quality and intensity, which are aimed at an object, give the persons concerned a characteristic experience, and often lead to physiological changes and certain types of behavior" (Meyer, Schützwohl and Reisenzein 1993).

In modern psychology, emotions are also defined as a system comprising feelings, considered a subjective element, as well as physiological agitation with characteristic expression and behavioral changes (Tyng, Amin, Saad and Malik 2017). "Feeling or feeling state is defined as an approximate synonym for emotion" (Ketai 1975). Affect, on the other hand, is sometimes defined as an intensive, sudden and short-lived reaction described in briefer temporal terms than mood (compare Ketai 1975: 1215).

Emotions are caused by specific events, usually starting at the biological level, whereas the origin of a particular mood is often unclear or hidden. Generally, we can distinguish five components responsible for emotions to occur: appraisal, neurophysiology, motivation, expression and experience (see Figure 1). Appraisal theories define emotions as processes rather than states, and emotions are defined as adaptive responses to the environment (Moors et al. 2013: 119). In other words, emotions reflect "appraisals of features of the environment that are significant for the organism's well-being" (Moors et al. 2013: 119). Emotions result from appraisal structures rather than from a single appraisal (Silvia 2005).

Neurophysiology represents the neurophysiological component, like physical symptoms and body system regulation (Hauke and Dall'Occhio 2013). "Motivation" represents the motivational component, such as impulses to act and preparation and orientation of actions (Hauke and Dall'Occhio 2013). The "expression" represents the component that influences the use of language, like communicating intentions or visceromuscular reactions like breathing motion and posture (Hauke and Dall'Occhio 2013).

Figure 1. Five emotional episode components and functions (Hauke and Dall'Occhio 2013)



The motor expression component of emotion has "a strong impact on communication which may also have important consequences for social interaction" (Scherer 2016: 702). Experience represents the experience component, for example, interaction with the environment and subjective perception (Hauke and Dall'Occhio 2013). A distinction should be made between emotions and mood. According to the PWN dictionary, a mood is "a mental condition continuing for a certain period of time" and "impressions and feelings of individuals at a certain place and time." Interesting distinctions between mood and emotions are presented by Peter Terry and Andrew Lane (Table 1).

Emotions are not steady states but processes (Scherer 2005: 702). They allow for a readjustment depending on circumstances (Scherer 2005: 702). Their duration should be relatively short to not tax the organism's resources (Scherer 2005: 702). Emotions convey more than a generally positive or negative reaction because they are experienced (compare Ketelaar and Clore 1997: 379). The intensity of emotions can be relatively high, distinguishing emotions from moods (Scherer 2005: 702). To sum up, emotions are generally more sudden, dynamic and intense than moods. Moods are often hidden, whereas emotions are generally more visible and accompanied by specific behavior and motoric features, like gestures.

Table 1. Main characteristics and criteria of mood and emotion (Terry and Lane 2011).

Criterion	**Emotion**	**Mood**
Awareness of cause	Individual is aware of cause	Individual may be unaware of cause
Cause	Caused by a specific event or object	Cause is less well defined
Consequences	Largely behavioral and expressive	Largely cognitive
Control	Not controllable	More controllable
Display	Displayed	Less visible
Duration	Brief	Enduring
Intensity	Intense	Diffuse
Intentionality	About something	Not about anything in particular
Stability	Fleeting and volatile	More stable
Timing	Rises and dissipates quickly	Rises and dissipates slowly

Moods can be defined as "diffuse affect states, characterized by a relative enduring predominance of certain types of subjective feelings that affect the experience and behavior of a person" (Scherer 2005: 705). Moods are rather predominant, pervasive and long-lasting. Mood "varies with time of day, alone or in interaction with amount of prior sleep" (Perlis et al. 2016). The relation between mood and emotion is "transactional in nature" (Terry and Lane 2011). An existing mood influences "the emotional reaction to a situation and the subsequent emotional experience, in turn, contributes to mood" (Terry and Lane 2011). If we are in a bad mood, we may overreact to a situation. Irritability is an example of oversensitivity to affronts (Antal 2007: 7).

Moods can be decomposed into normal or dysphoria, euthymia, ecstasy, mania, irritability, hypomania, alexithymia[1]. Behavioral characteristics of euphoric moods are in contrast to depressed moods (Johnson 1937). The pharmacological response of patients shows how strong a dysfunction is, e.g., a positive response to a medicine indicates a lighter form of dysfunction (Frączek 2021). However, even a light form of dysfunction must be treated because diagnosed subjects may perform irresponsible

[1] Experiment participants with higher alexithymia rated more extreme emotions like anger and fear as less intense than low alexithymia scorers (Luminet, Nielson and Ridout 2021).

actions that damage their image, health and finances, e.g., they may borrow money or drive a car under the influence of drugs or alcohol (Frączek 2021).

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2. Physiological, cognitive, behavioral, sociocultural, constructionist, and neurological approaches to the study of emotions

Different interpretations and theories of emotions exist and are often categorized according to six elements:

(a) physiological,
(b) behavioral,
(c) cognitive,
(d) sociocultural
(e) constructionist, and
(f) neurological.

According to the physiological model, our body is responsible for emotions that can manifest themselves through rapid breathing, pain, blood pressure, respiration, heart racing or increased sweating (a). Emotions often stem from behavioral or motivational systems (b). Any motivational system, just like any behavioral system, is goal oriented and is derived from evolution as exhibiting some emotions that yield significant gains for individuals and species' survival (Williams 2017: 3). In the case of fear or anxiety, emotions can be expressed by fleeing, which is a defensive reaction to danger. The expression of fear may inform other members that something is wrong. A dog reacts to the sound of a door knock by barking.

In the 1960s, Aaron Beck proposed a cognitive model of affective disorders that "focused upon the negative content of thoughts, in contrast to the then dominant behaviorist model that saw emotional problems as a set of learned responses to stressful or threatening situations" (May 2013: 436). According to the cognitive model, emotions come from our mental activity and thoughts (c). Cognitive appraisal theories state that all human emotional responses, e.g., fear and anger, arise from how we understand and interpret the situation we experience (Wagner 2014). For instance, when we try to find out what or who the source of a threat is. Thus, in the cognitive theory of emotion, emotions depend on our interpretation. The type of elicited emotion and the emotional intensity require cognition about the eliciting events (Reisenzein 2020).

Aspects of studied emotions can also be placed in a sociocultural context (d). Emotions appear to unfold during social interactions and relationships as they serve a social purpose (Mesquita and Boiger 2014). People communicate emotions through language, and the sociocultural context influences the semantics of expressed emotions. Emotional semantics depends on the culture and geographic region (Bann and Bryson 2013b). Usually, emotions described with simple, clear words can be felt more deeply. Emotional semantics as well as semantic distinctiveness, depend on the type of emotion expressed (compare Bann and Bryson 2013a).

Constructionist theories treat emotions like chemical compounds (e). They predict that more basic psychological elements, such as exteroceptive sensations, combine with various representations of knowledge about emotions (Lindquist, MacCormack, and Shablack 2015). Exteroceptive sensations are represented by audio-visual sensations. Constructionists consider language a fundamental element of emotions as it constitutes both emotional experiences and perceptions (Lindquist, MacCormack, and Shablack 2015).

Elements that contribute to emotions are: 1) representations of sensations inside the body, also known as affect, 2) representations of sensations from outside the body, also known as exteroceptive sensations, 3) and concept knowledge that makes such sensations meaningful in a context (Lindquist, MacCormack, and Shablack 2015). The constructionist view hypothesizes that portions of the orbitofrontal cortex (OFC) play a key role in "core affect as a site that integrates exteroceptive and interoceptive sensory information to guide behavior" (Lindquist et al. 2015).

The neurological model studies emotions on chemical and neural circuitry levels in our brain (f). Locationist theories hypothesize that emotions are located in concrete areas of our brain, as opposed to non-locationist theories, where emotions affect the whole brain area. Another studied possibility is that each discrete emotion is represented by a specific combination of brain areas that co-activate and cooperate in time as a functional unit (Lindquist et al. 2015). The human mind is seen as a collection of semi-autonomous organs, and each organ serves its purpose and has its cooperation mechanism. Happiness, fear, sadness, disgust, anger, and surprise reside in our organs, e.g., in the occipital lobe, the left insula, the left thalamus, the amygdala, the precuneus, and the hippocampus (see Table 2).

Changes in the brain entail emotions, including emotional status, the patient's personality, and the ability to process emotions (Moawad 2017). For example, we might experience a stronger emotional reaction when someone feels sick and unhappy than when someone feels healthy and happy. In addition, personality influences how we experience and display emotions. As an example, prefrontal cortex (PFC) analysis shows anger experienced in response to an insult, which is often accompanied by the personality disposition to experience angry feelings (Lindquist et al. 2015).

Table 2. Emotions and brain activity (Moawad 2017)[2]

Emotion:	Emotions manifests in the following organs:
happiness	right frontal cortex precuneus left amygdala left insula
fear	bilateral amygdala hypothalamus areas of the left frontal cortex
sadness	right occipital lobe left insula left thalamus amygdala hippocampus
disgust	left amygdala left inferior frontal cortex insular cortex
anger	right hippocampus amygdala both sides of the prefrontal cortex insular cortex
surprise	bilateral inferior frontal gyrus bilateral hippocampus

Emotions are often categorized according to an anthropomorphic and neurotropic model. In the anthropomorphic model, emotions reflect our subjective attitude, whereas, in the neurotropic model, emotions depend on our neural system and its mechanisms, with neurological manifestations. For neuroscience, emotions are complex reactions the body has to various stimuli, e.g., our heart begins to race, we experience tension headaches and gastrointestinal problems, fluency disorders (stuttering) and more.

[2] The locationist account does not hypothesize specific roles for the dorsomedial prefrontal cortex (DMPFC), ventromedial prefrontal cortex (VMPFC), medial temporal lobe (MTL), and retrosplenial cortex/posterior cingulate cortex (PCC) regions of the brain when it comes to emotion because they are usually considered to have a "cognitive" function (Lindquist et al. 2015).

The research on emotions can be centered around short or long, or lasting emotions. Randall Collins, for instance, does not focus on short-lived effects, such as happiness, fear or anger, but instead considers longer-lasting emotions which may trigger interactions between people (Collins 2011). There are several theories as to whether mixed emotions exist. They claim that:

1) positive and negative emotions co-occur,
2) positive and negative emotions do not co-occur,
3) positive and negative emotions can co-occur when the intensity of the emotions is not strong, e.g., subjects who reported mixed emotions merely vacillated between positive and negative emotions (Larsen and Mcgraw 2011).

Mixed emotions are sometimes placed on the positive-negative, hope-fear, fear-happy, disgust-amusement or pleasure-displeasure space along with happy-sad, the most studied space (Berrios, Totterdell and Kellett 2015). An example of mixed emotions is jealousy, consisting of anxiety, anger and sadness (Collins Dictionary 2021: mixed emotions). Another example of emotions containing mixed evaluations is nostalgia. Nostalgia contains positive and negative evaluations of past experiences, making it either a warm, positive emotion or a negative, disruptive one (Bantinaki 2012: 388).

More complex emotions such as guilt, pride or disgust are valued differently across cultures. Paul Ekman categorized disgust as a primary emotion. However, the English word "disgust" has no exact translation in Hindi or Malayalam (compare Kollareth and Russell 2017). The English word disgust refers to "reactions to both unclean substances and moral violations; Hindi and Malayalam translations referred mainly to moral violations" (Kollareth and Russell 2017). Moreover, Europeans, Americans and Australians value feelings of pride more positively than people from China and Taiwan; the opposite is true for feelings of guilt (Leersnyder, Boiger and Mesquita 2015: 8).

3. Categorical versus dimensional models

Models of emotions in modern psychology can be divided into categorical and dimensional. Hybrid models combine categorical and dimensional models. Furthermore, research theories are also based on gradients of emotions or associate emotions with temperature. Below I focus on categorical versus dimensional models of emotions. Categorical models, also called discrete emotion models (DEMs), typically use six emotion classes: fear, anger, joy, sadness, disgust, and surprise. More classes can be conceptualized according to a specific domain, e.g., education, boredom, confusion, joy, flow, and frustration (Sreeja and Mahalaksmhi 2017: 652). Human emotions are thus simplified into easy-to-understand emotion labels.

We can distinguish three main categorical models: Paul Ekman's six basic categories (Ekman: 1992), Robert Plutchik's eight categories in opposite pairs with different intensities (Plutchik 1980), and Andrew Orthony, Gerald Clore and Allan Collins (OCC) model with 22 emotion classes (Ortony, Clore, and Collins 1988). Beyond Western culture, we can find the Navarasa taxonomy of nine emotions. Discrete emotion theory is based on the claim that a small number of core emotions exist. This emotion theory contrasts other theories that consider each emotion as equal but differing in intensity or pleasantness (Ekman 1999: 138). Dimensional emotion models categorize emotions into dimensional spaces.

Emotional spaces are uni-dimensional or multi-dimensional. Robert Plutchik presented a two-dimensional wheel of emotions with valence and arousal. Emotional valence is the "value associated with a stimulus as expressed on a continuum from pleasant to unpleasant or attractive to aversive" (APA Dictionary of Psychology 2014). The question is if valence is an irreducible component of emotional experience or whether positivity and negativity are entirely separated (Larsen and Mcgraw 2011). The Robert Plutchik two-dimensional model suggests that emotions are distributed in a two-dimensional circular space containing arousal and valence dimensions. Emotions are color coded compared to a color palette. They form the so-called wheel of emotions, presented as a cone to visualize such emotions' degree and intensity (Plutchik 1980).

In the pleasure-arousal-dominance (PAD) model or Valence-Arousal-Dominance (VAD) model by Albert Mehrabian and James Russell (1974; 1977), emotions were the basis of temperament (see annex, Figure 5). In the initial period of their research, researchers focused primarily on non-verbal communication. However, they concluded that diverse forms of motoric expression and movements through which humans interact with others could be interpreted from the point of view of their specific communication meanings based on emotions.

Together with his colleagues, they distinguished three basic dimensions of emotional states (Mehrabian and Russell 1974; 1977):

(a) pleasure-displeasure,
(b) arousal-absence of arousal, and
(c) dominance-submissiveness.

Indicators of the pleasure-displeasure dimension are smiles and laughter, the dominance of positive or negative emotions, ecstasy and feeling of happiness, or feeling of sadness and unhappiness (a). Indicators of arousal-absence of arousal can be found in agitation, activity, excitement levels, or relaxed attitude (b). Finally, the dominance-submissiveness dimension manifests itself in the freedom to act in any chosen way, a sense of power and influence, control of the situation or a sense of lack of impact on the environment or control (c).

Together, these dimensions form the so-called PAD emotional state model (pleasure, arousal, dominance), which is used to describe and measure all emotions. The dominance dimension of PAD was conceptualized as part of the appraisal process, thus forming a new theory of emotions called the circumplex model of affect (Russell 1980, Feldman Barrett and Russell 1998). According to this theory, all emotions come from two basic neurophysiological systems connected to valence and arousal.

The Positive Activation - Negative Activation (PANA) model, also called the consensual model, was created by David Watson et al. (1999). This model distinguishes between two systems divided into positive and negative affects or the "Negative Activation" (NA) and "Positive Activation" (PA). The model is based on two axes: vertical (negative impact, from low to high) and horizontal (from low to high, negative impact).

According to Klaus Scherer (2005), emotions consist of synchronized processes that include a cognitive appraisal, bodily symptoms, action tendencies or motivations, facial or vocal expressions and unique inner experiences called feelings (compare Bălan et al. 2019). Klaus Scherer (2005: 713–715) created an extensive list of semantic categories that index different types of affects, including emotions and moods illustrated in Table 3. Klaus Scherer (2005: 716) found terms that constitute synonyms, near synonyms, or related emotion family members.

Table 3. Semantic categories (stems) of emotions, moods and other transitory affect states and brain activity (Scherer 2005: 713–715). (...) indicates stem reduction to root form.

Admiration or awe	admir(...), ador(...), awe(...), dazed, dazzl(...), enrapt(...), enthrall(...), fascina(...), marveli(...), rapt(...), reveren(...), spellbound, wonder(...), worship(...)
Amusement	amus(...), fun(...), humor(...), laugh(...), play(...), rollick(...), smil(...)
Anger	anger, angr(...), cross(...), enrag(...), furious, fury, incens(...), infuriat(...), irate, ire(...), mad(...), rag(...), resent(...), temper , wrath(...), wrought(...)
Anxiety	anguish(...), anxi(...), apprehens(...), diffiden(...), jitter(...), nervous(...), trepida(...), wari(...), wary, worried(...), worry(...)
Being touched	affect(...), mov(...), touch(...)
Boredom	bor(...), ennui, indifferen(...), languor(...), tedi(...), wear(...)
Compassion	commiser(...), compass(...), empath(...), pit(...)
Contempt	contempt(...), denigr(...), deprec(...), deris(...), despi(...), disdain(...), scorn(...)
Contentment	comfortabl(...), content(...), satisf(...)
Desperation	deject(...), desolat(...), despair(...), desperat(...), despond(...), disconsolat(...), hopeless(...), inconsol(...)
Disappointment	comedown, disappoint(...), discontent(...), disenchant(...), disgruntl(...), disillusion(...), frustrat(...), jilt(...), letdown, resign(...), sour(...), thwart(...)
Disgust	abhor(...), avers(...), detest(...), disgust(...), dislik(...), disrelish, distast(...), loath(...), nause(...), queas(...), repugn(...), repuls(...), revolt(...), sicken(...)
Dissatisfaction	dissatisf(...), unhapp(...)
Envy	envious(...), envy(...)
Fear	afraid(...), aghast(...), alarm(...), dread(...), fear(...), fright(...), horr(...), panic(...), scare(...), terror(...)
Feeling	love, affection(...), fond(...), love(...), friend(...), tender(...)
Gratitude	grat(...), thank(...)
Guilt	blame(...), contriti(...), guilt(...), remorse(...), repent(...)
Happiness	cheer(...), bliss(...), delect(...), delight(...), enchant(...), enjoy(...), felicit(...), happ(...), merr(...)
Hatred	acrimon(...), hat(...), rancor(...)
Hope	buoyan(...), confident(...), faith(...), hop(...), optim(...)
Humility	devout(...), humility(...)
Interest/Enthusiasm	absor(...), alert, animat(...), ardor(...), attenti(...), curi(...), eager(...), enrapt(...), engross(...), enthusias(...), ferv(...), interes(...), zeal(...)
Irritation	annoy(...), exasperat(...), grump(...), indign(...), irrita(...), sullen(...), vex(...)
Jealousy	covetous(...), jealous(...)
Joy	ecstat(...), elat(...), euphor(...), exalt(...), exhilar(...), exult(...), flush(...), glee(...), joy(...), jubil(...), overjoyed, ravish(...), rejoic(...)
Longing	crav(...), daydream(...), desir(...), fanta(...), hanker(...), hark(...), homesick(...), long(...), nostalg(...), pin(...), regret(...), wish(...), wistf(...), yearn(...)
Lust	carnal, lust(...), climax, ecsta(...), orgas(...), sensu(...), sexual(...)
Pleasure/Enjoyment	enjoy(...), delight(...), glow(...), pleas(...), thrill(...), zest(...)
Pride	pride(...), proud(...)
Relaxation/Serenity	ease(...), calm(...), carefree, casual, detach(...), dispassion(...), equanim(...), eventemper(...), laid-back, peace(...), placid(...), poise(...), relax(...), seren(...), tranquil(...), unruffl(...)
Relief	relie(...)
Sadness	chagrin(...), deject(...), dole(...), gloom(...), glum(...), grie(...), hopeles(...), melancho(...), mourn(...), sad(...), sorrow(...), tear(...), weep(...)
Shame	abash(...), asham(...), crush(...), disgrace(...), embarras(...), humili(...), shame(...)
Surprise	amaze(...), astonish(...), dumbfound(...), startl(...), stunn(...), surpris(...), aback, thunderstruck, wonder(...)
Tension/Stress	activ(...), agit(...), discomfort(...), distress(...), strain(...), stress(...), tense(...)
Positive	agree(...), excellent, fair, fine, good, nice, positiv(...)
Negative	bad, disagree(...), lousy, negativ(...), unpleas(...)

The vector model (Bradley et al. 1992) is based on two vectors resembling a boomerang that point in two different directions. The model is also based on valence and arousal. The purpose of valence is to indicate the direction of particular emotions. This model is used to research verbal and visual stimuli. The main difference between the circumplex and vector model is that there can be emotions, or emotional stimuli, that are characterized by high arousal and neutral valence (Rubin and Talarico 2009).

The Lövheim cube of emotion by Hugo Lövheim (2012) is an attempt at linking the three monoamine (noradrenaline, dopamine and seratonin) neurotransmitters in the brain to emotion. It is a three-dimensional model for emotions represented by a cube where neurotransmitters form the axes of a coordinate system, and eight basic emotions are placed in the cube's eight corners.

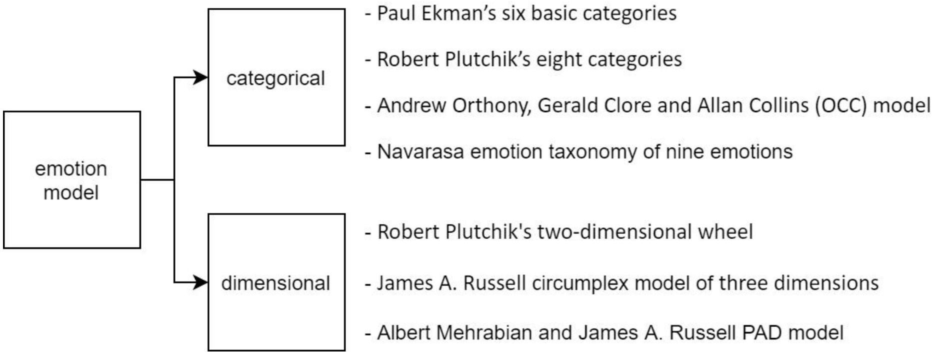
The spherical model of emotions has four dimensions (Vartanov and Vartanova: 2018: 608). Axis one is represented by the following signs: good, useful, nice, bad, harmful, and unpleasant. Axis two represents information certainty and is placed on a confidence-surprise continuum. The remaining axes represent motivation. Axis three represents attraction, and axis four represents a defensive reaction, aggression, and passive avoidance.

Randy Larsen and Ed Diener (1992) conceptualized pleasant-unpleasant and high-low activation dimensions. A few years back, they also studied, along with Steve Levine and Robert A. Emmons (1985: 1255), structures of subjective well-being within a person over time: frequency of positive versus negative affect and the intensity of that affect and whether there is a relation between them. Positive affects are represented by positive emotions such as "happy," "pleased," "joyful," "enjoyment," "fun," and negative affect as "unhappy," "depressed," "blue," "frustrated," "angry," "hostile," "worried," "anxious," and "fearful" (1985: 1256).

As we can observe, dimensional models appear to have a wide domain (see Figure 2). For example, the two-dimensional Robert E. Thayer's contains an emotion classification system for music (Thayer 1978). Robert E. Thayer's mood is separated into clusters calm-energy like exuberance, calm-tiredness like contentment, tense-energy like frantic and tense-tiredness like depression (Seo and Huh 2019: 4).

Alan Cowen and Dachler Keltner (2017) suggested a more complex distribution as compared to discrete and dimensional theories of emotional states and the presence of so-called gradients between 27 emotions: admiration, adoration, aesthetic appreciation, amusement, anger, anxiety, awe, awkwardness, boredom, calmness, confusion, craving, disgust, empathic pain, entrancement, excitement, fear, horror, interest, joy, nostalgia, relief, romance, sadness, satisfaction, sexual desire and surprise.

Figure 2. Categorical and dimensional models of emotions – example



Escobar et al. (2021) asked participants to associate emotions with temperature. Researchers found out that 0 °C was observed for "blue (sad)" or "uninspired," 10 °C for "passive" and "quiet" or "blue (sad)" and "uninspired," 20 °C for "secure" and "at ease," "relaxed" and "calm," or "happy" and "satisfied," 30 °C for "energetic" and "excited," and finally, 40 °C for "energetic" and "excited" and for "tense" and "bothered" (Escobar et al. 2021). Furthermore, participants held implicit associations between the word hot and positive high-arousal emotions, whereas the word "cold" was "associated with negative and low-arousal emotions (Escobar et al. 2021). By analyzing the bodily topography of emotions associated with words, we can draw a map that "shows regions whose activation increased (warm colors) or decreased (cool colors) when feeling each emotion" (Nummenmaa, Glerean, Hari and Hietanen 2014: 647).

4. Categorical models

Paul Ekman's categorical emotion model needs to be analyzed further as it constitutes the basis of the natural language processing analysis of emotions in chapter five. Paul Ekman's theories stem from expressions and gestures that Charles Darwin analyzed. Marcel Duchamp and David Efron also influenced Ekman. Expressions exhibited by Man under various states of mind were first analyzed by

Charles Darwin, who studied emotions from a functional perspective and divided them into the following groups:

1) suffering and weeping,
2) low spirits, anxiety, grief, dejection, despair,
3) joy, high spirits, love, tender feelings, devotion,
4) reflection, meditation, ill-temper, sulkiness, determination,
5) hatred and anger,
6) disdain, contempt, disgust, guilt, pride, helplessness, patience, affirmation and negation,
7) surprise, astonishment, fear, horror, and
8) self-attention, shame, shyness, modesty, blushing (Darwin 1897: 115–346).

Emotion served a biological function when humans "existed in a much lower and animal-like condition" (Darwin 1897: 12). In 1967 Paul Ekman began to study a secluded culture in Guinea that had not come in contact with Western culture, which allowed him to develop a theory of basic emotions published in 1972. Those basic emotions are happiness, sadness, disgust, fear, surprise and anger (Ekman 1972).

Paul Ekman wanted to settle the question of whether or not there is a difference between two cultures in terms of gestures and facial expressions of emotions. For this study, Paul Ekman also visited Japan and wanted to prove that emotional reactions, such as anger, fear, disgust, sadness, enjoyment, surprise, and contempt, have a specific universal signal that can be represented by the tone of voice or facial expressions. Other emotions like envy, jealousy or shame do not share this signal. Emotions also cause a physical reaction. Similarly, co-verbal gestures were considered universal. Five classes were identified by researchers: facial expressions, emblems, illustrators, regulators, and adapters (Ekman and Wallace 1969).

Emotions were originally described on the basis of facial observations of expressions. Paul Ekman studied both micro and macroexpressions, which differ in their duration (Ekman and Friesen 1969). He wanted to link microexpressions, which are shorter in duration, to deception. Emotions expressed through macroexpressions are happiness, sadness, disgust, surprise and anger. Happiness might be characterized by tightened muscles around the eyes, raised cheeks, lip corners raised diagonally, and particular wrinkles around the eyes. Sadness might be characterized by the inner corners of the eyebrows raised, lowered corners of the lower lip and relaxed eyelids. With disgust, eyebrows are pulled down, wrinkles form on the nose, the upper lip is pulled up, and the lips are loose or lowered. Fear is expressed by way of the jaw dropping, the inside of the eyebrows and upper eyelids pulled up and close together, and the mouth usually stretched.

With surprise, our entire eyebrows and eyelids are pulled up, and our mouth is opened. With anger, our upper and lower lids are pulled up, our eyebrows are lowered, the margins of the lips are rolled in, and the lips are usually tightened and stretched. Later, Paul Ekman added other emotions to the list, i.e., ones derived from basic emotions and not based on facial muscle movements. As Ekman continued his cross-cultural research, he thus analyzed amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame (Ekman 1992).

Other categorical models that represent the most used categorical emotion models in NLP are the Plutchik's eight categories and the Ortony, Clore and Collins (OCC; 1988) model. According to Robert Plutchik's theory (1980), emotions are divided into two groups: basic and complex. Basic emotions include acceptance, anger, anticipation, disgust, joy, fear, sadness and surprise. Complex emotions are emotions resulting from a combination of basic emotions. Complex emotions are, for instance, love, loathing, envy or hope.

Table 4. Main categorical models of emotions (Izard et al. 1993)

Author:	**Emotions:**	**Number of emotions:**	**Year:**
Paul Ekman	anger, disgust, fear, joy, sadness, and surprise.	6	1972
Paul Ekman	amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame.	11	1999
Nico Frijda	desire, happiness, interest, surprise, wonder, and sorrow.	6	1986
Robert Plutchik	acceptance,anger, anticipation, disgust, joy, fear, sadness, and surprise.	8	1980
Silvan Tomkins	desire, happiness, interest, surprise, wonder, and sorrow.	9	1962, 1963
Carroll Izard et al.	anger, contempt, disgust, fear, guilt, interest, joy, sadness, self-hostility, shame, shyness, and surprise.	12	1993

The OCC model represents another psychological model, along with Paul Ekman's categorical model, which is popular among computer scientists. The OCC model defined 22 emotions as "valence" reactions. It signifies that affective reactions occur in each person on the basis of the perception and understanding of "goodness" or "badness of things." It, therefore, represents a cognitive view of emotions. Emotion classes are divided into three branches that can be joined together, they originate from 1) consequences of events, 2) actions of agents, and 3) aspects of objects (Steunebrink et al. 2009).

Emotions trigger different defense mechanisms. Fear, for instance, inspires the fight-or-flight response. Finally, according to the Navarasa theory, where rasa means an emotional state of mind and nava means nine, the nine discrete emotions are love and beauty, laughter, sadness, anger, heroism or courage, fear and terror, disgust, surprise or amazement, peace and quiet. Richard Lazarus and Bernice Lazarus (1994) have described in detail 17 human emotions: aesthetic experience, anger, anxiety, compassion, depression, envy, fright, gratitude, guilt, happiness, hope, jealousy, love, pride, relief, sadness, and shame. A selection of categorical models is presented in Table 4.

5. Core emotions and mood disorders

5.1. Happiness and joy

Before we proceed with the influence of emotions on negotiations, we need first to describe certain core emotions utilized in machine learning in chapter five. Moreover, when analyzing sentiment with automated methods, it is important to understand what characterizes a positive or negative sentiment. A positive attitude dominates human behavior. We are more likely to find positive sentiment in textual data, such as congratulatory messages or expressions of sympathy or neutral messages. Messages that express a positive and neutral sentiment do not draw attention since they represent the norm (Naruszewicz-Duchlińska 2015: 8). A negative attitude that transpires in our messages draws attention (Naruszewicz-Duchlińska 2015: 8).

Discrete emotions affect the negotiations immediately and directly. According to some authors, only six basic emotions are shared by all cultures of the world: happiness, sadness, anger, fear, surprise and disgust"[3] (Persaud 1997: 298). Some

[3] Surprise is one of the emotions used in machine learning but not in this work. According to Paul Ekman (1972), surprise is the shortest of all emotions that can last up to a few seconds. After a while,

argued that there are no culturally universal signals of emotions on the facial expression level since, as humans evolved, these signals served more as social interactions rather than biological purposes (Jack et al. 2012). They reflected "diverse social ideologies and practices of cultural groups" (Jack et al. 2012).

When experiencing happiness, the perception of what is around us also changes. We can feel that the world is becoming "prettier," and people are becoming "nicer," which influences communication, e.g., we tell people that they are "great," and we encourage them to come into contact with us and spend time together. When happy people surround us, we are likelier to become happy (Fowler and Christakis 2008). It is the reason why so-called happy people avoid so-called sad people. A common-sense intuition suggests that happiness and sadness are "infectious." Some evidence supports this intuition (Moss 2021). Happiness is sometimes characterized by a sincere smile, a good mood, bliss, and general contentment. Appraisal theories suggest that "happiness arises when goals have been met (or good progress is being made towards attaining them) and expectations are positive" (Van Kleef 2010: 332).

The concept of happiness is studied in philosophy, religion and social sciences and can be felt physically. We can find the first philosophical views on happiness and how it can be achieved during ancient times. One of the first philosophers who wanted to conceptualize happiness was Plato, who considered happiness as not achievable in human life. Contrary to him, Aristotle believed that a state of happiness could be achieved in life. Epicureans and Stoics also disagreed about the feeling of happiness, especially on the source of happiness or where it originates from. Epicureans claimed that the path to happiness leads through the achievement of pleasure, while Stoics saw happiness in virtues. Happiness was, in this view, achievable by every person, regardless of circumstances.

There was also a belief that happiness can be achieved when a person overcomes adversities and the absence of worry and sadness. The concept of eudaimonism, a philosophical term coined in ancient Greece, was known as a state of complete happiness and satisfaction with one's own life. Reaching this state was the principal and highest achievable goal that every human being should pursue. In

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when we know what is happening, surprise can turn into fear, amusement, anger or disgust, depending on the situation. Thus, there can be pleasant and unpleasant surprises. Surprise encompasses an appraisal of novelty, which stems from suddenness and unexpectedness combined with other appraisals that "determine whether the surprise will be experienced as pleasant or unpleasant" (Ludden, Hekkert, and Schifferstein 2006: 3). Surprise can have different intensity levels from amazement to shock (Bălan et al. 2019).

modern times, well-being, the object of study of positive psychology, falls into two general groups: the hedonic group, which encompasses "subjective well-being, happiness, pain avoidance and life satisfaction," and the eudaimonic group studied by Aristotle, which encompasses self-realization, well-being, self-actualization and vitality (compare Fava and Bech 2016). Self-realization is concerned with discovering who we are, and self-actualization's primary concern is using our talents in the best possible way and to their maximum potential, a virtue that Plato advocated (Plato's work about ideal state in "The Republic"). In modern psychology, well-being is associated with the proper control of the emotions of anger, depression and anxiety (Spielberger and Reheiser 2009).

Happiness in social sciences is understood within two categories, emotional and cognitive. Happiness is conceptualized as having two characteristics: infrequent or absent negative emotions such as fear, anger or sadness and prevalence of positive emotions such as joy, love or gratitude (Armenta, Fritz and Lyubomirsky 2020). These elements are part of subjective well-being (SWB), in which a happy person is defined as being "young, healthy, well-educated, well-paid, extroverted, optimistic, worry-free, religious, married person with high self-esteem, job morale, modest aspirations, of either sex and of a wide range of intelligence" (Wilson 1967: 294). Each person's reaction is different depending on the same circumstances and the evaluation of unique values, expectations and experiences (Diener, Suh and Lucas 1999: 277).

Definitions of a good life vary across research, but well-being represents a core component of happiness. Jackson Brown (1991) claims that "success represents achieving what you want, and happiness is wanting to achieve something." A person is likely to feel happy if he is satisfied with his life and achievements. Cognitive assessment of one's own life as successful, valuable and meaningful is thus essential, as well as the proper balance of life experiences: positive versus negative. As mentioned, positive feelings must prevail in order for happiness to thrive, but we cannot experience happiness without experiencing negative emotions as well. For example, seeing others in pain encourages empathy because we feel the same pain ourselves (Schafer 2016). Shared experiences of pain or negative emotions create strong personal bonds (compare Schafer 2016).

Being kind to others leads to "more positive emotion, less negative emotion, and more psychological flourishing, compared to self-focused acts of kindness," and "pro-social behavior increases well-being even without interpersonal interaction" (Titova and Sheldon 2021). As happiness is generally held to be the most important goal in life (Fordyce 1988: 355), different scales to measure happiness were created such as 1) the Satisfaction with Life Scale (Deiner, Emmons, Larsen and Griffin 1985), 2) the Positive Affect Negative Affect Scale or Panas Scale (Watson, Clark, and Tellegen 1988: 3) the Emotions Questionnaire (Fordyce 1988), 4) the Subjective Happiness Scale (Lyubomirsky and Lepper 1999), and 5) the Oxford Happiness Inventory (Hills and Argyle 2002).

Joy can be considered a stronger, less common feeling than happiness. In its intent, joy happens suddenly and unexpectedly. Thus it is not a sought feeling. As a positive emotion, joy also expresses a favorable evaluation or feeling (compare Hume 2014). Abraham Maslow (1964) describes joy as a peak experience. Peak experiences are "moments of highest happiness and fulfillment" (Maslow 1964). They are "rare, exciting, oceanic, deeply moving, exhilarating, elevating experiences that generate an advanced form of perceiving reality, and are even mystic and magical in their effect upon the experimenter." (Maslow 1964). The feeling of happiness accompanies the activities of peak experience, ranging from simple to intense and them. Peak experiences are experiences associated with a sudden feeling of intense happiness. Happiness is an actively pursued feeling and represents a process (Cottrell 2016: 1513). This process is called the pursuit of happiness. On the other hand, unhappiness might be caused by "a specific event or set-back, or it could be a more general feeling experienced over a longer time frame" (Staff Health and Welfare n.d.).

5.2. Sadness

Sadness is broadly considered a contrasting emotion to happiness or an absence of joy. Occasionally, sadness can occur without a particular reason. A key characteristic of people who often feel sad is aloneness with other interchangeable terms, such as social isolation, withdrawal, and loneliness. Low self-esteem is another key aspect associated with sadness and other emotions, such as fear. An example is social anxiety. With the rise of social media popularity that provides access to information and people, there is also fear of missing out on opportunities, not being on the same level as our peers, or being rejected. Sadness can also be caused by an unpleasant incident, a loss of a loved person, or breakdown of a relationship.

5.3. Sadness and depressive syndrome

Depressive disorder represents a mood disorder that is characterized by the feeling of sadness as the predominant symptom. Sadness is the main clinical component of the depressive syndrome, though sadness is not sufficient nor required for the diagnosis of depression (Mouchet-Mages and Baylé 2008, Lazarus and Lazarus 1994: 77). Table 5 illustrates symptoms schematized by the National Institute for Clinical Excellence.

Table 5. Summary of depression symptoms (Miller and Richardson 2017)

Social Symptoms	Psychological Symptoms	Physical Symptoms
Decreased work performance	Prolonged low mood and sense of sadness	Decreased speech rate and movement speed
Avoid contact with friends or family	Hopelessness and helplessness	Changes in appetite, diet behavior and weight
Avoiding various social activities	Low self-esteem	Weight loss
Neglect hobbies and interests	Feeling tearful	Constipation
Difficult at coping with home or family life	Feeling guilt ridden	Unexplained aches and pains
-	Anxiety and constant worry	Lack of energy
-	Irritability and intolerance to others	Libido loss
-	Loss of interest in previously enjoyed activities	Menstrual cycle changes
-	Persistent indecisiveness	Disturbed sleep patterns
-	Suicidal or self-harm thoughts	-

Another shorter summary of depression symptoms is shown in Table 6. Symptoms of depression can be divided into social, psychological, and physical (psychosomatic). Subjects can display certain personality traits that can put them at a greater risk of depression. They encompass: 1) perfectionism, 2) introversion and 3) a high level of neuroticism, which includes a recurrent tendency to experience negative emotions such as sadness and fear (Maj 2017a: 14–15). On a biological level and within sick patients' group, 50% of somatic causes of depression is represented by tumor and 90% by pain (Maj 2017a: 13).

Lack of serotonin and dopamine can also indicate depressed mood. Depression is also accompanied by tiredness and fatigue due to an imbalance of neurotransmitters in the brain (Ghanean H., Ceniti A.K. and Kennedy S.H. 2018). More physical symptoms reported by patients include: disturbance in attention, headaches, chest pains, weight loss and organ mass loss, and digestive system disorders (Maj 2017b: 29).

Table 6. Summary of depression symptoms (Cornah 2006: 10)

Social Symptoms	Psychological Symptoms	Physical Symptoms
Feeling that even the smallest tasks are almost impossible	Sadness	Back pain
Loss of appetite for company	Hopelessness	Stomach cramps
-	Misery	Unexplained tiredness and fatigue
-	Worthlessness	Libido loss
-	Unjustified feelings of guilt	Sleep problems
-	-	Loss of appetite for food

Loss of interest is common. Anhedonia is the inability to feel pleasure, thus abandoning activities one used to enjoy. Anhedonia is "a symptom of depression, schizophrenia, addiction and as a behavior found in the general population" (Szczypiński and Gola 2017). The subject does not seek pleasure and, in turn, does not learn from pleasure experiences.

Depressed patients think that happiness never lasts. The fear of happiness is correlated with depression (Mcewan, Catarino and Baião 2014). Children associate positive feelings with punishment, as they are punished when enjoying themselves (Mcewan, Catarino and Baião 2014). Depressed subjects might say, "I do not want to feel happy," or "I am afraid she will hurt me." Inhibition of self appears to be correlated to the fear of hurting others or oneself. Commonly used phrases in relation to depression are:

"I feel empty."
"I feel tired."
"I feel sleepy."
"I feel insignificant."
"I feel alone."
"I feel out of touch."
"I am not hungry."
"I can not smile."
"I want to withdraw" (Plutchik 1984: 4).
"I don't belong here."
"I am worse than others."
"I am ridicule."

Relevant symptoms of depression also include hopelessness and helplessness (Weishaar and Beck 1992), where the subject thinks he can do nothing to improve his situation and loses hope. Subjects that have lost someone they hold dear are up to nine times more at risk of depression (Maj 2017a: 15). As far as despair is concerned, in current psychopathological literature, the concept of despair in depression is almost redundant (Bürgy 2008)[4].

A common characteristic of depression is the low frustration tolerance (LFT) or frustration intolerance (FI) that occurs when subjects cannot deal with daily frustrating situations such as stressful or unpleasant situations. Frustration is defined as a "negative state induced by the unexpected and sudden omission, reduction in magnitude, quality degradation or inaccessibility to appetitive reinforcers," and it is associated with "emotional distress, aggression and low motivation" (Rivero, Torrubia, Molina and Torres 2020: 343). Humans, similarly to animals, generally direct their behavior in such a way as to obtain appetitive reinforcers or "rewards" and avoid aversive reinforcers or "punishments" (compare Ilango, Wetzel, Scheich and Ohl 2010: 752).

Conceptualized warning signs of depression include 1) signs (something observed in another person) and 2) symptoms (something reported to someone else, Rudd et al. 2006). Frequently identified warning signs for depression include:

1) self-harm,
2) obsessions with death, which include writing and talking about death,
3) sudden changes in personality,
4) behavior, eating, or sleeping patterns,
6) feelings of guilt,
7) decreased academic or work performance (Rudd et al. 2006).

Time frames for warning signs are different. They imply near-term risk, whereas risk factors suggest risk over much more longer periods (Rudd et al. 2006). In Polish literature, we can find the following factors that influence suicide attempts:

1) strong and lasting depression, repeated feelings of guilt and low self-esteem,

[4] Some authors consider depression different from despair. Depression is essentially object related while despair is not (Agazarian 1994: 68). An act of complaint can accompany depression. Depression might manifest as a cry for help. Despair is the cry of the hopeless who knows no one listens (Agazarian 1994: 68).

2) insomnia,

3) demographic situations, e.g., lone male above 45 years of age,

4) bad financial situation,

5) personality disorders, e.g., antisocial personality disorder (sociopathy) and borderline personality disorder,

6) records of suicide attempts of the subject, suicide attempts of the subject's relatives or other people important to the subject,

7) alcohol and psychoactive substances abuse, and

8) somatoform disorders (Michalak 2017: 78).

The risk of suicide may increase in the presence of one of the following elements: 1) suicidal ideations (SI, Harmer et al. 2022), 2) psychosocial stressors, 3) traumas, or 4) a history of depression. Suicidal ideation represents the subject's desire to die, expressed in words, actions, thoughts and ideas. Suicidal ideation (SI) is common in major depressive disorder (MDD; Olgiati 2022)[5]. Different scales to measure suicide risks were created, such as the SAD PERSONS Scale (Patterson et al. 1983), the Modified SAD PERSONS Score (Hockberger and Rothstein 1988), and the Manchester Self-Harm Rule (Cooper et al. 2006; see annex, Table 5, 6, and 7).

Deaths from suicide are influenced by time and day apart from personal reasons[6]. Suicide risk may also depend on emotional maturity and emotional intelligence. Emotional maturity (EM) refers to the capability of an individual to deal practically with real-life situations, control one's emotions and behave objectively (Kumar and Kiran 2017). Emotional intelligence (EI) also represents a key variable;

[5] There are two types of depressive disorders: major depressive disorder and dysthymic disorder. The latter is also called a persistent depressive disorder. Major depressive disorder (MDD) is a mood disorder characterized by "persistent sadness and other symptoms of a major depressive episode but without accompanying episodes of mania or hypomania or mixed episodes of depressive and manic or hypomanic symptoms" (APA Dictionary of Psychology 2021). MDD affects 20% of the worldwide population (Wang, Zhou and Liu 2014). Dysthymic disorder (DD) is a mood disorder characterized by symptoms that are less severe but last longer than major depressive disorder (APA Dictionary of Psychology 2021). Dysthymic disorder (DD) is considered to be part of the chronic mood disorder group, while major depression falls into the unipolar depression category (APA Dictionary of Psychology 2021). Histrionic Personality Disorder (HPD) is one of ten personality disorders in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5). HPD subjects are emotional, overly dramatic and attention-seeking. More clinically known depressions include atypical depression, situational depression, perinatal depression, premenstrual dysphoric disorder (PMDD), seasonal depression, depressive psychosis and manic depression (APA Dictionary of Psychology 2021).

[6] Among other factors, evidence from Japan over 41 years and 873,268 suicide deaths suggest that people tend to commit suicide mainly for economic reasons early on Monday morning (Boo, Matsubayashi, and Ueda 2019). A study by University of Pennsylvania shows that from 11 p.m. to 7 a.m. the human brain is programmed to turn off the frontal cortex, which is responsible for decision making (Perlis cited in: Phillip 2014).

on the emotional and behavioral level, it protects against irrational decisions, such as suicide attempts (compare Domínguez-García and Fernández-Berrocal 2018).

Frequent internalizing is typical for depressed subjects, who keep their feelings or issues inside without sharing their concerns. Apart from the implosion of feelings that are not appropriately externalized, subjects may frequently engage in inner speech, inner conversation, inner dialogue, or self-talk and ignore the external world.

Anna Kuncy-Zając (2019: 214–233) analyzed the language of Polish and Italian blog posts dedicated to depression. She found that depressed persons are not always passive about their sickness and want to "fight" depression in order to become normal. In the Italian corpus, depression is perceived as an enemy that "hits," "wins," or "destroys" the sick, but it also "terrifies," "grips," "assaults," "tortures," "bends," "breaks," "nullifies" our efforts or has the upper hand.

In the Polish corpus, the verbs are more diverse (Kuncy-Zając 2019: 216). Numerous are also the examples in which depression "reaches" and "captures" its prey, "takes away life's most essential elements," such as the "will to live," our "job" and our "time," or tries to "possess the body," the "mind" and the "soul" of the depressed person (Kuncy-Zając 2019: 216).

Depression is associated with losing grip over our lives and fighting depression with regaining grip. Sometimes rage can be based on hope. For that reason, and in situations when it helps fight depression, anger and rage can be considered a positive feeling. Life can be perceived as monotonous, empty, and gray in a depressed subject or fulfilling and significant in a healthy subject (Hänninen and Valkonen 2019). Depressed subjects tend to feel a co-occurring sense of entrapment and defeat (Griffiths et al. 2014), compare Table 8. Depression can also lead to positive outcomes associated with "rest and disconnection, reflection, reorientation, and reorganization of life" (Hänninen and Valkonen 2019).

Regaining control might be accompanied by anger, e.g., for the time and opportunity lost due to depression. A lot of the subject's successful recovery depends on social influence. Social distancing is known to affect mood, depression, anxiety, and in more general terms, psychological well-being and mental health. In the case of alcoholic patients on the road to recovery, a study found that entrapment and social isolation are negatively correlated to motivation for recovery. In contrast, emotional support is positively correlated to motivation for recovery (Lee, An and Suh 2021: 5).

Another key characteristic of depression is represented by irritability associated with anger. Irritability means excessive reaction to stressors, like bursting with anger easily Irritability is "associated with SI concurrently, and more significant reductions in irritability earlier in treatment are associated with lower levels of subsequent SI" (Jha et al. 2021).

5.4. Anger and disgust

Anger can be considered an emotion that covers up underlying, primary emotions. It can also be a sudden reaction to being hurt or be related to more long-term factors like the feeling of injustice. We resort to anger in order to protect ourselves. Thus, anger comes from a perception of endangerment, which comes not only from physical threat but also a "symbolic threat to self-esteem or dignity: being treated unjustly or rudely, being insulted or demeaned, being frustrated in pursuing an important goal" (Whitehouse 2006: 6).

Emotional responses, like anger, do not always immediately follow an event: if we are mugged on the street, we "may not feel a sense of anger until much later - perhaps days or months after the episode" (Farrall, Jackson and Gray: 2006: 8). Sometimes, anger may be accompanied by helplessness and powerlessness. Anger is an emotion that can cause bitterness, rage, and in some cases, aggression. Anger can also be a response to rejection. If someone is trying to reassert a sense of control, he might become aggressive in an attempt to force the other side into submission or to pay more attention to what we say (compare Weir 2012). Thus, anger can be used to talk some sense into someone or reconcile with someone.

Typically anger can be accepted in a social context if the other side is acquainted with us; for instance, in a situation like a conversation with a relative or a friend, especially if our intentions are good and we want to help. Reaction to strangers that express anger may provoke more extreme reactions, especially if our intent is perceived as harmful or unjust. Anger can be defined as an "outwardly directed communicative signal establishing differentiation and conflict within interpersonal relationships and affective bonds" (Williams 2017). Anger also increases "risk-seeking behavior and the motivation to engage in political action" and leads people to attack and eliminate the source of anger (compare Wagner 2014).

The words disgust and anger are often used interchangeably to describe offence toward immoral behavior (Herz and Hinds 2013). "Grossed out" is thus reserved not only for viscerally repulsive stimuli, e.g., "I am disgusted by how you are treating this woman." In that case, rather than representing disgust-relevant language and structures related to food and ingestion, disgust becomes representative of anger (Herz and Hinds 2013; Miller 2004: 158)[7]. The emotion of disgust is often accompanied by aversion, dislike, and uneasiness. Disgust can also be directed towards people and their actions and contain an element of exclusion, degradation (Miller 2004: 158), contempt, and hate speech.

5.5. Fear

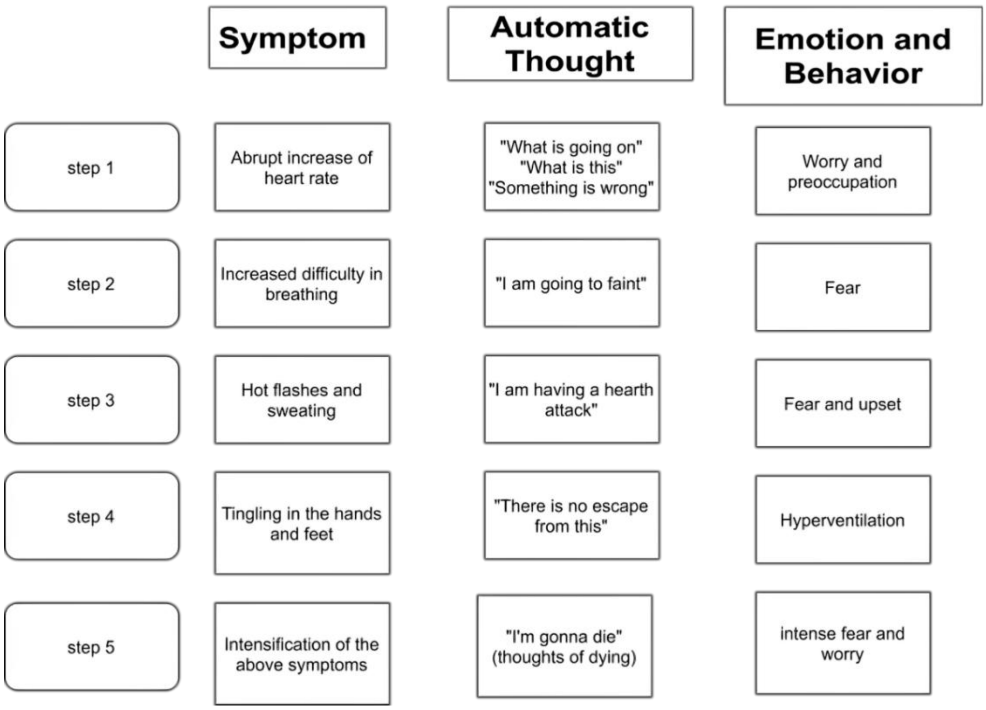
Fear is a response to a threat. It may be caused by a vision of both physical and mental pain. Fear can cause us to weaken our self-confidence. Sigmund Freud (1924) argued that anxiety causes a physiological response associated with tension, worry and apprehension. Fear can grow and be accompanied by anxiety and dismay; it can also transform into panic. When fear grows too high in intensity, it can lead to unexpected and irrational results. The Symptoms Automatic Thoughts Emotions Behavior (S.A.E.B.) system shows connections between stages of the escalation process, setting the stage for the next step of panic symptoms (see Figure 3).

Fear can dissipate quickly and, as an event, be forgotten, but prolonged fear, anxiety and stress are detrimental to cognitive and mnemonic processes and decision-making skills. Fear and anxiety are part of negative affective responses (D'Ambrosio 2002: 2005). A short anxiety period causes individuals to rely less on habit and pay more attention to information (compare D'Ambrosio 2002: 2005). Anxiety motivates to learn, engage in discussions, and think about decisions, behaviors and results more carefully (compare D'Ambrosio 2002: 2005). Anxiety also leads to "problem-focused information, risk-averse behavior and increased vigilance" (Wagner 2014). Fear

[7] One of the emotions that are used in machine learning but not in this work is also disgust. Disgust does not consistently serve the microbiological security of our body, e.g., by rejecting stale food, but it consistently promotes psychological security (Miller 2004: 6). Disgust appears unnecessary in infancy and maturates later from displeasure (Miller 2004: 3, 11). Disgust can be compared to a defensive reaction to external stimuli that we perceive as unpleasant, inconvenient, or unwanted. These can be stimuli associated with our senses, e.g., smell, sight, touch, or taste. It can be expressed, for instance, by the utterance containing an interjection: "Yikes! What is that smell?." Disgust equals dislike, distaste, or repugnance; among all the basic emotions presented in this subchapter, it is the most visceral (compare Bălan et al. 2019).

motivates people "to be cautious and avoid harm," which makes this feeling different from anger (compare Wagner 2014).

Figure 3. The S.A.E.B. system (based on Dattilio 2001: 393)



6. The influence of emotions on negotiations

Emotions serve social functions and have interpersonal consequences (Van Kleef and Sinaceur 2013: 331). Emotions influence the quality of life, interactions with other people, thoughts, actions, subjective perceptions of the environment and behavioral responses (Bălan et al. 2019). Emotions shape negotiations in two ways: felt emotions shape how we process information about the negotiation and expressed emotions shape how others react. Emotions thus shape information processing (Olekalns and Druckman 2008: 4).

Negative emotions influence our perception of an issue; we focus only on the conflict, and the issue becomes exacerbated over time (Shapiro 2005). Negativity is characterized by "skepticism and a disagreeable tendency to deny or oppose or resist suggestions or commands" (Antal 2007: 7). On the other hand, positive emotions make participants concentrate attention on the "big picture" and "broaden a person’s perceptual attention focus" (Ehrig et al. 2020: 11). Negotiating represents a dynamic process. For instance, when the counterpart's actions are counter-productive to the realization of a negotiation objective, the other side will likely react with negative emotions and displeasure (compare Griessmair 2017). The counterpart then tries to maintain harmony between participants and readjust behavior and emotional display, which helps reach the common objective.

Furthermore, a positive mood increases the variety of future options considered before making a choice (Ehrig et al. 2020: 11). When negotiators make progress toward achieving their objectives, it is likely that pleasure and positive emotions such as happiness or joy will emerge (compare Griessmair 2017). Conversely, frustration and anger may arise if the parties reach an impasse.

6.1. The influence of anger, guilt, and compassion on the negotiation outcome

Expressions of anger facilitate particular behavioral responses such as "moving away," which means either exiting from the negotiation or forming coalitions with other individuals, "moving toward" (conceding), or "moving against" (fighting; Yip and Schweinsberg 2017: 707). Furthermore, an experiment suggests that angry expressions 1) contribute to negotiation impasses or exiting strategies, 2) negotiators are more likely to infer that their counterpart is selfish when displaying anger, and 3) angry expressions violate normative expectations of appropriate displays of emotion in negotiation which may contribute to punitive actions from the other side (Yip and Schweinsberg 2017: 708–710). More than that, anger during a negotiation tends to reduce trust due to harm to interpersonal relations and make the other side angry (Ahmad et al. 2022). Anger may have negative, long-lasting interpersonal consequences (Uehara, Mori and Nakagawa 2019).

Anger is typically used to gain control and power over the other party through aggression. Anger displayed by the negotiator that turns out to be faked as an act of emotional deception does not typically yield better negotiation outcomes either. Roger Fisher and William Ury (1993: 20) recommend to not react to rage, since it leads to violent quarrels. Parties should accept only one person getting angry at the negotiation table (Fisher and Ury 1993). Reaction to aggression demonstrates a loss of self-control and face (Fisher and Ury 1993). Anger is influenced by moral emotions such as shame and guilt. Shame and guilt are similar in that they are self-conscious emotions, implying self-evaluation and self-reflection (Miceli and Castelfranchi 2018).

A study shows that manifestations of guilt reduce aggression (Stuewig et al. 2009). Thus, guilt is a protective barrier to anger and aggressive individuals (Stuewig et al. 2009). Guilt can lead individuals to apologize or to make amends (Stuewig et al. 2009). Shame is also positively linked to hostility and aggression, whereas "shame-free" guilt is inversely related to anger, hostility, and the externalization of blame (Stuewig et al. 2009). Instead of fostering anger and blame, "shame-free" guilt has been consistently linked to empathy and other-oriented empathy acts (Stuewig et al. 2009). Instead of fostering anger and blame, "shame-free" guilt has been consistently linked to empathy and other-oriented empathy acts (Stuewig et al. 2009).

Anger can also be studied in relation to compassion. A study shows that compassionate feelings increased trust but did not necessarily reduce distrust during negotiation (Liu M., Wang C. 2004). The anger and compassion negotiators feel for each other influence the negotiation more than the mood (Liu M., Wang C. 2004: 177). Compassion is in contrast with anger. With anger, we attack the other side's face; with compassion, we enhance the other party's face (Allred et al. 1997). Anger pushes negotiators to prioritize strategic targets, such as getting a better deal than their counterparts (Liu M., Wang C. 2004: 177). Compassion promotes collective goals such as maximizing both parties' profit, promoting information exchange, and a positive relationship (Allred et al. 1997). The prevalence of anger over compassion typically creates disadvantages for negotiators without providing meaningful advantages.

Empathy and compassion impact low-power negotiators more than high-power negotiators (compare Sinaceur et al. 2015: 1851). Although compassion represents an essential element in negotiations, we must cut the emotional strings when dealing with dangerous personalities that are social puppeteers (Navarro 2013). Finally, it must be added that displaying emotions in a negotiation makes us vulnerable, e.g., a revelation of emotions can open us up to being manipulated, as observable reactions offer the other party hints about our true concerns and intentions (Saphiro 2004: 738).

6.2. The influence of sadness on the negotiation process

Anger and sadness are emotions that can harm negotiations as they result in poor information processing. Sad mood decreases trust and negatively influences negotiated outcomes, as shown in psychological tests (PON Harvard Staff 2011). Sadness seems to be a dominant feeling in a negotiation involving a suicide subject. However, some negotiations reveal that the primary feelings of a suicide subject can also be anger and pride (Young 2020). Pride should not be studied in isolation but with the contrasting emotions of shame, as its function is to erase feelings of shame (compare Sullivan 2007: 176, 179).

Sadness can be potentially dangerous as it is associated with self-harm and less dangerous frustration. Frustration happens when we are impeded or undermined, which can quickly lead to anger and aggravation (Staff Health and Welfare n.d.). On the other hand, sadness can be used strategically to our advantage when one party feels sorry for the other party due to what it considers to be a valid reason. One party might make more favorable concessions towards the party he feels sorry for. Anger and sadness influence negotiations depending on whether we deal with low-power versus high-power situations and operate within cooperative versus competitive interactions.

The power of expressed emotions depends on social context. Emotion strength depends on the relative social power and ranks in the relationship the emotion manifests. Power can be defined as the "potential to influence another in psychologically meaningful ways, inducing changes in behavior, opinions, attitudes, goals, needs or values of another person or group" (Maiwald: 2015: 4). A high-power negotiator uses "more threats and punishments as a strategy than the low-power negotiator in negotiation" (Maiwald 2015: 8).

In claiming and arguing for a position, an experiment demonstrated that sadness was effective only in low-power situations, whereas anger was effective only in high-power situations (compare Sinaceur et al. 2015: 1859). Expressions of sadness invited cooperation in cooperative interactions but were ignored or frowned upon in competitive interactions (compare Sinaceur et al. 2015: 1849).

6.3. The influence of depression on the negotiation process

Half of the non-hostage cases involve a subject affected by diagnosed mental disorders, most frequently: paranoia, depression and antisocial personality disorder (Álvarez 2014: 119). Subjects affected by a personality disorder or mental illness experience intense emotional distress, overwhelming their ability to cope and think clearly (Álvarez 2014: 119). Their acts often reflect destructive, irrational, unstable, and non-goal-directed behavior (see Álvarez 2014: 119). Subjects with a depressive disorder tend to 1) have a higher recall and encoding of negative words, 2) demonstrate an attentional (cognitive) bias towards emotional stimuli, 3) selectively attend to emotional cues, 4) interpret ambiguous information in a negative manner, 5) have a negative bias in all type of their information processing (Ferrugia 2019: 46–47), and 6) often demonstrate a decline in empathy. Decreased sensitivity to emotional cues, often observed in depressed subjects, means losing the ability to understand other people's emotions.

Depressed people are not used to positive feelings and tend to interpret the "world and everyday events in a negative manner that other people might see as neutral or even positive" (May 2013: 436). When recalling events, they would include more negative events (May 2013: 436). The Grant Sattaur negotiation shows, for instance, that the suspect recalled his negative experience with his girlfriend and the hospital he was held in, which influenced the negotiation outcome. Moreover, depressed subjects tend to ignore parts of information, have difficulty recognizing other persons' feelings (compare Szanto et al. 2012), and fully understand what is happening around them, which may result in heightened aggression and violence. Recognizing feelings impacts the mirroring process necessary for both negotiations and interrogation methods.

An interview with a subject who attempted suicide after a successful negotiation revealed that the subject did not commit suicide because the law enforcement agents did not crowd him (Young 2020). He was disappointed, however, that the negotiator talked too much as he could not catch his breath and think (Young 2020). The subject, who was hungry and exhausted but also disrupted and overwhelmed by relationship problems, did not remember that he was standing on the edge of the building (Young 2020). The police negotiator, on the other hand, was empathetic and slowly convinced the subject to move to a safe position and shake his hand (Young 2020). The police did not rush these actions, which is important as most casualties happen at the beginning of a late negotiation stage (compare Young 2020).

Negative emotions can have a disruptive effect on negotiations. If we label negative emotions and the source of negative emotions, we are less likely to positively affect our negotiation decisions (Pon Harvard Staff: 2021a). The negotiator should focus on positive emotions that lead to trust, comfort, and rapport to defuse negative emotions, trying to understand the situation from the perspective of the person in crisis (Vecchi et al. 2005: 539).

6.4 The impact of fear, anxiety and stress on the negotiation process

Physical and mental stress impact negotiations in a negative manner, especially if the subject is affected by mental illness. Depression and anxiety can impede empathic communication ability (Nakamura et al. 2020). Hostage negotiations present a stressful and uncommon situation, further exacerbating the problem. I already mentioned some of the adverse effects of stress on interrogations and interviews in chapter two. In the long term, stress causes harmful and toxic substances to be produced in our bodies. Common adverse reactions to epinephrine include: "nausea, dizziness, vomiting, tremor, headache, palpitations, excitement, and pallor" (Wood, Traub and Lipinski 2013: 245).

Stress can influence our sleep. Consequences of prolonged or chronic sleep deprivation are "high blood pressure, diabetes, heart attack, heart failure, or stroke" (compare Moss 2021). For example, the Branch Davidians during the Waco siege in Texas were deprived of sleep and pressured with stress enacting tactics like loud music and scary noises for many days. The FBI wanted to ensure continual sleep disruption to persuade the barricaded residents to leave and surrender. However, at the same time, as I mentioned in chapter four, they undermined negotiation efforts, especially the thought processes and decision-making capabilities of hostages and barricaded suspects. Another key negotiation feeling is anxiety, which affects both perpetrators and victims. As Martin Saymond (1983: 75 cited in Fuselier 1988: 178) put it:

> "an individual beset by basic anxiety responds with primitive and adaptive behavior. Adaptive responses learned in maturity evaporate, to be replaced with infantile survival mechanisms. I call this response in victims traumatic psychological infantilism. It compels an individual to cling to the very person who is endangering his life."

Stress and anxiety should be kept under control. Negotiations are exhausting and "nerve wrecking," so their emotional impact must be reduced. We can defuse business negotiation anxiety by focusing on opportunities and re-framing anxiety as excitement (PON Harvard Staff 2021a). A hostage negotiator can use persuasion by telling the other side that their fear ("I might faint" or "I am going to die") is unsubstantiated or by educating them (compare Dattilo 2001).

Post-traumatic stress disorder (PTSD) is observed in both officers and the other side after a crisis incident. For law enforcement agents, the cause of PTSD comes from the inherent conflict between the personal level of humanity and the need to use lethal force (Young 2020). Most untrained officers put humanity first over personal safety in order to help (Young 2020). Most officers cannot cope when forced to protect themselves against dangerous subjects and immediately after the incident would say, "why you made me do that? I told you to stop" (Young 2020).

6.5. The impact of humor on crisis negotiations

Vincent Hurley (2019), a former police negotiator, said that hostage negotiations dealing with minors as perpetrators should be mainly focused on:

(a) humor,
(b) controlling the tone of voice,
(c) letting the minor vent frustrations,
(d) not pushing the subject too hard during a difficult moment, and
(e) being patient.

The importance of using humor in mediation when speaking to a minor was highlighted by Zofia Frączek (2018: 153). In crisis negotiations, humor can be used to defuse an argument (a). Humor, however, must be respectful and never used at the expense of a negotiating party (Forester 2014: 1). Humor can be used to maintain harmony and to subvert authority but represents a complex technique to master and can have unexpected results. Each subject might have a different sense of humor and react to humor differently. In positive psychology, humor is seen as a way of coping with stress (Martin 2003: 5). Subversive humor "challenges existing power relationships, whether informal or formal, explicit or implicit; it subverts the status quo" (Holmes and Marra 2002: 71). Humor can connect us and place us on the same level in the conversation. Laughter can "express not just release but also mutual acknowledgment" (Forester 2014: 6). Using humor or other distractions reduces stress, worry or anxiety.

7. Rehearsing psychodrama and re-framing techniques

A hostage negotiator should be aware of at least some rules and methods of psychotherapy. Psychodrama and role-playing can be leveraged to develop negotiation skills, understand certain emotions and human behavior better, and, in some instances, help overcome past traumatic events. Jacob Levy Moreno invented psychodrama in the early 1920s, but the first professional society adopted it in 1942 (Kedem-Tahar and Kellermann 1996: 27–28). The term comprises the Greek word "psyche," which means soul, and "drama," which means action. It explores psychological and social problems, encouraging participants to act on relevant moments rather than narrate them.

Psychodrama was initially an experimental and improvised theatre without distinction between actors and audience, to turn into structured group psychotherapy (Kedem-Tahar and Kellermann 1996: 28). The use of sociodrama and drama therapy allows to discharge tension and plays a catharsis role (Creekmore and Madan 1981: 31; Giacomucci 2019). It helps the subject to become more flexible and responsive to the environment (Creekmore and Madan 1981: 31).

Psychodrama includes three essential stages: warm-up, enactment, and sharing, which mirrors sociometry, psychodrama, and group psychotherapy (Giacomucci 2019). Psychodrama can be used to cure psychosomatic symptoms (López-González, Morales-Landazábal, and Tropa 2021: 18–19). Groups can rehearse not only bad moments but also positive moments in order to get used to feeling happy, an important element for depressed subjects. Different goals of sociodrama may be categorized into five different applications separated for heuristic reasons (see Table 7). Sociodrama deals with the following problems represented by the Table below:

1. group responses to catastrophic events of national importance that cause trauma,
2. power and equality problems that cause conflict,
3. prejudice caused by diversity, stigmatizing stereotypes, racism, prejudice, negative bias,
4. interpersonal tension is a social process that transforms violence into less dangerous ways of conflict management, and

5. post-conflict reconciliation and community rehabilitation, e.g., violations of equality and results as symptom of reduced social cohesion (Kellermann 2007: 64).

Rehearsing sociodrama can train people, including negotiators, to become more empathic and compassionate. It also teaches us to re-frame the other party's statements with empathy. Ervin Goffman's (1974: 21) frames allow us to "locate, perceive, identify, and label" events through a "schemata of interpretation." The theory implies that the method used to represent an event or situation influences people's choices about how to absorb and process it. Through the framing technique, we systematize our lives in the social space and give them meaning. For example, politicians can use framing to create sharp polarization between supporters and opponents. The framing process involves selecting some aspects from reality and giving them special meaning, allowing for a moral evaluation. Similarly, negotiators can use framing techniques to manipulate the subject.

Table 7. Five applications of sociodrama (Kellermann 2007: 64).

Applications:	**Focus:**	**Ideal:**
Crisis	Collective trauma	Safety
Political	Social disintegration	Equality
Diversity	Prejudice	Tolerance
Conflict management	Interpersonal tension	Peace
Postconflict reconciliation	Justice and rehabilitation	Coexistence

8. Expressing emotions with language

Emotions can be experienced as well as expressed. Feelings are easier to compare with language as they are nebulous and fluid (Wierzbicka 1995: 234). Emotions may be experienced similarly but expressed differently across cultures (Leersnyder, Boiger and Mesquita 2015: 4–5). Affects and emotions can be considered a cultural-material hybrid, which is difficult to understand without its manifestations in discourse (compare Breeze 2018). Therefore, we can find different emotional styles across cultures (compare Breeze 2018). Expressing emotions does not necessarily mean experiencing them. Language does not always represent psychological reality (Ekman 1994: 56–58). Expressed emotions arise from various experiences and situations. Richard Wollheim (1999: 188) argues that certain emotions, like shame or guilt, arise as long as there are eyes to see (experiencing shame) and there are voices to reach us (experiencing guilt). It should be emphasized that experiencing emotions does not necessarily mean expressing them.

We often describe or express our feelings about a situation through various means. In order to explore emotions experienced by people, we consider a wide spectrum of emotions expressed in culture, e.g., in painting, literature, sculpture or music. In sociolinguistics, according to Stanisław Grabias, expressive sociolects fulfill predominantly expressive functions, e.g., slang intended to convey emotions or the secret language developed by children (Grabias cited in Lewandowski 2010: 63). Emotions are expressed on all linguistic levels, including phonological, morphological, lexical and syntactic (Foolen 2012: 349). On a figurative level, emotions are expressed by using metaphors and metonymy (Foolen 2012: 349). There is a close link between figurative language and emotions. Conceptual metaphors can use combinations of "up-down" that are necessary to express emotions, where "happy" means up and "sad" means down:

"I am feeling up,"
"I am feeling down,"
"things are finally looking up,"
(Lakoff and Johnson 1980: 463–465),
"he has been feeling very down since his wife went away,"
"all these problems are getting her down" (Macmillan dictionary 2021).

"Up-down," "high-low," "upper-under," "uphill-downhill," "top-bottom" can influence the meaning of a sentence, and can express a positive or negative emotion or evaluation: depravity versus virtue, social status, bad versus good, and product quality:

"That was a low trick,"
"The music is highly underrated,"
"He has risen to the top,"
"Her life went downhill after drug abuse"
(compare Lakoff and Johnson 1980: 463–464).

The word "south" is also used to indicate that something went bad or wrong, e.g.:

"things went south after his arrival"

Not only content words, such as nouns, verbs, adverbs or adjectives, are crucial to express emotions but also prepositions (Foolen 2012: 349):

"to long for,"
"hold resentment towards,"
"hate against,"
"bear grudge against,"
"be in love with."

Psychological verbs, e.g., love, fear, adore, frighten, please, or delight, describe emotions and entail a mental state in the Experiencer argument (Rozwadowska and Willim 2016: 1). Subject Experiencer (SE) can be illustrated with the English verb to fear; Object Experiencer (OE) can be illustrated with the English verb to frighten, and Dative Experiencer (DE) is found in verbs such as to please, or to appeal to (Rozwadowska and Willim 2016: 1). In more general terms, we can categorize three methods of expressing emotions with language (Lewiński 2006: 53–54):

1. Non-verbal method - it consists of expressing emotions through facial expressions, gestures, body posture, exchange of glances, as well as the distance between interlocutors (Lewiński 2006: 53–54).

2. Paraverbal method - a method based on the so-called paralinguistic sounds, they include vocalization and suprasegmental features. Vocalization can be composed of crying, laughing, sighing or whistling, but also affirmation and negation sounds such as "uh-huh" (affirmation) or "uh-uh" (negation; Pennycook 1985: 259). The so-called suprasegmental features are, for example, the pace at which the sounds are uttered: rhythm and tempo, as well as the articulation, tone, range, pitch and resonance of the voice.

3. Verbal method - it can be expressed through a descriptive approach, directly as well as indirectly, for instance, using a particular style. Most often to describe our emotions we simply have to name them (Lewiński 2006: 53–54).

To find emotions in text, we should take into account written sources that can be divided into four categories:

1) communicating emotions by naming them (e.g., to be sad, happy, angry),
2) communicating emotions by describing them (e.g., somebody "jumps for joy"),
3) expressing emotions by using expressive constructs (e.g., "thank God for!"),
4) manifesting emotions by using various textual and para-linguistic means (Mikołajczuk 2006: 84–87).

Emotions can be communicated directly or indirectly. We communicate emotions indirectly if we are unaware of their expressive value. In many languages, positive feelings are conceptualized as bright and negative feelings are conceptualized as dark (Pajdzińska and Tokarski 1996: 155), e.g.:

"His face is radiant with joy,"
"Her eyes light up,"
"With joy everything shines,"
"A glimmer of hope,"
"He has found his place in the sun,"
"A piece of my heart found light tonight,"
"The bright side of this event,"
"His mood darkened,"
"He blackened his name,"
"That woman has a black heart,"
"The man has a dark side."

As we can see from the examples, "hope," "good life," or "love" are associated with something bright; "black" is a synonym for evil or corruption. The color that stands out in that regard is "blue," which is associated with depression, and black, which is associated with grief. "We wear white to weddings and black to funerals" (Jonauskaite et al. 2020). White also signifies purity, cleanliness, and virginity, which is associated with positive emotions but also with fear and cowardice (Rogers 2020). Contrasting words such as big and small are also used to convey emotions and state of affairs. The word "big" denotes positive feelings:

"I made it, and I feel so big."
"man, that is huge, congratulations!"

The word small denotes negative feelings:

"I feel so small."
"I received small support."

Similarly, we can use the opposite words of warm and cold:

"She received a warm welcome."
"It warms my heart to see them together again."
"That was cold, you should comfort her."

Inversely, hot can be used in a negative fashion and cold in a positive fashion, e.g., as to denote desirable or undesirable characteristics at work:

"This job requires cold surgical precision."
"He was too hot headed, we had to fire him."

Typically warm (hot) is also associated with a higher arousal level, and cold with low arousal. Another example of contrasting words is "free" versus "enslaved." Freedom is associated with the feeling of being alive. Being enslaved is associated with prison or chains, which means, among many things, a lack of opportunities. The opening sentence of Rousseau's The Social Contract illustrates this aspect well: "Man is born free and everywhere he is in chains." To communicate negative feelings, one might say:

"I feel enslaved by the system."
"I am a slave of my own desires."
"I live in an unspeakable prison."

Another dichotomous pair of words is represented by heavy and light, e.g. :

"This event weighted heavily on his soul."
"I passed all the exams, and I feel light as a feather" (a feeling you experience when you are free of pain, sadness, anxiety and worries).

Pair of sweet and sours that affect taste also denote positive and negative feelings, respectively, e.g. :

"All was not sweetness and light."
"The situation has left me with a sour taste."
"I was able to negotiate a sweet deal."
"The negotiation turned sour."

Strong emotions are associated with "fire" (Pajdzińska and Tokarski 1996: 155):

"If love is fire then I'll burn for you,"
"His eyes flamed with anger,"
"He flames of desire/passion,"
"Her cheeks burned with shame."
"You were getting very hot under the collar about the game."
"He was on fire with this marvelous sight,"
"In a state of ignition."

As we can see from the examples, "fire" can be associated with shame or guilt, anger or excitement. "I see red" means "I am angry," which derives from blood rushing to one's face (Jonauskaite et al. 2020). Valentine's Day color is red, the color of love and passion through association with something warm or hot. Red also signifies danger. From the perspective of religion, "fire" can be associated with a positive purifying force but also with an opposing force, e.g., "the fire of Hell," "eternal torment," or "hellfire." Evil forces are red or black, and forces of good are white and blue. Blue as a celestial color is also associated with noble birth, e.g., in the expression "blue blood." The blue background of the EU flag was chosen due to its association with harmony (Pastourou 2000).

In many religious traditions, blue symbolizes heaven and is considered the color of truth (Parikh 2011). Pink and blue represent the color of gender (Frassanito and Pettorini 2008). Another particular color is green. The Shakespearean utterance "green with envy" means to be jealous (envious).

Expressive morphology allows to "use expressive words to refer to sensorial or emotional experiences vividly often non-available in plain morphology. Expressive morphology is associated with an "expressive, playful, poetic, or simply ostentatious effect" (Zwicky and Pullum n.d.: 6) that the writer wants to communicate to the reader. It is achieved through morphosemantics by adding an element to the word's root form (stem). The stem's meaning is thus altered by this additional morphological component, which adds or blends a new semantic layer to the base root's original meaning (Le Guen 2014). Regular morphology can use added elements that usually modify the word class:

base adjective	added element -ness (noun)	added element -ly (adverb)
quick	quickness	quickly

In contrast, expressive morphology can modify the meaning and leverage emphatic interjections, e.g., abso-blooming-lutely, un-bloody-believable. They are often used in vulgar slang, e.g., in-fucking-credible. Other methods of vulgar slang word formation include derivation (prefixes, suffixes and infixes), reduplication, clipping, compounding, onomatopoeia, borrowing, backward letters and syllables, inflection, acronym, mixes, multiple processes, coinage, and blending (Tambunsaribu 2019: 205–206).

9. Expressing emotions indirectly

Indirect expressions of feelings are feelings that are often not expressed consciously. We often do not express an emotion deliberately but mainly through routine activity or particular lexical items. Indirect messages may not be perceived in a way we expect, may not be immediately noticed, or may not be noticed at all. Indirectly expressed feelings can be decomposed into:

1) expressive phrases,
2) punctuation marks,
3) letter capitalization, and
4) dialogue speech acts.

Using punctuation marks and letter capitalization can indicate how intense emotions are. Punctuation marks are commonly used to "strengthen an expression or louder tone within the text" (Pak and Tee 2018). Recent research proves that capitalization can also enforce different intensities of expression (Pak and Tee 2018). Expressive phrases, on the other hand, can be divided into:

1) special lexemes,
2) derivations,
3) emotion lexemes,
4) interjections,
5) rhetorical questions, and
6) prosodic features.

Special lexemes serve the purpose of revealing emotions like happiness, satisfaction, and relief, which can be expressed by sentences such as: "by good luck," 'by happy chance," and "thank goodness." According to descriptive linguistics and traditional grammar, derivations are the formations of words achieved by changing the form of the base or by adding affixes to it, e.g., joy to "joyful," "hope" to "hopeful." Emotion lexemes are lexemes containing an emotional component in the semantic structure, e.g., "artwork."

Interjections often followed by an exclamation point (!) express various emotional states, although they do not have strictly assigned meanings. For example, "Ouch!" can be used as an exclamation expressing sudden pain or dismay (Macmillan English Dictionary 2020). "Yikes!" can also express empathy with unpleasant or undesirable circumstances (Yourdictionary 2021). "Ouch!" can also be used for the same purpose, e.g., "Ouch! That had to hurt!."

Rhetorical questions can convey emotions. Rhetorical questions are "used to alert or challenge addressee’s problem or behavior" and are "prone to evoke negative emotions, such as anger, disgust, and contempt" (Lau and Lee 2018: 373). Emotions can be expressed through various prosodic features, intonation, stress, tone, accentuation, pauses and rhythm. Not all indirect expressions of emotions are affected by the morphological and semantic structure. Examples are expressive illocutionary speech acts. Expressive speech acts are based on psychological states and relate to expressing feelings or emotions to the receiver, e.g., "It has been a sad day" (Nastri, Pena and Hancock 2006: 1029).

Indirect expressive illocutionary speech acts are composed of welcoming, greeting, saluting, thanking, the state of pleasure and expressions of feeling. With boasting not included in John Searle's classification, the writer expresses positive feelings and judgment of his actions towards an addressee more. It has two functions: to impress others with one's prior achievements, so they start to admire us, and to suppress competition or resistance (Norrick 1978: 290). With lamenting, the writer expresses either sorrow or regret when speaking to an addressee (Norrick 1978: 279). Neal Norrick considers lamenting a partially defective as an expressive illocutionary act because it does not need to be addressed to anyone in particular (Norrick 1978: 288).

If a writer is directly impacted by a life situation in a negative way, he can express his discontentment through the deploring speech act (Norrick 1978: 288). When the writer feels personally affected, more neutral phrases are used. For example, the writer might criticize somebody or a particular event, condemn or disapprove of something. Indirectly expressed emotions can also be found in various greetings. Greetings can be divided greetings into time-free and time-bound (Halliday 1979).

Time-free greetings are performed "without any particular reference to situational context during which an exchange occurs, "whereas "time-bound greetings are those which are performed with particular reference to the situational context at which an exchange takes place" (Hakim, Indrayani and Amalia 2018: 27). Time-bound greetings can follow a daily or seasonal greeting schedule. Examples of time-free greetings are:

"Glad to meet you!"
"Good to see you again!"
"Nice to see you again!"

Examples of time-bound greetings are:

"Mary happy returns."
"Happy birthday."
"Good day/evening/night."

These sentences may express emotions, albeit indirectly or represent exclusively routine activities of greeting somebody. Greetings and other daily routine expressions can also be studied with the help of politeness theories and methods, which are studied in chapter four.

CHAPTER 4

A LINGUISTIC PERSPECTIVE ON CRISIS COMMUNICATION

1. A review of chosen language analysis methods in crisis communication

In this chapter, I discuss the main analytical theories that can be leveraged in crisis communication analysis, such as forensic linguistics, institutional discourse, coherence and cohesion, speakers' cooperation, turn-taking, critical discourse analysis, action-implicature discourse analysis, politeness theory, discursive psychology, psycholinguistics and sociolinguistics. In addition, chosen linguistic aspects of crisis negotiation are also studied, such as the role of dialogue speech acts, hate speech, metaphors, rude language and jokes[1].

1.1. Forensic linguistics

Forensic linguistics is a branch of applied linguistics that focuses on methods that provide valuable insights into the forensic context. It can encompass insights gathered during an investigation to assist in the identification of suspects or witnesses, to assist in the identification and understanding of various textual data, or to find evidence submitted in court (Fadden and Disner 2014: 1729–1730). Forensic linguistics focuses on elements closely related to crime, such as hate speech, threats, coercion, bribery, prohibited literature, and peripherally crime-related issues (Fadden and Disner 2014: 1730). In addition, forensic linguistics can identify various idiolects, languages, and other patterns that help identify specific subjects or textual information. In order to achieve that, forensic linguistics uses an interdisciplinary approach encompassing computer science, anthropology, discourse and critical discourse analysis, author identification, stylistics, phonetics, semiotics, text variation or idiolects (Ariani, Sajedi and Sajedi 2014).

1.2. Institutional work

Institutional work theories analyze the relationship between language, power and institutions (Mayr 2008). Prominent representatives of this theory are Paul Drew and John Heritage (1994). Institutional work aims at converging two central tendencies: (a) "the development of sociolinguistic approaches to language that

[1] Humor, as we saw in chapter 3, can be leveraged when dealing with young people and minors.

address the contextual sensitivity of language use" and (b) the emergence of analytic frameworks that recognize the nature of language as action and which handle the dynamic features of social action and interaction" (Drew and Heritage 1994: 6). Institutions are shaped by discourses (Mayr 2008). In order for an institutional discourse to take place, at least three conditions must be met:

1) verbal exchanges must occur between two or more persons in which at least one speaker is representative of a work-related institution,
2) the speaker's interaction and goals should be partially determined by an institution,
3) at least one participant must define the interaction as work-related (Freed 2015).

The role of questions in institutional discourse is crucial when negotiating an institutional encounter, as questions represent the primary means by which institutions gather facts and determine truth (Tracy and Robles 2009: 133). Moreover, questions elicit and assert accounts of reality (Tracy and Robles 2009: 133). Magnus Fredriksson (2014) highlights the interdisciplinary approach of institutional work theories when combining crisis communication with institutional discourse. As he puts it, crisis communication can be understood as a:

> "form of institutional work aiming for the maintenance of an institution; at the same time as it has to be adapted to the very same conditions where the interests of individual organizations are subordinated to collective interests and social structures" (Fredriksson 2014: 319).

1.3. Coherence and cohesion

Coherence and cohesion methods analyze resources necessary for text construction, the range of meaning associated with what is being spoken or written and the semantic environment in which the text is written (Halliday and Hasan 1976). A text has texture as it functions as a unity with the environment. Single sentences form a larger unit, a text, and the linguist must identify how that unity is achieved. Cohesion contributes to coherence or contextual unity. Contextual unity involves connections between the discourse and the context in which it occurs (Campbell

1994). Coherence and register together define text. A text is coherent because it respects the context of the situation and it is "coherent with respect to itself" (Halliday and Hasan 1976: 23). Cohesion or co-textual unity involves connections within the discourse (Campbell 1994). Lexical cohesion as a cohesive device is used in systemic functional linguistics (SFL), which perceives language as a system of choices as language needs purpose and function to develop. Michael Alexander Kirkwood Halliday and Ruqaiya Hasan's (1972) model of lexical cohesion is based on two main cohesive device groups: reiteration and collocation. Two occurrences of an item in a text will constitute a tie, e.g., "A boy is climbing that tree. Most boys love climbing trees" (Tanskanen 2006: 32).

A tie refers to a single instance of cohesion and a pair of cohesively related items (Halliday and Hasan 1976: 3). Collocation is an association achieved when two lexical items are typically associated with one another even though they are not systematically related, e.g., "boat" and "row" (Tanskanen 2006 :33). Collocated words appear in a similar environment or are related lexicosemantically, which occurs for opposites, e.g., "boy" and "girl" (Tanskanen 2006: 33). The list of items that may be involved in building textual unity is composed of morpho-syntactic elements such as voice, tense, aspect, gender, number, phase, and clause structure, as well as semantic elements, such as synonymy, overlap, hyponymy, antonymy, and deixis (compare Campbell 1994). On a grammatical level, cohesion involves substitution, anaphora and ellipsis (Grisot 2018: 8).

1.4. Speakers' cooperation

Speakers' cooperation theory claims that human beings communicate with each other logically and rationally, and cooperation is embedded into people's conversations (Hadi 2013: 69). Cooperation is intended not as mere joint efforts, teamwork, or coordination but as something rational, as rationality is central to human actions (compare Davies 2007). Paul Paul Grice introduced the idea of speaker-meaning. Paul Grice focused on the difference between sentence-meaning and speaker-meaning and the notion of systematicity in language (Davies 2007). Paul Grice (1989) believes in two basic types of meaning: natural and non-natural. The natural meaning of an utterance is connected to the natural state of affairs. For example, "That skin complexion means fever" refers to our body's physicality or physiology (compare Pólya 2001). Non-natural meaning is about recognizing the speaker's intentions, as the same word may sound different depending on the context. Non-natural meaning is based on conventions or communicative principles (Pólya 2001). The speaker intends to direct the addressee's attention to his intention through an utterance to inform the addressee of something (Pólya 2001).

Non-natural meaning formula developed into a cooperative principle based on maxims. The cooperative principle is thought of as a quasi-contractual matter between participants that stretches outside the discourse analysis area (Grice 1989: 29). E.g., if my computer malfunctions, I expect the hearer to offer help or advice on how to solve my issue. In Paul Grice’s theory, we derive what is unsaid when "it is unnatural to understand what is said" (Kawaguchi n.d.) when an utterance does not rely on various conversational maxims. An example of what is unsaid is "conversational implicatures"; aspects of a speaker’s meaning which go beyond utterance meaning are not decoded but inferred (Allott 2005: 217).

1.5. Conversation analysis (CA) turn-taking rules

To better comprehend natural language, linguists have developed conversational analysis (CA) turn-taking rules. With turn-taking, participants have to "abide by common turn-taking rules, which involves that the current speaker allows the other speaker(s) to take their turn before continuing to speak themselves" (Sacks, Schegloff and Jefferson 1974). Furthermore, the turn-taking analysis assumes that the conversation occurs "in natural, everyday interactions between equals in contexts where turn-taking is spontaneous, and turn allocation is free to vary" (Todd 2009: 198).

Harvey Sacks, along with Gail Jefferson and Emanuel Schegloff (1974), analyzed a series of mundane telephone calls where they identified elements such as 1) overlapping talk, 2) repair, 3) topic initiation, topic closing, 5) greetings, 6) questions, 7) invitations, and 8) requests in association to their a) sequences or adjacency pairs, b) agreement, c) disagreement, d) storytelling, and e) integration of speech with verbal activities (Drew and Heritage 1992: 3). Conversation analysis (CA) turn-taking rules constitute a system, for example: 1) the speaker change recurs, or at least occurs, 2) the system allocates single turns to single speakers, so only one party can speak at a time, and if more speakers talk at the same time 3) these occurrences can be common but are always brief (see more: Sacks, Schegloff and Jefferson 1974: 706). Repair mechanisms or a cycle of options exist for dealing with turn-taking errors and violations, e.g., interruptions that do not allow the turn to complete. "The turn-taking system lends itself to, and incorporates devices for, repair of its troubles; and the turn-taking system is a basic organizational device for repairing any other troubles in conversation" (Sacks, Schegloff and Jefferson 1974: 724).

1.6. Critical discourse analysis (CDA)

Discourse analysis extends beyond the sentence boundary. Critical discourse analysis (CDA) studies language use and social relationships that concern issues of solidarity, status, distribution of goods, and power (Rogers 2004: 13, 33). Noncritical or discourse analysis approaches treat social communication practices solely as patterns of social relationships. These patterns are partially constitutive of specific social practices considered routine activities through which people carry shared goals based on shared knowledge (Gee 2004: 22, 33). Moreover, practices are embedded into other practices. Thus social interactions are based, on the surface, on a network of practices (compare Gee 2004: 33).

CDA considers more elements at stake when forming these networks, such as politics. The critical discussion field was developed in the 80s (van Eemeren & Groodendorst 1992) and continued in later works (van Eemeren 2001; 2002). Critical discussion combines theoretical/normative and empirical/descriptive approaches, including dialectical and pragmatic perspectives on argumentation. The theoretical/normative approach provides a framework for evaluating arguments, while the empirical/descriptive approach helps identify and analyze relevant facts. Argumentation is made possible by introducing a disagreement space which creates room for debate and helps define points of view and refine opinions.

1.7. Action-implicature discourse analysis (AIDA)

Action-implicature discourse analysis (AIDA) is a method aimed at understanding the character of interactional problems, the conversational strategies used to address them, participants' situated ideas about handling them, and participants' identity (Tracy 1995: 198). AIDA focuses on reflectivity, or the ability to "regard with refraction the social, cultural, political, and interpersonal fields of discourse analysis" (Stevens 2004: 208). AIDA tries to reply to the following questions:

"Who and what should I be in this situation to handle the issue?"
"What is expected of me?
"What my talking implies about how I see the other party?"
"What relationships should be established? How I reconcile concerns and constraints?" (Tracy 1995: 198).

1.8. Discoursive psychology (DP)

Discursive psychology (DP) is a broad term that encompasses research across many disciplinary contexts, such as communication, language, sociology, and psychology (Hepburn and Wiggins 2005: 595). DP aims to investigate the psychological issues from the participant's perspective and how they practically manage psychological themes and concepts such as "emotion, intent, or agency within talk and text, and to what end" (Molder 2012). Discursive psychology, for example, emphasizes perceptual and cognitive issues on top of the discourse theory. Critical discursive psychology (CDP; Wetherell and Edley 2014; Locke and Yarwood 2017) addresses even more issues outlined in critical discourse research. It highlights, for instance, the historical or political contexts which encourage qualitative debates. It can thus be based on social issues, e.g., men and hegemonic masculinity (Wetherell and Edley 2014) as well as conflicts, such as approaches to violence against women, psychology of domestic violence, terrorism, analysis of the American gun control debates or the Israeli-Palestinian conflict.

1.9. Psycholinguistics

Psycholinguistics, together with sociolinguistics, represents the major field of Applied Linguistics. Psycholinguistics studies the mental faculties of perceiving, producing, and acquiring language (Merriam-Webster 2021: psycholinguistics). Psycholinguistics or psychology of language, according to the PWN Encyclopaedia (2021), is a scientific discipline that studies the issues of language acquisition by humans (developmental psycholinguistics) and language use (general psycholinguistics). Most works in psycholinguistics focus on language acquisition by children (Encyclopædia Britannica 2021: psycholinguistics). Moreover, psycholinguistics is the study of the use of language and speech as a window to the human mind (Schovel 1998: 4). It is a domain with fuzzy boundaries that embraces:

(a) language processing,
(b) lexical storage and retrieval,
(c) language acquisition,
(d) the brain and language, and
(e) second language acquisition and use (Field 2004: 11).

Language processing studies the memory and the language skills of reading, writing, speaking and listening (Field 2004) (a). Lexical storage and retrieval focus on how we store words in our minds and retrieve them when needed (Field 2004) (b). Language acquisition studies children's ability to learn a language and whether it is an innate ability or not (Field 2004) (c). Psycholinguistics also studies the link between the brain and language and whether it is a faculty unique to human beings (Field 2004) (d). Psycholinguistics studies ways of language perception by the human mind and the linguistic competence of people. Psycholinguistics can also be divided into theoretical and applied linguistics, which comprises learning foreign languages and the study of all issues related to the use of those languages (Field 2004) (e). Second language acquisition and use constitute an independent study in the field that considers sociological, cognitive and pedagogical factors (Field 2004: 11).

Some research topics include the existence or non-existence of the phoneme, which is considered a blurred notion. Phonemes help identify, for instance, dyslexia, as "dyslexics were found to have severe difficulties in reading due to the phonological demands of having to map graphemes to phonemes" (Serniclaes and Sprenger-Charolles 2003). Identifying such issues helps identify a particular person behind the text, which is helpful in forensic linguistics.

1.10. Politeness theory (PT) as socio-communicative verbal interaction

Politeness theory (PT) is part of the pragmatic approach as well as the sociological and conversational (discourse) approach in linguistics, focusing on socio-communicative verbal interaction. Politeness represents universal principles of human interaction that is reflected in language (Brown and Levinson 1987: 13). It represents a growing academic discipline that also developed a sub-branch of "rudeness studies." The need for politeness in human interactions is essential, apart from conflict reduction, incivility, rude, impolite and discourteous behavior leads to decreased psychological well-being and occupational burnout. Politeness theory (PT) claims that people use particular strategies that allow them to achieve a successful and comfortable environment for communication (Goorabi 2019: 1).

Relative politeness is an act associated with a particular context, whereas absolute politeness refers to acts independent of context (Leech 1989). Another focus is the three sociological variables of politeness: the social distance between the speaker and the other side, the relative power that the speaker has over the other side, and the ranking of impositions in a particular culture (Brown and Levinson 1987). There are also three main strategies of politeness:

1) positive politeness,
2) negative politeness, and
3) off-record politeness (Brown and Levinson 1987).

Positive politeness is the expression of solidarity, negative politeness is the expression of restraint, and off-record politeness is the avoidance of unequivocal impositions (Brown and Levinson 1987: 2). Positive politeness juxtaposes criticism with compliments, establishes common ground between participants, and where is appropriate, uses jokes, nicknames, honorifics, tag questions, special discourse markers ("please"), and in-group jargon and slang (Nordquist 2020). In addition, positive politeness emphasizes showing friendliness (Nordquist 2020). On the other hand, negative politeness focuses on respect and esteem, presenting disagreements as opinions (Nordquist 2020).

Off-record politeness relies upon implication where there is a mismatch with what is "said." In some situations, the use of "maximized (hyperbole) and minimized (understatement) off-record strategies plays a significant role in achieving respect and politeness" (Mohammed 2019). Communication tropes are primarily utilized in off-record politeness. Off-record politeness is a politeness strategy that relies upon indirect means of expression. Directness is typically associated with a lack of politeness, whereas indirectness is associated with politeness and is frequent in woman's or Asian groups' speeches (compare Sifianou 1997: 163). Understatement is used to remain polite by minimizing the problem of discomfort or difficulties (Mohammed 2019: 56). Understatement is considered a tool for politeness and tactfulness (Flayih 2011: 64).

A polite attitude allows us to achieve two goals: "a short-term transactional goal of achieving the desired state of affairs and the longer-term relational goal of maintaining good relationships" (Darics and Koller 2018: 92). In negotiations, politeness can be considered a mean of minimizing confrontation or reducing the possibility of confrontation occurring at all, as well as the possibility that a confrontation will be perceived as threatening (Lakoff 1979: 102). "Politeness, like formal diplomatic protocol (for which it must surely be the model), presupposes that potential for aggression as it seeks to disarm it, and makes possible communication between potentially aggressive parties." (Brown and Levinson 1987: 1).

Previous studies mainly focused on speech forms of honorifics. A newer approach to politeness by Penelope Brown and Stephen Levinson includes perspectives of language form, e.g., "how to say something," and contents of utterance, e.g., "what to say" (Kiyama, Tamaoka and Takiura 2021). Penelope Brown and Stephen Levinson devised a theory of facework that deals with the mitigation of the face-threatening acts (FTA) that is essential in hostage negotiation. FTA theory focuses on two sociological concepts of saving face and losing face. Politeness theory (PT) seeks to exclude rude, impolite and inappropriate behavior from all forms of communication. Politeness guarantees that interpersonal contacts run smoothly and that another person's face is not threatened (Odebunmi 2009: 5). The theory of facework (FTA) analyses discourse dialogue, the relationship between speaker and addressee and the potential offensiveness of the message content. Examples of face-threatening acts are inappropriate requests or insults.

Positive face refers to self-esteem, while negative face refers to the freedom to act as human beings. Positive impoliteness focuses on using strategies and acts designed to damage the addressee's positive face. Conversely, negative impoliteness focuses on using strategies and acts designed to damage the addressee's negative face. Jonathan Culpeper (1996) suggested a provisional list of output strategies for positive and negative impoliteness (see Table 1).

Table 1. Positive and negative impoliteness strategies (Culpeper 1996)

Positive impoliteness	Negative impoliteness
Ignore, snub the other (e.g., ignore someone's presence).	Frighten
Disassociate from the other (e.g., avoid sharing same space or meal)	Condescend, scorn or ridicule
Be disinterested	Invade the other's space
Use inappropriate identity markers (e.g., use a nickname when a distant relationship pertains)	Explicitly associate the other with a negative aspect
Use obscure or secretive language	Put the other's indebtedness on record
Seek disagreement	-
Make the other feel uncomfortable	-
Use taboo words	-
Call the other names	-

Politeness is tied to self-esteem, and self-esteem is tied to our face. Face resides inherently in an individual to which we can attribute an infinite number of faces. Faces and the concept of losing face are fundamental parts of hostage negotiations. Faces are like masks that can be worn depending on the social role and context. The face is considered a person's public self-image and encompasses the "emotional and social feeling of self which an individual has and expects others to recognize" (Odebunmi 2009: 5). Face represents individuals' self-esteem. Two types of face staging exist: positive and negative. When someone wants to be liked, approved of, respected, and appreciated, they stage a positive face (Odebunmi 2009: 5). When someone wants to be free of others' restrictions, they stage a negative face (Odebunmi 2009: 5). The perception between positive and negative face can differ between civilizations (Odebunmi 2009: 5).

We can further distinguish between the institutional status-based requirements of the face and the more personal side of the face. For example, institutional requirements can refer to etiquette, tact or good manners. In contrast, the personal side of the face to personal feelings of others (Brown and Levinson 1987: 14). Etiquette is a system of rules and conventions that regulates social and professional behavior (Ryabova 2015: 91). Etiquette norms can be found in sayings, special forms of address, proverbs, idioms and set phrases such as:

"welcome,"

"how do you do,"
"how do you feel,"
"excuse me,"
"please,"
"farewell!,"
"Mr.," "Miss," "Mrs.," "Madame," "Ms,"
"thank you!" (Ryabova 2015: 91).

Etiquette also manifests itself through the use of interrogative sentences instead of imperative ones:

"Could you possibly help me?"

Etiquette norms encompassing acts of greetings should also be analyzed from a sociolinguistic perspective as they provide information through which we can "find out what is valued in a particular culture" (Moradi 2017: 295). Furthermore, from the perspective of pragmatics, they show that the other side is important to us and that the speaker feels a positive sentiment towards the hearer and wants the hearer to know that (Trysińska 2015: 93). The genre of invitations can also be understood as a collection of conventions (Krauz 2004: 179) that can also be studied from the perspective of politeness theory.

1.11. A sociolinguistic perspective of language

Whether sociolinguistics stems from the rejection of structuralism is under debate (Tirvassen 2018: 5), and the line of demarcation between sociolinguistics and dialectology is thin (Tirvassen 2018: 5). Ferdinand de Saussure was the leading structuralist, while Karol Dejna is his equivalent in Poland. Karola Dejna created the Łódź School of Structural Dialectology, which referred to the Prague school. Sociolinguistics includes the social variable in its linguistic dialectology. Ferdinand de Saussure (1983/2013) discerned between language and words: *langue et parole*, where:

1) language is the effect of social convention given to humans, and
2) word is the personal usage of language by humans: style, rhythm, syntax,

pronunciation.

Ferdinand de Saussure started the research into and the description of the construction of language as a system, or a structure, using objective analytical methods, forming a science around the facts of *langue* (Lima 2013). Examining individual elements in isolation from how they were interconnected was considered useless. Ferdinand De Saussure treated language as a logical and mental construct or logical network. However, language is not only such logical networks, although various texts can form a network. Language is not just structure and grammar.

Language is not being spoken and written in the same way by everybody, "language is tremendously varied" (Clark 2007). In sociolinguistics, the language system can be perceived as something real and human. Text is freedom, while grammar, in a sense, restricts this freedom. Text can be "alive" and dynamic, studied as an activity, a process, a dialogue speech act and in relation to "you" and "me" (compare Wilkoń 2002b: 22).

The difference between sociolinguistics in the strict sense, and the sociology of language, is that sociolinguistics uses concrete language manifestations. Correlative (variational) sociolinguistics is presented in the works by William Labov (e.g., 1963; 1966; 1969) pictures the correlation of speech features with social behavior (Darnell 1975) through thorough empirical studies of linguistic variation and quantitative methods. William Labov focused on language structure, searching for independent social structures and behaviors that impact linguistic behaviors.

Descriptive sociolinguistics (descriptive sociology of language) describes the social patterns of language use (Severo and Görski 2016). Interpretative (interactional) sociolinguistics, also called "functional," is represented by the works by John Gumperz (1955–1996) and focuses on pragmatic inferencing in face-to-face interaction and social behaviors, considered to be strictly intertwined and influenced by the linguistic and social structure. His primary focus was also the explanation of linguistic change within the context of a speech community (Gumperz 1972).

Linguistic knowledge is interrelated with a common ground, such as speech communities, that possess shared knowledge. Shared knowledge depends on the intensity of contact and communication networks, and speech community boundaries tend to coincide with "wider social units, such as countries, tribes, religious or ethnic groupings" (Gumperz 1972: 16). John Gumperz's work was in contrast with structuralists, as they tended to neglect linguistic varieties and see linguistic knowledge as structured in systematic ways.

In language analysis from a sociolinguistic angle, it is worth focusing on linguistic aspects such as vocabulary, semantics, linearity of verbal utterance, and textuality. Language needs appropriate vocabulary and semantics; at the same time, linearity of verbal utterance is of the essence. Linearity of verbal utterance means the order of words in a sentence, e.g., subject, verb, modifier and object. A logical structure of sentences, where sentences are composed of words in a linear order. Textuality is related to text – the features of text; text has a certain structure which characterises it.

Moreover, two elements of language are important: linguisticality and graphicalness. Linguisticality is a set of species-specific capacities that allows humans to learn and use languages (Haspelmath 2020). Graphicalness means that written text must be presented graphically. Text can be seen as a live manifestation of language. Text differs from speech or music. A text can be seen dynamically as a process and statically as a ready product (Wilkoń 2002b: 38).

The world of humans is the world of language with two basic elements: phoneme and morpheme that are part of the following structure:

phoneme → morpheme → lexeme → sentence → text

Phonemes form a phonological system, and morphemes form a morphological system. Generally, morphemes are the smallest units. For example, the written Chinese language uses signs based on logograms, where each symbol represents a morpheme. In addition, language has two further elements: lexemes forming the lexical system and text. The lexemes forming the lexical system are simple and complex sentences and elliptic sentences. As Marcin Woliński (2014) said, lexemes are treated as sets of flexemes which, in turn, are sets of word forms. It is possible to adopt the following hierarchy:

phoneme → morpheme → flexeme → lexeme → sentence → text

A text can be composed of lexemes, even the simplest ones, such as: subject – (answers to questions: who? what? e.g., Jan), verb (answers to questions: what is he/she/it or are we/they doing? e.g., singing), object (answers to questions: who with?, what with?, to whom?, to what?, who?, what?, e.g., to Peter), qualifier (answers to questions: where?, where from?, where to?, when?, how?, what kind?, e.g., nicely). Thus, a sentence is formed as follows:

"Jan is singing nicely today."

As we can observe there are many stages for the analysis of a sentence: morphology, syntax, semantics, and pragmatics. It could be said that we move higher in the abstraction level as we advance through morphology to pragmatics. In the morphological stage, we analyze different forms of words, such as gender, tenses, or parts of speech. The syntactic stage or syntax is a set of rules that govern the sentence structure and analyzes relations between words, like subjects, objects, or verbs.

Text typologies are studied in linguistics[2], theory of literature and translation studies (Organ 2011: 330). Text typology refers to the way in which language functions are classified on the basis of text types (Organ 2011: 330). A society can designate standard or non-standard language but the distinction is mainly political and social (compare Gee 2004: 22). From a linguistic standpoint, the distinction is not too important because each native speaker speaks a dialect of his own that respects the rule of being complex, communicative and rule-governed (compare Gee 2004: 22).

Language is considered a method of communication created on the basis of interpersonal relations; at the same time, it is a way of building and maintaining social links and collecting cultural accomplishments (Rogalski 2011). Conrad Brann (1994) distinguished between four different classifications of language: 1) central language, designated by the government for official business and education, 2) the standard language, community language or demolect, used as lingua franca for communication across the country, 3) the national language or territorial language, spoken in the national space, and 4) the regional language, spoken in areas of the country's territory (see also Stroinska and Andrews 2018: 243)[3]. Text depends on the culture and language in use, which is something worth considering when analyzing different language variations (see Table 2).

[2] Useful insights are provided by anthropological linguistics and sociolinguistics.
[3] Conrad Brann (1993) further distinguishes between 1) "schizoglossia" meaning the separation between spoken and written language, 2) "choralect" for a regional language, 3) "demolect" or language of the people, meaning a vehicular language or "lingua franca", 4) "hierolect" that signifies a sacred language, 5) politolect for the language of administration or originally of the city-state, 6) "autoglossia" meaning the people's own language use, and 7) "chthonolect" or language of the soil, a term also used for a "territorial" language.

Table 2. Chosen terms of language variety (compare Heidary and Barzan 2019; Brann 1993, Brann 1994; Kloss 1967; Houppermans 2012)[4]

standard language	national language	regional language	local language	classical language	global language
historic language	pigdin	lingua franca	creole	diglossia	hierolect
bilingualism	multilingualism	style	register	accent	choralect
dialect	sociolect	idiolect	local language	native language	demolect
chthonolect	exglossia	endoglossia	politolect	autoglossia	schizoglossia
colinguism	ethnic dialect	-	-	-	-

Style means the variation in someone's speech or writing depending on the situation, place, time, the parties involved and their personal choices such as the tone,

[4] The central language is also called politolect by Conrad Max Benedict Brann (1994), and it is considered the country's official language or mother tongue. A central language is a language variety with grammar, a politolect spoken and written officially in a country protected by a government. A national language is a demolect that is used across a nation. Sometimes indigenous peoples' are forced into learning the central language while others are neglected. Coercive measures against the will of the speakers of various threatened languages were adopted throughout history. A standard language is "a dialect with an army," where linguistic issues can "arouse passion and occasionally violence" (The History of Dutch Language n.d.). Sometimes coercive measures initiated by a government lead to the formation of various linguistic hybrids and mixed identities. Such hybrids and mixed identities can be found in various post-colonial settings. Colinguism means the cohabitation of different layers of one national language (Houppermans 2012: 120). Bilingualism is the ability to speak two languages equally well, and it takes place when someone learns two languages from birth. In some regions, interactions between two adjacent and bilingual regions led to the adoption of a bilingual discourse (Kabatek 2016: 632). Multilingualism or plurilingualism is similar to bilingualism. Two or more languages characterize multilingualism, but the lingua madre typically represents one, and the other is learned through education, migration, having a foreign parent, commercial exchanges of goods or due to a geopolitical setting. For instance, we may use one language in one setting and a different language in another setting. Pidgin is a simple language with a limited vocabulary and a simple grammatical structure. It is used in situations where different speakers using different languages have to develop a common way to communicate, e.g., sporadic communication between the researcher and isolated tribes. Creole is more complex than pidgin and is developed for daily communicative needs. Lingua franca is similar to pidgin, but it refers to a specific area, the Mediterranean ports. It is composed of elements of Greek, Arabic, French, Italian (Venetian, Tuscan, Genoese, Sardinian and Sicilian), Provençal, Turkish, and Spanish (compare: Nolan 2015: 100). Diglossia occurs when two language varieties or dialects exist side by side and are used for different contexts. We can distinguish between two dialects in use: 1) "in-diglossia," also called "endoglossia," for internal or native dialects and 2) "out-diglossia," or "exoglossia," for external dialects (compare Kabatek 2016: 626). Near-dialectized languages stem from the standard language that provides a "roof" called "ausbau" by Hans Kloss (1967). More than that, we can find a pairing of a standard language with a genuine dialect, a pairing of two superseded varieties of a standard language (Kloss 1967: 36), and roofless dialects independent of the standard language. A regional language is a language that is present within a region. Local language refers to a local area where the language manifestations take place. Local language presupposes a low social distance, while a global language has a high social distance (Mahboob and Lin 2008). Thanks to the Internet, we can observe language manifestations shared in blogs, forums or through other means spoken by a virtual community whose participants come from different places. Native language refers to the place where we were born, and it is where we learned the language by living there. Ethnic dialect is the dialect spoken by an ethnic group. Classical and historical language refers to a period of time. A classical language refers to the language used in classical antiquity, while historical language refers to other historical periods that can also be characterized by elaborate literature and tradition.

the choice of words, and manner of expression. Style can be formal and informal (conversational, casual or colloquial). Informal styles include slang, jargon or other forms of colloquialism that are not used in formal language. Artistic styles represented a recorded language variation adopted during a historical period and expressed by poets, writers and artists. Artistic styles are characterized by richness and complexity (see more Wilkoń 1999; Wilkoń 2002a).

A register refers to a linguistic repertoire associated with particular social practices and those who engage in those practices (Agha 2005: 24), e.g., people with the same occupation or interests. A register can have unique and modified words, sentences, and grammatical constructions.

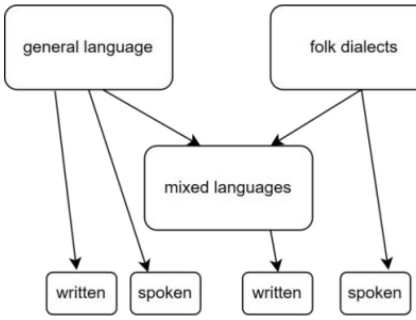
Accent refers to the sound, intonation and stress and is often specific to a particular region or individual. Dialect differs from accent because it is a language variety with its grammar. It manifests itself in a specific area or region. Sociolect is similar to dialect, but it is a variety of languages tied to a particular social class. Sociolects are often confused with register. An idiolect is a personal way of speaking within a language, including personal choice in utterances, speech rhythm and pitch. As Jadwiga Stawnicka and Iwona Klonowska (2016: 30) put it:

> "Each one of us uses a unique style or idiolect, and it is possible, with greater or lesser degree of probability, to determine whether the perpetrator (author) shares individual characteristics and features that can link him to the evidence or the text representing the evidence".

The context in which language is used is controlled by culture, ethnicity, profession, age, geography and education. Aleksander Wilkoń (1989/2010) divides language into systemic and non-systemic. Typologies of systemic language comprise phonetic, word-formative and inflectional grammatical variants. The general language is usually both written and spoken, while folk dialects are typically only spoken unless they blend with the general language (see Figure 1).

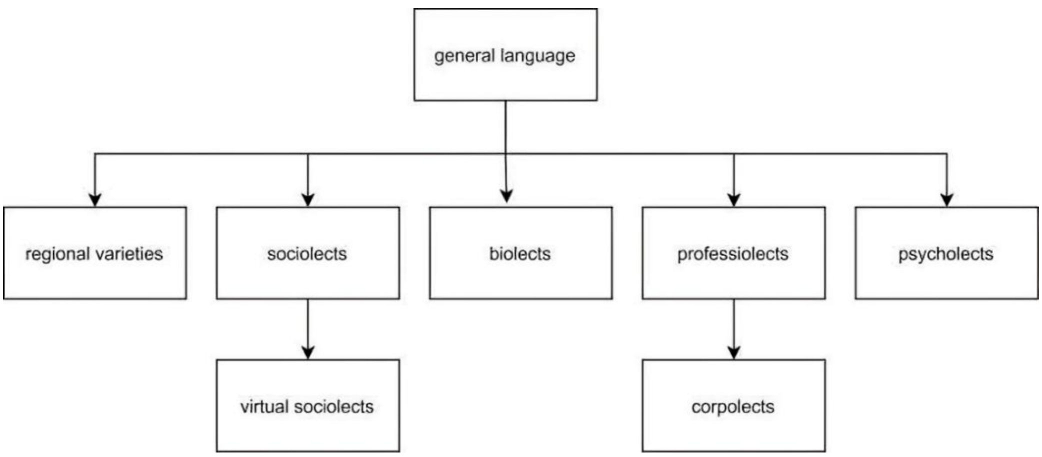
There are significant differences between spoken and written language, even within the same language type, like, for instance, the general language (see more Wilkoń 1982: 28–31). In addition, we can distinguish vertical and horizontal language varieties. Horizontal language stratification may include territorial dialects, whereas vertical diversification includes social varieties. In Anglo-Saxon sociolinguistic thought, sociolects are used interchangeably with social dialect (Lewandowski 2010). They include parameters such as gender, age, and occupation (Lewandowski 2010: 61). Aleksander Wilkoń was the first to use the concept of sociolect in Polish sociolinguistic literature (Lewandowski 2010: 61).

Figure 1. General language vs. folk dialects (Wilkoń 1989/2010)



Aleksander Wilkoń (1989/2000) distinguishes five varieties of the general common language (compare Figure 2). Regional varieties represent a language spoken in a particular region, defined by geographic or political boundaries, culture and tradition. Sociolects are social language varieties, e.g., military language (Wilkoń 1989/2000). Biolects are languages that depend on the physical features of a person: the language of a text produced by a woman or a man (Wilkoń 1989/2000). An individual's biology influences his perception, which in turn affects his language.

Figure 2. Language varieties (based on Wilkoń 1989/2000; for virtual sociolects see Smoleń-Wawrzusiszyn 2021; for corpolects, see Cierpich 2017; Cierpich 2019)



Psycholects are language varieties that take into account psycholinguistic or psychosomatic varieties (Wilkoń 1989/2000). Professiolects are languages associated with professional environments (Wilkoń 1989/2000). Vocabulary will play an essential role in the social language varieties (variants); however, this requires some clarification. The term profession is often defined as "a body of people in a learned occupation" (IACP 2011: 3). The professional varieties take three forms:

1) colloquial jargon,
2) general language varieties, and
3) strictly professional variety.

As a colloquial jargon, language is used within a certain social group in informal or unofficial communications. This general language variety is open to a wide general public and is applied in both general and official communications. The strictly professional variety is an internal variety associated with practical activities. The professional variety includes not only the language of business but also teaching and learning activities. The language used can be about everyday or casual discourses or specialized or technical discourses (Mahboob and Lin 2018). For example, it could be a slang used only in a doctor-doctor-nurse-nurse setup, such as the phrase (example 1):

"The new admission is a trainwreck. It'll be a rough night" (see more Nurse Buff 2019)
"I'm having a code brown in room 134" (see more Nurse Buff 2019)

Numerous metaphorical terms and vivid phrases comprise the semantic bloc of medicine. For example, these are names of medicines, treatments, illnesses, medical diagnoses, prescriptions, medical procedures, and medical instruments. By analyzing the topic of discussion, e.g., medicine and treatment, it is possible to discern, for example, the mood disorder that affects the interlocutor, such as depression.

The study of lects is expanding and evolving, and today we can find "virtual sociolects" (Smoleń-Wawrzusiszyn 2021), that are lects used among virtual communities and "corpolects," lects used in a corporation (Cierpich 2017; Cierpich 2019). However, today's sociolect categories are difficult to adopt due to increasing social mobility observed in youth (Kołodziejek 2006: 35–42).

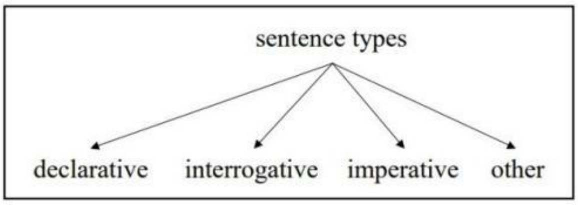
2. Chosen aspects of dialogue speech act theory

In linguistics, once we know about the structure and the symbols, semantics comes into play to analyze the meaning of words. As mentioned before, at the highest abstraction level, pragmatics deals with language and its contexts. Charles Morris was the first to use pragmatics in a systematic technical way and to perform the division of syntactic, semantics and pragmatics in an attempt to structure the field of semiotics (see Witczak-Plisiecka 2009: 86). The speech act theory is a subfield of pragmatics that considers the context of a dialogue and linguistic utterances that refer to an action (Witczak-Plisiecka 2013).

Language is not only communicating "about something, but it is a type of action" (Austin 1962). The speech act theory focuses on how we present information with words. A dialogue speech is an utterance shared between participants (compare Hidayat 2016). A speech act is any act a speaker may perform in an utterance. Dialogue speech acts depend on successive utterances produced by the parties involved in a dialogue so that they are discourse units rather than single sentences (Popescu-Belis 2005: 7).

Every speech act is placed within a structure tied to what happens at a personal or a cultural level (Grabias 2019: 39). Thus, speech acts are created according to specific social situations. Language not only describes but shapes our perception of the world (Onuf 1989: 82). Sentences should provide semantic input, which is further analyzed in contextualized pragmatic studies such as dialogue speech act theory and related to the "juxtaposition of form and function, and to the concept of locution versus illocution" (Witczak-Plisiecka 2009: 87). Whether or not dialogue speech acts represent a finite set of act types; what the size of this set is; and whether or not this set is universal, all are valid questions. We yet need to find the answer to the first two questions. However, there seem to exist universal acts such as 1) "institutionally circumscribed acts like finding guilty, proposing toasts, or declaring," or those with 2) "general functions such as telling, questioning, requesting, greeting, agreeing, or initiating repair" (Levinson 2016: 11–12). Grammar helps identify dialogue acts thanks to verbs concerning their typology, and sentence types help determine the degree of directness versus indirectness (see Figure 3).

Figure 3. Sentence types (Siemund and König 2007: 2)



We can study dialogue speech acts on three levels: (a) locutionary, (b) illocutionary, and (c) perlocutionary. Locutionary act refers to the information, i.e., the act of saying something (a), for example, stating or sharing information about a situation, without any further intention, including hidden intention. Stating the facts as they are. Locutionary acts can be phonetic, phatic, and rhetic. The speaker intentionally produces noises (phonetic acts) and words in syntactic arrangements (phatic acts) that, with certain intentions and in certain contexts, convey certain messages (rhetic acts; Halion 1989).

The philosopher John Langshaw Austin (1962) introduced the concept of the illocutionary act into linguistics. Another of John Austin's core insights is that the function of language is not to deliver meanings but to deliver speech acts, which our brain needs to decode immediately to give meaning and attribution, which allows us to provide a relevant response (Levinson 2016: 6.). The "where are you going?" utterance could be 1) an idle question, 2) a challenge, 3) a reprimand, 4) a prelude to a request, e.g., a request for a ride, or 4) an offer, e.g., an offer to give you a ride (Levinson 2016: 6.). Linguists have proposed different classifications of illocutionary speech acts (see Table 3).

Illocutionary act refers to the force, i.e., the act made in saying something (b). They are about what we mean by saying something. Illocutionary acts usually carry additional information, such as a request for help. For instance, the "sentence is hot in here" might indicate that we want someone to "open the windows." Illocutionary acts, which represent the main focus of researchers, are speeches filled with the intent to inform or obtain a particular effect. Illocution is what the speaker means to convey. Speech acts represent either the speaker's purpose or intent. The intention is necessary for a speech act to be truly performative (Tucker 1990).

The principal five categories of illocutionary speech acts mentioned are assertive (asserting and conjecturing), expressive (apologizing and thanking), directive (e.g., ordering and requesting), commissive (promising and vowing) and declarative (e.g., adjourning a meeting or christening; Siebel and Searle 2002: 1). The goal of the assertive category is to inform the subject. Directives try to make or force the addressee to perform specific actions. "Commissive speech acts relate to committing oneself to a future action" (Nastri, Peña and Hancock 2006: 1029). They comprise, for instance, promises, threats, plans, vows, bets, and offers (see tab. 4). Among these categories, promises are "the most prototypical and most discussed members of the class of commissive speech acts" (Kissine: 2016).

Expressive speech acts express emotions, i.e., how the speaker feels about a situation. Declarative speech acts cause events, like changing the state of affairs. Finally, perlocutionary acts focus on the effect of what we say, i.e., the act made by saying something (c). In other words, perlocutionary acts focus on what happens to the hearer after the speaker has spoken. When we study perlocutionary acts, we study "the relation between the utterance and its causal effects on the addressee" (Kissine 2008).

Speech acts have their effects not only due to particular thoughts a person has but because these thoughts are publicly expressed; in other words, they are "socially noticeable events, bound to have certain conventional social consequences" (Capone 2006). Speech acts can be divided into "macro acts" and "micro acts." "Macro acts" represent the whole document. They are a construction of the following components: sentences, predicates, announcements, notices and emotional expressions (Skowronek 1993). These components can be further divided into "micro acts."

Table 3. Example of illocutionary acts classification by chosen linguists (compare Hosnol Wafa, Hum and Vahmita 2017: 124)

Illocutionary acts:	**Linguist:**
expositives, commissives, behabitives, exercitives, and verdictives.	John L. Austin
assertives (representatives), expressives, directives, commissives, and declaratives	John Searle
expositives, commissives, behabitives, interrogatives, exercitives, verdictives, and operatives.	Zeno Vendler
assertives, commissives, acknowledgments, directives, verdictives, and effectives	Kent Bach and Robert M. Harnish
statements, expressives, invitationals, and authoritatives	Keith Allan

Table 4. Illocutionary acts classification by John Rogers Searle (compare Kissine: 2016; Tsovaltzi, Walter and Burchardt n.d.)

Illocutionary act:	**Sentence example:**	**Speech act types:**
Assertive (inform)	"The windows are closed."	suggesting, putting forward, swearing, boasting, and concluding.
Directive (request)	"Shut the window! Is the window shut?"	requesting, ordering, pleading, inviting, advising, asking, and begging.
Commissive (promise):	"I will shut the window."	promising, threatening, planning, offering, vowing, betting, and opposing.
Declarative (cause events in themselves):	"I name this window the Skylight."	-
Expressive (express emotions and evaluate)	"I wish my window was the Skylight."	exclamations, apologizing, good wishes, thanking, welcoming, and deploring.

Different genres and situations will have different groups of macro and micro speech acts; in other words, in each domain, we can observe the dominance of certain functions and acts. In politics, for instance, main language functions can be decomposed into persuasive, cognitive, expressive and phatic (Skowronek 1993). Speech acts are made of content, mood, and force (Recanati 2013). Each speech act consists of "uttering (or inscribing) the content with a certain force" (Ripley 2011: 622). Illocution corresponds to the function or force of an utterance (Witczak-Plisiecka 2009). The same locutionary act can have different illocutionary forces:

"I'll be back" (the utterance could count as a warning, promise or prediction) (Degand 2006: 676).

Some authors use another term, motivation which helps classify certain acts. Strong, categorical motivation acts are acts of orders, commands, and instructions (Chengcheng and Fernandez: 2019). Speech acts of weak motivation are speech acts of proposal. Moreover, some speech acts, such as assertives, are based on current facts or the current state of affairs and some, like commissives, represent an action that will happen in the future, e.g., threats (compare Nastri, Peña and Hancock 2006). As we will see later, dialogue speech acts can also be divided into direct, indirect, and hints (adjuncts).

Direct speech acts take place when there is a direct relationship between the structure and the function of the utterance (Hafifah 2020: 87). Indirect speech acts will happen if there is an indirect relationship between the structure and the function of the utterance (Hafifah 2020: 87). The structure refers to declarative, imperative, and interrogative forms (Hafifah 2020: 87).

Direct speech acts like invitations can be composed of an imperative sentence, whereas indirect speech acts like invitations can be composed of declarative and interrogative sentences (Amelia 2015). The boundaries between various speech act categories are generally perceived as fuzzy, resulting in their directness or indirectness being viewed as a matter of degree (Łącka-Badura 2014: 225). "Hints" are speech acts that contain extra-linguistic elements or contextual elements that constitute a particular speech act (De Pablos-Ortega 2020).

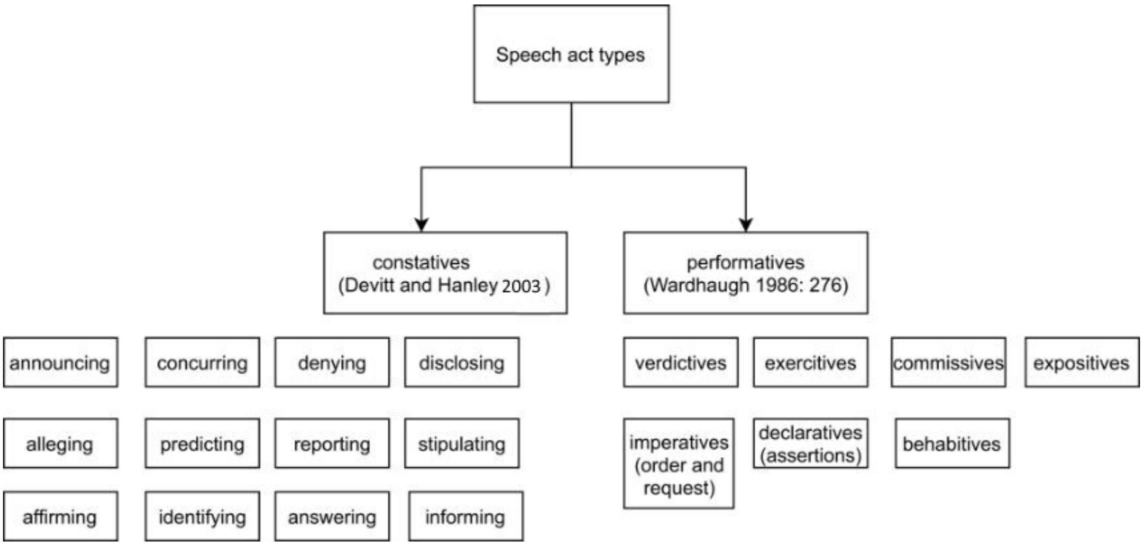
Speech acts can also be (a) literal and (b) non-literal (Handayani 2015 102–103). A literal speech act is expressed literally with declarative sentences or with questions expressed interrogatively, as well as commands, requests or imperative sentences (Handayani 2015) (a). Non-literal speech act contains a meaning that contrasts with what is being expressed or when the meaning of the utterance and the intention of the speaker do not match (Handayani 2015) (b).

Another distinction can be made between constative and performative utterances, as presented by John Austin (1962). Constative (reportative) statements are utterances describing the world, reporting, or constating some facts (López Álvarez 2005: 685). Within the constative utterance category, the speaker constates something as true or false (Hafifah 2020). In performative utterances, some action is performed at the moment of uttering by the person who utters (López Álvarez 2005: 686).

Performative action results can be either felicitous or infelicitous, "depending on whether they are performed correctly, completely, and sincerely in accord with some antecedent set of conventions" (Searle 1968: 405–406). With performative statements, the speaker has an intuition about the truth conditions of the utterance because these are always true when uttered (compare Condoravdi and Lauer 2011: 3). Different speech acts are associated with constative and performative utterances (see example in Figure 4). Performative utterances can be explicit and implicit.

Explicit performative utterances are those whose illocutionary force is made explicit by the verbs appearing in them (Condoravdi and Lauer 2011: 1). Implicit performative acts are performative utterances with performative verbs that are not explicitly stated (Amalia 2017). Finally, orders and requests represent the stereotypical uses of imperatives, but imperatives can also express wishes, such as well-wishes, ill-wishes, curses, and even addressee-less or "absent" wishes (Condoravdi and Lauer 2012: 37–39), e.g., " I wish I could fly."

Figure 4. Different speech acts types in constatives versus performatives example (based on: Hafifah 2020: 86–87)



Another interesting topic is represented by the concept and interactions between the speaker, the hearer and the bystander. A bystander within close enough range that was not originally intended to be a hearer may, depending on circumstances, accept or reject the role of hearer without loss of face (Allan 1998, see example 1). An eavesdropper can admit to listening at the risk of losing face and affronting the speaker (Allan 1998).

Example 1:

X to Y as addressee: "Shut up or I'll lay one on you."

Y to Z as ratified participant: "You heard him threaten to hit me, didn't you?"

X to Z as bystander: "You mind your own business".

Z to X and Y, rejecting the role of Hearer: "I wasn't listening".

3. Chosen acts of speech in crisis negotiations

Crisis communication strategies, albeit chaotic, follow a certain logic. First, declaratives and statements usually initiate a negotiation. For instance, the negotiator establishes contact by saying, "Hi. This is John Doe, I am a trained negotiator, and I want to help you; tell me what happened?." The negotiator might proceed by asking basic questions, such as name, first.

Moreover, the negotiator invites the other side to negotiate. Whether the other side will accept their invitation represents a critical moment. After the initial presentation, the negotiation focuses on 1) establishing positions and formulating demands, 2) exploring weaknesses of positions to find elements in the other side's proposal that offer the greatest room for compromise, and 3) reaching a conclusion as both sides gain more from a settlement than a breakdown (Defense Information Access Network 1987: 19–20).

A comprehensive list of variables of crisis communication was provided by Francis Taylor, who separated the possible dialogue strategies and outcomes into 1) avoidance statements, 2) distributive statements and 3) integrative statements (see annex, Table 10).

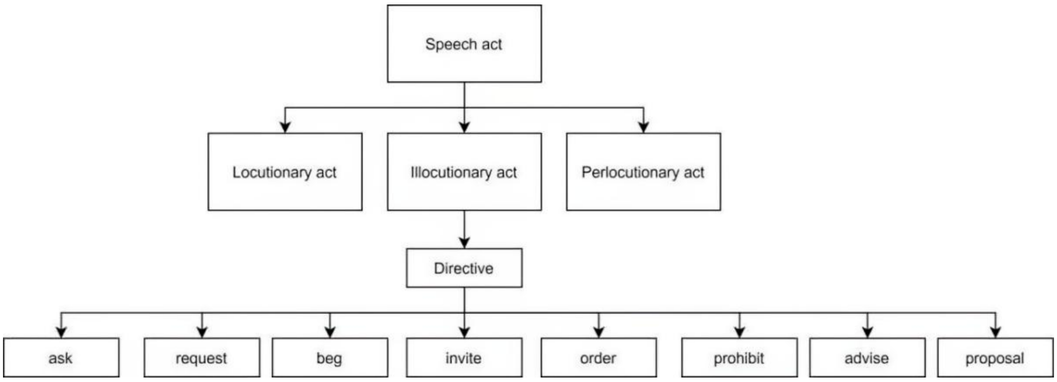
3.1. Directive speech acts

3.1.1. Typology of directive illocutionary acts

Directive speech acts are among the most valuable dialogue acts to analyze from the crisis communication perspective. Directive speech acts encompass a large group of dialogue acts such as order, prohibit, ask, request, beg, propose, invite, or advise (see Figure 5). Speech acts that fall outside of this category but are worth analyzing are the acts of confirmation, refusal, argumentation, expressive speech acts such as acts of compassion, acts of complaint and acts of apology, commissives such as threats, constative speech acts such as denying or alleging (accusing somebody of something), and verdictives. I discuss these acts after the directive acts.

We can also group speech act depending on distributive bargaining or integrative approach in negotiations. In the integrative soft negotiation approach, a frequent speech act is "comply," whereas "threat," which implies some punishment if the other side does not comply, occurs less (compare Twitchell 2012: 137). In a hard negotiation with distributive bargaining approaches, directive speech acts are more likely to be used (compare Mamet 2004: 86). In a soft negotiation with integrative approaches, the negotiator tries to enhance the image of the other side with the intent of manipulating (compare Mamet 2004: 86). This can be achieved through acts of approval, praising and complimenting, acts of compassion or weak directives, such as advice (Mamet 2004: 86; Searle 1968). Argumentation, together with acts of apology and acts of initiating repair, are also likely to appear in a soft negotiation.

Figure 5. Typology of directive illocutionary acts - an example (compare Hosnol Wafa, Hum and Vahmita 2017: 124)



As mentioned, directive speech acts are meant to induce or convince the subject to perform or stop performing specific tasks. Directive speech acts are utterances in which the speaker asks one or more subjects to carry out an action by ordering, commanding or inviting. They require a particular relationship to occur between the speaker and the other side but also require the sender to reciprocate any action of his own. Directness level of intensity can also be characterized according to the three already mentioned strategies:

(a) direct strategies,
(b) conventionally indirect strategies, and
(c) non-conventionally indirect strategies (Center for Advanced Research on Language Acquisition n.d.).

Direct strategies are marked explicitly as requests by using imperative (a). If we want the other side to do something for us, we can use the verb ask, e.g., "I ask you to send me the file by tomorrow" (a). Conventionally indirect strategies refer to "contextual preconditions necessary for its performance as conventionalized in the language" (b). Questions can have a function of demand in the following example: "I asked you the other day to do it, didn't I?." "How about cleaning up?" (b). Non-conventionally indirect strategies are the already mentioned hints that refer to an object depending on contextual clues, e.g., "you have left the kitchen in a right mess" (c). Carlos de Pablos-Ortega (2020) has found more categories of directive speech acts that depend on context and force:

(a) strong direct,
(b) weak direct,
(c) conventionally indirect I,
(d) conventionally indirect II, and
(e) non-conventionally indirect/hints.

"Strong direct" structures are typically characterized by the presence of present imperative with "you" form (a). "Weak direct" structures include imperative in combination with polite markers (please), gerunds (going) and other linguistic constructions (want/order/command + you + infinitive) (b). "Conventionally indirect I" phrases are limited to the use of modal verbs such as "can," "could," and "may" (c). "Conventionally indirect II" structures include strategies such as modal verbs or specific constructions with the verb wish, e.g., "I wish you to (...)" or expressions that make the DSA indirect, such as "wonder," "mind," "to be sure" (d). "Non-conventionally indirect/hints" are not designed as DSA. However, the contextual and extra-linguistic elements make them suitable DSA candidates (e).

Table 5. Examples of directive speech acts (De Pablos-Ortega 2020)

Strong Direct	**Weak Direct**	**Conventionally Indirect I**	**Conventionally Indirect II**	**Non-conventionally Indirect/Hints**
"Out now!"	"Go out, will you?"	"You must go out."	"You could not go out, could you?"	"It is really nice outside."
"Go out!"	"Go out please!"	"Will you go out?"	"Would you like to go out?"	"I would go out."

Directive acts such as commands and orders are utterances with the intent of forcing the other side into doing something in the future with the use of "want" or a requirement performative verb such as "order," "demand," "bid," "enjoin," "prescribe," "govern," "require" or "command" (compare Hosnol Wafa, Hum and Vahmita 2017: 125). The core semantic content of a command is structured as follows:

- command:

I order you to do X ("Do X")
I order so because I want you to do x
I order so, because I know that you have to do what I want you to do
- report and reply:
I reply X ("Yes, I'll do X")
I reply X because I know that you expect a message from me
I reply X because I know that you have the right to expect a message from me
(Wolińska 2004: 282).

Prohibitions are orders that forbid the speech partner to do or not do something and concern a future action. Prohibitive performative verbs include "enjoin," "forbid," "prohibit," "proscribe," and "restrict" (Hosnol Wafa, Hum and Vahmita 2017: 125). With prohibitions, the hearer expects some punishment for not respecting the speaker's prohibition. "Prescribing" something to someone would be fitter for an invitational act rather than order.

With the confirmation speech act, the negotiator demonstrates interest, expresses consent by agreeing with the partner, approves of the interlocutor's ideas and puts himself on the same level, e.g., "you are right, but let us analyze your situation again" (Stawnicka 2016: 36). The negotiator "underwrites," "confirms," "concedes," "endorses," "admits" and often "asks" questions such as "is it true/right?" "do you understand me?."

3.1.2. Questioning speech acts (QSA)

Questioning speech acts (QSA) or acts of asking are a sub-type of directives that induce the subject to respond and can be associated with assertions (Kissine 2016). Similarly to other directives, questions provoke a response. Questioning performative verb contains a request for information that can comprise "question," "ask," "inquire," "interrogate," and "quiz" (Hosnol Wafa, Hum and Vahmita 2017: 125).

A response to a directive can be associated with an action. Questions are associated with assertions when there is a response to a question. The function of an assertion is to reduce ignorance within the context of the conversation (Kissine 2016).

Therefore, reflective and rhetorical questions are not considered information requests and do not reduce ignorance.

From the negotiator's or investigator's standpoint, particularly interesting are the mentioned earlier open-ended questions that provoke an open-ended response. Questions beginning with consonants "w" and "h" and interrogative pronouns "who," "whose," "what," "when," "which," "why," "where," and "how." As we saw, they are associated with the verbs "tell," "explain," "say," "talk," or "describe." Questions can be direct or indirect. Below I show examples beginning with "why":

"just tell me why?,"
(direct question)
"could you tell me why?,"
"can you please tell me why?," or
"do you think you could tell me why?" (indirect questions).

Direct and indirect questions have different degrees of politeness. Direct questions can be direct requests in the imperative mood meant to subordinate the listener. Indirect questions signal a higher level of politeness. The negotiator should pick, however, only specific open-ended questions and be careful not to ask other types of questions. The questions "why" make people defensive in most cultures, so this form of question should be avoided (Voss 2020)[5]. Questions such as "what" and "how" should be asked instead, e.g.:

"what about this works for you?,"
"what is the biggest problem you face?,"
"how is this an obstacle?,"
"how have you run into problems in the past" (Voss 2020).

The most important part of good communication flow is listening and reacting to the answer to the "what" and "how" questions (Voss 2020). Essential questions are also leading or probing questions and tag questions. Probing statements achieve a similar effect to probing questions. The effect and reaction to these questions are different between victims and suspects. Victims tend to perceive probing questions as

[5] I think that "why" questions are very important when negotiating with borderline subjects.

"bordering on personal insult" and the expression of disrespect towards their traumatic experiences (Acquaviva et al. 2013: 645). Tagging questions intend to maintain a high level of control over the other side, and for that particular purpose, they are considered the most effective when interrogating a suspect (Hall 2008: 73).

Leading questions prompt the other side to answer specifically by including certain terms and phrases (QuestionPro n.d.). Leading questions thrive on the other side's personal input (QuestionPro n.d.). Leading questions can be based on an assumption, interlinked statements, direct implication, coerciveness, and tagging (see more QuestionPro n.d.). A tag question is attached to a statement and follows a statement, e.g., "You did see the gun, didn't you?." A tag question is composed of a declarative statement with an appended clause created by reversing the negativity of the tense-bearing verb and adding an appropriate anaphoric pronoun to match the subject (Ainsworth 1993: 278):

Declarative: "Chicago is a big city."
Tag question: "Chicago is a big city, isn't it?."

In hostage negotiations, tag questions reinforce a collaborative problem-solving frame by minimizing the significance of the subject's hostile actions and "turning orders into requests to influence the subject's decision-making" (Gabriela Beyatriz 2016). From the perspective of investigative techniques, assumption and follow-up questions are often used. An assumptive question can be adopted only if the interrogator believes the subject is ready to admit guilt, e.g.:

"Paul, what's the most amount of money you took in any single day?"
(Zulawski and Wicklander 2002).

Follow-up questions are used when the subject wants to admit guilt, but has not answered the assumptive question yet; the interrogator might ask:

"It wasn't $10,000, was it?" (Zulawski and Wicklander 2002).

Follow-up questions are used to support the subject's admission of guilt and let him know that we know he is guilty, e.g.:

"What's the most you took in on any day? Could it have been as much as $9,000?" (Zulawski and Wicklander 2002).

Follow-up questions can be used in framing strategies. They were used strategically by David Koresh, the leader of the Branch Davidians in the Waco 1993 negotiation. When the negotiator asked him for a favor, David complied by saying: "Here is how I could help you out" and followed up with the question: "Would you like to know the Seven Seals"? which cornered the negotiator (Agne 2007: 562). If he responded "no," the response to his favor would forecast a rejection; if he responded "yes," he would be invited to help. A help he does not want or cannot accept (Agne 2007: 562).

In each domain, we can find a particular set of questions. When considering the pragmatic aspect of questions adopted in court, we can take into account the classification of their functions in the perspective of linguistic intentionality as proposed by Barbara Boniecka (2000: 97–107, Szymków-Gac 2018: 106–107):

1. Protocol questions: a request for pointing out, identification, naming or specification of an object, with the intention to determine its properties or definition, by using question words such as: "Who?" "What?" "How much/many?" "What kind?" "Where?" "When?" "Where to?" "What for?" "Why?" "What is (or was) he/she doing?" "What is (was) happening?". A protocol question restricts the repertory of answers provided to the area defined in its pattern.

2. Conceptual questions: they present an implicit coherence between a question and an answer in the area of presupposition "How?".

3. Referring questions: the author's intention is to obtain information from a free account (report) offered by the interlocutor. In other words, the addresser requests an account of an event – the case at issue, facts, sequences of events at a particular point of time, e.g., "What is your knowledge about the pending court case?".

4. Prompting questions: questions constituting the so-called superstructure in relation to other groups of questions (Boniecka, 2000, p. 106); the addresser intends to encourage the addressee to provide a well-thought-of and exhaustive answer by using

the following expressions: "And then what?," "And how was it?," "And?," "So, what does that mean?," "What was next?." The group of prompting questions also includes:

4a navigating questions: "But I’ve heard that you used psychoactive substances (?),"
4b questions suggesting answers (based on assumption): "And what, he did beat his wife?,"
4c commenting questions: "Oh, so you weren’t afraid of partying with criminals (?),"
4d correcting questions: "But where did you see the defendant last week? He has been detained for a month, so this is rather impossible, is it?,"
4e reassuring questions: "You want to testify?," and
4f continuing questions: "Please tell us what was next (?)."

5. Persuading questions: the addresser intends to trigger or prevent certain behaviors in the addressee, however, this intent is not communicated directly: "What is your point, ma’am? I guess these issues do not concern the case in question (?)." The addressee is thus forced to "cut to the chase" to respond directly to a question in a clear, concise manner.

3.1.3. Acts of request

Questions can be very similar to acts of request; therefore, we can separate them by analyzing intent. With acts of request, the speaker is asking for a response, whereas questions serve the purpose of obtaining information. A speech act of request (SAR) is a directive speech act, the illocutionary purpose of which is to get the hearer to do something in circumstances in which it is not apparent that he will perform the action in the normal course of events (Searle 1969). By initiating a request, the speaker believes that the hearer is able to act.

The act of request begins at the mental level of the message's sender (Kondratczyk-Przybylska 2021). It can also be a request for information, but we have a relationship between the hearer and the speaker. The hearer typically feels obliged to respond. The hearer may feel that the request is an intrusion on his freedom of action or even a power play (Center for Advanced Research on Language Acquisition n.d.). The purpose of the request is to induce actions and to stimulate the addressee to act.

The subject can refuse to perform the request or accept it (Stawnicka 2016). Acceptance can be regarded as a speech act of complying (SAC; Stawnicka 2016). The request can have various degrees of intensity, and we can find various degrees of intensity in the response content. There can be many combinations of senders and goals that influence the content of such acts (Kondratczyk-Przybylska 2021). The "request" can transform into "begging" and become a different act of speech. Requestive performative verbs include "to ask," "to beg, "to beseech," "to implore," "to insist," "to invite, "to petition," "to plead," "to pray," "to request," "to solicit," "to tell." and "to urge" (Hosnol Wafa, Hum and Vahmita 2017: 125).

3.1.4. Speech acts of the proposal (SAP)

Speech acts of the proposal (SAP) are directives of weak motivation divided into three types:

(a) ordinary speech acts of proposal,
(b) resolute (imperative) speech acts of proposal, and
(c) irresolute speech acts of proposal (Chengcheng and Fernandez 2020).

Ordinary speech acts of proposal use performative verbs such as "suggest," "propose," or "invite" (a). Resolute (imperative) speech acts of proposal, such speech acts are expressed by the imperative mood of verbs: "make sure," "be sure," and "you should" (b). Irresolute speech acts of proposal are often carried out by the subjunctive mood or interrogative sentences (c).

Speech acts of accusing and proposing are of interest to students of argumentation because the speaker undertakes a burden of proof that is demanded of him (Kauffeld 1997). With acts of proposal, the proposer must openly commit himself to speak in defense of his resolution (Kauffeld 1997). To make an accusation, a speaker must state his charges, that concern a valid reason, against the addressee.

Typically, for the speaker to make an accusation, he must believe that he has some proof. The act of accusing is performed by saying that the accused did something wrong and demanding that the accused answers to the charge through denial, admission of guilt, justification, data, reasons, evidence, excuse or other means (compare Kauffeld 1997).

3.1.5. Acts of inviting

The subjunctive mood is one of three moods in English grammar that is used to express wishes, suggestions, or desires. With the act of inviting, the sender commits the receiver to a proposed future action while also directing the receiver to participate in some particular activity that takes place at a particular place and time. The semantic composition of an invitation is structured as follows:

- the sender of the message (who is uttering the invitation?)
- the act of inviting (the verb "to invite" or other stylistic variants)
- the message receiver or the addressee (who is invited?)
- a suitable occasion or objective (on what occasion the addressee is invited? to do what? to go where?)
- the data concerning the invitation (e.g., street address, time)

(Krauz 2004: 171)

Invitations can be 1) declarative, imperative, performative, hoping, and conditional sentences, 2) indirect invitations, and 3) asking for willingness invitations, e.g., "would you like to participate" (Al-Hamzi et al. 2020: 44). Cushioning tactics can be adopted to revise the initial invitation or proposal, ("well, ordinarily I would") or to re-frame the original proposal as a personal favor ("Could you do me a favor?") (Agne 2007: 563).

3.1.6. Acts of advice

Advice is a weak directive whose illocutionary force is to suggest a future action to the hearer that the adviser believes will benefit the hearer (Searle 1969). The act of advice can be both an act that initiates an action on its own and a reaction to other actions (e.g., asking for advice). As mentioned, advice presents an important element in the Behavioral Influence Stairway Model (BISM) steps (McDonald 2014). For example, when the other side realizes that he must change his behavior in step 1, he may ask for advice from the negotiator in step 2, which leads to a peaceful resolution of conflict. Positive assessment speech acts or acts of approval are used in crisis negotiations and police interviews, for instance, during John Reid's Nine Steps of Interrogation when presenting an alternative justification for the suspect's crime (step a7).

3.2 The speech act of refusal (RSA)

The speech act of refusal (RSA) occurs when somebody is unwilling to cooperate. This is important in sociolinguistics and politeness theory. From a sociolinguistic perspective, RSA can become complex and depend on many factors, such as the status of the interlocutor (Beebe, Takahashi, and Uliss-Weltz 1990). It might be easier to deliver a refusal if the speaker acts from a position of power. More than that, some people accept orders from law enforcement agents or people with authority. Thus the social context influences the refusals. Refusals may involve a long-negotiated sequence of utterances (Beebe, Takahashi and Uliss-Weltz 1990).

Refusal acts are uttered in order to reassure the other side that we have appropriate reasons and that the other side has understood those reasons. Thus the initiating refusal act might carry a long chain of utterances or "recyclings" and copies of the initial refusal (Maróti 2016). In politeness theory, the speech act of refusal is considered to be part of a group of face-threatening acts (Brown and Levinson 1987). In my opinion, refusals are rapport-challenging speech acts. Similarly to directives, refusal speech acts (RSA) can be grouped into:

(a) direct,
(b) indirect, and
(c) adjuncts.

An adjunct is a remark that cannot stand alone as RSA and is often used to mitigate refusals from the other side (a). When using prepositioned hedges such as "I do not know," the speaker is "not fully committed to what follows in the turn of talk" (Weatherall 2011). Below I show Refusal speech acts (RSA) categories and examples (Table 6). Orsolya Maróti proposes another more elaborated example of refusals (2016: 81–82); see annex, Table 11. Argumentation is regarded as an illocutionary act connected to the perlocutionary act of convincing (Drid 2016: 25). Argumentation is also construed as an illocutionary act related to a whole piece of discourse rather than a single sentence (Drid 2016: 25).

The performance of the illocutionary act of argumentation is "not only intended to make the listener understand that the speaker is trying to justify or refute a particular opinion but it is also designed to convince the listener of the acceptability or unacceptability of that opinion" (van Eemeren and Grootendorst 1984: 47). By marking his acceptance or rejection to an expressed opinion, the hearer explicitly makes it plain that he regards himself as committed, positively or negatively, to that expressed opinion (van Eemeren and Grootendorst 1984: 71).

Table 6. Refusal speech acts (RSA) (compare Gungormezler 2014: 9; Beebe, Takahashi and Uliss-Weltz 1990)

Refusal strategies:	**Examples:**
Direct	
Performative verbs	"I have to decline" "I have to reject your offer"
Negative ability	"I cannot"
Indirect	
Reason/Explanation	"I have to study" "I have to work"
Regret	"I am sorry"
Past acceptance	"If I knew it beforehand I would have done so" "If I had known sooner, then I would be able to make it"
Repetition	"Monday?"
Postponement	"we will talk later" "I will let you know" "not now" "maybe some other time"
Prepositioned hedge	"I do not know"
Adjuncts	
Positive opinion	"That is a good idea, but..."
Gratitude	"Thank for your invitation, but..."
Pause fillers	"Uhh/well/uhm"

A dispute arises when the speaker advances a point of view, and the hearer casts doubt on that point of view. He can either leave the dispute or attempt to resolve the dispute and initialize a discussion by attacking the speaker's point of view (van Eemeren and Grootendorst 1984: 85). The speaker then becomes a protagonist while the hearer an antagonist. "A discussion designed to resolve a dispute will have to be concluded with an answer to the question of whether the dispute has been resolved" (van Eemeren and Grootendorst 1984: 86).

3.3. Denials

Denials are typically understood as a special kind of assertion, while rejection is a special kind of belief (compare Ripley 2011). Denials represent the assertion of a negation, and a rejection represents a belief in a negation (Ripley 2011). Denials are rapport-challenging speech acts (compare Ho 2021). Denials typically contain the lexical item "not" or "deny." This "negative" aspect unifies denials and negations and makes denial different from "normal" assertions (Ripley 2020). Some researchers claim that denial should be separated from the assertion of a negation (Ripley 2011). Negations are challenging to analyze because they are not merely represented by "not," e.g., "I am not his wife; he is my husband" as an utterance in which "not" is not a negation (Ripley 2011: 628).

Denials also depend on the polarity of the utterance objected to; a denial may be a negative or a positive statement:

"Herb is tolerant" (denial of the utterance "Herb is not tolerant"),
"Herb is not tolerant" (denial of the utterance "Herb is tolerant").
(Sandt and Maier 2003: 3)

3.4. Verdictives

Denials, similarly to refusals, typically follow other acts of speech, like, for instance, verdictives. Verdictives are speech acts in which the speaker provides a verdict, an assessment or judgment about the acts of the addressee or about the addressee itself. As we saw earlier, judging the other side should be avoided in hostage negotiations. The burden of proof is the speaker's obligation to support the utterance. Presumptions can be seen as a subtype of verdictives, where the burden of proof is passed on to the interlocutor (Corredor 2017: 3). Which, as we saw, is the contrary of what occurs with proposals and accusations. Only new pieces of evidence or reasons make it unreasonable to stick to the verdict or the presumption (compare Corredor 2017: 3).

3.5. Expressive speech acts (ESA)

3.5.1. Typology of expressive speech acts (ESA)

Expressive speech acts (ESA) have an elusive definition in contrast to other types of speech acts. Having to do with social behavior and attitudes, they are named "behabitives" (Maíz-Arévalo 2017). Expressive speech acts are miscellaneous; among this group, we can find:

1) expressions of sorrow and greetings,
2) exclamations,
3) agreement/disagreement,
4) volition,
5) offering thanks, and
6) apologies (Ronan 2015: 25).

As mentioned earlier, illocutionary speech acts such as expressives are based on psychological states and relate to expressing feelings or emotions to the receiver. According to Norrick (1978: 279), expressive speech acts communicate psychological conditions, not beliefs or intentions, that originate from various situations. Most scientific attention receives those acts that regard "thanking" and "compliments", or acts that regard "politeness" in general (Ronan 2015: 25). Expressive speech acts (ESA) also encompass apologies and complaints. Below, I present acts that are associated with positive and negative emotions. In the terminology of Leech (1983: 104–05), apologizing is a convivial speech act. From a negotiation perspective, apologizing, complaining, and compassion are particularly interesting as they constitute an essential part of crisis communication models developed after 1972. The goal of apologizing and complaining acts coincides with the social goal of maintaining harmony between the speaker and the hearer (Trosborg 1995: 373). Complaints, however, have the potential of breaching that harmony.

3.5.2. Complaint speech acts (CSA)

A complaint speech act (CSA) is defined as an illocutionary act in which the speaker communicates his dissatisfaction, negative feelings or disapproval towards the state of affairs or events indicated in the proposal and holds the opposing side responsible, either directly or indirectly (Ghaznavi 2017). The speaker expresses displeasure, annoyance, disappointment or grievance in response to an action perceived as unjust or unfavorable (Ghaznavi 2017). Complaints are related to face politeness theories as they threaten the hearer’s positive face because of the speaker’s damage to his perception of self and the hearer’s negative face because the complaint contains an implicit compensation request from the hearer (Ghaznavi 2017).

Complaints might not necessarily be directed towards the addressee but to third parties or unrelated situations or events. The speaker might fully or partially blame the hearer. Complaints may also contain an element of self-contempt, self-accusation or self-punishment stemming from feelings of guilt or disappointment. The speaker can also accuse himself when he wants the complaint to be heard by the hearer to provoke a reaction or to enhance or threaten his face. To improve his situation, the complaint might contain a justification of his acts that serve the purpose of saving face.

3.5.3. Speech acts of apology (SAA)

Speech acts of apology (SAA) might be used to settle a dispute or to initiate repairs due to a debt or a human mistake. They have the potential to restore harmony between the hearer and the speaker. An apology can also be used as an evasive tactic to escape a conversation with a difficult, dangerous and angry subject and to de-escalate the conflict. As mentioned in chapter three, apologies and acts of initiating repair are associated with moral emotions of guilt. If the hostage negotiator makes a mistake, an apology is an essential tactic to adopt. In business negotiations, apologies are generally avoided, as modern business negotiation tactics involve treating the other side as a partner who is on the same level as we are. Old business negotiation strategies followed the "customer is always right" maxim and advocated the use of apologies. We should generally avoid negotiating from a weak or servile position. As previously stated, apologies are classified as behabitives and part of the expressive speech acts group. The social functions of apologies can be decomposed into:

1) "admitting responsibility for a state which affected someone in an adverse way (thereby implicating contrition)",
2) "asking to be forgiven,"
3) "showing good manners,"
4) "assuaging the addressee's wrath," and
5) "getting off the hook" (Norrick 1978: 280).

Apology speech acts can be decomposed into four components:

1) illocutionary force indicating device (e.g., "I apologize", "I am sorry"),

2) apologetic account (expressing regrets),
3) expressions of personal responsibility, and
4) offers of repair and promise of forbearance (see more Valkova 2013: 46).

In apology, more is at stake than in expressing regrets - "a speaker usually apologizes, expresses regret, to some end" (Trosborg 1995: 376). Apologies are uttered in the hope of being forgiven or that the addressee will dismiss the matter (Trosborg 1995: 376).

3.5.4. The speech act of compassion (SAC)

The speech act of compassion (SAC) and compassionate feelings play a crucial role in hostage negotiations. Compassion must be sincere and felt by the speaker to some extent. Faked compassion is difficult to simulate and requires rehearsal. It is better to refrain from saying something we do not feel is true rather than improvise or sound uncertain. Compassion is not only about showing compassionate behavior but more about effectively applying empathy and keeping the communication respectful.

Kindness can be misused to take advantage of someone or be perceived as an attempt to take advantage. Therefore, we avoid negative phrases to show empathy. However, sometimes empathy can be shown with negative phrases such as "I will not allow anything bad to happen to you". Compassion can be expressed using verbs associated with "compassion" in the first person, either singular or plural (compare Stawnicka n.d.). The first person may communicate greater attachment and engagement with the hearer. Compassion is often associated with verbs such as "care," "help," or "worry". In the case of the Oceanside Police negotiation with Grant Sattaur (2007), the police and the dispatcher used utterances such as:

"I care about you,"
"I care about what happens to you,"
"What we are worried about is your health and your safety,"
"We are worried about getting you out of the house safe, get you the care you need."

Other instances of compassion implement the verb "sorry":

"I feel sorry for you",
"I am so sorry (…) in relation to what you say (…) you were treated very unfairly."
(Stawnicka 2016)

The negotiator often reacts to the perpetrator's story about the experience of injustice in daily life in the act of compassion (Stawnicka 2016). More indirect expressions of compassion can be uttered in the form of a question, e.g., "What would I do without you?." Another similar act is the act of comforting, which serves a pro-social function. Pro-social actions can be categorized into helping, sharing, and comforting (Dunfield 2014). Acts of comforting can often follow acts of compassion. In a crisis communication setting, they are used to reassure and calm the subject and are associated with a future action, e.g., "I feel very sorry for you. Everything will be all right."

3.5.5. Greetings and compliments

Greetings and compliments are speech acts that positively evaluate someone, including someone's face or image. Acts of compliments can refer only to people, while acts of praising both things and people (Trysińska 2015: 87). With praising and complimenting, we build a positive image of the crime perpetrator, and we enhance the other side's face. Compliments can be adjectival and nonadjectival. Adjectival compliments are typically made of "nice," "good," "beautiful," "pretty," and "great" (Herbert 1991: 489). Nonadjectival compliments depend on semantic positive verbs: "like," "love," "enjoy," "admire," and "be impressed by" (Herbert 1991: 489). A typical communicative pattern of compliments requires an adjacency pair, i.e., a compliment paid and a compliment response accepted or rejected, e.g.:

COMPLIMENT	COMPLIMENT RESPONSE
"That's beautiful".	— "Thank you".
(IF — compliment paid)	— (PF — compliment accepted)
"You did a great job cleaning up the house".	— "Well, I guess you haven't seen the kids' room".
(IF — compliment paid)	— (PF — compliment rejected)

(Válková 2013)

The acts of criticizing, disagreement, blaming or scolding pertain to the same group, contrasting with compliments. The group usually denotes a negative sentiment of the speaker towards the addressee (compare Trysińska 2015: 87). Scolding refers to the negative evaluation of the other side's behavior. Feelings of regret and remorse might follow them. The function of blaming is to inform using the noun "fault," e.g., "it was your fault." When blaming is directed at someone, it can inform but also evaluate a person and the acts committed negatively (Trysińska 2015: 88). Blaming is typically associated with anger.

3.6. Acts of threats

Finally, threats occur when someone "knowingly utters, conveys, or causes any person to receive a threat" (Walton 2000). Acts of threats are associated with fear and anger. Threats can be delivered directly or in a more subtle, veiled, implicit and indirect way. Direct threats are directed towards a specific target and are delivered in a "straightforward, clear, and explicit manner" (University Police 2020). Indirect threats are typically "vague, unclear, and ambiguous," and the target and motivations are "masked or equivocal" (University Police 2020). A conditional threat is often seen in extortion cases and hostage negotiations, and its function is to warn the hearer "that a violent act will happen unless certain demands or terms are met" (University Police 2020). Implicit threats seem to be the most effective when enacted during the early stages of the negotiation (Twitchell et al. 2013: 140).

In contrast to promises, the future action of threats is not to the benefit of the hearer, and the proposition may be impolite (Indiana University Bloomington 2011). Acts of threat are, in many contexts, illegal acts connected to self-harm and harm to other people. Threats use the argumentum *ad baculum* as part of fear-inducing tactics (Walton 2000). The speaker can shift from force to (indirect) threats (Walton 2000: 41–45). Threats are a powerful tool in the hands of the perpetrator who, for instance, wants to convince or influence witnesses in court to change their statements or to make sure that witnesses remain silent.

Hate speech or incitement to hatred represent another illegal act. The offensive language, which, depending on circumstances, is also illegal, can be considered a severe offense if aggravated by hate speech or incitement to violence. From the pragmatics perspective, however, hate speech "is not a specific type of speech act but a perlocutionary act that may assume many various linguistic forms" (Obrębska 2020: 11). Due to its complexity, it is best analyzed separately and from a broader perspective.

4. Hate speech and offensive language

Offensive language is likely to occur in a crisis. Swearing can be considered a response to emotive episodes and serves the purpose of performing emotional regulation (Stephens and Zile 2017). Evidence suggests that swearing provokes emotions. However, evidence of swearing provoked by emotional activation is only anecdotal (Stephens and Zile 2017). Richard Stephens and Amy Zile examined the relationship between emotional arousal and swearing fluency. They demonstrated that certain activities increase swearing frequency compared to daily swearing frequency. Swearing, cursing or offensive language can be best described as a "form of linguistic activity utilizing taboo words to convey the expression of strong emotions" (Vingerhoets, Bylsma and De Vlam 2013). Taboo words contain a binary opposition, referring to "human experiences, words, or deeds that are unmentionable" because they are either "ineffably sacred" or "unspeakably vile" (Hughes 2006: 15). Surprisingly, people who swear not only evoke fear and hostility in other people but can elicit positive reactions in others.

The Guideline on Assisting Hostage Negotiation for Mental Health Professionals (Ministry of Health of Malaysia n.d.: 20; Miller 2015) suggests avoiding profanity and adopting a clear conversation. Researchers have attributed cussing along with justifications, repeated interruptions, and the use of plain language and sentence structure to distributive rather than integrative interactions and outcomes (Rogan and Donohue 1991). Swearing typically represents a primitive act of speech, a reaction to an annoyance or frustration. It is not much different from the growling of animals, which is not only a way to communicate aggression and fear, but, in some cases, to encourage play and elicit humor (compare Vingerhoets, Bylsma and De Vlam 2013).

Swear words, curse words, taboo words (language), expletives, foul or coarse language, cursing, profanity, blasphemy, obscenity, vulgarity, slang, slander, epithets, insults, slurs, and scatology can be analyzed as separate entities or one entity, e.g., when we adopt one cover term that represents all the other terms. The difference between these terms is often negligible. The sense of a curse as the expression of wishing something wrong to happen to someone is not so different from using profanity. Obscenities relate to sexual context, blasphemy and profanity to a religious context, curses, insults and slurs are directly offensive while taboo or scatology words are not (compare Widhi, Wahyuningsih, and Putranti 2019: 76). When taboo words are used in an angry tone they can become epithets (compare Widhi, Wahyuningsih and Putranti 2019: 81–82). Libel, slander and defaming aim to damage the image and reputation of a person by making false statements.

Three sociolectal categories that should be mentioned are professionalism, secrecy, and expressiveness (Lewandowski 2010: 62). Secrecy is the information code accessible to selected groups; professionalisms are linguistic devices adopted during the professional activity of a group (Lewandowski 2010: 62). Expressive sociolects, contrary to occupational sociolects, are dominated by the expressive function of conveying attitudes and emotions (Lewandowski 2010: 63). This slang is intentionally left uncoded (Lewandowski 2010: 63). Within occupational sociolect domain, e.g., business language, it is unlikely to find much expressiveness which is dominant during hostage negotiations.

While professional and hostage negotiations languages are uncoded, the jargon used by groups excluded from society at large, such as criminals or prisoners, is coded and dominated by secrecy (compare Lewandowski 2010: 63). Legal groups such as students express emotions in most ways, illegal groups are driven by basic emotions, legal professional groups adopt the least expressive language (Grabias 2019: 133).

As we can see, curse words depend on the group that utters them. For instance, religious groups might use curse words such as:

"Damn you.", "Goddamn you." "Damn your hide." "To hell with you."
(Jay 1992: 2).
"Rot in hell." "May God forsake you!." "May the devil take you!." "Woe unto you!."

As mentioned, each sub-group adopts its slang for ease of communication, e.g., drug users and dealers might use words such as "mule," "pimp," "pusher," and "score." Slang and cants are code languages "developing among particular urban groups, although over time some terms radiate outward into the wider speech community" (Hughes 2006: 125). The difference between offensive language and hate speech must be better understood, mainly when these two aspects are analyzed cross-culturally. Hate speech lacks a universally accepted definition and varies between cultures. Each individual perceives hate speech differently.

It seems that a core component of hate speech is hatred related to violence, usually triggered based on history and persistence of relations of advantage and disadvantage (Baider 2013: 8). In poor or conflict areas, hate speech plays an important role as it is able to support a sense of local injustice, which pushes some individuals into radicalization (Innes et al. 2007: 3). Hatred can also be seen as a mental state based on private knowledge (Baider 2013: 8). Ethnic slurs, or ethnophaulisms, are used to refer in a derogatory fashion about members of a given ethnicity or racial group. Abraham Roback (1944/1979) wrote a dictionary of international slurs and ethnophaulisms, also included in the encyclopedia by Geoffrey Hughes (2006). Some examples of hate speech include (compare Allen 1983; Brown 2019; Roediger 1995; Shora 2009):

"white fella,"
"black fella," (Australian derogatory terms based on skin color)
"ofay," (term for a white person, used by black people)
"honkey," (persons of white skin color)
"canuck," (nickname for a Canadian)
"muckraker,"
"hoosier,"
"northerners,"
"southerners,"
"redneck," (a politically reactionary person, according to Oxford Languages 2021)
"hillbilly," (an unsophisticated country person, according to Oxford Languages 2021)
"wop," (other geographical or political terms)
"kike," (a Jewish person)
"gringo" (a person who is not Hispanic or Latino)
"wigger," (a person that tries to assimilate the culture and behavior of black people)
"guinea," (referred to persons of Italian birth or origin)
"nigga," and "negro,"
"black," and "blacky,"

"colored," (language and discourse of African American enslavement, compare: Brown 2019)
"peckerwood," (epithet toward poor white people)
"camel jockey,"
"raghead,"
"towel-head,"
"sand nigger,"
"diaper head" (denigratory terms used for Muslims, compare Shora 2009: 46).

Gender-related slurs are common, e.g., "slut," and "bitch" are often related to so-called slut-shaming (compare Ashwell 2016) and homophobia, e.g., "gay," "sissy," "homo," and "fag." Hate speech is also associated with an antichristian sentiment (christophobia), ableism, antiziganism, antigypsyism (antiromanyism, romaphobia), antisemitism, antizionism, antistatism, anticapitalism and anticommunism, ageism (agism), adultism (prejudice against young people), racism, xenophobia, chauvinism, transphobia, and Islamophobia. Racial discrimination associated with hate speech means any "distinction, exclusion, restriction or preference based on race, color, descent, or national or ethnic origin" (Gómez 2020: 6).

White supremacy is based on three pillars (Smith 2016: 67–69). The logic of the first pillar is slavery (Smith 2016: 67). The logic of the second pillar is the disappearance of indigenous people to allow non-indigenous peoples' "rightful" claim over their land (Smith 2016: 68). The third pillar is defining itself as a superior civilization by constructing itself in opposition to an "exotic" but inferior other (Smith 2016: 68). An example of black supremacy can be found within the Afro-Athlican Constructive Gaathly movement (Sellers 2015). The Anguillan preacher Robert Athlyi Rogers articulated a "black supremacist ideology embedded within a religious framework"; and repurposed the ideas of the "white supremacy oppressive discourse" (compare Sellers 2015: 325, 338). Vulnerable groups such as refugees are particularly prone to exclusion and discrimination. According to the Committee of Ministers (1997), "hate speech" represents:

> "all forms of expression which spread, incite, promote or justify racial hatred, xenophobia, anti-semitism or other forms of hatred based on intolerance, including intolerance expressed by aggressive nationalism and ethnocentrism, discrimination

and hostility towards minorities, migrants and people of immigrant origin."

An important element of hate speech is the element of judgment and stereotyping when we infer that a person possesses a set of characteristics and abilities that we assume all members of that group have. However, it is not clear whether hate speech can be considered a direct incitement to violence against citizens or groups with certain characteristics, such as ethnicity, nationality, or beliefs, that make them objects of discrimination, as hate speech is often considered to be less intense than an incitement to violence, or a form of indirect incitement to violence (Díaz and Conlledo 2019: 168). The so-called haters release anger by denigrating and insulting others but also seek to influence the attitudes and behaviors of other people (Kondzioła-Pich 2018).

Hate speech is a growing problem online where people can maintain their anonymity. The think tank Demos has found that 10,000 tweets with racist content are posted daily on Twitter (Demos 2015). Mainack Mondal, Leandro Araújo Silva, and Fabrício Benevenuto (2019) analyzed 27 million whispers and 512 million tweets (see Table 7). They demonstrated that on Twitter, the most occurring sentences contain the words "I hate," which constitutes 70.5% of all tweets, and the main targets of hate are "nigga" and "white people." Whisper's most common sentences also contain the words "I hate," which constitute 10.1% of the posts, and the main targets of hate are "black people" and "fake people."

Table 7. Top 10 hate intent and targets of hate in Twitter and Whisper (Mondal, Silva and Benvenuto: 2019: 5)

Top ten hate intent in Twitter and Whisper.

Twitter	% posts	Whisper	% posts
I hate	70.5	I hate	66.4
I can't stand	7.7	I don't like	9.1
I don't like	7.2	I can't stand	7.4
I really hate	4.9	I really hate	3.1
I fucking hate	1.8	I fucking hate	3.0
I'm sick of	0.8	I'm sick of	1.4
I cannot stand	0.7	I'm so sick of	1.0
I fuckin hate	0.6	I just hate	0.9
I just hate	0.6	I really don't like	0.8
I'm so sick of	0.6	I secretly hate	0.7

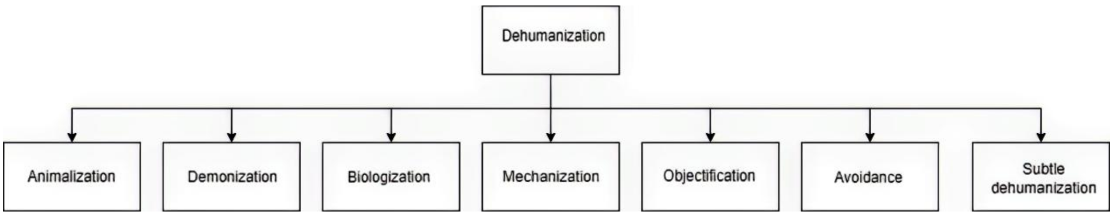
Top ten targets of hate in Twitter and Whisper.

Twitter		*Whisper*	
Hate target	**% posts**	**Hate target**	**% posts**
Nigga	31.11	Black people	10.10
White people	9.76	Fake people	9.77
Fake people	5.07	Fat people	8.46
Black people	4.91	Stupid people	7.84
Stupid people	2.62	Gay people	7.06
Rude people	2.60	White people	5.62
Negative people	2.53	Racist people	3.35
Ignorant people	2.13	Ignorant people	3.10
Nigger	1.84	Rude people	2.45
Ungrateful people	1.80	Old people	2.18

Hate speech can cause psychological symptoms that share similarities with post-traumatic stress disorder. Victims of hate speech can experience pain, fear, anxiety, nightmares, and intrusive thoughts of intimidation and denigration (Saha, Chandrasekharan and De Choudhury 2019). Hate speech can be associated with dehumanization. Sometimes, for hate speech to occur, the dehumanization process must occur first. Before calling other people "rats" or "parasites" becomes a norm, we are first influenced by an ideology of an organization, a political party or a political system that condones this behavior. We can distinguish seven types of dehumanization (Figure 6):

(a) animalization,
(b) demonization,
(c) biologization,
(d) mechanization,
(e) objectification,
(f) avoidance, and
(g) subtle dehumanization (Wincław 2021: 96–103).

Figure 6. Dehumanization variants throughout history (Wincław 2021: 96–103)



With animalization, subjects compared to animals are considered to be irrational, immature, and deprived of culture, which entails other people killing them or threatening them unfairly (a). An example of a sentence containing this type of dehumanization might be: "I cannot tell negros from animals." Demonization entails that subjects are accused of being non-human, a demon, a devil or a witch, which entitles other people to kill or torture them (b). Demonization can be associated with anti-semitism and the belief that "Jews are the direct biological offspring of the Devil" and, thus, that they "were never human beings" (Barkum 1997: chapter 8).

Biologization entails terms and metaphors used for despised individuals and groups, stigmatizing them as microbes, viruses, diseases, plagues, cancer, tumor, dirt, or infection (c). People can be treated as disposable waste, parasites or toxins that a healthy organism must combat. This type of hate speech can be found not only during the medieval period but also in modern politics. During the official gathering of the Italian party Lega Nord, their cultural Gianfranco Miglio (example 1) said:

> (...) the level of "civicness" depends on the number and presence of parasites (...). If the parasites become more numerous, the animal dies and similarly, our society dies. (...) A parasite is one who does not produce wealth, but lives by consuming the wealth produced by others. (...) Centralism and parasitism are closely related phenomena. (...) The country we are called to change is a country infected by an army of fleas. (...) (Miglio 1993).

With mechanization, we perceive others as automatons, robots that are forced into submission (d). We may treat others as a mechanized workforce unable to feel emotions. Mechanization thus overtakes basic human traits. Objectification occurs when someone is perceived as an object, tool or commodity (e). With avoidance, we consciously ignore other people, e.g., by not making verbal or non-verbal contact (f). We may exclude certain people from activities or jobs or make them feel unwelcome in certain areas or places, which can be considered a subtle form of racism. With subtle dehumanization, we see others as less human than ourselves and the group with which we identify, e.g., less intelligent or having basic, primitive emotions (g).

The process of dehumanization influences negotiations. Members of racial minorities may suffer in negotiations because of their race and the phenomena called "explicit bias" (PON Harvard Staff 2021c). Subconscious and unintentional racism represents a more common source of discrimination called "implicit bias" (PON Harvard Staff 2021c). The type of dehumanization also influences the type of language adopted (example 1). Language can lead to violence, seen as physical harm to an individual or environment (Gibson 2018: 4). Structural violence influences language use. Structural violence is maintained by systemic, political, and social factors that contribute to inequality (Gibson 2018: 4), which, through a vicious circle, contributes to violence, terrorism and language manifestations such as hate speech.

A dehumanization process may take place to legitimize the refusal to negotiate, both from the perspective of legal authorities and crime perpetrators. Examples of this are interactions with terrorists. Swear words are typical during police intervention and arrest. Slurs and epithets can be directed towards the police agents from bystanders or the suspect. The primary function is to threaten the police agents' face, or in other words, image and dignity, and to instill fear and doubt. From law enforcement's perspective, using profanity during professional duties leads to unfavorable or outright negative evaluations of performance and often to excessive force complaints (Patton 2018).

Swear words are often observed during police training, where trainees use expletives to react to fear, while on the surface, it looks like a manifestation of anger (Young 2020). The other side might use swearing to add power to a threat and intimidate. Derogatory language can also foreshadow the intention to use physical force. Thus, reactive aggression, characterized by the reaction to fear, and proactive aggression, characterized by the identification of weaknesses and readiness for an attack, should be recognized by the police officer. Law enforcement agents do not react to offensive words directed against their persona but allow the other side to vent frustration and help the suspect with the right choice of words for expressing what they feel (Young 2020). Trained personnel, including negotiators, avoid expletives. Profanity affects how people are judged (DeFrank and Kahlbaugh 2019), but it also shows the negotiator's lack of control (Ury and Fisher 1991).

Most crisis negotiation manuals do not recommend using swear words, especially offensive language. The negotiator can adopt, however, particular slang to mimic the other side's behavior and language. As we saw in chapter one, the matching style ability is crucial in establishing rapport, and one tactic is to repeat the last couple of words spoken by the other side (Vecchi et al. 2005: 544). Like humor, swearing, if not at the subject's expense, can release tension and shift attention to different topics but must be used cautiously. The negotiator should refrain from judging the person that uses swear words and should never try to correct them, as it may cause hostility and aggression. Where every word count and the time are limited, the negotiator should focus on getting the other side to cooperate.

5. Communication tropes

A trope is a figurative utterance that deviates from its literal meaning in one of several common ways (Wilson and Sperber 2012). Tropes such as metaphors, metonymy, synecdoche, antonomasia, euphemism, litotes, hyperboles and irony are words that undergo a "semantic change and take up a different meaning from its literal meaning" (Di Bari and Gouthier 2002: 4). A metaphor can be defined as follows:

> "A metaphor is a linguistic expression that refers to something that belongs to a domain distinct from the one to which the expression's basic, essential, and literal senses primarily belong. This reference is made on the basis of some kind of similarity that exists between the two things or domains and is established based on encyclopedic, contextual, or experiential knowledge that is shared within the same language community." (Ishii and Sohmiya 2006: 381)

Metaphors in negotiations structure the participants' understanding and articulation of their activities (Clancy 1999: 12). They also improve the understanding and control of the processes in which the actors are engaged (Clancy 1999: 12). Metaphors, analogies, or specific cases that illustrate a point are also used in re-framing, when one party proposes a new way to approach the problem (Lewicki, Barry and Saunders 2016: 149).

Hyperbole, metaphor, irony, understatement, rhetorical questions, impoliteness (mock), and jocularity (Averbeck 2015: 87–109) are discursive negotiation tools. Irony, sarcasm and satire indicate mockery of something or someone (Partington 2006: 182). Humor can be achieved by the use of various rhetorical tropes. Sarcasm shields the speaker's face, and is used by speakers to mock and criticize others (Brown and Levinson 1987). Hyperbole represents the least studied trope when compared to metaphor or irony (Burgers et al. 2016). Hyperbole is a "rhetorical and literary technique where an author or speaker intentionally uses exaggeration and overstatement for emphasis and effect" (Gaiman 2021). It can be identified as a figure of speech that can be used for different purposes. Examples below illustrate the use of hyperbole as form of figurative speech:

(a) "There's enough food in the cupboard to feed an entire army!"
(b) "She's going to die of embarrassment."
(c) "Spring break will never come."
(d) "She's running faster than the wind."
(e) "This is the worst day of my life."

(f) "My father will kill me when he comes home."

(g) "The good times outweigh the bad times a million to one."

(h) "There are a million ways to improve your English."

Verbs also play a crucial role when forming rhetorical tropes, for instance, when sentences are adapted to the future indefinite or continuous tense. Sentences that form hyperboles contain expressions such as: "endlessly," "without limit," "never/ever," or "indefinitely," e.g., "we will be doing this forever" or "the football team signed a contract to use the football stadium indefinitely." Latin expressions, such as *usque ad nauseam* or *ad infinitum*, and other borrowings can also constitute a hyperbole. A scientific definition of hyperbole sees it as an "expression that is more extreme than justified given its ontological referent" (Burgers et al. 2016).

Hyperbole is sometimes considered a subclass of sarcasm (Averbeck 2015) and shares similar characteristics. Hyperbole is also used as an understatement or a metaphor (Carston and Wearing 2015: 2). As we saw earlier, hyperbole and understatement indicate politeness in a discourse. Several scholars identified distinguishable characteristics of hyperbole, such as exaggeration, overstatement, extremity and excess (Burgers et al. 2016). Table 8 shows the most relevant synonyms of hyperbole found in some of the most popular online dictionaries: Thesaurus, Merriam-webster, Lexico and synonyms. The main distinguishable elements of hyperbole can be identified as follows:

1) it can be expressed through a scalar value with regard to its degree of exaggeration,
2) it is capable of combining a range of different tropes,
3) it involves a "specific shift between the propositional and the intended meaning,"
4) it includes a "specific referen,"
5) it is often accompanied by other tropes such as irony or sarcasm,
6) it is vague,
7) it involves saying something that is strictly speaking not true,
8) it is a form of indirect language use (compare Burgers et al. 2016).

Table 8. Most relevant synonyms of hyperbole found in most popular online dictionaries

Source:	**Most relevant synonyms:**
www.thesaurus.com	hype, metaphor, overstatement, PR, amplification, coloring, distortion, embellishment, enlargement, magnification, big talk, embroidering, laying it on thick, mountain out of a molehill, tall talk.
merriam-webster.com	amplification, enhancement, fabrication, misrepresentation, fudging, hedging, hype, puffery, superlative.
lexico.com	exaggeration, overstatement, magnification, amplification, embroidery, embellishment, overplaying, excess, overkill.
synonyms.com	exaggeration, overstatement, magnification.

Judging from this incomplete comparison, the main synonyms of hyperbole are "exaggeration," "overstatement," "amplification," and "magnification." Furthermore, the scalar hyperbole values can be of two types: qualitative and quantitative. Hyperboles identified by quantitative values can contain information about time, e.g., with extremely high waiting time given the context, that can extend to infinity (sentences a-d) or extremely small numbers that can be extended until zero is approached (sentences g and h):

(a) "It took years for the boat to anchor."

(b) "It took months for the boat to anchor."

(c) "It took weeks for the boat to anchor."

(d) "It took days for the boat to anchor."

(e) "It took hours for the boat to anchor."

(f) "It took minutes for the boat to anchor."

(g) "It took seconds for the boat to anchor."

(h) "It took microseconds for the boat to anchor."

The only plausible sentences for the boat anchoring time would either be: "it took hours for the boat to anchor" or "it took minutes for the boat to anchor." The rest of the sentences should be interpreted as hyperboles. On the other hand, qualitative hyperboles can be distinguished from quantitative ones when they contain a qualitative dimension: the "good" and the "bad." Therefore, researchers analyzed hyperbolic tropes on a gradient scale (Figure 1):

Figure 1. Multimodal hyperbole (Ferré 2014)

good	<	bad	<	awful	<	really awful	<	extra awful
positive		less negative						more negative

Hyperboles are used to emphasize a point or for persuasive purposes. The expression "nothing tastes better than" can be interpreted as a stronger argument. Politicians often use hyperbolic expressions such as "nobody" or "everyone" to strengthen arguments. Hyperbole can be used to overstate the number of people who agree on a certain subject, allowing an argument to be presented as a proven fact. Arguments presented with the use of hyperbole are often challenging to attack:

(a) "I told you the complete truth,"
(b) "it is an unquestionable fact that (…)"

Speakers can use hyperboles to avoid committing themselves to precise information to avoid being attacked on those arguments later. Hyperboles can be used to hide a weak point in the argument. Similarly to hyperboles, metaphors could be used to shift attention and emphasis to a different subject. Moreover, metaphors are closely related to stories that are often shared by many people. This special kind of language can be used to reinforce an argument and convey various emotions. Shared metaphors validate social actions (Docherty 2004: 848). For all these reasons, metaphors are useful in persuasion[6].

Careful attention to metaphors can reveal more profound meaning in textual data. Metaphors and irony are central tropes with different interpretive effects (Robyn 2015). "Conceptual metaphors are a way of understanding often abstract realms of experiences in terms of another typically concrete domain" (Escobar et al. 2021). Metaphors "unite reason and imagination, and are therefore critical in contributing to our understanding of the world" (Escobar et al. 2021). Understatements or litotes are statements that describe "something in a way that makes it seem less important,

[6] Persuasion can be defined as communication that is established to "influence others by modifying their beliefs, values, or attitudes" (Simons 1976: 21, Simons 2001: 7). Persuasion is a form of attempted influence to alter how others feel, think or act (Simons 2001: 7).

serious, bad, etc. than it is," as well as utterances that contain the word "understatement" (Cambridge Dictionary 2021).

With understatements, we use a weaker term without violating the truth. The listener is aware of this (Flayih 2009: 57). Understatements are also generated by denying the opposite or contrary of the term that we would normally use (Flayih 2009: 57). Double negations are other indicators of understatement (Flayih 2009: 58), e.g., "that wound does not look too bad." Such constructions can convey an ironic sentiment and typically intensify the sentiment intended by the writer (Flayih 2009: 57). The "essential feature of irony is the indirect presentation of a contradiction between an action or expression and the context in which it occurs" (Dictionary.com 2023). Irony can be conveyed through language or symbols and images. On a linguistic level, different ironic strategies can be categorized into four general types:

1) meaning reversal (e.g., "you're right!" to mean "you are wrong")
2) meaning replacement (e.g., "and I am the Queen of England" to mean "you are wrong") (Kapogianni 2011; Reichl and Kapogianni 2018),
3) semantic reversal, and
4) echoing (Wilson and Sperber 1998).

Different manifestations of irony are:

1) verbal irony,
2) situational irony, and
3) tragic irony (Dynel 2019).

Verbal irony is a type of "implicit criticism involving either echoing or semantic reversal" (Wilson and Sperber 1998). The broad term echoing includes not "only the reproduction of what someone else said or thought but also social norms, desirable states and standard expectation" (Jeong n.d.). Semantic reversal utterances form by creating implausibility by reversing participant roles and causing a linguistic violation, e.g.:

"The pill will swallow the child with hot tea."
"The gifts have loved the children."

"The fries will eat the boys." (Kyriaki, Schlesewsky and Bornkessel-Schlesewsky 2020).

"The flowers are watering the girl" (Hutson and Powers 1974: 100).

There is also a group of "improbable active sentences" that are similar to verbal irony, e.g., "The baby washes the mother" (Hutson and Powers 1974: 103). Verbal irony can occur as long as it is placed within a linguistic domain and can be used when we want to truly convey the opposite of what we say. The presence of contrast and duality thus characterizes verbal irony. Situational irony is when we expect one thing to be communicated but receive the opposite. The main difference between verbal and situational irony is that the former pertains to the domain of language use, the latter to the domain of human experience (Jeong n.d.). Finally, tragic or dramatic irony is used in artistic content, such as movies or books. Tragic irony occurs when the reader or the audience seems to know more about a situation, an event, an action or a dialogue than the characters presented in a work of art.

Humor "can be defined in simple words as an experience which is either produced or appreciated and causes smiling or laughter, the social indicators of humor" (Loizou and Recchia 2019: 1). There are also other definitions that explain humor based on "specific situations or events, such as irony, satire, teasing, and sarcasm" (Loizou and Recchia 2019: 1). Humor can lead to positive emotions or mood. We often think of something funny to cheer ourselves up.

However, depending on the situation, humor may indicate that the negotiator is not fully committed to the situation or has little respect or empathy for the subject[7]. Negative humor is inappropriate in some situations because it violates social norms and expectations and provokes anger or sadness (compare Chaniotakis and Papazoglou 2014: 132). Dark humor, typically manifesting on an artistic level, provokes positive emotional reactions despite dealing with difficult, repugnant, dark or taboo subjects like incest and bestiality (compare Herron 2016: 422).

Mocking in English has generally been approached in politeness or impoliteness theories (Hugh and Bousfield 2012). Typically, provocations such as mocking require a relation between the hearer and the speaker. As Helga Kotthoff (1996) puts it, impoliteness is in many cultures "an index for greater distance" and

[7] Showing respect and treating subjects with dignity, regardless of what they say, is difficult and may provoke laughter. Police officers are thus trained to resist unwanted physical or verbal reactions and act appropriately.

"politeness for less distance. Humorous violation of the rules of politeness is an index for a greater degree of interpersonal intimacy which can be referred to as familiarity" (compare Kotthoff 1996: 300). Banter (or jocularity) is equated with mock, but the term banter may be used to refer to "joking around or jesting in a playful manner" (Haugh and Boussfield 2012: 6). Wit is a more sarcastic, biting, and cruel source of laughter (Martin 2003).

6. Chosen linguistic insights on negotiation language

Business negotiations, similarly to hostage negotiations, are dominated by particular dialogue speech acts and action verbs which can be associated with particular phases uttered during business activities: (a) exchange of information, (b) recommending offered products and services, (c) making promises, (d) assertiveness, (e) integration, (f) drawing attention and attracting customers (Schultz 2021). The language of negotiations is connected with the language of business negotiations. From the pragmatics perspective, the most frequently used speech act is the representative act that sellers adopt to inform the other side of "the cost and price of products and the strengths of products" (Satavetin 2018).

In business, parties tend to negotiate a better position for themselves. Business activities are connected with buying and selling something, which is not too different from the mutual-gains approach to hostage negotiations. Many persuasion attempts are also made. Another common tactic is to establish goals and strategies as the negotiation begins and asses if the goals are reached when the negotiation progresses. Moreover, business activities are also focused on building rapport to facilitate and maintain the exchange of goods. For this reason, they are interesting from a hostage negotiation standpoint.

In the Oceanside Police negotiation with Grant Sattaur (2007) and The Branch Davidians in the Waco standoff in Texas (1993), we face a scenario where parties communicate remotely. Language in face-to-face conversations differs from remote communication, where parties are isolated. It is even more differentiated if they cannot see each other's faces, e.g., in the communication that occurs in telephone calls or letters.

People who do not meet someone face-to-face are more pessimistic, presumptuous and convey that they are entitled and not easy to work with (Leight

2020: 185–186). It is an important characteristic, as most hostage negotiations are not conducted face-to-face due to security concerns. However, in many negotiations with a person who wants to commit suicide, the police negotiator tries to get as close as allowed. This happens if the person plans to fall or jump but is unarmed.

Some characteristics of crisis communication language were presented in the previous chapters, mainly chapters one and two. Below, I focus on action verbs and particular verbs related to disrupting communication flow, such as "hear" and "listen." It is necessary, however, to provide factual information on the studied negotiations first.

6.1. The Oceanside Police negotiation with Grant Sattaur

Grant Sattaur barricaded himself in his house during the absence of his parents in 2007 in San Diego. According to what he said, Grant had a pistol and threatened to use it against himself and a potentially dangerous dog breed that would defend the house. The firearm's presence led to a long two-hour negotiation to get Grant Sattaur out of the house unarmed. The negotiation was conducted by San Diego Police Department's Emergency Negotiation Team (The Crime Report 2008). Grant had already been treated in a mental institution and had a previous violent record and a restraining order related to a love affair that did not work out as he had planned. Judging from the transcript, his relationship issues were the leading cause of his constant sadness and depressive mood.

A licensed mental health professional from the Psychiatric Emergency Response Team (PERT) was on scene but was not allowed to assist with the negotiator (ACLU 2008). Grant was not allowed to hear from his relatives (including his girlfriend), and his parents were not contacted during the crisis (ACLU 2008). The police continued pointing guns at the house (ACLU 2008), increasing Grant's fear. Grant did not want to come out, fearing violent arrest and returning to the mental institution (e.g., during the negotiation, Grant said: "I am not going back to Vista"). Some experts argued that the negotiator lacked adequate training (ACLU 2008). Grant Sattaur, age 20, committed suicide the day after Christmas during a phone call with the police negotiator (The Crime Report 2008). Both presented cases are controversial and still under debate by experts.

Crisis negotiations are also characterized by many action verbs that can be separated into mental and physical action verbs. A physical action verb has a subject performing a physical action (see Table 9).

Table 9. Action verbs and physical action verbs (marked in grey) and their frequencies in Oceanside Police negotiation with Grant Sattaur in 2007

do	279	hurry	26	understand	14	try	10	move	7
talk	54	care	24	want	13	stay	9	end	5
tell	46	let	23	keep	11	like	9	sit	5
hurt	38	kill	22	hold	11	live	8	cry	4
work	33	talk	17	mean	10	break	8		
put	31	see	17	cares	10	upset	8		
happen	31	say	17	give	10	shut	8		
help	30	arrest	15	walk	10	contact	8		
call	30	listen	16	leave	10	guarantee	7		
make	28	find	15	believe	10	unlock	7		
say	28	come	15	get	13	take	7		

The verb "listen" appears 16 times throughout the Oceanside Police negotiation with Grant Sattaur, and the verb "hear" four times indicates communication problems. Listening to the police recording reveals a communication problem where the speaker and the listener are sometimes barely audible. During the last moments before Grant Sattaur took his life, this communication problem was more significant, and it was stacked with the police negotiator's negative attitude (e.g., "Shut up and listen to me!") that began in the second part of the conversation. The negotiator repeated "like I said" five times and the suspect once, indicating that the interlocutors wanted to ensure they were understood[8].

The negative attitude stemmed, apart from inadequate negotiation strategies, partially from communication problems and partially because of Grant Sattaur's negative attitude and refusal to comply (example 1), which triggered the negotiator to try to impose his will more aggressively (example 2).

POLICE NEGOTIATOR: Okay. You think you are going to want to come outside later.

[8] On the other hand, it may also indicate that one of the interlocutors was losing patience. We may communicate that, for instance, by saying: "I said I would take that deal" or "I have already told you I am not interested."

GRANT: I don't know.
POLICE NEGOTIATOR: Okay. Can I get you at least to put the gun down?
GRANT: No.
(example 1)

POLICE NEGOTIATOR: Are you going to be a coward to stay in the house or you are going to be a man and come outside and take care of your problems?
GRANT: I don't know.
POLICE NEGOTIATOR: So you are a coward?
GRANT: Yes.
(example 2)

Known functions of turn constructional units (TCUs) such as "I do not know" are: 1) providing an imprecise description of when an actual past event happened, 2) negative assessment or self-deprecation, 3) complaints and criticisms, 4) responding to assessments and questions (Weatherall 2011). For example, there are five short "I do not know" sentences followed by a pause in the police transcript that, judging from the context, indicate that Grant Sattaur is resigned and does not want to cooperate. Instances of more extended responses to questions include: "I do not really want to talk about anything?", "I do not want to hurt anybody else," "I do not know what I need," "I do not know it is going to help me," "I do not know, what good is staying alive going to do?".

The lack of trust and recognition of police manipulation patterns by the subject represents another problem. An example can be found in the following sentence uttered by Grant: "But you guys like to play the waiting game just so that you have a couple of hours so it gets dark let me negotiate with you for the whole day, and then you guys will bust in." Another example of recognized manipulation attempt can be found in the sentence: "You are going to point guns and block off the street to make sure I am okay, but I haven't broken any laws?." The sentence was uttered after the negotiator said that Grant had not broken any laws.

Most importantly, the negotiator failed to de-emphasize the negative outcomes of surrender. The subject worried about how the police would handle him during his surrender. His experience with the police was negative: "As soon as they pulled out they were yelling at me to get out of the car and before I even got the door open they yanked me out of the car and threw me on the ground."

Moreover, the subject did also feel unsafe due to the guns being pointed at the house: "If I have not violated any laws, then can you tell me why the police are like blocking off the street and why they have guns pointed at the house?." Finally, I did not find acts of apology or acts of initiating repair.

As a result of these actions, the suspect refused to comply and adopted a defensive stance. As mentioned, defensive communication takes place when the subject feels attacked or insulted (Montemurro 2011). By behaving in a non-threatening way, negotiators avoid the person in crisis actively defending their stance, and increase the probability of behavioral change (Cleveland, Kevoe-Feldman and Stokoe 2022: 105).

On a positive note, the negotiator asked many questions and kept the subject busy, as indicated by the large number of instances where the negotiator gathered information (240 sentences in total). The negotiator uttered numerous rapport-building sentences typical of soft negotiations, using the words "care" 58 times, "worry" 2 times, and "help" 71 times, trying to comfort the suspect.

6.2. The Waco Siege negotiation

The Waco Siege took place at Mount Carmel in Waco, Texas, between February 28 and April 19, 1993. The New Mount Carmel Center was a large compound used by the Branch Davidians, a religious group in the Axtell area outside Waco, Texas, United States. Steve Schneider was David Koresh’s spokesman during the Waco Tragedy. Schneider, who received a Ph.D. in comparative religion from the University of Hawaii, was highly influenced by Koresh, the leader of the sect, who also played an active role in the negotiation process. Schneider was considered a stabilizing influence (see tape 171), while Koresh a destabilizing influence.

The Branch Davidians negotiated either with the FBI or with the negotiation team. There were thus many negotiating parties from both sides, including the negotiation expert Gary Noesner. Two hundred hours of telephone negotiation over 51 days did not produce substantial results. Coercive methods were not coordinated with a coherent communication strategy. There was also a lack of understanding of the other side's wants. Psychological pressure tactics, such as sleep deprivation and the absence of electricity, only worsened the situation. The negotiations ended up being chaotic and prevented the residents of Mount Caramel from thinking clearly, and they thus entrenched themselves deeper into their system of beliefs. The sect believed that evil forces were against them. The FBI was considered a "powerful agency" by Steve Schneider (see tape 171), and the external world was defined as the "system."

Steve Schneider also used the David versus Goliath allegory, calling the external world the "Goliath" or "the beast" (see tape 171). The situation was worsened by political factors that required a quick resolution of the problem. The authorities were suspicious of child abuse and concerned due to illegal weapons at the compound. There were also gun charges against Koresh. Because there was a violent confrontation with law enforcement during the initial interaction, trust could not be established. In April 1993, another confrontation caused the deaths of 76 Branch Davidians, including 25 children and two pregnant women.

As far as linguistic analysis is concerned, the main issue that the negotiators had to face can be ascribed to bad communication flow. Robert Agne (2017) counted 78 moments in which listening was an expressed problem during tense situations with the Branch Davidians in the Waco standoff in Texas. In the two hundred telephone calls, approximately 15 minutes of conversation were devoted to utterances revolving around problematic "listening" or "hearing" moments (see Table 10).

Table 10. Listen and hear in the Branch Davidians negotiation during the Waco standoff in Texas (Agne 2017: 7)

Time	utterances (%)	total time (%)	no. of (tense) problematic moments
1–3 seconds long responses	64.5%	12%	51
3–30 seconds long	29.5%	25%	23
30 seconds or longer	6%	63%	4

An extract of the FBI tape no. 168 illustrates this problem well:

(...)

JOHN: Stone, Stone, listen to me.

MR. MALCOIM: Un-hum.

JOHN: Rather than rambling, just listen to me for a second.

(...)

JOHN: I said don't be rambling. Listen to me.

MR. MALCOLM: Um-hum.

(...)

The problem of listening and hearing within the Branch Davidian context was exacerbated by:

1) the presence of many parties involved in the negotiation,
2) the change of negotiators, which had to be enacted because negotiators had to be ready 24/7,
3) the lack of unique, cohesive strategies,
4) the conflict between the negotiating team and decision-makers, e.g., the incident commander interfering with the negotiation team,
5) the conflicting and incompatible points of view between the negotiators and the other side,
6) the use of metaphors and religious language by the Davidians,
7) the presence of a warlike image of the police agents protected by armored vehicles that heightened the tension (Noesner 2010: chapter seven),
8) lack of effective isolation so that only one team of negotiators would communicate without interference, and
9) pressure tactics that undermined negotiating team's work.

The law enforcement agents often refused to listen to what was perceived as "religious babble" and "psychotic babble." The Davidians' views and actions centered around religion were reinforced by a charismatic leader, David Koresh. Negotiation strategies based on what to say had little to no effect on him and the other religious members due to his influence. Gary Noesner (2010: Chapter Seven) supervised the negotiations. He described Koresh as a manipulative sociopath who would only release children because he wanted their parents ready to fight and do as they were told.

As said, psychological pressure tactics also impair rational decision-making. Other members of the Branch Davidians wanted to get out and surrender; however, they had not enough strength to resist the influence of David Koresh. Because standard communication strategies had to fail, David Koresh adopted controversial framing strategies to his advantage that were also seen as an obstacle for the negotiators (see more Agne 2007: 570). David Koresh reframes the FBI law-enforcement frame to a religious one, he makes the knowledge of the Seven Seals central, "placing those who do not know the Seals on the side of evil slotted for eternal punishment" (Agne 2007: 565).

Furthermore, the FBI adopted the expression "I mean" as a strengthening tool of the argument for releasing hostages (Suh 2016). "I mean" typically announces a less-face-threatening rephrasing of the act of initiating repair (compare Suh 2016). The Branch Davidians used a register of language used in the domain of religion that is also worth studying. Current research in linguistics aims at "identifying those structures and functions of religious language (lexicon, syntax, phonology, morphology, and prosody) that differentiate it from its non-religious counterpart" (Pandharipande 2018). We can study a religious language on a linguistic level, i.e., the language in use or on a metalinguistic level, i.e., the language about an existential language such as sacred and philosophical texts (Holt 2006: 4–5).

Warnings, commands, invitations, judgments, promises, exhortations, or pledges of love are part of performative utterances that express a divine purpose (Cho and Forster 2017, Thiselton 2006a: 86). Even in religious texts, however, we can find both "figurative" and "literal" sentences, e.g.:

"Where were you when I founded the earth?" (Job 38: 4) – figurative meaning

"Saul...applied for letters to the synagogues at Damascus authorizing him to arrest any followers of the new way" (Acts 9: 1–2) – literal meaning
(Holt 2006)

Conversations between religious people or sects are unlikely always to contain patterns of religious language. However, we find a particular lexicon in Branch Davidian's speech. For instance, the use of "thorns in my flesh" instead of "problems" (tape 170). As Steve Schroeder was a researcher, religious language was also intertwined with academic language. Academic language can be seen in sentences such as "allow him to sit down with a panel of scholars" (tape 171). Due to its interlocutors, the Branch Davidians discourse is rich in metaphors and allegory.

When the Branch Davidians adopted a religious lexicon and narrative, it usually caused a negative reaction in the negotiators' dialogue content. The negotiators tried to correct the other side forcing it to adopt a common and ordinary (non-religious) language and objective criteria. Conversely, the Branch Davidians tried to correct but also to teach and educate their interlocutors and the media in the hope that they would embrace their system of beliefs and what can be considered a matter of faith and subjective criteria.

7. Chosen linguistic insights on police language during the interview process

During the investigation and interview, law enforcement agent language shares certain common characteristics, some of which were illustrated in chapter two. These characteristics include: 1) the use of a particular vocabulary and set phrases, 2) the interrogator's preference of time statements that leverage the twenty-four-hour digital system (23:00 instead of 11:00 p.m.), 3) interactional focus and control over discourse by establishing motive and knowledge of the situation, 4) the use of the sequence composed of a subject followed by a temporal adverb, 5) and rapport building strategies (compare Hall 2008). Motive and knowledge are established by adopting set phrases composed of inquisitive tagging questions and scripted sentences, e.g.:

"A male (female) individual,"
"I put it to you that,"
"We are now assisting with our inquiries,"
"Can you now tell me?,"
"Would you agree with that?,"
"Is that correct?,"
"Would you accept this?,"
"Did you then (also) agree,"
"Middle-aged (young or old) female (male),"
"There is more? Isn't there?,"
"You did something else? Didn't you?,"
"I must know,"
"I want to know why you did it,"
"I want to know what made you do it,"
"You'd feel better if you told us what it was all about?,"
"What made you do it?,"

"You hit her with something else, didn’t you?," and
"Do you know any person who may have wished to harm your wife (husband, son, daughter etc.)?" (compare Hall 2008).

Studying both crisis negotiations and police interviews reveals certain differences. In a police interview, police officers also make formal utterances at the beginning, such as presenting themselves (Heydon 2005: 150). The police role is that of an animator to maximize the police interviewer’s adherence to police regulations (Heydon 2005: 91, 196). Further formal utterances include: identifying other participants, explaining the reason for the interview, acknowledging the time of the interview, eliciting the suspect’s identification and informing the suspect of his rights and obligations (compare Heydon 2005: 196).

In today's interrogations, police routinely give Miranda warnings, and suspects routinely waive their rights (Zalman and Smith 2007: 890). Police rarely use coercive tactics to elicit information (Zalman and Smith 2007: 890). Particular language includes verbs such as "assist," "sustain," and "tell"; or nouns such as "gun," "mate," "individual," "persons," "weapon," and "vehicle" (compare Hall 2008). Common words describe locations or an object such as "patio," "living room," "sofa," e.g.:

"I saw somebody running through my backyard."
"My lights caught somebody on the patio."
"I don't know what door he came out of."
"He was standing in the family room" (Shuy 1998 : 22–3).

Depictions of locations, people, objects and weapons can also be found in hostage negotiation language as the negotiator, similarly to the police interrogator, tries to gather as much information as possible. The law enforcement agent also uses methods of placing a subject right before an adverb, e.g., "The time now is 20:20" (Hall 2008: 82). The investigative discourse is also likely to be oriented towards maintaining control of the direction taken in an interaction, including control of the questioning process (Hall 2008; compare Gibbons 2008: 116). The police interrogation thus reflects a type of institutional discourse based on "evidence collection or prosecution and defense" (Anumudu and Samson 2019: 3). Resources used to control important aspects of the institutional discourse, such as the topic of the discussion and length of suspect's contributions are distributed in favor of the interviewing officer and inaccessible to the suspect (Heydon 2005: 198).

The investigation (interview) language is focused on establishing "motive, opportunity, intent, preparation, plan, knowledge, identity," "absence of mistake," or "accident" (Hall 2008: 68). Textual data of police interrogations reveal a composition of short sentences between two and ten words (Khudair and Betti 2014: 8). Short sentences are more common in police officers' speech for they usually ask questions directed at establishing the truth (Khudair and Betti 2014: 8–9). The major language acts are elicitation, reply, informative acts (Khudair and Betti 2014: 9) and declarative sentences which express an attitudinal opinion, e.g., "You are a fraudster!" (Anumudu and Samson 2019: 8). Judges or police interrogators produce constative speech acts as they describe the law as it exists (Dunn 2003: 499). At the same time, however, the utterances of judges or police interrogators must be performative during decision-making (Dunn 2003: 499).

Another characteristic is the use of legal language by the police interviewer and repeated questions directed at the suspect, asking if he understands everything. On the one hand, the police themselves acknowledge that legal language and jargon are "likely to be problematic or incomprehensible to suspects, but on the other hand, they consistently rely on institutional words and phrases" (Heydon 2005: 173). In police interrogations, we can distinguish between closed yes–no, forced-choice, multiple, re-asked, and clarification questions accompanied by opinions and statements (Snook et al. 2012: 1332). The next chapter covers the automated detection of emotions and communication tropes, hate speech and rude language.

CHAPTER 5

AUTOMATED TEXT ANALYSIS METHODS

1. Public datasets used in machine learning

1.1. The choice of datasets

Natural Language Processing (NLP) is used to detect emotions and communication tropes. The classification includes sentiment, emotion, rude behavior, hate speech, sarcasm, persuasion and suicidal thoughts. To perform this NLP task, a dataset is necessary for training and testing[1]. The choice of datasets is affected by four important variables: (a) what information is analyzed; (b) the type of data; (c) the approach adopted; and the (d) the goal that we want to achieve. Documents can be analyzed at the paragraph, sentence, sub-sentence (span or word)[2] level as well as at the aspect level (compare Behdenna, Barigou and Belalem 2016). On the aspect level, we study entities or aspects inside the document to determine sentiments or emotions expressed about them (Liu 2015). I perform sentence-level classification (SCLS; Ma et al. 2021) or short-text classification. As we saw in chapter three, emotions in psychology can be mainly analyzed as categories or dimensions.

I focus on discrete categories for all the dataset's classes and classification tasks. To measure emotions or communication tropes, it is possible to rely on deep learning, lexicons, or mixed approaches that leverage both lexicons and machine learning (Samuel 1959; Jordan and Mitchell 2015). Instead of focusing on hand-crafted lexicons, I leverage deep learning (LeCun et al. 2015; Goodfellow et al. 2016) to train the model and draw inferences from new data. The term "deep" in the "deep learning methodology refers to the concept of multiple levels or stages through which data is processed for building a data-driven model" (Sarker 2021: 3). Different public datasets exist that can leverage artificial intelligence (AI) detection from text.

1.2 Public datasets overview

1.2.1. Sentiment analysis datasets

Sentiment analysis or opinion mining (OM) is the "computational treatment of opinions, sentiments, and subjectivity of text" (Medhat, Hassan and Korashy 2014). Text can be written with a positive, negative, or neutral tone based on the writer's

[1] Or, depending on the split adopted, for training, testing, and validation.
[2] Also called Word-level classification (WCLS; Ma et al. 2021).

personal opinion. OM can be defined as a crossroad of "information retrieval and computational linguistics" concerned not with "the topic a text is about, but with the opinion it expresses" (Esuli and Sebastiani 2006). Main English sentiment analysis datasets include:

1) the "Internet Movie Database (IMDb)" dataset that contains an equally split 50 000 documents (Maas et al. 2011),
2) "Sentiment140" dataset (Go, Bhayani and Huang 2009), which consists of over 1.6 million tweets,
3) the "Restaurant Review Dataset" of 52 077 documents (Ganu, Marian and Elhadad 2009),
4) the "Trip Advisor Hotel Reviews" dataset of 20 000 documents (Alam, Ryu and Lee 2016),
5) the "OpinRank Data" dataset of 300 000 documents (Ganesan and Zhai 2011),
6) the "Stanford Sentiment Treebank" dataset (SST-5 or SST fine-grained; Socher et al. 2013) of 11 855 sentences are based on a dataset that contained scraped Rotten Tomatoes' movie reviews (Pang and Lee 2005),
7) the "Hotel Reviews" dataset of 515 739 sentences scraped from Booking.com (Liu 2017),
8) the "Twitter US Airline Sentiment" dataset of 14 641 sentences (Figure Eight 2015),
9) the "Yelp" dataset of 229 907 business reviews (Sajnani et al. 2019),
10) the "Amazon Reviews Dataset" (He and McAuley 2016; McAuley et al. 2015) of 142.8 million reviews,
11) the "Bert-multilingual-uncased-sentiment" multi-class dataset (NLPTown 2022) of 150 000 English sentences,
12) the "SemEval 2013" corpus (Nakov et al. 2013), which contains 15 151 tweets classified as positive, negative, or neutral, and
13) the "SemEval 2017" corpus, which also contains three classes and around 40 000 tweets (Huggingface 2017; Pérez, Giudici, and Luque 2021).

1.2.2. Emotion detection datasets

Emotion detection focuses on recognizing the emotion evoked by the text or expressed in the text (Zhang and Provost 2019). The following English datasets specific to textual emotion recognition can be utilized in categorical text classification:

1) "Affective Text" composed of 1200 news headlines (Strapparava and Mihalcea 2007),
2) "Blogs" with 5205 sentences (Aman and Szpakowicz 2007),
3) datasets created using the "CrowdFlower" service (Gupta 2020; Liu, Osama and De Andrade 2019),
4) "DailyDialogs" composed of 13 118 sentences (Li et al. 2017),
5) "DENS: Dataset for Multi-class Emotion Analysis" made of 9710 sentences (Liu, Osama and De Andrade 2019),
6) "Electoral-Tweets" of 100 000 responses to questionnaires (Mohammad et al. 2015),
7) "Emobank" of 10 000 sentences (Buechel and Hahn 2017),
8) "EmoInt" of 7097 tweets (Mohammad and Bravo-Marquez 2017),
9) "ISEAR" which contains 7666 sentences (Scherer and Wallbott 1994),
10) "The Stance Sentiment Emotion Corpus" of 4868 tweets (Mohammad, Sobhani, and Kiritchenko 2017),
11) "Tales" or "FairyTales" composed of 15 302 sentences taken from fantasy literature by Beatrix Potter, Hans Christian Andersen and the Brothers Grimm (Alm, Roth and Sproat 2005),
12) "The Twitter Emotion Corpus" of 21 051 tweets" (TEC; Mohammad 2012),
13) the "fb-valence-arousal" made of 2895 user posts (Preotiuc-Pietro 2016),
14) the "Contextualized Affect Representations for Emotion Recognition" (CARER ; Saravia et al. 2018) dataset of 416 810 sentences, and
15) the "Emotion-Stimulus Dataset" (Ghazi, Inkpen and Szpakowicz 2015) of 2500 sentences.

At least two variants exist of datasets made with "CrowdFlower," a service that leverages user input to tag each sentence collected from social media:

1) The "Emotion in Text" dataset of thirteen classes and 39 740 tweets (Gupta 2020) suffers from a severe class imbalance problem, and the

2) the "CrowdFlower dataset," which was adopted for the "BalanceNet" model prototype (Liu, Kang and Ken 2017). It comprises 47 288 sentences and five classes (Liu, Osama and De Andrade 2019).

1.2.3 Toxic comment and toxic question datasets

The toxic comment classification helps distinguish between unwanted (rude or toxic) and non-toxic comments. The comments that forum users are usually allowed to express contain non-toxic or neutral comments. The toxic comment classification requires information about the labeling schema convention. Three toxic comment classifications exist: 1) the "Toxic comment classification" made of "Wikipedia Comments" in 2018 (223 550 sentences), 2) the "Jigsaw Unintended Bias in Toxic Comments" made from "Civil Comments" in 2019 (943 149 sentences), and 3) the "Jigsaw multilingual toxic comment classification" made of "Wikipedia Comments" and "Civil Comments" in 2020 (223 550 sentences; Hugginface.co 2018).

Daniel Borkan et al. at Jigsaw created the "Civil Comments" dataset (2019), composed of two million words. This dataset results from a collaboration between Google and its sister firm, Jigsaw. Together, they created the Perspective API, a Google bot capable of detecting "toxicity" in written text, of reducing the moderation load on social media by encouraging commentators to improve their behavior and user experience. The "Civil Comments" (Borkan et al. 2019) dataset is based on crowdsourcing and is included in TensorFlow (TensorFlow Datasets 2017). At the end of 2017, the "Civil Comments" platform shut down, and the dataset became publicly available (TensorFlow Datasets 2017).

The "Quora Insincere Questions classification" (Mungekar et al. 2019) is composed of 80 810 "toxic" and 1 225 312 "non-toxic" questions gathered from the Quora website (Kaggle 2022). It can be described as 1) having a non-neutral or exaggerated tone, 2) having a disparaging, shocking or inflammatory content, 3) suggesting a "discriminatory idea against a protected class of people, or seeking "confirmation of a stereotype," 4) "disparages against a characteristic that is not fixable and not measurable," 5) being not grounded in reality, and 6) being based on false information or otherwise absurd assumptions (Kaggle 2022). All the mentioned datasets are very similar regarding what they try to achieve.

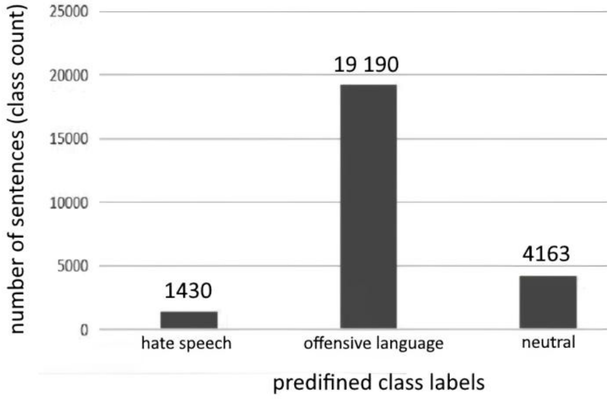
1.2.4. The suicidal ideation datasets

The primary suicidal ideation dataset is the "Full Reddit Submission Corpus" created in 2015 (Shing et al. 2018) which consists of 1 556 194 posts mined from Reddit from which several other datasets stemmed. An example is the "CLPsych 2019 Shared Task," which introduced an assessment of suicide risk (Zirikly et al. 2019). Independently from this achievement, Snigdha Ramkumar, Tulasi Prasad Sariki, Bharadwaja Kumar, and Jagadeesh Kannan (2020) and Eldar Yeskuatov, Sook-Ling Chua, and Lee Kien Foo (2022) created a large suicide risk assessment datasets mined from social media. Apart from large datasets, there are several smaller datasets: 1) the "Suicidal Ideation Detection in Online User Contents" created in 2018 that includes 5326 suicidal ideation samples and 20 000 non-suicide samples (Ji et al. 2018, Ji et al. 2020), 2) the "Suicide Notes" (498 sentences; Kaggle 2020) and 3) "Depressive Tweets" by Hien Nguyen (3842 sentences; 2022).

1.2.5. Hate speech and offensive language datasets

Several large-size corpora dedicated to abusive language exist, such as the "Wikipedia Abusive Conversations" (WAC), composed of 384 000 abusive comments (Cécillon et al. 2020), the "Wikipedia Comment Corpus" (WCC; Wulczyn, Thain, and Dixon 2017) split between "Personal Attack" (115 864 comments), "Aggression" (115 864 comments), and "Toxicity" (159 686 comments), "WikiConv" (91 million conversations in the English Wikipedia component, Hua et al. 2018) spanning five languages, and "PreTox" (Karan and Šnajder 2019) based on WikiConv (Cécillon et al. 2020: 1384).

Figure 1. Unequal distribution of sentences in the "Hate speech and offensive language" dataset (Davidson et al. 2016)



In addition, Thomas Davidson, Dana Warmsley, Michael Macy, and Ingmar Weberwas (2017) made a small dataset of 24 783 sentences that suffers from a class imbalance problem, where some classes have fewer sentences than others, see Figure 1.

1.2.6. Sarcasm, jocularity and metaphor detection datasets

A high-quality dataset dedicated to sarcasm is the "Sarcasm in News Headlines Dataset" by Rishabh Misra (2019). Other datasets dedicated to sarcasm detection mostly use Twitter collected using hashtag-based supervision (Misra and Arora 2019). Such datasets, however, are "noisy in terms of labels and language" (Misra and Arora 2019)[3]. The "Language Computer Corporation (LCC)" largest annotated metaphor dataset by Michael Mohler, Mary Brunson, Bryan Rink, and Marc Tomlinson (2016) is composed of 36 247 literal and non-literal sentences and is helpful for metaphor detection as well. The "LCC dataset" is known for achieving better metrics than other similar datasets such as "TroFi" (Birke and Sarkar 2006; Birke and Sarkar 2007) or "MOH" (Mohammad et al. 2016) with machine learning. Yulia Tsvetkov et al. (2014) also created a database of 2000 adjective-nouns called the "TSV" dataset. Other known corpora are the VU Amsterdam Metaphor Corpus (Steen et al. 2010) and the MultiMET Dataset (Zhang et al. 2021).

1.2.7. Persuasion detection datasets

Main persuasion detection datasets include the "NPS Persuasion Corpus" (Gilbert 2010) based on four sets of negotiation transcripts containing 18 847 utterances, the "SemEval2021 Task-6 on Detection of Persuasive Techniques in Texts and Images" (Dimitrov et al. 2021), and the "Multilingual Persuasion Dataset" gathered by scouring video game's dialogues (123 114 sentences; Pöyhönen, Hämäläinen and Alnajjar 2022). In addition, the "SemEval2021 Task-6 on Detection of Persuasive Techniques in Texts and Images" and the "Multilingual Persuasion Dataset" are publicly available online.

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[3] Jocularity can be analyzed by using the "Humor detection dataset" (Annamoradnejad and Zoghi 2020) consisting of 200 000 formal short texts (100 000 positive and 100 000 negative) , which combines two datasets: 1) the "News dataset" of 200 853 news headlines obtained from Huffington Post divided into four categories of "politics," "wellness," "entertainment," and "parenting," and the 2) "Jokes dataset" of 231 657 short texts dedicated to humor and jokes mined from "/r/jokes" and "/r/cleanjokes" subreddits (Annamoradnejad and Zoghi 2020).

2. Tools

2.1. Text mining tools

Data mining tools for gathering textual data include:

1) Python libraries such as Python Reddit API Wrapper (PRAW), multithread Pushshift API Wrapper (PMAW), and PushShift API Wrapper (PSAW),
2) BigQuery,
3) Tweepy,
4) RapidMiner,
5) Steamreviews application programming interface (API), and
6) Reddit extractor.

PRAW, PSAW, PMAW, Steamreviews, or RapidMiner fetch existing messages, whereas the streaming session of Tweepy captures live messages (tweets). PRAW is a Python wrapper used to access Reddit's API created initially by Timothy Mellor as Reddit_API and maintained and developed by Bryce Boe (PRAW 2022). Both PRAW and PSAW are used to mine Reddit social media posts. PRAW can mine existing or recent Reddit posts, and Reddit's API rates limit it. Reddit API's rate limit is set to 60 requests per minute, allowing a request to up to 100 items simultaneously. PRAW only collects recent posts. Because of these limitations, the use of PSAW is suggested.

The PSAW Python wrapper for the Pushshift API allows access to Reddit archives. PSAW provides "extended functionality by providing full-text search against comments and submissions, and has larger single query limits." (Walsh 2022). PSAW, however, requires additional preprocessing steps in comparison to PRAW to filter out deleted comments. In addition, PMAW rates are more lenient and are defined by two different rate-averaging and exponential backoff (see more: Podolak 2022). The maximum recommended value is 100 requests per minute (Podolak 2022). To avoid these rate limitations, BigQuery can be used to access large historical datasets (see more Google Cloud 2022).

Tweepy is used to mine social media Twitter posts. In Tweepy, an instance of the "tweepy.Stream" function creates a streaming session and sends messages to an instance of the "StreamListener" (Tweepy 2022). The Representational State Transfer

(REST) Application Programming Interface (API) fetches data from Twitter. The streaming API delivers messages to a persistent session, allowing users to download data relatively fast (Tweepy 2022). RapidMiner software becomes useful if we want more control of what is gathered owing to its graphical user interface (GUI). For example, RapidMiner's "Search Twitter" operator allows finding sentences based on a word or word pairs, while "Turboprep," through the cleanse functions, can remove missing values and duplicates (RapidMiner 2022).

The Steamreviews API makes scraping game reviews from Steam easier. Steam reviews represent a good source of hate speech and offensive language because, as we saw in chapter four, specific game reviews contain more abusive language. However, due to the gaming domain of these reviews, it is not easy to implement the gathered dataset into classification tasks from different domains. Finally, Reddit Extractor is an R package for extracting new comments from Reddit. It stands out from the other tools for the construct_graph and the user_network functions, providing a visual network-like structure of threads and comments (Swofford 2019).

2.2. Dedicated tools for data analysis

Dedicated IT tools to analyze text documents can be split into simple and more advanced. A simple text analysis tool allows researchers to obtain basic statistics from documents and corpora, such as the frequency of occurrence or co-occurrence of words. Examples of such tools include TextSTAT, AntConc, Key Word in Context (KWIC), and the Wordsmith corpus software. Visualization tools for documents and corpus analysis include Concordance Mosaic, Metafacet, and ComFre (Sheehan and Luz 2019: 694). Advanced text analysis tools leverage clustering techniques and the possibility of building ontologies. Such tools include SAS Text Miner, Oracle Text, and OntoGen Text Garden (Potiopa 2011: 414).

Advanced tools also specialize in deception and emotion recognition. For example, linguistic Deception Cues (LDC) can profile online conversations and detect deception in textual data. Dialog Act Modeling (DAM) can predict the completeness of various stages of grief (Pennebaker, Mayne and Francis 1997). Linguistic Inquiry and Word Count (LIWC) was developed in the early 1990s by James Pennebaker and Martha Francis (Pennebaker and Francis 1999) and later updated by Roger Booth and Ryan Boyd. LIWC identifies dimensions such as affect, social and cognitive processes, personal concerns, and informal language. For example, the identified affective language might indicate lying or emotional words.

The software has different subsets of emotion categories, e.g., the negative emotion category is represented by an 1) "anxiety/fear" pair encompassing 62-word derivatives, such as "nervous," "afraid," and "tense," 2) "anger" encompassing 121 words, such as "hate," "kill," and "pissed," and 3) "sadness/depression" comprised of 72 words such as "grief," "cry," and "sad" (Kahn et al. 2007: 266). The frequency of affective words characterizes the document's tone that can conflict with the expressed content (see more Lord and Cowan 2010). LIWC represents a valid method for measuring verbal expression of emotion (compare Kahn et al. 2007). The presented software can be used in police work and research. However, Pete Burnap et al. (2017) highlight the inadequacy of sentiment analysis tools for binary classification. With the development of NLP and machine learning, conducting a more customized text analysis has become possible.

2.3. Data preprocessing tools

Main natural language processing tools for text preprocessing include:

1. Stanford Core NLP, which is a Java-based library developed at Stanford University,
2. Natural Language Toolkit (NLTK) that was created at the University of Pennsylvania using Python,
3. Gensim, which is most commonly used for topic modeling and similarity detection,
4. AllenNLP, which is built on PyTorch,
5. Polyglot, which is based on NumPy, and
6. SpaCy, a production-oriented open-source project written in both Cython and Python.

Popular libraries for text cleaning include NLTK, SpaCy, CleanText, and Texthero. CleanText was built upon the work by Burton DeWilde for Textacy, a library for performing NLP tasks based on the SpaCy library (Chartbeat-labs/textacy 2022, clean-text 2022). Texthero is designed to be used alongside Pandas, a popular data manipulation tool, to clean and preprocess text with out-of-the-box solutions (jbesomi/texthero 2022). Visualization of data is essential for exploratory data analysis. Main tools for data visualization include Altair, Bokeh, Matplotlib, Plotly, pyLDAvis, Scattertext, Seaborn, and Wordcloud. Essential text operations include tokenization, stemming, lemmatization, and tagging.

2.4. Tokenization tools

Tokenization is the process of splitting documents into smaller units called tokens, e.g., sentences, words or sub-words. We can divide sentence tokenization into different tools:

(a) using the split function, which is commonly found in Python and other programming languages,
(b) using regular expressions (regex),
(c) using the NLTK library,
(d) using the SpaCy library,
(e) using the WordPiece tokenizer, and
(f) using other tokenizers[4].

Python's basic and built-in word tokenization is achieved with the split() function. Similarly, NLTK uses the nltk.word_tokenize function, which "divides strings into lists of substrings" (NLTK 2022). The "SpaCy" library converts a text document into an "nlp object" before performing tokenization, which is relatively slow. SpaCy uses en_core_web_sm, which is a "small English pipeline trained on written web text (blogs, news, comments), that includes vocabulary, syntax and entities" (Spacy.io 2023a). Spacy splits text into sentences based on training data that was provided during the training procedure. It extracts "reasonable sentences when the format and domain of the input text are unknown. It is a rules-based algorithm

[4] Other tokenizers that split documents into sentences include the PunktSentenceTokenizer and the RegexpTokenizer. RegexpTokenizer can also perform word-level tokenization (Sarkar 2019: 120 and 125). Word tokenizers include the RegexpTokenizer, the TreebankWordTokenizer, the TokTokTokenizer, the Penn Treebank, and the and the built-in Keras, Gensim, and Textblob tokenizers (Sarkar 2019: 126). The OpenNMT tokenizer (Klein et al. 2017) separates punctuation from words (Domingo et al. 2019: 3). The Moses tokenizer (Koehn et al. 2007) separates punctuation from words, also preserving unique tokens (Domingo et al. 2019: 3). WordPiece (Schuster et al. 2012: 5150) and SentencePiece (Kudo and Richardson 2018) are examples of sub-word tokenizers. SentencePiece implements two subword segmentation algorithms, byte-pair encoding (BPE; Sennrich et al. 2016) and uni-gram language model (Kudo 2018), with the "extension of direct training from raw sentences" (Kudo and Richardson 2018). Byte-Pair Encoding (BPE) performs pre-tokenization and counts the frequency of each possible symbol pair (Sennrich et al. 2015). For other languages that do not use spaces to separate words, SentencePiece, XLNetTokenizer and the Uni-gram algorithm are used (Kudo and Richardson 2018).

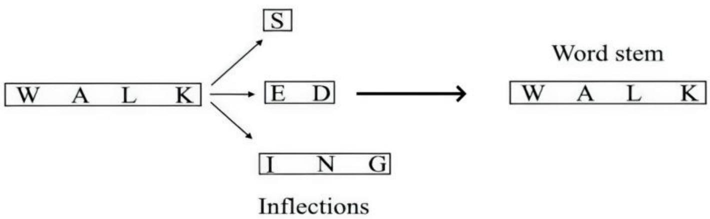
based on The Golden Rules - a set of tests to check the accuracy of segmenter in regards to edge case scenarios developed by TM-Town dev team" (Spacy.io 2023b).

Bidirectional Encoder Representations from Transformers (BERT) model uses the WordPiece tokenizer (Schuster and Nakajima 2012), which splits words into their complete forms or word pieces. Common words "get a slot in the vocabulary, but the tokenizer can fall back to word pieces and individual characters for unknown words" (TensorFlow 2022). Thanks to WordPiece, rare words are decomposed and separated from familiar words. The Bidirectional Encoder Representations from Transformers (BERT) model can thus process words it has never seen before. UnigramLM (Kudo 2018) goes in a different direction, as it initializes to a more extensive vocabulary size than the number of existing sub-words (Gasparetto et al. 2022). A substantial improvement was provided by SentencePiece, a language-independent subword tokenizer that can train subword models directly from a raw stream of characters (Kudo and Richardson 2018).

2.5. Stemming and lemmatization for exploratory data analysis

Noise is that part of data that does not add meaning or information to data and can be removed, which helps avoid degradation in the model's performance (Kumar, Makhija and Gupta 2020: 17–18). Noise removal can be achieved with stemming or lemmatization, stop-word and punctuation removal, or by normalizing text. Stemming is the process of reducing inflection (and derived words) to their root word (stem) (Lovin 1968, Gupta and Lehal 2013). In other words, stemming represents the process of removing affixes from words, e.g., mean+ing, distribut+ion, and walk+ing, see Figure 2.

Figure 2. The inflection removal process (based on Sarkar 2019: 149).



Stemmers can be statistical, rule-based or both (Majumder, Mitra and Datta 2006). Popular stemming tools are the n -gram Stemmer, the Dawson Stemmer, the

Lovins Stemmer, the Porter Stemmer, the Krovetz Stemmer (KSTEM), XSTEM, the HMM Stemmer, the YASS Stemmer, the Xerox Stemmer, the Snowball Stemmer, and the Lancaster Stemmer aka the Paice/Husk Stemmer (Lovins 1968, Dawson 1974, Porter 1980, Paice 1990, Krovetz 1997, Jivani 2011, Java T Point 2022)[5]. Stemming suffers over- and under-stemming (compare Meral et al. 2014, Gawrysiak, Wróblewska, and Andruszkiewicz 2018). Errors of omission and commission can also be called miss-stemming.

Lemmatization can be defined as a morphological transformation that changes a word or a lexeme as it "appears in running text into the base or dictionary form of the word, which is known as a lemma, by removing the inflectional ending of the word" (Liu 2012: 1). A lexeme can be considered a set of "abstract units that gather sets of forms which denote the same physical object" (Woliński 2014). Contrary to stemmers, lemmatizers try to find the roots of similar words by focusing on meanings instead of spelling. How does lemmatization differ from stemming? The objective of both is to condense derivative words into their primary forms. It depends upon correctly identifying part of the speech or lexical category.

Stemming typically produces faster results as it merely chops off the end of a word using heuristics without any knowledge of the context in which a word is used. Lemmatization uses more informed analysis to group words with similar meanings based on the context around them, so lemmatization is more precise. Popular lemmatization can be performed with Wordnet, Spacy, TextBlob, CLiPS Pattern, Stanford CoreNLP, Gensim, Bitext or TreeTagger lemmatization tools. WordNet is a lexical database that groups words (nouns, verbs, adjectives and adverbs) into

[5] The HMM Stemmer uses unsupervised methods and is also language-independent (Jivani 2011: 1937). The YASS Stemmer uses a hierarchical clustering approach, corpus and distance measures (Jivani 2011: 1937). The Dawson Stemmer stores suffixes in reversed order that are indexed by length and last order. The Lovins stemmer (Lovins 1968) removes the longest suffix from a word that is converted back to its short form. The Porter (Porter 1980) stemmer focuses on a combination of short and long English suffixes. The Krovetz stemmer (Krovetz 1997) converts the plural form of a word to its singular form, the past tense of a word to its present tense, and removes the suffix "ing." The Krovetz Stemmer can be used for pre-stemming for other more advanced stemmers and operates fast. The Krovetz Stemmer encounters problems with words that are outside of lexicon words, and lexicons have to be built manually. Moreover, the performance and accuracy are poor on large documents. The Xerox Stemmer, made by the linguists at Xerox corporation, takes prefixes into consideration and works well on large documents but suffers from not utilizing new words. Moreover, it is bound to the English language and lexicon. XSTEM is a multi-pass stemming algorithm that overcomes the out-of-vocabulary problem present in Krovetz (Baker 2022: 4). The Snowball Stemmer can be found as part of the Natural Language Toolkit (NLTK). The Lancaster Stemmer is also imported from NLTK. Finally, the n - Gram Stemmer is a statistical stemmer, a set of n -gram characters are extracted from words and then compared for similarity.

synonym sets called "synsets" (Fellbaum 2005). Each wordnet consists of lexical items indexed to a set of synsets (Fellbaum 2005). BioLemmatizer is a "lemmatization tool for morphological processing of biomedical text" (Liu et al. 2012). Stemming and stop-word removal must be adopted for exploratory data analysis (EDA) to learn more about the data. EDA, on the other hand, helps identify more unnecessary information that can be discarded later.

2.6. Removing stop-words and expanding verbs

Stop-words removal involves eliminating commonly used words that carry little useful information. Examples of so-called stop-words are:

"about," "above," "after," "again," "against," "all," "am," "an," "and," "any," "are," "as," "at," "be," "because," "been," "before," "below," "being," "between," "both," "but," "by," "can," "did," "do," "does," "doing," "down," "has," "have," "have," "he," "her," "here," "hers," "herself," "him," "himself," "his," "how," "if," "is," "it," "its," "itself," "just," "low," "me," "more," "most," "my," "not," "off," "on," "only," "once," "same," or "we."

Contractions, or short forms, are word combinations simplified by removing letters and replacing them with apostrophes. They commonly combine a pronoun or noun and a verb, e.g.,

"There's no doubt he’s afraid of her/ there isn't any doubt he is afraid of her."

They can also contain a verb and a word used to indicate negation, e.g.,

"aren’t/are not," "can’t/cannot," "couldn’t/could not," "didn’t/ did not," "hasn’t/has not," "isn’t/is not," "mustn’t/must not," "shan’t/shall not," "shouldn't/should not," "wasn’t/was not," "weren’t/were not," "won’t/will not," wouldn’t/would not."

The Python package "pycontractions" can expand these contractions without disambiguation errors between sentences with different meanings but the same pronoun or noun and a verb combination by leveraging Word Mover’s Distance (WMD; pycontractions 2019). The potential problem of this package is compatibility, as it requires Java programming language to run. The "contraction" package, on the other hand, can resolve contractions and slang without such issues (Contractions 2022).

2.7. Language detection, cleaning, normalization and splitting

Sentences collected from social media posts often contain other language expressions. Even if we set data mining tools to collect sentences from a specific language, some sentences may pass through cleaning. To remove these sentences, specialized tools can detect and remove foreign languages. Langdetect is a port of Nakatani Shuyo's language-detection library that supports 55 languages and shows decent accuracy and performance. Other known language detectors include SpaCy-Langdetect, Langid, and FastText (Joulin et al. 2016). Another method is translating and thus keeping those sentences that are different from the non-target language.

2.8. Tools for text classification

Dedicated IT text analysis tools can be divided according to their 1) classification, 2) regression, 3) clustering, and 4) association purposes. Popular tools for classification tasks include, among many others, Scikit-Learn (Pedregosa et al. 2011), PyTorch, TensorFlow, Weka, Accors.Net, Shogun, Keras.io, Google Natural Language and AutoML Natural Language, as well as Rapid Miner. As far as sentiment analysis is concerned, established tools for sentiment analysis include NLTK's Vader sentiment analyzer (Hutto and Gilbert 2014), TextBlob (TextBlob 2022), Flair, DeepMoji, Amazon Comprehend, IBM Watson Tone Analyzer, and Google Natural Language sentiment analyzer.

Keras is a Python-based deep learning framework with an application program interface (API) that can run alongside the Microsoft Cognitive Toolkit (CNTK), TensorFlow, and Theano. Keras provides only high-level APIs, whereas TensorFlow provides both high-level and low-level APIs. While Keras is specifically a neural network library, TensorFlow is an open-source library capable of various machine learning tasks. The sequential model in Keras is a linear stack of layers where each object feeds into the next, which is especially useful for simple classification networks or Encoder-Decoder models (Keras 2020).

Table 1. A comparison of machine learning tasks supported out-of-the-box in popular low-code and machine learning libraries for text data (Maiya 2022: 5).

Task	ktrain	fastai	Ludwig	AutoKeras	AutoGluon
Classification/Regression	✓	✓	✓	✓	✓
Sequence-Tagging	✓		✓		
Unsupervised Topic Modeling	✓				
Semantic Search	✓				
End-to-End Question-Answering	✓				
Zero-Shot Learning	✓				
Language Translation	✓	✓			
Summarization	✓	✓			
Text Extraction	✓				
QA-Based Information Extraction	✓				
Keyphrase Extraction	✓				

I utilized Google's Colaboratory (Colab) Cloud Service, which supports PyTorch, Keras, and TensorFlow libraries, and Google Natural Language to perform document classification tasks. The machine learning workflow is divided into three stages: 1) model construction, 2) model inspection, and 3) model application (see Maiya 2022: 1).

Ktrain simplifies the training, building, and debugging process of the Keras neural network. Ktrain allows integration with both high-level and low-level APIs. Ktrain also addresses the problem of learning rates. Ktrain uses tf.keras in TensorFlow instead of standalone Keras (Maiya 2022). Ktrain allows performing additional tasks from "Fastai" (Howard and Gugger 2020), "Ludwig" (Molino, Dudin and Miryala 2019), "AutoKeras" (Jin, Song and Hu 2019) and "AutoGluon" (Erickson et al. 2020), see Table 1.

The "get_learner" allows users to compile a model similar to Keras. Ktrain also facilitates text operations with the Textract package as it loads sequence-labeled data from comma or tab-delimited text files. Ktrain is a valuable toolbox for experienced practitioners needing to rapidly prototype, deploy, and test models and data (Maiya 2022: 5). Another useful function concerning model deployment is the "keras callbacks" API, which helps save the model's weights. Finally, regarding dataset building, ktrain sheds light on the data by displaying sentences that are the most severely misclassified during the evaluation phase (by calling "learner.view_top_losses"). These top losses allow finding and substituting misclassified sentences, which helps build a better classification dataset.

2.9. Tools for exploratory data analysis

Exploratory data analysis can be defined as a tool to "examine the data for distribution, outliers and anomalies to direct specific testing of your hypothesis. It also provides tools for hypothesis generation by visualizing and understanding the data usually through graphical representation" (Komorowski et al. 2016). Exploratory data analysis (EDA) is often a necessary task in hyperparameter tuning, uncovering hidden patterns, detecting outliers and unnecessary data, or identifying important variables (compare Bokaba, Doorsamy, and Paul 2020: 1). I tested exploratory data analysis (EDA) tools and methods that include word or n - gram frequency distribution, TIF-IDF as well as Latent Dirichlet Allocation (LDA; Blei, Ng, and Jordan 2003) and BERT-Topic (Grootendorst 2022a) for topic modeling. An n -gram is a set of n consecutive characters extracted from a word (Ekmekçioglu, Lynch, and Willett 1996). Topic modeling is a method of finding groups of words or abstract topics in a corpus of text using a probabilistic model (Posner 2012). Latent Dirichlet Allocation (LDA) is a popular technique for topic discovery (Blei, Ng and Jordan 2003).

However, in NLP, LDA performs poorly on short textual data when utilizing TIF-IDF by default. LDA can leverage the Countvectorizer in its stead. Tweakable hyperparameters in LDA are: 1) the document density factor (α), which controls the number of expected topics in a document, 2) the topic word density factor (β), which controls the word distribution in each topic, 3) and the number of topics selected (K), that controls how many topics are being extracted (Hill 2020). Apart from LDA, other common (compare: Hill 2020) topic modeling techniques are Latent Semantic Analysis (LSA; Deerwester et al., 1990), Probabilistic Latent Semantic Analysis (PLSA; Hofmann 2013), Correlated Topic Model (CTM; Blei and Lafferty 2005), and Bidirectional Encoder Representation from Transformers BERT-Topic (BERT-Topic; Grootendorst 2022a).

BERT-Topic allows to leverage various BERT transformers models and Class-based TF-IDF, which joins all documents within a class. As a result, BERT-Topic achieves better metrics from LDA and follows the more recent clustering approach of topic modeling (Grootendorst 2022a). Furthermore, BERTopic supports Sentence-Transformers, Flair, Spacy, or Gensim to embed documents (Grootendorst 2022b). Finally, BERT-Topic supports visualization tools such as the Intertopic Distance Map and Topic scores (Grootendorst 2022b). It must be noted that performing EDA on text without stemming and stop-word removal is counter-productive due to the noise from unnecessary information. Therefore, I adopted a custom list of stop-words (see the stop-word list in section 4.1.2.).

3. Methods

3.1. The role of natural language in case-based reasoning

Natural language focuses on human–computer interaction and ontological text interpretation. Natural language is thus used to communicate task requirements to autonomous machines to minimize friction in task specification (Zhou and Small 2021). In addition, natural language is often used for domain ontologies creation, which provides a "contextual framework and a semantic representation" of a target domain (Zazo et al. 2015). Another natural language goal is data gathering, management, representation, search and retrieval. Information contained inside knowledge bases allows us to solve new problems. Such an experience-based approach is called Case-Based Reasoning (CBR). Case-based reasoning is useful in automating learning by an autonomous machine, and thus, it is associated with machine learning (ML; Oyelade and Ezugwu 2019). The processes of searching and analyzing text documents can involve the following methods and systems:

1) Information retrieval (IR),
2) Information Extraction (IE),
3) Text mining, and
4) Natural Language Processing (NLP; Potiopa 2011: 410).

3.2. Information retrieval (IR), Information Extraction (IE), data mining and text data mining

Information retrieval (IR) involves searching for a specific document using a Boolean Logic Model (BLM) or a ranked-output system. A BLM model splits the relevant and irrelevant data using logical operators such as AND, OR, or NOT (Potiopa 2011: 410). A ranked-output system calculates the similarity between documents and ranks them accordingly using weighting or vector similarity measurement algorithms (cosine measure or the Jaccard coefficient; Potiopa 2011: 410 and 416). Information extraction (IE) involves finding instances of predefined classes of events (Potiopa 2011). IE extracts specific information from objects. IE comprises a processor that usually leverages one or more NLP shallow text analysis methods, e.g., lexical analysis, and a domain-specific pattern generator that contains sections called slots (Potiopa 2011: 411).

Slot filling aims at "extracting answers for queries about entities from the text" (Adel and Schütze 2019). In text data mining (TDM), patterns are unknown and discovered during the mining process (Potiopa 2011: 411). Data mining (DM) analyses, transforms and summarizes structured numerical data using mathematical models. In contrast, text data mining (TDM) focuses on transforming and processing a large quantity of unstructured data (Soldacki 2006: 10). Both are used for clustering, classification, building ontologies, and pattern retrieval that leverage NLP (Potiopa 2011: 412).

3.3. Natural language processing (NLP)

There are three natural language processing intersecting concepts: Natural Language Processing (NLP), Natural Language Understanding (NLU), Natural Language Generation (NLG), and Natural Language Inference (NLI). NLU allows a computer to understand spoken language. Such an understanding leads to a semantic representation of the input text (Waldron 2015). NLG is the field of computational linguistics devoted to the automated production of high-quality linguistic content (Foster 2019). The main goal of the NLI problem is to determine whether or not a given natural language hypothesis *h* can be inferred from a natural language premise *p;* given two sentences – hypothesis and premise – NLI classifies the relationship between them into one of three classes: "entailment," "contradiction," or "neutral" (Wang et al. 2019: 7208).

NLP's data processing consists of a micro analysis of predefined patterns and grammar, while Text Data Mining (TDM) would find expected and unexpected relations and patterns in data (Soldacki 2006: 15). TDM processes are mainly automated and focused on big data (Soldacki 2006: 15). TDM is associated with Knowledge Discovery in Databases (KDD). Contrary to TDM, NLP is better suited for relatively small text, and it is largely controlled by the user (Soldacki 2006: 15). It is challenging to establish what is a big versus a small dataset size and the level of automation required. That aspect makes the distinction between NLP and TDM vague.

The research and development in NLP up until the mid-90s can be categorized into the following areas: Natural Language Understanding (NLU), Natural Language Generation (NLG), Speech or Voice recognition, Machine Translation, Spelling Correction and Grammar Checking (Church and Rau 1995).

Nowadays, the main tasks associated with NLP are 1) Stemming and Lemmatization, 2) Stop Word Removal, 3) Text Extraction (also referred to as Keyword or Keyphrase Extraction), 4) Topic Modelling, 5) Noun Phrase Extraction, 6) Named Entity Recognition (NER), 7) Relation Extraction (RE), 8) Text Summarization, 9) Aspect-Based Opinion Mining (e.g., Aspect-Based Sentiment Analysis), 10) Term Frequency-Inverse Document Frequency (TF-IDF), 11) Bag of Words (BoW) 12) Regression, 13) Classification (classification of words, sentences or paragraphs, e.g., sentiment analysis or emotion detection), 14) Sequence-Tagging, 15) Semantic Search, 16) End-to-End Question-Answering, 17) Language Translation, 18) QA-Based Information Extraction, 19) Parts-of-Speech Tagging (POS), 20) Language Modeling, and 21) Document Similarity (compare Maiya 2022: 5). These tasks are often related.

3.4. Computer-aided classification tasks

In natural language processing, the classification task represents "classifying Natural Language texts from a predefined set of categories" (Sumathi, Indumathi and Rajkumar 2020). However, classification is not only about NL and textual data. Analyzing data using a set of mutually exclusive ordered categories where the answer variable has been categorized is known as categorical data analysis (Watson 2014). The most common form of classification is a binary classification which assigns one of two categories to an object by measuring attributes (Parmigiani 2001, Miner et al. 2012: 881).

Other types of classification include multi-class classification, multi-label classification, and hierarchical classification (compare: Chandola et al. 2021: 35–36). For example, in sentiment analysis, a binary classification document can be either positive (+ sign representing positive values) or negative (– sign representing negative values). A multi-class classification task means that we classify more classes than two, e.g., the sentiment analysis task can contain positive (+ sign and positive values), negative (– sign and negative values), and neutral classes (neutral values around zero).

Another example can be found in multi-class emotion detection, where we classify six basic emotions (anger, fear, disgust, sadness, surprise and joy, Ekman: 1992). The model will select one class, e.g., fear, and the rest, e.g., anger, disgust, sadness, surprise and joy, will not be selected. Classes can be ordered (–), (0), (+) or unordered, e.g., red, green, or blue. A multi-label classification allows a document to have multiple labels which do not exclude each other, e.g., in unwanted (toxic) comment classification, the categories can be labeled as "threat" and "insult" at the same time. With hierarchical classification, the classes are arranged in a hierarchy structured as a tree or a directed acyclic graph (Borges, Silla and Nievola 2013).

3.5. Data preprocessing methods

As mentioned, analyzing natural language text is possible thanks to data processing steps. Data may be initially cleaned, integrated, transformed or reduced (Malley, Ramazzotti and Wu 2016: 115-116). Data cleaning involves removing errors and duplicates, noise, outliers, and missing or incomplete data while introducing the least amount of bias (Malley, Ramazzotti and Wu 2016: 115). Data integration means integrating various data sources into one dataset that includes all the data needed for analysis (Malley, Ramazzotti and Wu 2016: 115). Data transformation involves converting or scaling a variety of formats or units into those that are more relevant for analysis (Malley, Ramazzotti and Wu 2016: 116). Finally, data reduction involves removing extraneous records and variables and rearranging the data in a useful and orderly manner for analysis (Malley, Ramazzotti and Wu 2016: 116).

Machine learning algorithms typically require the input to be represented as a fixed-length feature vector. Machine learning algorithms prefer well-defined fixed-length inputs and outputs and cannot work with the text directly; the text needs to be converted into numbers to be fed into a model. Tokenization means breaking up a raw text into words, sentences, whitespace characters, punctuation marks, and other meaningful units called tokens. An ordered sequence of tokens is called a span. Tokenization is often called the "massaging" of text data from words in the corpus that we feed to algorithms. This happens before we create the feature vectors.

3.6. Older count-based vector representations of text

We can represent text with more complex vectors. Text vectorization is used for word splitting and indexing but also represents the process of encoding text as integers to create feature vectors. Feature vectors are n - dimensional vectors representing features and objects. Feature engineering is necessary to deal with unstructured textual data (Sarkar 2019: 201), and the quality of extracted features can impact the predictive performance of the model (Yeskuatov, Chua and Foo 2022). Feature engineering models can be split into deep learning-based and older (Sarkar 2019: 202). In the pre-word embedding period, examples of statistical based text vectorization techniques are n - grams, term frequency-inverse document frequency (TF-IDF), categorical data encoding, Pointwise mutual information (PMI, (Turney and Pantel 2010), and Bag of Words (BoW). Numerical representations of text can be divided into 1) count-based vector space non-semantic models, 2) non-context-based vector space semantic models or 3) context-based vector space semantic models.

Words co-occurrence statistics describe how words occur together, which can capture certain aspects of word meaning (Bullinaria and Levy 2012). Co-occurrences of words are stored in a matrix. A term-document matrix (TDM) "represents the relationship between terms and documents, where each row stands for a term and each column for a document" (Zhao 2013). The goal of TDM is to include every document in the matrix as a row, place all of the unique terms in the corpus in the columns, and calculate each term's occurrence count for each document (Miner et al. 2012).

The already mentioned n - grams are a series of adjacent n items from a specified text or voice sample. The field of n - grams application ranges from protein or DNA sequencing to computational linguistics. From a linguistic perspective, n - grams or lexical bundles were used to analyze administrative discourse (Biel, Koźbiał and Wasilewska 2019), medical discourse (Bączkowska 2018) or scientific text and fiction (Stubbs and Barth 2003: 62). n - gram units can comprise characters, words, base pairs or amino acids. The uni-gram, bi-grams, tri-grams, and four-grams naming convention depends on the number of units. Making predictions on bi-grams and tri-grams is often helpful to avoid data being too sparse.

TF-IDF involves "multiplying the IDF measure (possibly one of several variants) by a TF measure (again possibly one of several variants, not just the raw count)" (Robertson 2004: 503). TF-IDF shows crucial words in a corpus. Rare words become more important than common words in describing documents. C-TF-IDF, a variant of TF-IDF, threats all documents as a single class "c." C-TF-IDF "allows for a major speed-up but also makes use of the TF-IDF Transformer in Scikit-Learn" (Grootendorst 2020). Other encoding methods, among many, include "One-Hot Encoding," "Hash Encoding," and "Label Encoding." Bag of Words (BoW) describes the occurrence of words within a document. BoW puts words in a "bag," so to speak, to remove the noise around them to focus on unique vectors.

In text classification, the "BoW method records the number of occurrences of each bag that is created for each instance type or word disregarding the order of the words or the grammar" (Qader, Ameen and Ahmed 2019: 1). Any information about the order or structure of words in the document is discarded. The input of the code can be multiple sentences, and vectors represent the output. A bag of words thus breaks apart the words and represents them as a vector using individual word count statistics. Bag of words models also suffer from fixed-size input and output.

We can divide models into those that utilize embedding and those that do not have them, such as, for instance, those that utilize One-Hot encoding. There are several problems associated with encoding. Basic word representations, such as integer encoding, assign a unique integer to each word, losing semantic sense and word order. One-hot vectors' matrix is too large, and the representation of words is arbitrary. TDM is problematic the larger the corpus, although it can be reduced with TIF-IDF (Zhao 2013). Unlike sparse one-hot vectors, word embeddings can capture the similarity between words. Unlike a vocabulary, embeddings are short, dense vectors (Jurafsky and Martin 2021: 6).

3.7. Word embeddings

Distributional vectors, or word embeddings, are based on a distributional hypothesis in which terms that occur in a similar sense have a similar meaning (Harris 1968, Linden and Piitulainen 2004). Word embeddings, also named word representations, are a "collective name for a set of language models and feature selection methods. Its main goal is to map textual words or phrases into a low-dimensional continuous space" (Li and Yang 2018: 84). Embeddings allow us to represent relationships and similarity between words (Kozlowski, Taddy and

Evans 2019). Words can be related (syntactically, semantically, or topically) and hold particular emotional meanings.

An embedding is a low-dimensional space into which we can translate high-dimensional vectors (Google 2022). Embeddings make machine learning less taxing on large inputs of data (Google 2022). Embeddings also capture some of the semantics of the input by placing semantically similar inputs close together (Google 2022). Embedding can also be reused across models (Google 2022).

Word embeddings can be of two types: pre-trained or not trained. Embedding models can also be divided into sentence-level models and word-level models. Examples of word-level embedding models are Word2Vec (Mikolov et al. 2013), GloVe (Pennington et al. 2014), ELMo (Peters et al. 2018), FastText (Joulin et al. 2016), Flair (Akbik, Blythe, Vollgraf 2018), and ULMFiT (Howard and Ruder 2018). Examples of sentence-level embedding models are bag-of-words (BoW), Skip-thought vectors (Kiros et al. 2015), Quick-thought vectors (Logeswaran and Lee 2018), paragraph vectors such as Doc2Vec, FastSent (Hill et al. 2016), InferSent (Conneau et al. 2017) and Universal Sentence Encoder (Cer et al. 2018).

Word representations of numerical form can also be divided into 1) models preceding Long Short-Term Memory (LSTM) models such as the Recurrent Neural Network Language Models or RNNLM (see more Bengio et al., 2003; Castro and Prat 2003; Mikolov et al. 2010; 2011), Word2Vec, GloVe and FastText, 2) LSTM models such ELMo, ULMFiT and InferSent and post LSTM Transformer based models such as BERT or Universal Sentence Encoder. In addition, word embeddings can also be distinguished into non-contextual (static) embeddings, such as Word2Vec or GloVe or contextualized embeddings, such as LSTM-based models or BERT.

In contextual word embeddings, each word is influenced by the presence of nearby words. Furthermore, embeddings can be divided into non-parametric unsupervised word embeddings that utilize unsupervised methods, like Word2Vec and GloVe, that are optimized for preserving semantic similarity, and more modern parametric unsupervised sentence embeddings such as Skip-thought vectors (Dhingra et al. 2018: 62). An interesting summary of all the features of different types of word embeddings was provided by Faiza Khan Khattak et al. (2019).

3.7.1. Word2Vec, Doc2Vec, and GloVe

Word2Vec was developed by Tomas Mikolov et al. in 2013 (Mikolov et al. 2013a) at Google. Word2Vec is a predictive model for state-of-the-art (SOTA) results that uses a shallow, two-layered neural network to predict a word from the words around it. Captured word relationships can be morphological, semantic, contextual, or syntactic. Examples of a semantic relationship are male/female designations and country/capital, whereas syntactic relationships are the past versus present tense. Word2Vec ignores whether some context words appear more often than others, and the captured context is small. As a result, semantically similar words in spatial coordinates will be close, while semantically unrelated words are far. In addition, random vectors are used for words that are out of vocabulary words. Word2Vec uses two main models, CBoW and Skip-gram (Mikolov et al. 2013b).

The Doc2Vec method was presented in 2014 by Thomas Mikolov and Quoc Le. Doc2Vec is similar to Word2Vec, but computes a feature vector for every document in the corpus. The concept is the same as in Word2Vec, but Doc2Vec adds another vector Paragraph ID. The paragraph vectors are created by training a neural network to predict the probability distribution of words in a paragraph given a randomly selected word from the paragraph. Doc2Vec can leverage two techniques: 1) a Distributed Memory version of Paragraph Vector (PV-DM) and a Distributed Bag of Words version of Paragraph Vector (PV-DBoW).

Global Vectors for Word Representation (GloVe) were created by Stanford University researchers Jeffrey Pennington, Richard Socher, and Christopher Manning in 2014. GloVe also captures more practical meaning than Word2Vec, which is relatively faster during training. The approach adopted is similar to Word2Vec, but differs by being a count-based model, whereas standard Word2Vec is a predictive model (Gasparetto et al. 2022). Both Word2Vec and GloVe will not capture the representation of out-of-vocabulary words. Skip-though vectors (Kiro et al. 2015) were based on the Skip-gram model. Quick-thought vectors represent an essential development of the Skip-thought vectors (Logeswaran and Lee 2018).

3.9. Character and word-level embeddings

Facebook's FastText (Joulin et al., 2016) uses a combination of lower-level embeddings to extract more information from text data by focusing on characters instead of words. Furthermore, FastText generalizes unknown words if their characters are similar to known words, thus overcoming an important limitation of other described methods. Flair was developed in 2018 by Zalando Research. Flair's embeddings are trained without "any explicit notion of words" that are modeled as sequences of characters and "contextualized by their surrounding text, meaning that the same word will have different embeddings depending on its contextual use" (Akbik 2021).

ELMo and ULMFiT benefit from LSTM and harness the power of language modeling while also using tokens at the word level. Unlike Word2Vec or GloVe, which utilize a static word representation, ELMo and ULMFiT utilize LSTM to process the whole sentence before encoding a word (Deshpande 2020). ELMo was the first language model that focused on deep contextualization (Peters et al. 2018). ELMo is an NLP framework developed by Peters et al. at AllenNLP in 2018 (Peters et al. 2018). Character-level tokens were taken as inputs of a bi-directional LSTM to create word-level embeddings. ELMo's representations are used for calculating a task-specific weighted combination, "concatenated with static context-independent word embeddings" (Aßenmacher and Heumann 2020: 7). ULMFiT was developed in 2018 by Jeremy Howard and Sebastian Ruder. Both ELMo and ULMFiT were created to tackle syntax and semantics and thus the "complex characteristics of word use" and polysemy. ELMo uses a concatenation of LSTMs going in opposite directions (left to right and right to left), whereas ULMFit uses a unidirectional LSTM.

3.10. Bidirectional representations from Transformer

The BERT model (Devlin et al. 2018) modifies the Transformer (compare section 3.12.5) structure by removing the Decoder of the Transformer only to retain the Encoder (Yu, Wang and Jiang 2021: 2). BERT takes multiple Encoders and uses them in a stack. The output from the Encoder is sent as input together with the previous Decoder output to the 1) Multi-Head Attention, 2) then to the normalization layer (Add & Norm), 3) the connected feed-forward network inside the Decoder block, along with 4) linear and softmax layers. The multi-head self-attention ensures that the relationship between words is captured and fed to the neural network that generates the embeddings. Unlike standard Word2Vec and GloVe embedding layers that provide single context representations for each token, BERT takes the complete sentence information as input and produces token-level representations (Li et al. 2019).

3.11. Machine learning models

Single-layer and multi-layer perceptrons, decision trees, random forest, boosting algorithms, Naïve Bayes, support vector machines (SVM), and linear regression can be considered to pertain to the group of machine learning models that were first utilized in NLP. The single-layer perceptron (SLP) was studied in 1930, but the first modern SLP was proposed in the work of Frank Rosenblatt in 1958. The multi-layer perceptron (MLP) was presented in 1986 (Rumelhart, Hinton and Williams 1986). The TextBlob sentiment and document subjectivity analysis tool employs a single-layer perceptron (Ramírez Sánchez et al. 2021).

3.11.1. Ensemble methods

Boosting and bagging are common ensemble methods. Bagging is a machine learning method of "combining multiple predictors" (Kalaichelvi, Christobel, Usha Rani and Arockiam 2011: 148). With bagging, we combine or average homogeneous base learning algorithms that are trained independently (Kalaichelvi, Christobel, Usha Rani, and Arockiam 2011: 148). Bagging "improves classification and regression models in terms of stability and accuracy" (Kalaichelvi, Christobel, Usha Rani and Arockiam 2011: 148). With boosting, each decision criterion in the second input is altered by the decision made in the previous input, which "boosts" the efficiency of the process (Scikit-learn 2012). Boosting algorithms perform better than bagging on noise-free data (Kalaichelvi, Christobel, Usha Rani and Arockiam 2011: 148).

One of the most influential architectures is the Classification and Regression Trees (CART), which can be used for classification and regression problems (see more: Wei-Yin Loh 2014). CART algorithms were first published by Leo Breiman, Jerome Friedman, Richard Olshen, and Charles Stone in 1984. Random forest (RF) used bagging as the ensemble method and was developed by Leo Breiman in 2001. A random forest or random decision forest is an "ensemble of decision trees," and "each tree in the ensemble produces a noisy classification result" (Hilliges 2018: 80). A feature of a random forest is the increased ability to generalize (the model overfits less than a simple decision tree) and can only use a certain subset of attributes (each tree from its subset of attributes). To obtain an accurate classification result, we can "leverage results from multiple, non-biased classifiers together" (Hilliges 2018: 80). For classification tasks, the "output of the random forest is the class selected by most trees" (Elbasha, Elhawil and Drawil 2021).

Gradient boosting is used with fixed-size decision trees, such as CART. Multiple Additive Regression Trees (MART) are another implementation example of gradient tree boosting. There are several gradient boosting algorithms such as Adaptive Boosting or AdaBoost (Shapire and Freund 1997), BrownBoost (Freund 2001), LPBoost, LogitBoost (Friedman, Hastie and Tibishirani 2000), Extreme Gradient Boosting or XgBoost (Chen and Guestrin 2016), Stochastic gradient-boosted decision tree or GBDT (Friedman 2002), LightGBM, Stochastic Gradient Langevin Boosting or SGLB (Ustimenko and Prokhorenkova 2020) and CatBoost (Dorogush, Ershov and Gulin 2017).

AdaBoost is most commonly used with decision trees. XgBoost can perform faster than AdaBoost. Both XgBoost and AdaBoost are resistant to overfitting. XgBoost supports three forms of gradient boosting: 1) gradient boosting, 2) stochastic gradient boosting, and 3) regularized gradient boosting with L1 Lasso and L2 Ridge regularization, which improves model generalization. Other baseline methods for text classification include Naïve Bayes (NB) and Support Vector Machines (SVM, Wang and Manning 2012).

3.11.2. Naïve Bayes and multi-class Naïve Bayes-Support Vector Machine

Bayesian inference has been studied since the work of Thomas Bayes (1763) and was first applied by Frederick Mosteller and David Wallace (1964) (Jurafsky and Martin 2021: 3). Naïve Bayes models are a family of classifiers that make a naive or simplified assumption about how features interact (Jurafsky and Martin 2021: 2–3). The Naïve Bayes classifier assumes (naively) that the features are independent. Naïve Bayes family is composed of Gaussian, Multinomial and Bernoulli distribution. Multinomial Naïve Bayes (MNB) has been found to show good metric results on short text (Wang and Manning 2012).

Naïve Bayes - Support Vector Machine (NB-SVM) was introduced in 2012 as an interpolation between MNB and SVM, which performs well for all documents, i.e., both long and short text (Wang and Manning 2012). Another known combination is represented by BERT+NB or BERT+NB-SVM (Zhang and Yamana 2020). BERT focuses on semantics, and NB-SVM focuses on linguistics. BERT+NB-SVM combination performed well at Human Annotation Challenge at the Iberian Languages Evaluation Forum 2019 (IberLEF; Zhang and Yamana 2020: 1072).

3.11.3. Support Vector Machines

The Support Vector Machine (SVM) graphical representation was created in 1963 (Vapnik and Learner 1963), whereas the algorithm was conceptualized in 1964 (Vapnik and Chervonenkis 1964). In the document classification task, Support Vector Machines (SVMs) show good metric results for long texts, such as full-length movie reviews and are considered to be better than Multinomial Naïve Bayes (MNB) for this task (Wang and Manning 2012).

SVMs accomplish the classification task by constructing, in a higher dimensional space (often but not necessarily), the hyperplane that optimally separates the data into two categories: training points (+) and (–). Next, we add additional parallel planes in such a way that we maximize the distances between them. Then one is based on examples (+) and the other on (–). These examples are the support vectors. SVMs are thus based on the margin maximization principle (Adankon and Cheriet 2009). The "minimal distance between the hyperplane and the training points is called the margin, which is maximized by the SVM algorithm" (Demyanov et al. 2010: 4–5).

The SVM classifier was initially designed to classify data instants into binary classes (Mustaqeem 2018). A technique often adopted in the SVM algorithm is called the "kernel trick," demonstrated in 1992 by Bernhard Boser, Isabelle Guyon and Vladimir Vapnik (Boser, Guyon and Vapnik 1992). Ordinary SVM correctly classifies linearly separable data. However, the data is often not linearly separable, so the "kernel trick" is used to move the problem to a space with increased or infinite dimensionality, where the problem becomes linearly separable.

3.11.4. Logistic Regression

The first form of linear regression was the least squares method, discovered by Carl Friedrich Gauss and Adrien-Marie Legendre in early 1805 (Stigler 1981: 465). In econometrics, the logistic model, sometimes known as the logit model, was first presented by Joseph Berkson in 1944 (Hilbe 2009: 3). John Nelder and Robert Wedderburn developed the Generalized Linear Model (GLiM, or GLM) in 1972 as an advanced statistical modeling tool (Nelder and Wedderburn 1972). Examples of generalized linear regression models (GLM) are the logistic regression model (Nohara, Matsumoto, Soejima and Nakashima 2022), one-way analysis of variance (one-way ANOVA; Fisher 1918), multiple regression (Pearson 1930: 21), multinomial models, and log-linear models (Nelder and Baker 2006: 2–3).

Types of linear regression models include linear, multiple linear, ordinal, polynomial, multinomial, logistic, regularized (least absolute shrinkage and selection operator or lasso with L1 regularization, ridge with L2 regularization, elastic net with L1 and L2 regularization), and principal components (PCLR; with principal component analysis). Logistic regression is used when the dependent variable is discrete for problems with dichotomous outcomes (Swaminathan 2018). The goal of a logistic regression model is to "understand a binary or proportional response (dependent variable) based on one or more predictors" (Hilbe 2009: 15). For more than two classes, multinomial logistic regression is suitable.

3.12. Deep learning models

3.12.1. Convolutional Neural Networks

Convolutions and recurrence were the most commonly used deep neural networks in analyzing textual data until the invention of the self-attention mechanism (Onan 2022, Bahdanau et al. 2014). A Convolutional Neural Network (CNN) introduced in 1998 (LeCun et al. 1998) is mainly used for images (compare Krizhevsky, Sutskever and Hinton 2017) but has been proven effective in sentiment analysis (Aslan, Kiziloluk and Sert 2023) and question classification (Kim 2014).

The CNN comprises a convolution phase, a pooling phase, and a flattening phase. Unlike Recurrent Neural Networks (RNNs) or Long Short-Term Memory Networks (LSTMs), the CNN does not utilize a fully connected dense architecture, but "each convolution layer connects its nodes only to contiguous sets of nodes in the previous layer" (Cylance 2017: 128). We have one input, and from it, we receive one output. The CNN is also static and linear. The CNN is a feed-forward neural network with information passed from left to right. Moreover, the convolution layer takes smaller parameters than the dense layer, as input values share the same parameters as the input values.

3.12.2. Recurrent Neural Networks

Since the invention of the back-propagation algorithm (Rumelhart et al. 1986), Simple Recurrent Networks (SRNs) and the Recurrent Back-Propagation Networks (RBPs) have been developed further. The Simple Recurrent Network (SRN) was invented by Jeff Elman (1990) and paved the way for the recurrent neural (RNN) network architecture (Sutskever, Vinyals, Le 2014; Donahue et al. 2014; Liu, Qiu, Huang 2016; Wu et al. 2016). RNN analyzes each data with the exact copy of the neural network, but it uses the output of the neural network that came before as part of the input of the following neural network (Lin et al. 2019). This process is achieved by combining vectors in a linear function using a hyperbolic tangent or a sigmoid activation function (Lin et al. 2019).

RNNs entail a feedback system that retains information (memory) from the layers of neurons. RNNs rely on autoencoders. The feedback mechanism allows lower-level layers to "know the weights of higher-level features" (Caswell, Shen and Wang 2016: 2). Some information, however, is lost due to the vanishing gradient and activation function, which is why the RNN is considered a short term memory network type, which encounters difficulties when managing "long" memory data (Lin et al. 2019). In other words, the model would perform well with specific size sequences.

3.12.3. Long Short-Term Memory Network

Sepp Hochreiter and Jürgen Schmidhuber in 1997 proposed a Long Short-Term Memory Network (LSTM). LSTM keeps track of both long-term and short-term memory information. The LSTMs' architecture nodes in each hidden layer are replaced with memory blocks that contain one or more memory cells devoid of activation functions (Cylance 2017: 126). Every hidden unit is replaced by LSTM cells connected to a cell state. Memory blocks have three gate types: the forget, the input and the output gate with its weight setting (Cylance 2017: 126). Memory blocks "utilize gates, which determine how and when the states stored in each cell should be updated or passed on to memory blocks in the subsequent hidden layer" (Cylance

2017: 126). The input gate verifies whether the memory cell is updated, the forget gate verifies if the memory cell is reset to zero, and the output gate decides the next hidden state.

Variations of the LSTM model are LSTM cells with "peepholes" (Gers and Schmidhuber 2000) and Working Memory Connections (Landi et al. 2021). Peepholes connect the memory cell and the gates (Nvidia 2018). Working Memory Connections enabled "the memory cell to influence the value of the gates through a set of recurrent weights" (Landi et al. 2021: 4). The main design difference from the base LSTM was that the connection between the memory cell and the gates had a protection mechanism that prevented the cell state from being exposed directly (Landi et al. 2021: 2).

The Gated Recurrent Unit (GRU) is another variant of LSTM introduced in 2014 (Cho et al. 2014). The input and forget gate of LSTM are replaced by an update gate (Nowak, Taspinar and Scherer 2017: 555). With GRU, training is faster as fewer epochs are required to reach the final result (Nowak, Taspinar and Scherer 2017: 561). A popular form used for text classification is the Bidirectional GRU, or BiGRU, a sequence processing model composed of two GRU models representing a bidirectional recurrent neural network with only the input and forget gates (Rana 2016).

There are several other variants of the RNN/LSTM architecture. MultiFiT, introduced in 2020 (Eisenschlos et al. 2020), incorporates quasi-RNNs (QRNNs) to blend convolutions and reset/update gates from the LSTM. Timothy Liu et al. (2017) built "multi-channel combinations of convolutional kernels (aka CNN) and Long Short-Term Memory (LSTM) units to classify short text sequences." Both RNNs and LSTMs can also benefit from the Encoder/Decoder model.

3.12.4. Sequence-to-sequence models

Sequence-to-sequence (Seq2Seq) is a family of machine learning models created with machine translation in mind[6]. Seq2Seq can be divided into: 1) older, e.g., Seq2Seq that utilizes RNN, LSTM or GRU and 2) newer models, e.g., attention-based models, GPT Models, Transformers, and BERT. An Encoder/Decoder model for RNNs was introduced by Kyunghyun Cho et al. (2014). An Encoder/Decoder model

6 Since 2016, for instance, Encoder/Decoder is the main technology inside Google's translate service.

for LSTM was introduced by Ilya Sutskever (2014) et al. The autoencoder consists of an Encoder and a Decoder. The Encoder processes inputs, and the Decoder generates outputs. The original input is compressed into a compressed representation and then reconstructed.

3.12.5. The Transformer and the self-attention mechanism

Based on the Encoder/Decoder work, the attention mechanism was introduced by Dzmitry Bahdanau et al. in 2014. Previously, hidden units in the Encoder/Decoder RNN model or cells in the Encoder/Decoder LSTM were linked with a single connection, which created a bottleneck regarding information processing. Attention allows us to consider all the encoder hidden states and not just the bottleneck point, thus circumventing the bottleneck problem. The Transformer and its self-attention mechanism were introduced in 2017 (Vasvani et al. 2017). The main elements of the Transformer are self-attention, multi-head attention, and positional encoding. Transformers allow applying different "heads" during the training phase for different tasks such as masked language models (MLM), question and answer systems (QA) or classification.

The Transformer Encoder and Decoder blocks do not use RNNs/LSTM but the self-attention mechanism to encode sequences. Furthermore, the multi-head attention heads lead to "consistent performance improvements over conventional attention" (Liu, Liu and Han 2021). BERT, short for Bidirectional Encoder Representation from Transformers, was introduced in 2018 (Devlin et al. 2018). BERT was trained on Wikipedia and Book Corpus, which is a dataset of 10.000 books of different genres. The name BERT requires an explanation. It is a language "representation" model aiming to understand textual data by encoding it mathematically. "Bidirectional" refers to the ability of the model to use the information in the textual data from both left and right to capture its meaning. BERT takes parts from the Transformer concepts by keeping its encoder, while the original Transformer is composed of an Encoder and Decoder. BERT can be divided into base and large. BERT base has an encoder block that is constituted by a stacked Transformer unit of 12 layers or Transformer blocks, 12 attention heads, 768 embedding dimensions, and 110 million parameters. BERT Large employs 24 layers, 16 attention heads, 1024 embedding dimensions, and 340 million parameters.

3.12.6. The Transformer variants

All the transformer variants are hosted on Hugginface.co (Hugginface 2020). Typical variants of BERT are A Lite BERT or ALBERT (Lan et al. 2019), RoBERTa (Liu et al. 2019), ELECTRA (Clark et al. 2019), SpanBERT (Joshi et al. 2019), DistilBERT (Sanh et al. 2019), TinyBERT (Jiao et al. 2019), MobileBERT (Sun et al.) among many. These models either made the model more performant or modified the existing architecture. For example, ALBERT applies "parameter-reduction techniques in order to train faster models with lower memory demands" (Aßenmacher and Heumann 2020: 8).

Similarly, DistilBERT reduces the size of the BERT base by 40% and "enhances the speed by 60% while retaining 97% of its capabilities" (Sahn et al. 2021). Another distillation method was proposed with the work on TinyBERT, which resulted in a 7.5 times smaller and 9.4 times faster inference model than the BERT base model (Jiao et al. 2019). MobileBERT is 4.3 times smaller and 4.0 times faster than the BERT base, but it also achieves higher accuracy than the BERT base model (Sun et al. 2019). RoBERTa is an architectural replica of BERT with fine-tuned hyperparameters and a larger corpus used for pre-training (Aßenmacher and Heumann 2020: 8).

The masking strategy for pre-training is also changed from "static" (masking once during preprocessing) to "dynamic" (Aßenmacher and Heumann 2020: 8). As an alternative to the BERT mechanism of masking, ELECTRA uses a pre-training task (token detection) in which the model learns to distinguish input tokens from plausible alternatives (Clark et al. 2019: 1). Instead of masking, ELECTRA "corrupts the input by replacing some tokens with samples from a proposal distribution, which is typically the output of a small masked language model" (Clark et al. 2019: 1). SpanBERT extends BERT by (1) "masking contiguous random spans, rather than random tokens, and (2) training the span boundary representations to predict the entire content of the masked span, without relying on the individual token representations within" (Joshi et al. 2019).

3.12.7. XLNet and Generative Pre-trained Transformer (GPT)

XLNet (Yang et al. 2019) was introduced in 2019 by a team of researchers from Google Brain and Carnegie Mellon University. XLNet is able to outperform

Google's BERT in twenty tasks and addresses some of the issues of BERT, such as fine-tuning discrepancy (Yang et al. 2019, Arslan et al. 2021). XLNet solved mask token corruption of BERT, which masks a portion of each document input. BERT corrupts the input by replacing some tokens with [MASK] and then trains a model to reconstruct the original tokens (Clark et al. 2019: 1).

XLNet is based on Transformer-XL but implements an autoregressive method in which future values are based on past observations (Dai et al. 2019). The permutation operation allows to capture bidirectional context (Yang et al. 2019: 2). Moreover, while transformers are limited by a fixed-length context in language modeling, the Transformer-XL can learn dependency beyond a fixed length without disrupting temporal coherence (Dai et al. 2019). Transformer-XL uses relative positional encoding for longer text sequences (Dai et al. 2019).

Another example of complex autoregressive attention-based models is Generative Pre-trained Transformer (GPT) or OpenAI GPT, a project by Elon Musk. GPT performs well on many NLP tasks, including some Few-Shot learning tasks[7], as it is trained on a large amount of text data and leverages many parameters (compare Brown et al. 2020).

3.13. Fine-tuning datasets and models

3.13.1. Dealing with imbalanced class distribution problem

The class imbalance problem typically occurs when there are "many more instances of some classes than others" (Zhao and Cen 2014: 171). In that case, some classifiers are "overwhelmed by the large classes and ignore the small ones" (Zhao and Cen 2014: 171). In the scenario of imbalanced class distribution, one class can have a significantly lower number of sentences than others. Many tools are available to deal with the imbalanced class distribution problem. For example, random under-sampling randomly eliminates majority class samples, whereas random over-sampling increases the size of the minority class through its random replication (Batista, Prati and Monard 2004: 23). Both methods result in a more balanced dataset.

Artificially increasing the size of data can be obtained with data augmentation (Hedderich et al. 2021: 2547). Data augmentation means that "new instances can be

[7] Few-Shot learning is a tasks where few examples are present in the training set. Zero-Shot learning means classifying documents without training examples, whereas One-Shot learning is a classification task where one example is given for each class.

obtained based on existing ones by modifying the features with transformations that do not change the label" (Hedderich et al. 2021: 2547). Depending on the situation, noise to the training set can be removed or added, for instance, by generating synthetic samples. Data becomes harder to fit with noise, which may help the model overcome the overfitting problem. On the other hand, training directly on noisy data can hurt the model's performance (Hedderich et al. 2021: 2550). Synthetic oversampling techniques (SMOTE; Chawla et al. 2002) create synthetic minority samples to balance the data set.

A useful method in predictive classification is also represented by threshold-moving. Another technique to apply when the data is imbalanced is to give more weight to one class than another. Translating or paraphrasing text with machine learning to populate imbalanced classes and thus add noise could also achieve positive results. Trade-offs can be made between "collecting more data, expanding more data, and altering the network architecture and training procedure" (Swingler 1996: 105).

3.13.2. Hyper-parameter tuning and the role of exploratory data analysis

Definitions of exploratory data analysis were provided in section 2.9. An essential goal of hyper-parameter tuning is to find the best setting that allows the model to achieve the desired performance and metrics. In order to do that, we need to 1) learn about our text through exploratory data analysis (EDA) and 2) try various activation functions and parameters. Binary and multi-class classification also support different models and hyper-parameters. The sigmoid activation function can be used for binary classification problems; the softmax activation function can be used for multi-class problems, whereas the Rectified Linear Units (ReLU) can be used with multi-label classification.

The advantage of ReLU also lies in its performance that comes from sparsity (Xu et al. 2015). ReLU units can thus lose connection during training when a gradient passes through the neuron, which can cause the weights to update so that the unit never activates. Sometimes the number is negligible, but it can also amount to a large portion of the neural network presenting this issue. To tackle this problem, several functions, such as the Leaky Rectified Linear Unit (LeakyRelu; Maas, Hannun and Ng 2013) and its variants, were invented (Xu et al. 2015). The Parametric Rectified Linear Unit (PReLU) (He et al. 2015), the Randomized Leaky Rectified Linear Units

(RReLU) (Xu et al. 2015), the Scaled Exponential Linear Units (SELU) (Klambauer et al. 2017), ReLU-6 (Howard et al. 2017), the Clipped Rectified Linear Unit (Clip Relu) (Hannun et al. 2014: 2), the Concatenated Rectified Linear Units (CReLU) (Shang et al. 2016) or Maxout (Goodfellow et al. 2013), among many, solve the dying ReLU problem.

Before switching between different activation functions, it is advisable to adjust the learning rates to verify if there is an improvement. A higher learning rate will accelerate the model's training, but wrong learning rate values can cause the model's training to converge erratically (Smith 2017). A higher learning rate can harm the model's accuracy. The learning rate (LR) range test allows finding a learning rate to approximate the loss's sharp decline (Smith 2017). Model appropriate measures how well a machine learning model generalizes to unknown data as compared to the data on which it was trained. EDA summarizes the main characteristics of the data set. It typically uses visual methods like word clouds, different bar plots, or scatter plots. As mentioned, EDA can thus be used for hyper-parameter tuning in the NLP model.

The batch size parameter also impacts the model's performance during training (Radiuk 2017: 24) but consumes more resources. Wrong batch size input for a specific text will also harm the model's accuracy (Google 2020). Batch sizes also require small learning rates (Kandel and Castelli 2020). Increasing batch sizes can lead to poor results as the model may take the average of all the local minimal points, whereas decreasing batch sizes can lead to convergence at local optimal minima (Rastogi 2020). The batch size could be set according to the document's sequence length, see Table 2. The sequence_length is the number of tokens in each line of the batch (Huggingface 2020).

If the document is too long, we perform additional operations, as almost all Transformer models have the maximum length of the sequence to be generated capped at 512 tokens. Four options exist: 1) truncating the longer documents so only the first 512 tokens are fed to the neural network, 2) splitting the document into smaller pieces, and 3) feeding the tokens to a different neural network, e.g., concatenating various BERT models altogether. For summarization where text exceeds 512 tokens CogLTX (Ding et al. 2020), Blockwise BERT or BlockBERT (Qiu et al. 2019), Longformer (Beltagy, Peters and Cohan 2020), Reformer (Kitaev, Kaiser and Levskaya 2020), Linformer (Wang et al. 2020), Big Bird (Zaheer et al. 2020), or Transformer-XL (Dai et al. 2019) are preferable.

Table 2. Benchmark of the maximum batch size according to sequence length for BERT and XLNet (Google-research 2020; Gitlab 2022)

System	Seq Length	Max Batch Size	System	Seq Length	Max Batch Size
BERT-Base	64	64	XLNet-Base	64	120
...	128	32	...	128	56
...	256	16	...	256	24
...	320	14	...	512	8
...	384	12	XLNet-Large	64	16
...	512	6	...	128	8
BERT-Large	64	12	...	256	2
...	128	6	...	512	1
...	256	2	...	...	...
...	320	1	...	...	...
...	384	0	...	...	...
...	512	0	...	...	...

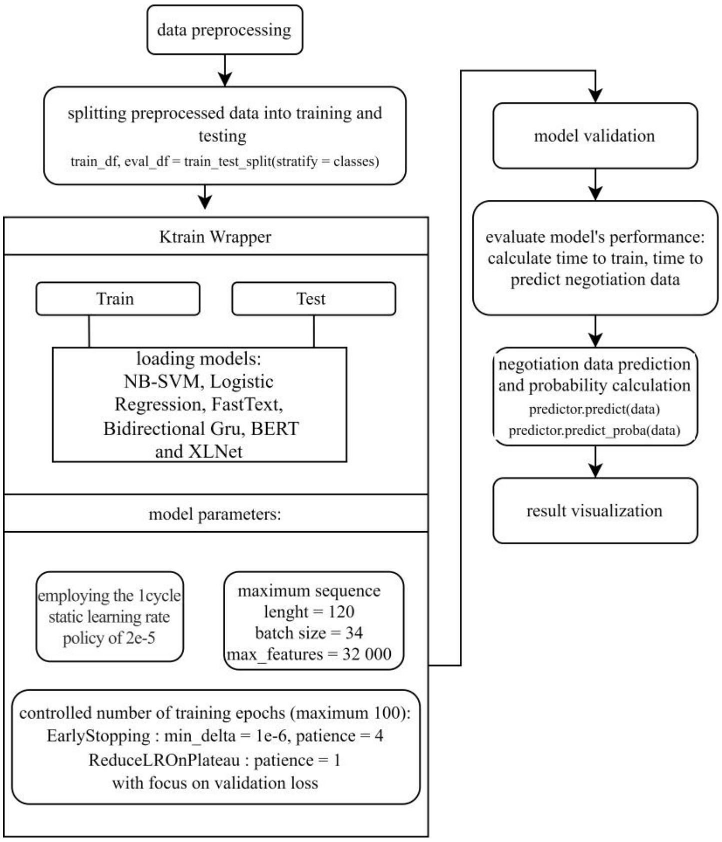
4. Proposed methodology

4.1. Methodology and chosen tools

4.1.1. Adopted methodology for all datasets

Before feature vectors are created, the data is usually split into two parts: training (80%) and validation (20%) or into three parts training (60%), testing (20%) and validation (20%). This is achieved by using the Sklearn library. I split the data into two parts for neural network training and testing using the train-test-split method from the Sklearn library. There can be two divisions: completely random or random, that preserves the distribution of classes. The information about the dataset split into training and testing is provided in the result section 5.1 onwards and depends on the model utilized and the task. The goal and focus of this work are predictions on negotiation data, to see what task might complement linguistic analysis. Experiments were performed 40 times on the negotiation data to find the optimal threshold values. The training step was also repeated 30 times to find the optimal hyperparameters such as training policy, ReduceRopOnPlateau or EarlyStopping. The goal was to train for more epochs with validation loss monitoring with the focus on XLNet. The training step was repeated 30 times to find the optimal dataset, feature size (or vocabulary size), and sentence length. The goal was to perform training, evaluation, and prediction on negotiation data without incurring in Out of Memory Error with the XLNet model. The whole procedure is shown in Figure 3.

Figure 3. Proposed methodology using the ktrain library and popular models for text data



The tested graphics processing unit (GPU) was the Nvidia TESLA T4 with 16 Gigabytes of Video Random Access Memory. Once the respective values were established, the experiments were performed twice on the negotiation data, except for four tasks which were performed once[8]. To maintain a good balance between validation loss improvement and training time, I set min_delta=1e-6, patience=4 for EarlyStopping and patience = 1 for ReduceLROnPlateau, with validation loss monitoring. EarlyStopping prevents the model from training if there is no further improvement of the validation loss, while ReduceLROnPlateau reduces learning rates when validation loss stalls. 100 epochs were specified for each model. Maximum

[8] Repeating the same experiment on all the tasks would be difficult. At the time of writing, the Nvidia TESLA T4 has 15 Gigabytes of Video Random Access Memory. Before Google reduced the VRAM size, some experiments were repeated. The experiment was repeated on emotion detection, due to the model mistake in class labeling ("sad" predicted as "joy"), and on sentiment analysis and religious sentence detection due to a saving bug within Colab (Colab did not save the notebook cells). The experiment was repeated on toxic question classification and toxic comment classification too as well. In toxic question classification I reduced the number of training samples (after negotiation data predictions, I saw that the model did not improve much with more training samples), whereas in the toxic comment classification I adopted an unbalanced split (much more sentences are allocated to the neutral class) which gave me good results on negotiation data where the XLNet model recognized toxic sentences in text well (compare section 4.1.6, Table 6). The experiment was also repeated on suicidal ideation detection.

sequence length was set to 120, batch size to 34, and max_features to 32 000. The learning rate was set to 0.00002, which is commonly adopted in BERT (Wang et al. 2023; Panov 2022, He et al. 2021: 2211).

The second goal is to train, deploy and run predictions preferably within six hour time per task, as GPU utilization in Google Collaboratory (Colab) is limited[9], while also utilizing recent NLP models. As mentioned, the number of samples, the feature and the vocabulary sizes were reduced for the XLNet model to prevent out-of-memory errors (OOMs). At 1000 samples for the test size, the XLNet model utilizes 17 Gigabytes (GB) of Video Random Access Memory (VRAM). Sometimes the OOM would happen at 900 sentences for testing. 800 samples for the XLNet model saturate 13.9 GB of VRAM. VRAM saturation also depends on a particular text. The dataset size varies depending on the situation for the rest of the models and tasks. If the size of the dataset was lowered, I would observe relevant changes in the metrics and negotiation prediction output; if not, I would keep lowering the train and test sample size for better performance.

4.1.2. Dataset cleaning process

For the dataset cleaning process, the following cleaning steps can be adopted:
1) removing languages other than the target language with the use of Langdetect,
2) removing duplicates by adopting the md5 hash encoding/decoding,
3) text normalization and cleaning, such as removing Personally Identifiable Information (PPI) and unwanted non-alphabetic signs, e.g., punctuation, hyperlinks, addresses, website links, emails, Twitter handles in replies, emojis, emoticons, numbers, pictographs, transport and map symbols, iOS flags, dingbats, and "
" lines breaks, and non-ASCII characters (a lot of Unicode characters are of Chines origin),
4) performing lemmatization with the use of the "WordNet Lemmatizer,"
5) expanding abbreviations and any contracted verbs with the use of the "Contractions" package (Contractions 2022),

[9] There is no specific data on how Colab handles GPU limits, but prolonged usage reduces the possibility to connect to a GPU runtime and more issues arise. It should be feasible to train a model for six hours a day without interruptions with the Colab Pro plan.

6) removing stop-words, e.g., with the "NLTK package," and adding custom recurring words such as "all," "due," "to," "on," "daily," "okay," "get," "go," "yeah," "suppose," "yes," and "I,"
7) verb conjugation conversion, which automatically converts all the verbs to present simple using NodeBox English Linguistics (or NodeBox),
8) removing redundant double characters are converted to one character,
9) lowercasing and removing more advanced spelling mistakes with the use of Textblob's automated text correction tool,
10) removing unnecessary whitespaces, NA (not available) or Not a Number (NaN) values,
11) converting and encoding data into word embeddings, and
12) keeping sentences between 10 to 120 tokens.

Operations such as lower-casing text or correcting spelling mistakes are called text normalization. Cleaning can significantly reduce a dataset's size and thus the memory footprint without losing too many important features, see Table 3. Spelling mistake correction takes the longest to complete; seven hours and ten minutes, compare Table 4.

Table 3. IMDb's dataset before and after cleaning, example on 9000 utterances

Text statistics before cleaning		**Text statistics after cleaning**
Number of total words:	2 102 507	1 132 170
Average number of words per sentence spoken:	233	125
Number of unique words:	67	43
Average repetition of words:	233	25

Table 4. Time to process 9000 utterances from the IMDb on 2 core (4 threads) Intel Xeon 2.20GHz CPU in Colab

Tool	**Method**	Time to process 9000 sentences (in seconds)
Langdetect	automatically remove non-English sentences	50.789
Python and Hashlib	remove duplicates with md5 encoding	0.058
Contractions	expand contractions	5.686
NLTK	remove stopwords	3.692
WordNetLemmatizer	lemmatize text	3.687
TextBlob	automatically correct spelling mistakes	25 820.852
NodeBox	reduce all verbs to present simple	337.567
Python and Regex	all other cleaning operations in one function	78.680

Question marks were not removed. Such aggressive cleaning was only performed on noisy data found in toxic comment classification, the hate speech and offensive language detection, and suicidal ideation detection. Lemmatization was only performed for EDA. The rest of the datasets require a simple Not a Number (NaN; removal is important for BERT preprocessing step in ktrain) values removal and discarding too long or too short sentences. Too short sentences such as "alright" or "ok" bring little to the classification and may confuse the model. In my tests, more recent models, such as XLNet and BERT, appear to be more accurate in predicting negotiation sentences when we do not apply lemmatization or stemming.

4.1.3. The choice of models, parameters and word vectors

To maintain a good balance between older and newer models, I adopted the ktrain implementation of NB-SVM (Wang and Manning 2012), Logistic Regression, FastText (Joulin et al. 2016), BiGRU (Rana 2016), BERT (Devlin et al. 2018). The XLNet (Yang et al. 2019) model was loaded separately from the hugginface package (Hugginface.co 2020) and then merged within ktrain for training[10], see Table 5. As mentioned, ktrain allows rapid model deployment (see more: Maiya 2022, 2023a, 2023b), which is a helpful feature considering the number of tasks and models, and includes the possibility to explore misclassified sentences more in-depth, which in turn helps build a better dataset for classification (compare section 2.8).

I adopted the cased version of BERT and XLNet. In addition, I employed a 1cycle policy (Smith 2018) with ktrain (Maiya 2022). The 1cycle policy is "a slight modification of cyclical learning rate policy for super-convergence; always use one cycle that is smaller than the total number of iterations/epochs and allow the learning rate to decrease several orders of magnitude less than the initial learning rate for the remaining iterations" (Smith 2018: 7). The 1cycle policy initiates from a base rate to a maximum rate for the first half of model training. It decays the learning rate for the rest of the training cycle.

A document term matrix was used for Logistic Regression and Naïve Bayes - Support Vector Machines (NB-SVM) model, whereas for FastText and Bidirectional

[10] The tokenization step was also performed separately from ktrain.

Gated Recurrent Unit (BiGRU) I used pre-trained word vectors[11]. After training, validation metrics are calculated on the test part of the dataset, such as accuracy, precision, recall, F1-score, macro average and weighted average. Finally, the trained model assigned a class to each test sentence of the negotiation dialogue in the form of categorical variables with values consisting of integers.

Table 5. Proposed models for text data and their parameter number (based on model.summary() method in Keras)

Model name:	The total number of trainable parameters:
NB-SVM (Wang and Manning 2012)	32 000
Logistic Regression	64 000
FastText (Joulin et al. 2016)	2 052 418
BiGRU (Rana 2016)	9 784 002
BERT (Devlin et al. 2018)	109 167 362
XLNet (Yang et al. 2019)	117 310 466

4.1.4. Quality measures

True positive (TP) represents the number of correctly classified items by the model as positive, e.g., depending on the classification task, a class representing sentiment, a particular emotion, a particular communication trope, a neutral class, rude (toxic) comments, or suicidal thoughts. True negative (TN) represents the number of correctly classified items by the model as non-positive, e.g., depending on the classification task, a class not representing sentiment, a particular emotion, a particular communication trope, a neutral class, rude (toxic) comments, or suicidal thoughts. Finally, false positive (FP) represents the number of misclassified non-positive items. False negative (FN) represents the number of items that were misclassified as non-positive.

Accuracy (A) is defined as "the number of correct predictions over the total number of samples" (Gasparetto et al. 2022)

$$A = \frac{TP + TN}{TP + FP + TN + FN} \quad . \tag{1}$$

[11] I used pre-trained word vectors trained on Common Crawl and Wikipedia available on the following website: https://dl.fbaipublicfiles.com/fasttext/vectors-crawl/cc.en.300.vec.gz.

Precision (P) is the fraction of predictions that have been predicted as positive ($TP+FP$; Gasparetto et al. 2022)

$$P = \frac{TP}{TP + FP} \ . \tag{2}$$

Recall (R) is the fraction of correct predictions that should have been predicted positive ($TP+FN$; Gasparetto et al. 2022)

$$R = \frac{TP}{TP + FN} \ . \tag{3}$$

F1-score (F_1) is the harmonic mean of precision (P) and recall (R; Gasparetto et al. 2022)

$$F_1 = 2 \cdot \frac{P \cdot R}{P + R} \ . \tag{4}$$

Macro-averaged precision (P_m) is defined as a simple arithmetic mean over all class-wise precision scores for single classes i, where n is the number of classes (Takahashi et al. 2021; Sokolova and Lapalme 2009)

$$P_m = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \frac{\mathrm{TP}_i}{\mathrm{TP}_i + \mathrm{FP}_i} \ . \tag{5}$$

Macro-averaged recall (R_m) is defined as a simple arithmetic mean over all class-wise recall scores for single classes i, where n is the number of classes (Takahashi et al. 2021; Sokolova and Lapalme 2009)

$$R_m = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \frac{\mathrm{TP}_i}{\mathrm{TP}_i + \mathrm{FN}_i} \ . \tag{6}$$

Macro average F1-score (F_{1m}) is the harmonic mean of macro average precision (P_m) and macro average recall (R_m; Takahashi et al. 2021; Sokolova and Lapalme 2009)

$$F_{1m} = 2 \cdot \frac{P_m \cdot R_m}{P_m + R_m}.$$

(7)

Weighted average "calculates metrics for each label and finds their average weighted by support" (the number of true instances for each label; Pedregosa et al. 2011, scikit-learn 2023). The weighted average precision (P_ω) is defined as

$$P_\omega = \frac{\sum_{i=1}^{n} \omega_i \frac{TP_i}{TP_i + FP_i}}{\sum_{i=1}^{n} \omega_i},$$

(8)

weighted average recall (R_ω) is defined as

$$R_\omega = \frac{\sum_{i=1}^{n} \omega_i \frac{TP_i}{TP_i + FN_i}}{\sum_{i=1}^{n} \omega_i},$$

(9)

weighted average F1-score ($F_{1\omega}$) is defined as

$$F_{1\omega} = \frac{\sum_{i=1}^{n} \omega_i \cdot F_{1\omega}}{\sum_{i=1}^{n} \omega_i},$$

(10)

where n is the number of classes, and ω_i is the weight of class i. The weight of class i is $\omega_i = \frac{N_i}{N}$ where N_i is the number of observations of class i and N is the total number of observations (Oancea 2023: 13).

4.1.5. Threshold moving

By calling "predict_proba," we infer class probabilities with estimators. The "predict_proba() method returns an array containing a row per instance and a column per class, each containing the probability that the given instance belongs to the given class" (Géron 2019), e.g., if the text sentence was predicted as "sadness" emotion class there is more than 50% chance that the text sentence represents a "sadness" emotion class. This step is essential to apply threshold moving. To discard less relevant predictions, a threshold was set to 0.9. As mentioned, experiments were performed 40 times on the negotiation data to find the optimal threshold.

A threshold of 0.55 slightly changes from the default 0.50 of algorithms capable of predicting a probability or scoring, which allows short texts to be predicted correctly, even with a slight class imbalance. Values of 0.85 and 0.95 were also tested. A threshold of 0.9 appears to capture the most relevant information in the negotiation data without losing too many sentences. A threshold closer to 1.0 is likely to represent a given class better. Thus the higher the threshold, the more probable of being "true" a given class is according to the model. By calculating class probabilities, we can calculate the neutral class artificially, e.g., if there are only positive and negative classes, the classes that do not pass a given threshold can be considered neutral. Another method to obtain the neutral class is to train a model with a dataset having separate sets of labels, e.g., "positive," "negative," and "neutral."

4.1.6. Result visualization

The output of the automated classification is a Microsoft Excel file, in which each column next to the uttered sentence represents class predictions, prediction probability, and predictions with the applied threshold, compare Table 6. Table 6 shows toxic comment classification results after the model predicted the negotiation data (compare section 5.3), i.e., it tagged the sentences with a predefined mutually exclusive set of classes ("toxic" vs. "non-toxic"). In the task shown by Table 6, the toxic tags represent rude or offensive language tagged as "toxic" (polite language without such features is tagged as "non-toxic"). Table 6 toxic comment classification results are sorted in descending order by column "prediction probability," so the most probable classes are shown first. Here, there are no neutral classes with a high enough threshold. The sentences in column "Threshold 0.9" passed the threshold set to 0.9 (are 90% likely to represent a toxic class) and are classified as "toxic". The "toxic" tags are displayed in Table 6 as passed (toxic) to denote that they passed the threshold.

The following sub-chapter 5.2. figures show the results of Grant Sattaur's negotiation data with the XLNet model. Bar charts show the sum of each class occurrence, e.g., in the case of binary classification, how many times class A was predicted or how many class B was predicted after the model classified the sentences (compare column predictions in Table 6); first without applying the threshold, and then with a threshold set to 0.9 (compare the column threshold 0.9 in Table 6).

Table 6. Toxic comment classification results with the XLNet model (compare section 5.3) sorted by prediction probability in descending order (there are no neutral classes that passed threshold 0.9)

Speaker	Uttered sentence	Predefined classes	Prediction probability	Class that passed the threshold 0.9
Negotiator	Choose yourself the coward way out.	toxic	0.99570435	passed (toxic)
Negotiator	you are just going to be a coward and kill	toxic	0.99512476	passed (toxic)
Negotiator	You may want to kick his arse sometimes but you know what he is your	toxic	0.99486285	passed (toxic)
Negotiator	Okay are you going to be a coward.	toxic	0.993334	passed (toxic)
Negotiator	Are you going to be a coward (…)	toxic	0.99290013	passed (toxic)
Negotiator	No so you are just going to be a coward and hide (…)	toxic	0.99268556	passed (toxic)
Negotiator	You shut up and listen to me Grant.	toxic	0.992101	passed (toxic)
Negotiator	We are not going to put our cops in danger because you are damn stubborn.	toxic	0.9895503	passed (toxic)
Negotiator	Grant shut up and listen to me.	toxic	0.9894168	passed (toxic)
Negotiator	You do not sound like a coward.	toxic	0.9891111	passed (toxic)
Negotiator	So you are a coward?	toxic	0.9825783	passed (toxic)
Negotiator	Okay. You kill yourself.	toxic	0.9817918	passed (toxic)
Negotiator	Will you do that keep your mouth shut.	toxic	0.9806802	passed (toxic)
Negotiator	So that is worth killing yourself over.	toxic	0.97846484	passed (toxic)
Negotiator	Is that right that they can not be in their own house because you are being stubborn and being a coward instead of being enough of a	toxic	0.97105193	passed (toxic)
Negotiator	Grant will you shut up for a second and listen to what I am saying.	toxic	0.96604866	passed (toxic)
Negotiator	You are going to be 21 you could drink some	toxic	0.96128595	passed (toxic)
Dispatcher	I want you to take the gun away from your chest and put it down.	toxic	0.96110255	passed (toxic)
Negotiator	So you think by killing yourself --	toxic	0.9569711	passed (toxic)
Negotiator	(...) you are not going to kill yourself and your parents house not to ruin that house for	toxic	0.9527071	passed (toxic)
Negotiator	Listen to me. You man up and come outside.	toxic	0.9525944	passed (toxic)
Negotiator	Just shut up and listen to me Grant.	toxic	0.95252776	passed (toxic)
Negotiator	Grant shut up and listen to me Grant Grant Grant Grant	toxic	0.94957495	passed (toxic)
Negotiator	Put the gun down and come outside.	toxic	0.9482899	passed (toxic)
Grant	xxxxxxxx	toxic	0.94697374	passed (toxic)
Grant	Somebody is going to kill themselves if they are going to have guns pointed at me.	toxic	0.9333789	passed (toxic)
Negotiator	You hurt yourself you do not want or kill yourself — you do not want your parents to think of Christmas every time you go.	toxic	0.932724	passed (toxic)
Negotiator	You may end up in hell.	toxic	0.93270063	passed (toxic)
Negotiator	I am a Pirate.	toxic	0.9277414	passed (toxic)

5. Results

5.1. Sentiment analysis classification task results on the Grant Sattaur negotiation

Sentiment analysis (SA) assesses whether there is a negative, positive, or neutral attitude toward an item or a person in the analyzed text (Nandwani and Verma 2021). Polarized texts carry positive or negative emotions. Therefore, sentiment analysis is often adopted in commercial applications (Church and Rau 1995) because it helps 1) companies who monitor user satisfaction and 2) consumers who need to make buying decisions by measuring the online reputation of a company (Colleoni et al. 2011: 1), product or service. For binary classification of sentiment, I utilized the "Internet Movie Database" dataset (IMDb; Maas et al. 2011: 149) that contains movie reviews with the emotion classes "positive" (25 000 tagged as "0") and "negative" (25 000 tagged as "1").

The dataset is large, well-organized, and balanced, contains highly polarized opinions, and is relatively noise-free. The IMDb dataset is based on user reviews of movies on the Internet Movie Database website, allowing up to 30 reviews per movie (Maas et al. 2011: 149). A positive review has a score greater than or equal to 7 out of 10, and a negative review has a score less than or equal to 4 out of 10; thus, only highly polarized reviews are considered (IMDb; Maas et al. 2011: 149). A comparison with other authors' results is shown in Table 7. Table 8 shows the time to predict 1429 sentences from Grant Sattaur's negotiation and time to train the models. Table 9 shows the model's quality measures after model training.

Table 7. Comparison of accuracy metrics between my results and other author's results on the "IMDb" dataset

method	Accuracy	source
XLNet	0.96	Yang et al. 2019
BERT	0.92	Sanh et al. 2019: 3
DistilBERT	0.92	Sanh et al. 2019: 3
my method	-	-
XLNet	0.90	-
BERT	0.87	-
BiGRU	0.85	-
NB-SVM	0.87	-
Logistic Regression	0.86	-
FastText	0.75	-

Table 8. Time calculations for six machine learning models

Model:	Time:	Model:	Time:
XLNet	Time to predict 1429 sentences:	**NB-SVM**	Time to predict 1429 sentences:
-	38 min 15 sec	-	3 sec
-	Time to train:	-	Time to train:
-	34 min 11 sec	-	25 min 7 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	24 sec	-	240 ms
-	Time to train:	-	Time to train:
-	30 min 17 sec	-	24 min 28 sec
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	8 sec	-	264 ms
-	Time to train:	-	Time to train:
-	13 min 37 sec	-	11 min 3 sec

Table 9. Precision, recall, F1-score, macro average, and weighted average results of sentiment analysis validation on the IMDb dataset and six machine learning models

Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.92	0.88	0.90	-	450
1	0.89	0.92	0.90	-	450
accuracy	-	-	-	0.90	900
macro avg	0.90	0.90	0.90	-	900
weighted avg	0.90	0.90	0.90	-	900
BERT	precision	recall	F1-score	accuracy	support
0	0.86	0.89	0.87	-	450
1	0.89	0.85	0.87	-	450
accuracy	-	-	-	0.87	900
macro avg	0.87	0.87	0.87	-	900
weighted avg	0.87	0.87	0.87	-	900
BiGRU	precision	recall	F1-score	accuracy	support
0	0.82	0.90	0.86	-	450
1	0.89	0.80	0.84	-	450
accuracy	-	-	-	0.85	900
macro avg	0.85	0.85	0.85	-	900
weighted avg	0.85	0.85	0.85	-	900
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.86	0.89	0.87	-	450
1	0.89	0.85	0.87	-	450
accuracy	-	-	-	0.87	900
macro avg	0.87	0.87	0.87	-	900
weighted avg	0.87	0.87	0.87	-	900
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.84	0.90	0.87	-	450
1	0.89	0.83	0.86	-	450
accuracy	-	-	-	0.86	900
macro avg	0.86	0.86	0.86	-	900
weighted avg	0.86	0.86	0.86	-	900
FastText	precision	recall	F1-score	accuracy	support
0	0.82	0.65	0.72	-	450
1	0.71	0.85	0.77	-	450
accuracy	-	-	-	0.75	900
macro avg	0.76	0.75	0.75	-	900
weighted avg	0.76	0.75	0.75	-	900

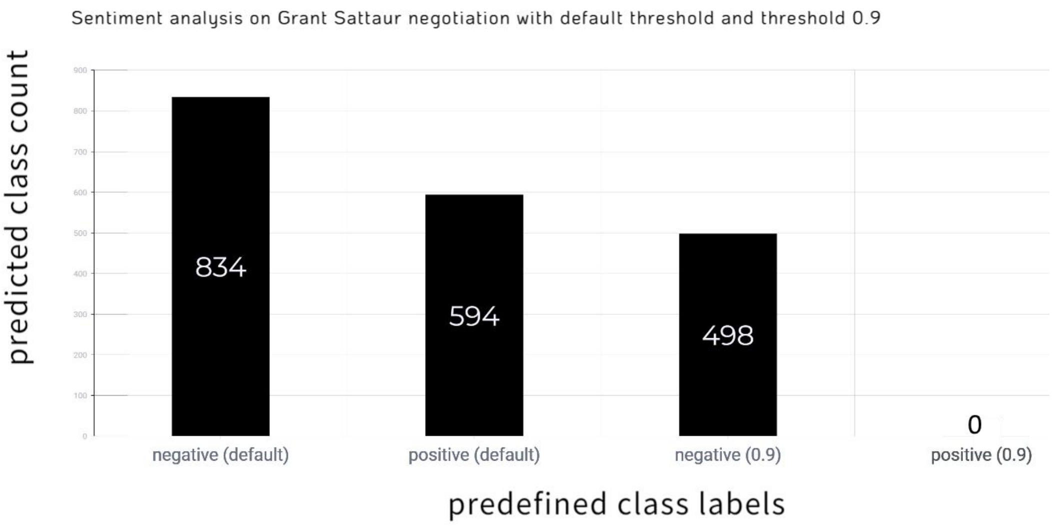
In the utilized dataset, data sampling is random, but the class distribution is equal (a 1:1 ratio between classes in both test and training sets). After training, I performed a test over five sentences to check the model's performance. These sentences are: 1) "terrible movie, terrible plot," 2) "this movie was great I love it," 3)

"This movie was horrible! The plot was boring. Acting was okay, though," 4) "The film really sucked. I want my money back," and 5) "What a beautiful romantic film. 10/10 would see again!". All sentences were predicted correctly. The last sentence indicates positive sentiment, the first four sentences negative sentences. A sentiment analysis trained on the "IMDb" movie reviews dataset reveals a balanced number of positive and negative feelings in the Grant Sattaur negotiation, with the prevalence of the latter.

Figure 4 shows sentiment analysis results with the default threshold and threshold set to 0.9. With the threshold set to 0.9, the model found 498 negative and no positive sentences. Examples of most negative sentences include: "I do not think that anybody can make me better (Grant Sattaur)," or "Just do not think anything least is going to help me (Grant Sattaur)." Examples of negative feeling sentences from the negotiator include: "Okay? It is going to piss off your parents; it is going to upset them greatly" or "No, so you are just going to be a coward and hide in your house."

Grant Sattaur's negative feelings are expressed in sentences like "What good is staying alive going to do?." More negative feelings were observed in the negotiator's speech. There is also a rise in sentences with negative sentiment at the end of the negotiation. The number of negative sentences should not be that high, but around 150 (compare section 5.11., Table 32), which indicates that sentiment trained on movie reviews may not perform well on negotiation data.

Figure 4. Sentiment analysis results on Grant Sattaur negotiation data with the default threshold and with threshold set to 0.9 (there are no predicted positive classes at threshold 0.9)



5.2. Emotion detection task results on the Grant Sattaur negotiation

The emotion detection task aims to analyze discrete emotion categories caused by some disrupting event (for the definition of emotions in a machine learning context, compare Ho and Cao: 2012). This task is based on a categorical psychological model of emotions (Ekman: 1992, Plutchik 1980, Ortony, Clore and Collins 1988). For the multi-class classification of emotions, I adopted "DailyDialog," (Li et al. 2017), "Emotion Stimulus" (Ghazi, Inkpen and Szpakowicz 2015), and the "International Survey on Emotion Antecedents and Reactions" ("ISEAR"; Scherer and Wallbott 1994) datasets.

The "DailyDialog" dataset is written to reflect our daily conversations (Li et al. 2017: 987). "Emotion Stimulus" leverages a synonym list from the Oxford Dictionary and Thesaurus.com, where human annotators had to verify each sentence (Ghazi, Inkpen and Szpakowicz 2015: 157–158). The "ISEAR" dataset is a questionnaire describing respondents' emotions (Razek and Frasson 2017: 22). These concatenated datasets were retrieved from: https://github.com/lukasgarbas/nlp-text-emotion and verified[12].

Compared with similar emotion detection datasets, such as the CrowdFlower-based datasets (Liu, Osama and De Andrade 2019; Gupta 2020), this dataset contains less noise and accurately tagged sentences. However, since this is a concatenated dataset, evaluation metrics from other authors are not presented.

The dataset consisted of 11 327 short messages and dialog utterances and was used to classify five emotions: "neutral" (2254 sentences tagged as "0"), "sadness" (2317 sentences tagged as "1"), "fear" (2171 sentences tagged as "2"), "anger" (2259 sentences tagged as "3"), and "joy" (2326 sentences tagged as "4"). Table 10 shows the resulting metrics of the models: XLNet, BERT, BiGRU, NB-SVM, Logistic Regression, and FastText.

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[12] The DailyDialog dataset contains 13 118 sentences, from which 1022 represent "anger," 353 "disgust," 74 "fear," 12 885 "happiness," 1150 "sadness," 1823 "surprise," and 85 572 dialogues tagged as "Other" (Li et al. 2017: 990). As far as the "Emotion Stimulus" dataset is concerned, researchers asked human annotators to verify annotations related to "happiness" (690 sentences), "sadness" (673 sentences), "anger" (651 sentences), "fear" (552 sentences), "surprise" (266 sentences), "disgust" (101 sentences), and "shame" (179 sentences, Ghazi, Inkpen, and Szpakowicz 2015: 157–158). There are 3112 sentences in total. The ISEAR's class "joy" contains 1094 sentences, the class "anger" 1096; the class "fear" 1095 sentences; the class "sadness" 1096 sentences; the class "disgust" 1096 sentences; the class "shame" 1096 sentences, and "guilt" 1093 sentences (Razek and Frasson 2017: 22) with a total of 7666 sentences (Razek and Frasson 2017: 22).

Table 10. Precision, recall, F1-score, macro average, and weighted average results of emotion detection validation with 10 427 samples for training and 900 for testing with time calculations on merged "DailyDialog," "ISEAR," and "Emotion Stimulus"

Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.78	0.77	0.77	-	179
1	0.79	0.85	0.82	-	184
2	0.93	0.82	0.87	-	173
3	0.79	0.84	0.82	-	179
4	0.85	0.83	0.84	-	185
accuracy	-	-	-	0.82	900
macro avg	0.83	0.82	0.82	-	900
weighted avg	0.83	0.82	0.82	-	900
BERT	precision	recall	F1-score	accuracy	support
0	0.80	0.81	0.81	-	179
1	0.80	0.82	0.81	-	184
2	0.90	0.80	0.84	-	173
3	0.78	0.87	0.82	-	179
4	0.87	0.84	0.85	-	185
accuracy	-	-	-	0.83	900
macro avg	0.83	0.83	0.83	-	900
weighted avg	0.83	0.83	0.83	-	900
BiGRU	precision	recall	F1-score	accuracy	support
0	0.71	0.77	0.74	-	179
1	0.64	0.56	0.60	-	184
2	0.66	0.57	0.61	-	173
3	0.60	0.66	0.63	-	179
4	0.66	0.70	0.68	-	185
accuracy	-	-	-	0.65	900
macro avg	0.65	0.65	0.65	-	900
weighted avg	0.65	0.65	0.65	-	900
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.86	0.39	0.53	-	179
1	0.74	0.58	0.65	-	184
2	0.58	0.72	0.64	-	173
3	0.50	0.84	0.62	-	179
4	0.74	0.64	0.66	-	185
accuracy	-	-	-	-	900
macro avg	0.68	0.63	0.63	0.63	900
weighted avg	0.69	0.63	0.63	-	900
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.78	0.47	0.59	-	179
1	0.63	0.54	0.58	-	184
2	0.51	0.66	0.58	-	173
3	0.51	0.70	0.59	-	179
4	0.66	0.57	0.61	-	185
accuracy	-	-	-	0.59	900
macro avg	0.62	0.59	0.59	-	900
weighted avg	0.62	0.59	0.59	-	900
FastText	precision	recall	F1-score	accuracy	support
0	0.72	0.70	0.71	-	179
1	0.70	0.55	0.62	-	184
2	0.61	0.66	0.64	-	173
3	0.60	0.63	0.61	-	179
4	0.57	0.64	0.61	-	185
accuracy	-	-	-	0.64	900
macro avg	0.64	0.64	0.64	-	900
weighted avg	0.64	0.64	0.64	-	900

For all the models, I adopted 10 427 sentences for training and 900 for testing. The class distribution is random, and the classes are not equally split. In the train set, there are 2075 sentences tagged as "0" (neutral), 2133 sentences tagged as "1" (sad or sadness), 1998 sentences tagged as "2" (fear), 2080 sentences tagged as "3" (anger), and 2141 sentences tagged as "4" (joy). In the test set, there are 179 sentences tagged as "0" (neutral), 184 sentences tagged as "1" (sad or sadness), 173 sentences tagged as "2" (fear), 179 sentences tagged as "3" (anger), and 185 sentences tagged as "4" (joy).

A neutral score, in this case, means that the text is not emotionally driven. After training, I performed a test over five sentences to check the model's performance. These sentences are: 1) "I am very disappointed, to the point I wanna die," 2) "I am so so sad," 3) "I am so angry," 4) "I am so happy," and 5) "I fear a lot of things, I fear to go out at night." The first two sentences were predicted as sadness, the third as anger, the fourth as joy, and the fifth as fear. Table 11 shows time calculations for six machine learning models.

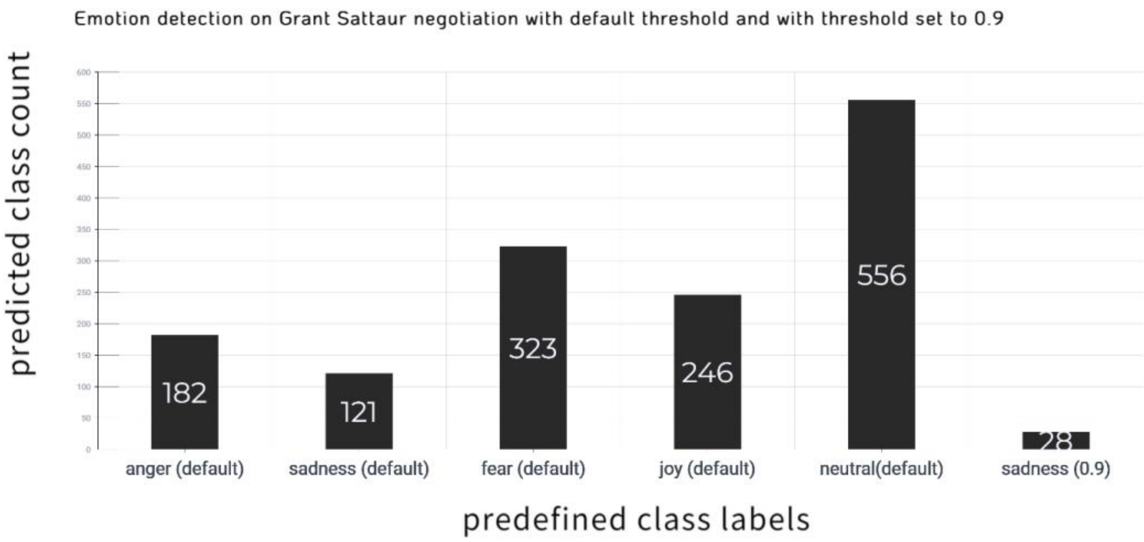
Table 11. Time calculations for six machine learning models

Model:	**Time:**	**Model:**	**Time:**
XLNet	Time to predict 1429 sentences:	**NB-SVM**	Time to predict 1429 sentences:
-	48 min 8 sec	-	6 sec
-	Time to train:	-	Time to train:
-	43 min 8 sec	-	30 min
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	36 sec	-	260 ms
-	Time to train:	-	Time to train:
-	32 min 12 sec	-	31 min 8 sec
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	22 sec	-	212 ms
-	Time to train:	-	Time to train:
-	30 min 10 sec	-	26 min 19 sec

Figure 5 shows the model's predictions (results) with the default threshold and a threshold set to 0.9 on Grant Sattaur negotiation data. The XLNet machine learning model found three dominant negative emotions: "sad," "anger," and "fear." However, numerous "joy" sentences indicate mixed emotions in the transcript, which sentiment analysis confirms. "Joy" sentences were used by the negotiator to persuade, e.g., "There are still many people out there they care about you okay and appreciate everything that you do," or "But if could take care of them it will be over before you know it and you can move on with your life, life is much more important." For this reason, the negotiator has many sentences with contrasting emotions, e.g., "sad" and "joy."

Moving the threshold from 0.5 to 0.9, the model found 28 sentences correctly classified as "sad," whereas the rest of the text was neutral. The negotiator sentence "And believe me, my heart was broken by my sweetheart at high school too" was considered by the model as the most probable to represent the sadness class in the Grant Sattaur transcript, followed by "You are not the only 20-year-old that is had his heart broken by a girl." Other interesting negotiator sentences are: "So sad think about your parents think about your kid brother," "Okay. No parent wants to see their son or child die or get killed or kill themselves and need to have good fine memories," or "Oh yeah, that is right, Brian killed himself the day after Christmas."

Figure 5. Emotion detection results on Grant Sattaur negotiation data with the default threshold and with the threshold set to 0.9 (only the class sadness passed the 0.9 threshold)



5.3. Toxic comment classification on the Grant Sattaur negotiation

Toxic comments are rude comments from users in which one person remarks something unpleasant, thus encouraging negative attitudes and behavior (toxicity) from other users by using more foul language or aggressive tone (Singh, Goyal and Chandel 2022). Toxicity refers to language that should be avoided in a forum, leading to *argumentum ad hominem*, rough language, off-topic discussions, and blaming. The goal of this task is the detection of harmful content to improve online conversations.

To detect rude language (toxicity), I retrieved the Toxic Comment Classification Challenge dataset[13] organized by Google (Conversation AI and Jigsaw)

[13] The "Toxic Comment Classification" challenge posted on Kaggle.com includes the following labels: "toxic," "severe_toxic," "obscene," "threat," "insult," and "identity_hate." These labels are not mutually exclusive. There are two more challenges and competitions revolving around "toxicity" worth mentioning: "The Jigsaw Unintended Bias in Toxicity Classification" and the "Jigsaw Multilingual Toxic Comment Classification." "The Jigsaw Unintended Bias in Toxicity Classification" contains main toxicity labels and additional labels about identity. The main toxicity labels are:

and hosted on Kaggle: www.kaggle.com/datasets/nichaoku/toxic-comment-merge-train-and-test-with-label. The dataset follows a multi-label schema[14]. I transformed the dataset into a binary classification with mutually exclusive labels "toxic" and "non-toxic"[15]; thus, evaluation metrics from other authors are not presented. The dataset of 223 550 sentences was reduced to 190 648 sentences after cleaning and minor data transformation.

For all the models, I adopted 189 748 samples for training and 900 for testing. The class distribution is random, and the classes are not equally split. In the train set, there are 18 043 sentences tagged as "1" ("toxic") and 171 705 sentences tagged as "0" ("non-toxic"). In the test set, there are 451 sentences tagged as "1" ("toxic") and 449 sentences tagged as "0" ("non-toxic").

Table 12. Time calculations for six machine learning models

Model:	**Time:**	**Model:**	**Time:**
XLNet	Time to predict 1429 sentences:	**NB-SVM**	Time to predict 1429 sentences:
-	1 h 6 min	-	630 ms
-	Time to train:	-	Time to train:
-	8 h 3 min 6 sec.	-	1 min 8 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	2 min 42 sec	-	230 ms
-	Time to train:	-	Time to train:
-	21 min 5 sec	-	25 min 3 sec
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	10 sec	-	215 ms
-	Time to train:	-	Time to train:
-	36 min 6 sec	-	22 min 6 sec

"severe_toxicity," "obscene," "threat," "insult," "identity_attack," "sexual_explicit," "male," "female," "homosexual_gay_or_lesbian," "Christian," "Jewish," "Muslim," "black," "white," and "psychiatric_or_mental_illness." Exploratory data analysis (EDA) shows that these categories are correlated. The "Jigsaw Multilingual Toxic Comment Classification" is the 3rd annual competition organized by the Jigsaw team, which combines labels from the previous challenges. This competition aimed to use English-only data to run toxicity predictions on many different languages by utilizing multilingual models (Hugginface 2018).

[14] Toxic Comment Classification Challenge dataset contains the main label named "toxic" and some additional mutually non-exclusive set of labels about identity ("severe toxic," "obscene," "threat," "insult," and "identity hate" columns which rows are also included in the toxic column)

[15] I took the rows from the column "toxic" tagged as "1," and rows from the toxic column that do not represent toxic language tagged as "0" (under the toxic column there were both toxic and non toxic sentences). From that I created two separate columns: a toxic column with toxic sentences, and a non-toxic column with polite (non-toxic) sentences.

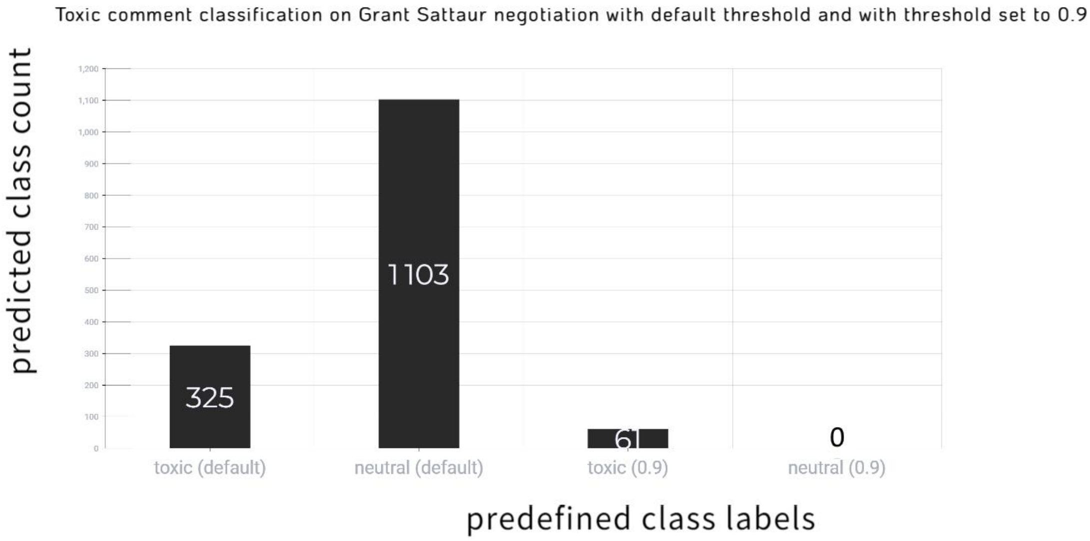
Table 13. Precision, recall, F1-score, macro average, and weighted average results of detection of rude behavior (toxicity) with 189 748 samples for training and 900 for testing with the "Toxic comment classification" dataset

Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.89	0.90	0.90	-	449
1	0.90	0.89	0.90	-	451
accuracy	-	-	-	0.90	900
macro avg	0.90	0.90	0.90	-	900
weighted avg	0.90	0.90	0.90	-	900
BERT	precision	recall	F1-score	accuracy	support
0	0.90	0.90	0.90	-	449
1	0.90	0.90	0.90	-	451
accuracy	-	-	-	0.90	900
macro avg	0.90	0.90	0.90	-	900
weighted avg	0.90	0.90	0.90	-	900
BiGRU	precision	recall	F1-score	accuracy	support
0	0.86	0.89	0.88	-	449
1	0.89	0.86	0.87	-	451
accuracy	-	-	-	0.87	900
macro avg	0.87	0.87	0.87	-	900
weighted avg	0.87	0.87	0.87	-	900
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.85	0.90	0.87	-	449
1	0.90	0.84	0.86	-	451
accuracy	-	-	-	0.87	900
macro avg	0.87	0.87	0.87	-	900
weighted avg	0.87	0.87	0.87	-	900
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.84	0.87	0.86	-	449
1	0.87	0.84	0.85	-	451
accuracy	-	-	-	0.86	900
macro avg	0.86	0.86	0.86	-	900
weighted avg	0.86	0.86	0.86	-	900
FastText	precision	recall	F1-score	accuracy	support
0	0.80	0.94	0.86	-	449
1	0.93	0.76	0.84	-	451
accuracy	-	-	-	0.85	900
macro avg	0.86	0.85	0.85	-	900
weighted avg	0.86	0.85	0.85	-	900

Table 12 shows time calculations for six machine learning models. Table 13 shows precision, recall, F1-score, macro average, and weighted average results of detecting rude behavior (toxicity). Despite the imbalance, the model can predict neutral and rude (toxic) sentences well in the Grant Sattaur negotiation. The model was tweaked to consider explicit language sentences cowered by "XXXX" to be "toxic."

Figure 6 shows the model's results on negotiation data without a threshold and with a threshold of 0.9 applied. The toxic comment classification model found 61 rude sentences. Examples of rude or otherwise offensive sentences uttered by the negotiator include: "Is that right that they can not be in their own house because you are being stubborn and being a coward instead of being enough of a man to come outside," and "You shut up and listen to me, Grant." Other examples of toxic sentences are provided by Table 6.

Figure 6. Toxic comment classification results on Grant Sattaur negotiation data with the default threshold and with the threshold set to 0.9



5.4. Toxic question classification on the Grant Sattaur negotiation

The "Quora Insincere Questions Classification" is a Kaggle.com competition hosted by the Quora.com platform (the data is entirely collected from Quora.com; Mungekar et al. 2019: 1) that enables us to ask questions and receive answers. The dataset was downloaded from: https://www.kaggle.com/c/quora-insincere-questions-classification/data. This dataset complements the toxic comment classification task as it focuses only on rude questions. The meaning of "sincere" vs. "insincere" classes is explained in section 1.2.3. As mentioned, insincere questions are questions that do not seek an answer but contain intentionally inappropriate content and, for this reason, can also be called toxic.

The dataset has three parameters: 1) Q ID: Unique question ID assigned to each question, 2) Question Text: The actual question, and 3) Target: Either "1" for sarcasm or "0" for neutral (Mungekar et al. 2019: 3). Table 15 shows the model's quality measures after model training. Table 16 shows the time to predict 1429 sentences and train the models.

Table 15. Precision, recall, F1-score, macro average, and weighted average results of detection of toxic question classification with 9000 samples for training and 900 for testing from the "Quora Insincere Questions Classification" dataset

Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.89	0.85	0.87	-	450
1	0.86	0.89	0.88	-	450
accuracy	-	-	-	0.87	900
macro avg	0.87	0.87	0.87	-	900
weighted avg	0.87	0.87	0.87	-	900
BERT	precision	recall	F1-score	accuracy	support
0	0.87	0.91	0.89	-	450
1	0.90	0.87	0.88	-	450
accuracy	-	-	-	0.89	900
macro avg	0.89	0.89	0.89	-	900
weighted avg	0.89	0.89	0.89	-	900
BiGRU	precision	recall	F1-score	accuracy	support
0	0.84	0.87	0.85	-	450
1	0.87	0.83	0.85	-	450
accuracy	-	-	-	0.85	900
macro avg	0.85	0.85	0.85	-	900
weighted avg	0.85	0.85	0.85	-	900
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.88	0.76	0.81	-	450
1	0.79	0.90	0.84	-	450
accuracy	-	-	-	0.83	900
macro avg	0.83	0.83	0.83	-	900
weighted avg	0.83	0.83	0.83	-	900
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.79	0.87	0.83	-	450
1	0.86	0.77	0.81	-	450
accuracy	-	-	-	0.82	900
macro avg	0.82	0.82	0.82	-	900
weighted avg	0.82	0.82	0.82	-	900
FastText	precision	recall	F1-score	accuracy	support
0	0.89	0.75	0.81	-	450
1	0.78	0.91	0.84	-	450
accuracy	-	-	-	0.83	900
macro avg	0.84	0.83	0.83	-	900
weighted avg	0.84	0.83	0.83	-	900

Table 16. Time calculations for six machine learning models

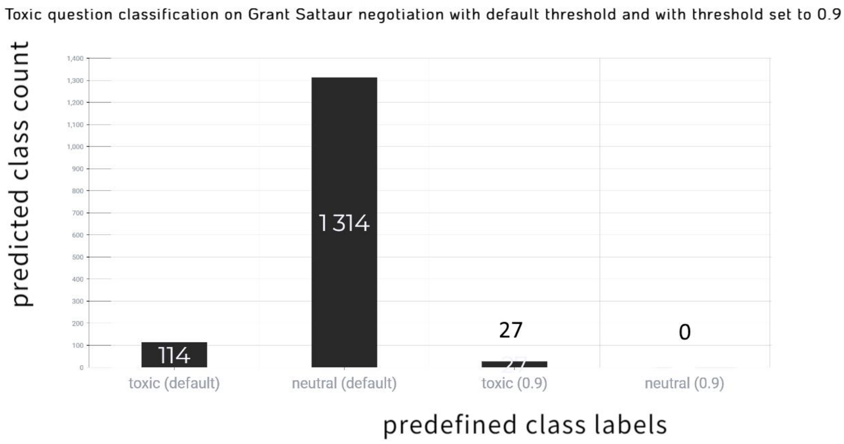
Model:	**Time:**	**Model:**	**Time:**
XLNet	39 min 15 sec	**NB-SVM**	Time to predict 1429 sentences:
-	Time to train:	-	560 ms
-	34 min 58 sec	-	Time to train:
-	-	-	25 min 38 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	4 min 3 sec	-	401 ms
-	Time to train:	-	Time to train:
-	21 min 5 sec	-	25 min 3 sec
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	49 sec	-	665 ms
-	Time to train:	-	Time to train:
-	36 min 6 sec	-	23 min 5 sec

Table 17. Comparison of accuracy metrics between my results and other author's results on "Quora Insincere Questions Classification" dataset

method	Accuracy	source
NB	0.95	Mungekar et al. 2019: 6
Logistic Regression	0.95	Mungekar et al. 2019: 6
Naïve Beyes + Logistic Regression	0.95	Mungekar et al. 2019: 6
SVM	0.93	Mungekar et al. 2019: 6
Decision Tree	0.93	Mungekar et al. 2019: 6
Random Forest	0.94	Mungekar et al. 2019: 6
SVM+BoW	0.85	Aslaw 2021: 144
my method	-	-
XLNet	0.87	-
BERT	0.89	-
BiGRU	0.85	-
NB-SVM	0.83	-
Logistic Regression	0.82	-
FastText	0.83	-

A comparison with other author's results is shown in Table 17. The tagging method adopted for this task is identical to "Civil Comments." In the original dataset, 1 225 312 sentences are tagged as "0," which denotes a neutral class, whereas 80 810 are tagged as "1," which equals to a toxic question. For this task, I adopted 9000 samples for training and 900 for testing. Data sampling is random (sentence order is randomized), but the class distribution is equal (a 1:1 ratio between classes in both test and training sets). Figure 7 shows the model's results on negotiation data without a threshold and with a threshold of 0.9 applied.

Figure 7. Toxic question classification results on Grant Sattaur negotiation data with the default threshold and with the threshold set to 0.9



With the threshold set to 0.9, the toxic question classification model found 27 rude sentences. There is a sudden rise of rude language towards the end of the negotiation, represented by sentences such as: "You are just going to be a coward and kill yourself?." Toxic questions were found in the negotiator's speech.

5.5. Sarcasm detection on the Grant Sattaur negotiation

Sarcasm is defined as a type of "more aggressive irony with the intent to mock or scorn a victim without excluding the possibility to amuse" (Frenda et al. 2022: 1). Sarcasm detection identifies changes in the dichotomy of a negative or positive utterance into its contrary (Ahuja et al. 2018), which can be utilized to humorously criticize something. All varieties of sarcasm "invert something that the speaker pretends to mean" (Camp 2012: 588). For sarcasm detection, I utilized the "Sarcasm in News Headlines" dataset (Misra and Arora 2019). The "Sarcasm in News Headlines" dataset contains sarcastic news posted by comedians on the Onion website and HuffPost.com. "0" represents the absence of sarcasm (29 971 sentences), whereas "1" denotes the presence of sarcasm in a sentence (25 357 sentences). Other sarcasm datasets contain more instances of noisy data (Liebrecht et al. 2013, Joshi et al. 2017).

Table 17. Comparison of accuracy metrics between my results and other author's results on "Sarcasm in News Headlines" datasets

method	**Accuracy**	**source**
CNN-LSTM	0.86	Shrikhande, Setty and Sahani 2020: 484
NB	0.78	Zanchak, Vysotska and Albota 2021: 131
my method	-	-
XLNet	0.90	-
BERT	0.91	-
BiGRU	0.83	-
NB-SVM	0.81	-
Logistic Regression	0.81	-
FastText	0.56	-

Table 18. Time calculations for six machine learning models

Model:	**Time:**	**Model:**	**Time:**
XLNet	55 min 2 sec	**NB-SVM**	Time to predict 1429 sentences:
-	Time to train:	-	8 sec
-	48 min 1 sec	-	Time to train:
-	-	-	23 min 2 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	7 min 12 sec	-	1 sec
-	Time to train:	-	Time to train:
-	25 min 6 sec	-	25 min
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	1 min 15 sec	-	684 ms
-	Time to train:	-	Time to train:
-	19 min 1 sec	-	2 min 1 sec

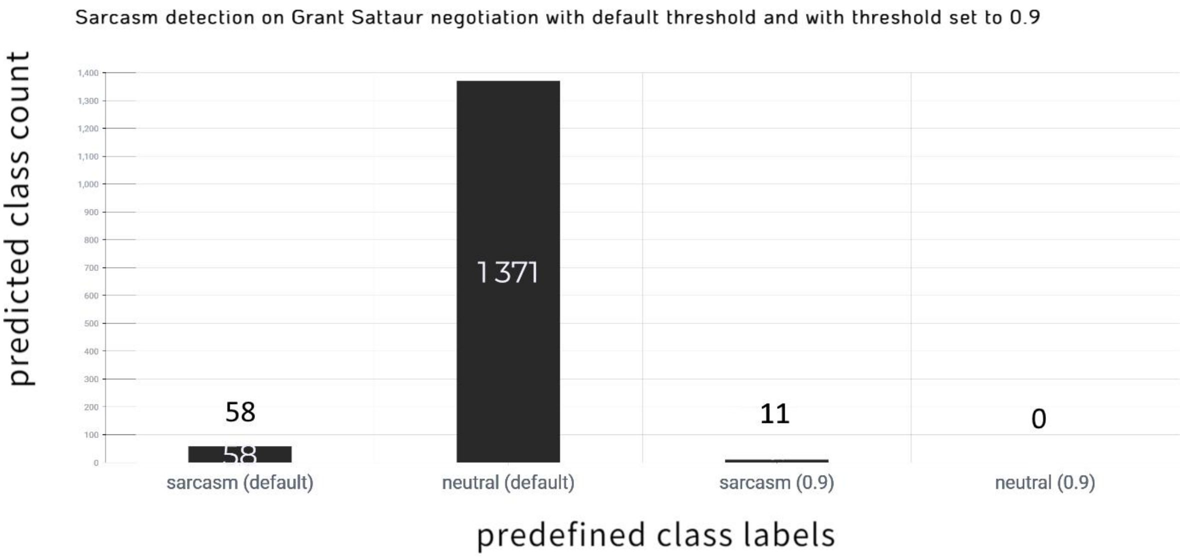
A comparison with other authors' results is shown in Table 17. Table 18 shows the time calculation for training and negotiation data predictions. I adopted 8100 samples for training and 900 for testing. Data distribution is random, and the classes are not equally split. In the train set, there are 4084 neutral sentences tagged as "0," and 4016 sarcasm sentences tagged as "1." In the test set, there are 466 neutral sentences tagged as "0," and 434 sarcasm sentences tagged as "1." Table 19 shows precision, recall, F1-score, macro average, and weighted average results of detecting sarcasm.

Table 19. Precision, recall, F1-score, macro average, and weighted average results of detection of sarcasm with 8100 samples for training and 900 for testing with the "Sarcasm in News Headlines" dataset

Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.89	0.92	0.91	-	466
1	0.91	0.88	0.89	-	434
accuracy	-	-	-	0.90	900
macro avg	0.90	0.90	0.90	-	900
weighted avg	0.90	0.90	0.90	-	900
BERT	precision	recall	F1-score	accuracy	support
0	0.91	0.92	0.91	-	466
1	0.92	0.90	0.91	-	434
accuracy	-	-	-	0.91	900
macro avg	0.91	0.91	0.91	-	900
weighted avg	0.91	0.91	0.91	-	900
BiGRU	precision	recall	F1-score	accuracy	support
0	0.82	0.86	0.84	-	466
1	0.84	0.79	0.82	-	434
accuracy	-	-	-	0.83	900
macro avg	0.83	0.83	0.83	-	900
weighted avg	0.83	0.83	0.83	-	900
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.82	0.81	0.81	-	466
1	0.79	0.80	0.80	-	434
accuracy	-	-	-	0.81	900
macro avg	0.81	0.81	0.81	-	900
weighted avg	0.81	0.81	0.81	-	900
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.82	0.80	0.81	-	466
1	0.79	0.81	0.80	-	434
accuracy	-	-	-	0.81	900
macro avg	0.81	0.81	0.81	-	900
weighted avg	0.81	0.81	0.81	-	900
FastText	precision	recall	F1-score	accuracy	support
0	0.55	0.82	0.66	-	466
1	0.59	0.28	0.38	-	434
accuracy	-	-	-	0.56	900
macro avg	0.57	0.55	0.52	-	900
weighted avg	0.57	0.56	0.52	-	900

Figure 8 shows the model's results on negotiation data without a threshold and with a threshold of 0.9 applied. The sarcasm detection model found eleven sentences with a threshold of 0.9. Such sarcastic sentences include: "No. Is anybody dead? No," "Grant, have you had anything to drink today or taken any dope or anything," "Everything going to Vista," or "if I go out with my hands clearly in the air naked, I think that there is a dozen guns pointing at me." These sentences may contain jocularity, which can be expressed through hyperbole, e.g., "Everything going to Vista" can be considered a hyperbolic statement[16].

Figure 8. Sarcasm detection results on Grant Sattaur negotiation data with the default threshold and with the threshold set to 0.9



5.6. Metaphor detection

A metaphor can be defined as a word or phrase that does not have its natural meaning, where something is described by stating another thing with which it can be compared (Youguo 2013: 560). Metaphor is not only about language but how we "conceptualize one mental domain in terms of another" (Lakoff and Johnson 1980). For metaphor detection, I used the "Language Computer Corporation (LCC)" dataset (Mohler et al. 2016). The "Language Computer Corporation (LCC)" leverages human annotators who were asked to rate the metaphoricity of sentences. The "Language Computer Corporation (LCC)" is the largest annotated metaphor dataset with 36 247 sentences. The "LCC dataset" is known for achieving better metrics than similar datasets. Table 20 shows F1-score result comparisons between by score and other authors.

[16] As mentioned, hyperbole is sometimes considered a subclass of sarcasm (Averbeck 2015).

Table 20. Comparison of accuracy metrics between my results and other author's results on the "LCC" dataset

method	**F1-score**	**source**
BERT	0.81	Ma et al. 2021
BERT	0.76	Dankers et al. 2019
my method	-	-
XLNet	0.72	-
BERT	0.73	-
BiGRU	0.69	-
NB-SVM	0.67	-
Logistic Regression	0.67	-
FastText	0.67	-

The class distribution is random, and the classes are not equally split except for the train set for the XLNet model. For the XLNet model, 35 448 sentences are utilized for the train set and 800 for the test set. In the test set, there are 386 neutral sentences and 414 metaphor sentences, whereas in the train set, 17 724 neutral sentences and 17 724 metaphor sentences. For the rest of the models, there are 32 629 sentences in the training set and 3619 in the test set. The training set has 16 314 neutral sentences and 16 315 metaphor sentences. The test set has 1803 neutral sentences and 1816 metaphor sentences. Table 21 shows time calculation regarding training and negotiation data predictions. Table 22 shows precision, recall, F1-score, macro average, and weighted average results with the "LCC" metaphor dataset.

Table 21. Time calculations for six machine learning models

Model:	**Time:**	**Model:**	**Time:**
XLNet	51 min 12 sec	**NB-SVM**	Time to predict 1429 sentences:
-	Time to train:	-	4 sec
-	48 min 8 sec	-	Time to train:
-	-	-	1 h 7 min 3 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	14 min 56 sec	-	215 ms
-	Time to train:	-	Time to train:
-	1 h 57 min	-	1 h 7 min 7 sec
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	14 sec	-	348 ms
-	Time to train:	-	Time to train:
-	49 min 9 sec	-	1 h 23 min 9 sec

Table 22. Precision, recall, F1-score, macro average, and weighted average results of metaphor detection with the "LCC" metaphor dataset

Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.69	0.77	0.73	-	386
1	0.76	0.67	0.71	-	414
accuracy	-	-	-	0.72	800
macro avg	0.72	0.72	0.72	-	800
weighted avg	0.72	0.72	0.72	-	800
BERT	precision	recall	F1-score	accuracy	support
0	0.73	0.72	0.73	-	1803
1	0.73	0.73	0.73	-	1816
accuracy	-	-	-	0.73	3619
macro avg	0.73	0.73	0.73	-	3619
weighted avg	0.73	0.73	0.73	-	3619
BiGRU	precision	recall	F1-score	accuracy	support
0	0.68	0.70	0.69	-	1803
1	0.69	0.68	0.68	-	1816
accuracy	-	-	-	0.69	3619
macro avg	0.69	0.69	0.69	-	3619
weighted avg	0.69	0.69	0.69	-	3619
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.69	0.64	0.66	-	1803
1	0.66	0.71	0.69	-	1816
accuracy	-	-	-	0.67	3619
macro avg	0.68	0.67	0.67	-	3619
weighted avg	0.68	0.67	0.67	-	3619
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.69	0.63	0.66	-	1803
1	0.66	0.71	0.69	-	1816
accuracy	-	-	-	0.67	3619
macro avg	0.67	0.67	0.67	-	3619
weighted avg	0.67	0.67	0.67	-	3619
FastText	precision	recall	F1-score	accuracy	support
0	0.66	0.67	0.67	-	1803
1	0.67	0.66	0.67	-	1816
accuracy	-	-	-	0.67	3619
macro avg	0.67	0.67	0.67	-	3619
weighted avg	0.67	0.67	0.67	-	3619

Figure 9. XLNet metaphor detection results on Grant Sattaur negotiation data without a threshold and with threshold 0.9 applied (metaphor detection task)

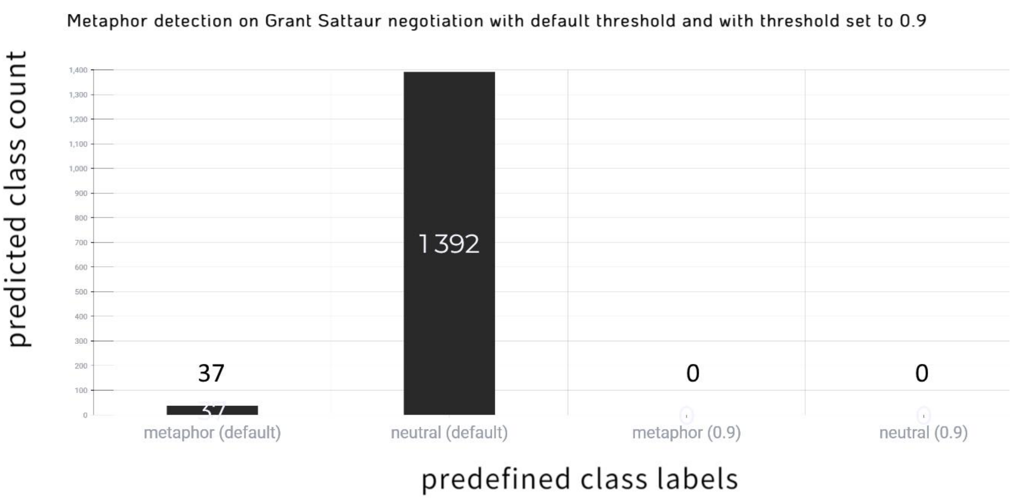


Figure 9 shows the model's results on negotiation data without a threshold and with a threshold of 0.9 applied. Neutral sentences prevail in text, and there is a rise of metaphorical language towards the end of the negotiation according to the XLNet model. With the default threshold, there are 37 metaphor sentences. With the threshold set to 0.55, the model found eleven sentences from the police negotiator. Interesting results were provided by the BERT model, which found the most probable non-literal expression to be: "He is going to nurse the rights" in the Grant Sattaur negotiation. Apart from figurative language, no typical metaphors were found. In this case, it is a correct behavior as no such tropes are present in the studied text.

5.7. Persuasion detection

As mentioned in chapter 4, persuasion is used to influence the other side by modifying or influencing beliefs, values, feelings, actions or attitudes (Simons 1976: 21, Simons 2001: 7). The "persuader" intentionally induces a behavioral change in the "persuadee," by leveraging arguments, flattery or threats (compare Ier, Sycara and Li 2017: 55). In a hard negotiation where the negotiator adopts hard tactics, directive speech acts or threats are more prevalent Mamet 2004: 86); in a soft negotiation where the negotiator adopts soft tactics, one should expect argumentation, acts of approval, acts of compassion, praising and complimenting, or weak directives, such as advice (Searle 1968).

Table 23. Comparison of accuracy metrics between my results and other author's results on "Multilingual Persuasion Detection Dataset"

method	accuracy	source
BERT	0.87	Pöyhönen, Hämäläinen and Alnajjar 2022: 8
my method	-	-
XLNet	0.83	-
BERT	0.80	-
BiGRU	0.72	-
NB-SVM	0.69	-
Logistic Regression	0.71	-
FastText	0.60	-

For automated persuasion detection, I used the publicly available "Multilingual Persuasion Detection Dataset" (Pöyhönen, Hämäläinen and Alnajjar 2022). Researchers extracted dialogues tagged in videogames as persuasion (Pöyhönen, Hämäläinen and Alnajjar 2022: 5) and built 1572 persuade sentences and

6 329 non persuade sentences (Pöyhönen, Hämäläinen and Alnajjar 2022: 6). Table 23 shows F1-score result comparisons between my metric results and other authors.

The model classifies sentences reasonably well, especially if there is a promise of reward, mention of trust, e.g., "you can trust me," or direct command (Pöyhönen, Hämäläinen and Alnajjar 2022: 10). I balanced the dataset to match the minority class and discarded short sentences. I utilized 1110 sentences for the "persuade" class (tagged as "1") and 1110 for the "non-persuade" class (tagged as "0"). 1998 sentences were adopted for training and 222 for testing. Data sampling is random, but the class distribution is equal (a 1:1 ratio between classes in both test and training sets). Table 24 shows precision, recall, F1-score, macro average, and weighted average results of persuasion detection. Table 25 shows time calculation regarding training and negotiation data predictions.

Table 24. Precision, recall, F1-score, macro average, and weighted average results of persuasion detection with 1998 samples for training and 222 for testing on "Multilingual Persuasion Detection Dataset"

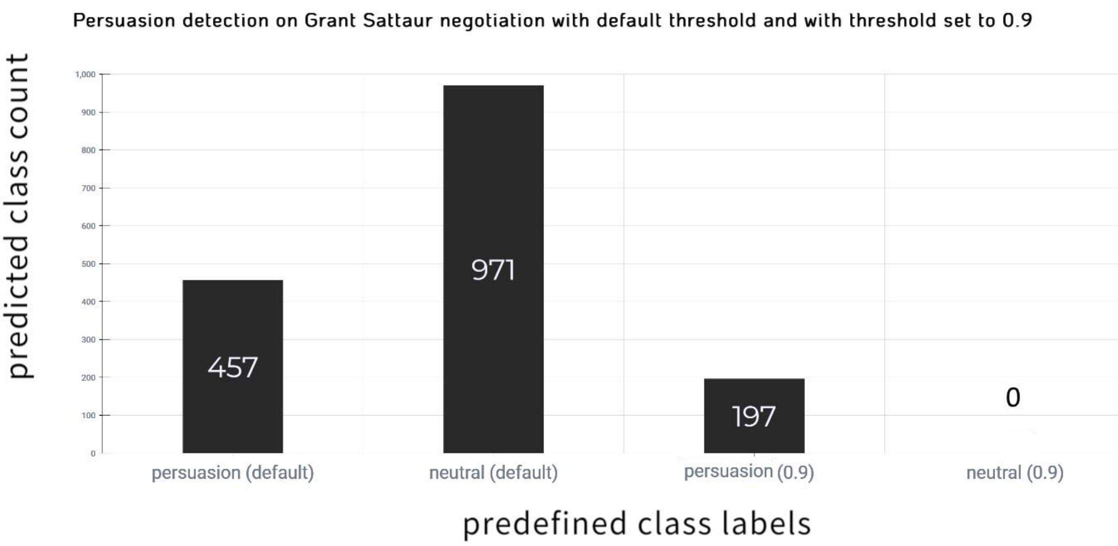
Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.86	0.78	0.82	-	111
1	0.80	0.87	0.84	-	111
accuracy	-	-	-	0.83	222
macro avg	0.83	0.83	0.83	-	222
weighted avg	0.83	0.83	0.83	-	222
BERT	precision	recall	F1-score	accuracy	support
0	0.88	0.70	0.78	-	111
1	0.75	0.90	0.82	-	111
accuracy	-	-	-	0.80	222
macro avg	0.81	0.80	0.80	-	222
weighted avg	0.81	0.80	0.80	-	222
BiGRU	precision	recall	F1-score	accuracy	support
0	0.71	0.73	0.72	-	111
1	0.72	0.70	0.71	-	111
accuracy	-	-	-	0.72	222
macro avg	0.72	0.72	0.72	-	222
weighted avg	0.72	0.72	0.72	-	222
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.63	0.90	0.74	-	111
1	0.83	0.48	0.61	-	111
accuracy	-	-	-	0.69	222
macro avg	0.73	0.69	0.67	-	222
weighted avg	0.73	0.69	0.67	-	222
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.65	0.92	0.76	-	111
1	0.86	0.50	0.63	-	111
accuracy	-	-	-	0.71	222
macro avg	0.75	0.71	0.69	-	222
weighted avg	0.75	0.71	0.69	-	222
FastText	precision	recall	F1-score	accuracy	support
0	0.63	0.49	0.55	-	111
1	0.58	0.71	0.64	-	111
accuracy	-	-	-	0.60	222
macro avg	0.60	0.60	0.59	-	222
weighted avg	0.60	0.60	0.59	-	222

Table 25. Time calculations for six machine learning models

Model:	Time:	Model:	Time:
XLNet	13 min 15 sec	**NB-SVM**	Time to predict 1429 sentences:
-	Time to train:	-	670 ms
-	11 min 1 sec	-	Time to train:
-	-	-	5 min 9 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	31 sec	-	140 ms
-	Time to train:	-	Time to train:
-	12 min 6 sec	-	5 min 4 sec
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	5 sec	-	4 ms
-	Time to train:	-	Time to train:
-	8 min 5 sec	-	51 sec

The XLNet machine learning model calculated 457 persuasion attempts and 197 with a threshold of 0.9. Almost all persuasion attempts come from the police negotiator, and more persuasion attempts are made toward the end of the negotiation. The sentence with the highest probability score is "All I am asking is for a little cooperation back from you." Other interesting sentences include "Could you come out and let us take care of you," "And you know that I want to help you take care of that problem," or "But you need to be there so they can love you." Generally speaking, it is a text with many persuasion attempts that indicates that we are dealing with a negotiation. For instance, 54 483 attempts at persuasion were made in the Waco negotiation dataset as calculated by the persuasion detection XLNet model (8 860 with the threshold set to 0.9).

Figure 10. XLNet persuasion detection results on negotiation data without a threshold and with threshold 0.9 applied (persuasion detection task)



5.8. Religious sentence detection

As we saw in chapter four, religious texts include particular lexical items, syntax, phonology, morphology, and prosody (Pandharipande 2010) and its vocabulary can be studied at the linguistic level or the metalinguistic level (Holt 2006: 4). The former can be understood as a language in use, e.g., the language of a religious group or sect, the latter as the language we adopt when describing a religious event or ceremony. Creating and using symbols is entwined with learning and using a language (Docherty 2001: 32). Religious groups may share esoteric knowledge and a particular language understood only by a chosen few or an enlightened inner circle. Members of this circle are likely to reference religious works or highlight existential issues. Their faith is often expressed through symbolic language.

For religious sentence detection, I retrieved the "20 Newsgroups" dataset (Mitchell et al. 1999, Lang 1995), a group of around 20 000 newsgroup documents spanning 20 different topics. Siwei Lai et al. (2015) used a modified CNN (bidirectional recurrent structure in a convolutional neural network) to train on four topics with keywords: "comp," "politics," "rec," and "religion," achieving 96.41% F1-score. The "20 Newsgroups" dataset is helpful for topic modeling, where a specific topic describes a set of objects, but I used it for binary classification, where a tag (class or label) is assigned to each predicted sentence. Table 26 shows time calculations, and Table 27 shows the metric results.

Table 26. Time to train and time to predict calculations

Model:	**Time:**	**Model:**	**Time:**
XLNet	23 min 58 sec	**NB-SVM**	Time to predict 1429 sentences:
-	Time to train:	-	832 ms
-	26 min 7 sec	-	Time to train:
-	-	-	4 min 2 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	16 sec	-	240 ms
-	Time to train:	-	Time to train:
-	25 min 5 sec	-	3 min 25 sec
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	779 ms	-	3 ms
-	Time to train:	-	Time to train:
-	6 min 6 sec	-	2 min 2 sec

Table 27. Precision, recall, F1-score, macro average, and weighted average results of religious text detection and time to predict analysis on the "20 Newsgroups" dataset

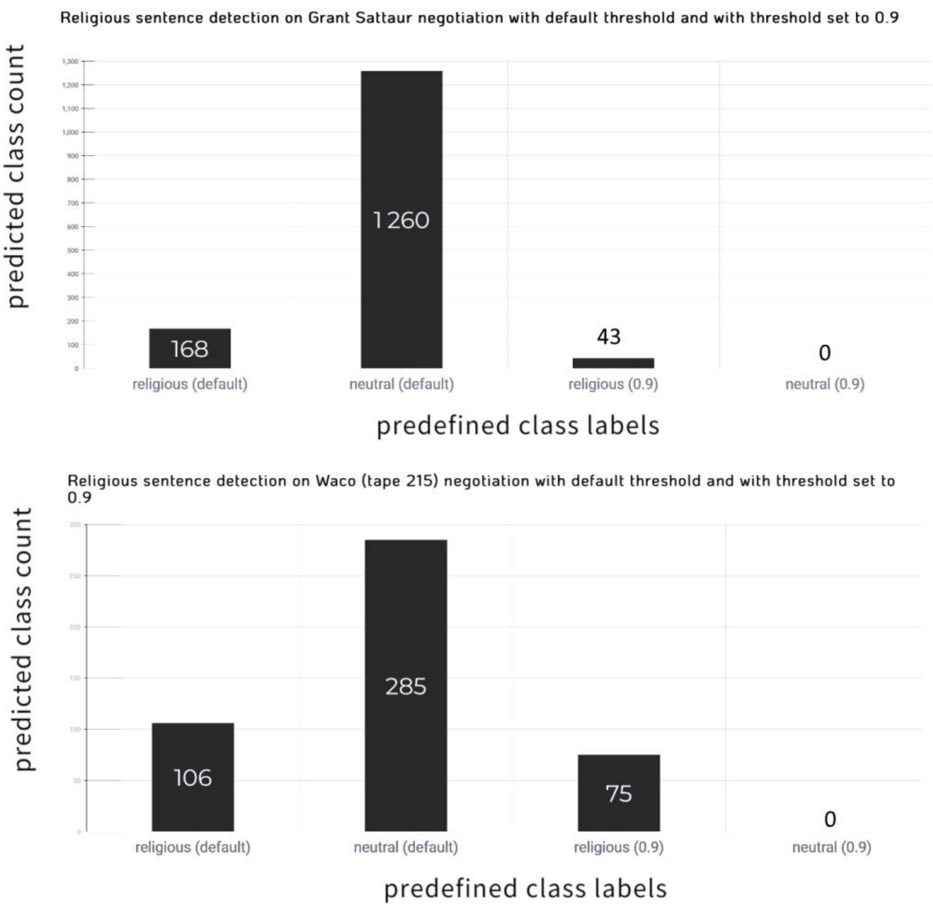
Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.86	0.99	0.92	-	400
1	0.99	0.84	0.91	-	400
accuracy	-	-	-	0.92	800
macro avg	0.92	0.92	0.91		800
weighted avg	0.92	0.92	0.91		800
BERT	precision	recall	F1-score	accuracy	support
0	0.86	0.98	0.92	-	400
1	0.98	0.82	0.91	-	400
accuracy	-	-	-	0.97	800
macro avg	0.92	0.91	0.91		800
weighted avg	0.97	0.91	0.91		800
BiGRU	precision	recall	F1-score	accuracy	support
0	0.75	0.99	0.85	-	400
1	0.98	0.66	0.79	-	400
accuracy	-	-	-	0.82	800
macro avg	0.86	0.82	0.82		800
weighted avg	0.86	0.82	0.82		800
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.74	0.99	0.85	-	400
1	0.99	0.66	0.79	-	400
accuracy	-	-	-	0.82	800
macro avg	0.87	0.82	0.82		800
weighted avg	0.87	0.82	0.82		800
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.73	0.99	0.84	-	400
1	0.99	0.63	0.77	-	400
accuracy	-	-	-	0.81	800
macro avg	0.86	0.81	0.80		800
weighted avg	0.86	0.81	0.80		800
FastText	precision	recall	F1-score	accuracy	support
0	0.70	0.98	0.82	-	400
1	0.97	0.57	0.72	-	400
accuracy	-	-	-	0.78	800
macro avg	0.84	0.78	0.77		800
weighted avg	0.84	0.78	0.77		800

All news categories were employed. Categories such as "atheism," "Christian religion," "talk religion," and "talk religion miscellaneous" were reduced to the "religious" class and tagged as "1" (1429 sentences). The rest of the categories, such as "graphics," "autos," "baseball," "hockey," and "politics," were reduced to one neutral class and tagged as "0" (9504 sentences).

After data preprocessing and balancing, I utilized 6843 neutral and 1028 religious sentences in the training set. 800 sentences were used for testing, and the classes were split evenly. There is a 1:1 ratio between classes in the test set. In the train set, however, 3421 sentences represent the religious class (tagged as "1") and 3422 sentences represent the neutral class (tagged as "0"). All sentences have been randomized. Figure 11 shows XLNet model results on Grant Sattaur and Waco negotiation data (tape 215) without a threshold and with a threshold of 0.9 applied.

The Grant Sattaur negotiation was compared to tape no. 215, which was selected randomly from the Waco negotiation.

Figure 11. XLNet results on Grant Sattaur and Waco negotiation data without a threshold and with threshold 0.9 applied (religious sentence detection task)



With the threshold set to 0.9, there are 43 religious sentences in the Grant Sattaur negotiation. For comparison, tape 215 from the Waco negotiation contains 75 sentences identified as religious, with the threshold set to 0.9. Tape 215 has three times fewer sentences (392) than the Grant Sattaur negotiation (1429). Sentences from the Grant Sattaur negotiator that contain the argument concerning religion include: "Where are you going to end up? What is going to happen to your soul," "You never know what is going to happen after you die," "do not know what is going to happen," "Is there a heaven? Is there a hell?" or "You may end up in hell." perhaps indicating that the negotiator is religious.

5.9. Hate speech and offensive language detection with a custom dataset

Hate speech refers to "insulting, degrading, defaming, negatively stereotyping or inciting hatred, discrimination or violence against people in virtue of their race, ethnicity, nationality, religion, sexual orientation, disability, or gender identity" (Brown 2017: 419–420). As mentioned in chapter 4, the difference between hate speech and offensive language is unclear. In this task, offensive language contains obscene, disgusting, indecent, or foul language, but it is not targeted at specific people or groups. The name "offensive language" is kept for consistency with the Thomas Davidson et al. dataset (2017). Contrary to hate speech, rude (offensive) language is not intended to necessarily induce negative and lasting psychological symptoms such as continuous low mood or sadness. As mentioned, a core component of hate speech is the element of judgment and stereotyping.

In order to detect hate speech and offensive language, I incorporated a dataset created by Thomas Davidson et al. (2017). In Thomas Davidson et al. (2017), 40% of the hate speech class is misclassified (false positives). The "Hate speech and offensive language detection" dataset (Davidson et al. dataset 2017) contains 1430 hate speech sentences, 19 190 offensive language sentences, and 4163 neutral sentences. First, the researchers took phrases identified by internet users as hate speech at Hatebase.org, from which a lexicon was formed (Davidson et al. 2017: 2). Using the Twitter API, researchers filtered relevant tweets by using this lexicon. Next, CrowdFlower (CF) workers were asked to label each tweet as one of three categories: hate speech, offensive but not hate speech, or neither (Davidson et al. 2017: 2). Table 27 shows recall and F1-score result comparisons between my metric results and Thomas Davidson et al. (2017). Table 28 shows result comparisons between my metric results and Thomas Davidson et al. (2017) on hate speech class only.

Table 27. Comparison of accuracy metrics between my results and other author's results on the Thomas Davidson et al. (2017) dataset (all classes)

method	**Recall**	**F1-score**	**author**
One-versus-rest	0.90	0.90	Davidson et al. 2017: 2
my method	-		-
XLNet	0.90	0.90	-
BERT	0.91	0.92	-
BiGRU	0.89	0.90	-
NB-SVM	0.90	0.90	-
Logistic Regression	0.87	0.87	-
FastText	0.88	0.89	-

Table 28. Comparison of accuracy metrics between my results and other author's results on the Thomas Davidson et al. (2017) dataset on the hate speech class only

method	**Precision**	**Recall**	**author**
One-versus-rest	0.44	0.61	Davidson et al. 2017: 2
my method	-		-
XLNet	0.88	0.91	-
BERT	0.92	0.87	-
BiGRU	0.92	0.80	-
NB-SVM	0.89	0.85	-
Logistic Regression	0.88	0.79	-
FastText	0.95	0.80	-

I balanced the dataset by collecting 7000 sentences per class which were reduced after cleaning. Wikipedia pages dedicated to hate speech and ethnophaulism were scraped, which resulted in the creation of a hate speech lexicon. I filtered relevant tweets by using this lexicon and the Tweepy library. For offensive language, I collected game reviews by using the Steam Reviews API and focused on first-person shooters, such as the Call of Duty series. As shown in chapter four, the likelihood of rude (offensive) language depends on the genre, and shooters may increase the likelihood of swearing (Stephens and Zile 2017). This test was conducted on users who were actively playing shooters (Stephens and Zile 2017), but such language may be used over a longer period of time when reviews are made by the players of such games.

After collecting the data, I verified if the sentences were representative of each class: the hate speech class, the offensive language class, and neutral language class. Class distribution is random, and the classes are not equally split. For all the models except for XLNet, 17 365 sentences were utilized for training and 1928 for testing. The training set has 6008 neutral sentences, 5789 offensive language sentences, and 5768 hate speech sentences. The testing set has 705 neutral sentences, 651 offensive language sentences, and 572 hate speech sentences.

In the case of the XLNet model, there are 18 493 sentences in the train set and 800 in the test set. The train set has 6164 neutral sentences, 6145 offensive language sentences, and 6184 hate speech sentences. The test set has 317 neutral sentences, 253 offensive language sentences, and 230 hate speech sentences. As mentioned, this is a multi-class classification where hate speech is tagged as "2," offensive language is tagged as "1," and the neutral class is tagged as "0" to denote that it does not contain rude or hate speech-language. Table 28 shows the time results, whereas Table 29 shows the metric results.

Table 28. Time to train and time to predict calculations

Model:	Time:	Model:	Time:
XLNet	Time to predict 1429 sentences:	**NB-SVM**	Time to predict 1429 sentences:
-	35 min 4 sec	-	6 sec
-	Time to train:	-	Time to train:
-	33 min 6 sec	-	49 min 3 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	1 min 17 sec	-	240 ms
-	Time to train:	-	Time to train:
-	53 min 8 sec	-	40 min 51 sec
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	17 sec	-	288 ms
-	Time to train:	-	Time to train:
-	21 min 11 sec	-	32 min 6 sec

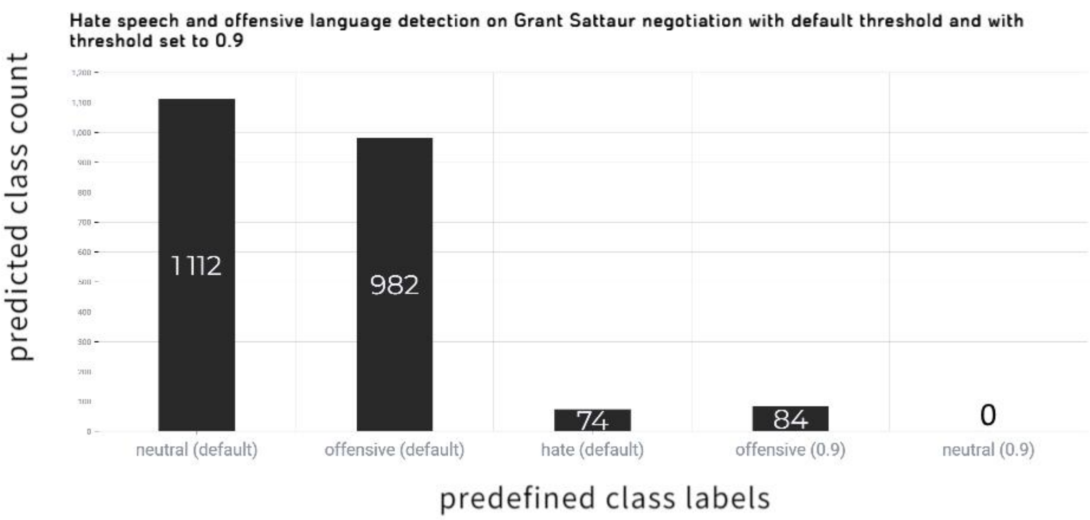
Table 29. Precision, recall, F1-score, macro average, and weighted average results (custom hate speech and offensive language detection dataset)

Model:	**Metrics:**				
XLNet	precision	recall	F1-score	accuracy	support
0	0.94	0.90	0.92	-	317
1	0.88	0.89	0.88	-	253
2	0.88	0.91	0.89	-	230
accuracy	-	-	-	0.90	800
macro avg	0.90	0.90	0.90	-	800
weighted avg	0.90	0.90	0.90	-	800
BERT	precision	recall	F1-score	accuracy	support
0	0.96	0.95	0.95	-	705
1	0.88	0.93	0.90	-	651
2	0.92	0.87	0.89	-	572
accuracy	-	-	-	0.92	1928
macro avg	0.92	0.91	0.92	-	1928
weighted avg	0.92	0.92	0.92	-	1928
BiGRU	precision	recall	F1-score	accuracy	support
0	0.92	0.96	0.94	-	705
1	0.86	0.92	0.89	-	651
2	0.92	0.80	0.86	-	572
accuracy	-	-	-	0.90	1928
macro avg	0.90	0.89	0.90	-	1928
weighted avg	0.90	0.90	0.90	-	1928
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.92	0.92	0.92	-	705
1	0.88	0.91	0.90	-	651
2	0.89	0.85	0.87	-	572
accuracy	-	-	-	0.90	1928
macro avg	0.90	0.90	0.90	-	1928
weighted avg	0.90	0.90	0.90	-	1928
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.93	0.90	0.91	-	705
1	0.83	0.93	0.87	-	651
2	0.88	0.79	0.83	-	572
accuracy	-	-	-	0.88	1928
macro avg	0.88	0.87	0.87	-	1928
weighted avg	0.88	0.88	0.88	-	1928
FastText	precision	recall	F1-score	accuracy	support
0	0.84	0.98	0.91	-	705
1	0.90	0.86	0.88	-	651
2	0.95	0.80	0.87	-	572
accuracy	-	-	-	0.89	1928
macro avg	0.90	0.88	0.89	-	1928
weighted avg	0.89	0.89	0.89	-	1928

Figure 12 shows the model's results on Grant Sattaur negotiation data without a threshold and with a threshold of 0.9 applied. At the threshold of 0.9, there are 84 sentences identified as "offensive language." Most of the offensive language and hate speech come from the negotiator, and there is a rise in hate speech sentences towards the end of the negotiation with the default threshold of 0.5. An example of rude sentences found by the model is, "You may want to kick his arse sometimes, but you know what? He is your little brother." The model confuses hate speech with offensive (rude) language at the default threshold.

Sentences with the word "coward" are sometimes indicated as hate speech, e.g., "No, so you are just going to be a coward and hide in your house," "You are just going to be a coward and kill yourself?" or as offensive language, e.g., "Okay are you going to be a coward." In the context of adultism (prejudice against young people), the term coward may indicate hate speech. The model was tweaked to consider explicit language sentences cowered by "XXXX" to be "offensive." The model considers "explicit language" sentences to be "offensive" as well[17].

Figure 12. XLNet hate speech and offensive language detection results on Grant Sattaur negotiation data without a threshold and with threshold 0.9 applied.



5.10. Suicidal ideations detection with a custom dataset

Suicidal ideations (SI), often called suicidal thoughts or ideas, is a "broad term used to describe a range of contemplations, wishes, and preoccupations with death

[17] For example, the sentence "[Explicit language]" used to cover slurs.

and suicide" (Harmer et al. 2022). Pete Burnap et al. (2017) developed a similar tool to predict subjects at risk of suicide that achieved a precision of 0.732 and recall of 0.729 across all classes when applying the RF approach combined with a Maximum Likelihood voting meta-classifier with Random Forest trained on 2 000 posts. For so-called suicide ideation detection, I used a custom-built dataset that incorporates two small datasets: "Suicide Notes" (498 sentences, Kaggle 2020) and "Depressive Tweets" (3842 sentences) by Hien Nguyen (2022). Both datasets contain only messages from people potentially affected by depression, and no separate classes exist.

The creation of the suicide ideation dataset required specific steps. Hashtags are used to convey feelings or express intent (compare Mohammad 2012: 248). First, categories (hashtags) were used to filter specific content obtained from the scientific literature on the subject cited in chapter three. In the case of suicidal thoughts and depression, the relevant sentences were not only those that represented "sadness" and "loss" but also those representing "defeat," "loss of interest," and "entrapment." The semantic bloc of medicine was also utilized, as mentioned in chapter four, these are names of medicines, treatments, illnesses, and prescriptions related to depression.

In order to gather sentences related to depression, social media sources were utilized. While Twitter was mined by applying the aforementioned categories, the customized suicide ideation detection dataset also encompasses Reddit user posts. One should expect noisy data from Twitter, unlike the data coming from forums and discussion groups where user thoughts appear more organized and centered around a specific topic. People suffering from depression are more likely to seek assistance through these forums. The problem of spam messages seems to appear more often on Twitter, which necessitates specific preprocessing steps described in section 4.1.2.

"R/SuicideWatch" is a Reddit discussion group where members express their suicidal thoughts, such as the desire to commit suicide and similar disorderly past attempts. To build a neutral class, I used neutral posts that did not contain any warning signs, such as "r/travel," "r/books," "r/jokes," "r/cooking," "r/legaladvice," "r/casualconversation," and "r/college." The idea to build the neutral class using this method comes from Snigdha Ramkumar et al. (2020) work. For the custom datasets for training, any Personally Identifiable Information (PPI) was removed from social media sources such as Reddit, Steam, and Twitter. The text was eligible for annotation if it contained between ten and 120 tokens. Depression or suicide ideation represents a complex and multi-faceted topic that had to be simplified for machine learning purposes using two distinct categories. Table 30 shows the time results. Table 31 shows the metric results.

Table 30. Shows the time to predict negotiation data and time to train.

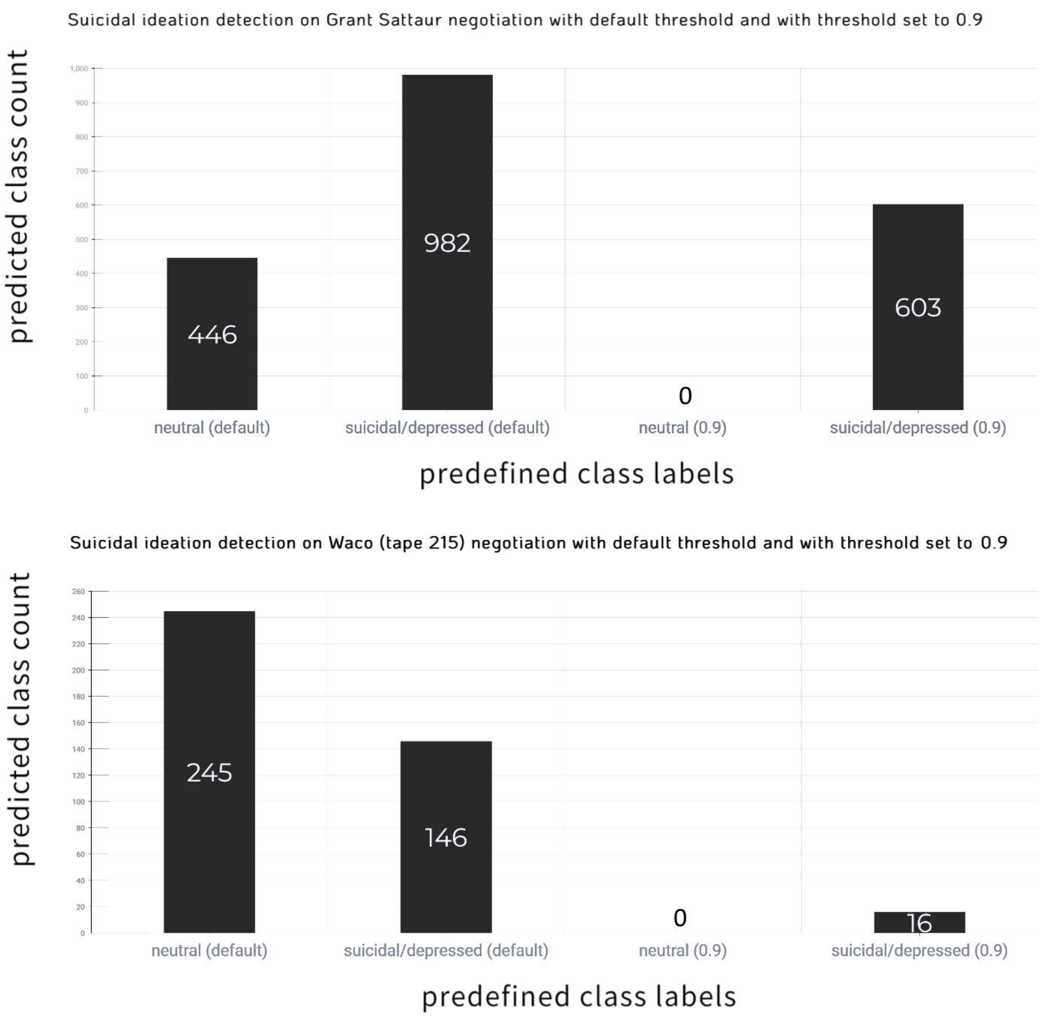
Model:	Time:	Model:	Time:
XLNet	23 min 10 sec	**NB-SVM**	Time to predict 1429 sentences:
-	Time to train:	-	670 ms
-	23 min 5 sec	-	Time to train:
-	-	-	11 min 2 sec
BERT	Time to predict 1429 sentences:	**Logistic Regression**	Time to predict 1429 sentences:
-	31 sec	-	175 ms
-	Time to train:	-	Time to train:
-	12 min 6 sec	-	2h 59 min
BiGRU	Time to predict 1429 sentences:	**FastText**	Time to predict 1429 sentences:
-	7 sec	-	4 ms
-	Time to train:	-	Time to train:
-	12 min 1 sec	-	2h 40 min

Table 31. Precision, recall, F1-score, macro average, and weighted average results of suicidal ideations detection with a custom dataset

Model:	Metrics:				
XLNet	precision	recall	F1-score	accuracy	support
0	0.81	0.70	0.75	-	451
1	0.73	0.84	0.78	-	449
accuracy	-	-	-	0.77	900
macro avg	0.77	0.77	0.77	-	900
weighted avg	0.77	0.77	0.77	-	900
BERT	precision	recall	F1-score	accuracy	support
0	0.79	0.76	0.78	-	2530
1	0.77	0.80	0.78	-	2516
accuracy	-	-	-	0.78	5046
macro avg	0.78	0.78	0.78	-	5046
weighted avg	0.78	0.78	0.78	-	5046
BiGRU	precision	recall	F1-score	accuracy	support
0	0.81	0.74	0.77	-	2530
1	0.76	0.82	0.79	-	2516
accuracy	-	-	-	0.78	5046
macro avg	0.78	0.78	0.78	-	5046
weighted avg	0.78	0.78	0.78	-	5046
NB-SVM	precision	recall	F1-score	accuracy	support
0	0.78	0.74	0.76	-	2530
1	0.75	0.80	0.77	-	2516
accuracy	-	-	-	0.77	5046
macro avg	0.77	0.77	0.77	-	5046
weighted avg	0.77	0.77	0.77	-	5046
Logistic Regression	precision	recall	F1-score	accuracy	support
0	0.77	0.75	0.76	-	2530
1	0.75	0.77	0.76	-	2516
accuracy	-	-	-	0.76	5046
macro avg	0.76	0.76	0.76	-	5046
weighted avg	0.76	0.76	0.76	-	5046
FastText	precision	recall	F1-score	accuracy	support
0	0.79	0.74	0.76	-	2530
1	0.75	0.80	0.77	-	2516
accuracy	-	-	-	0.77	5046
macro avg	0.77	0.77	0.77	-	5046
weighted avg	0.77	0.77	0.77	-	5046

A sentence was tagged as "suicidal/depressed" ("1") or "neutral" ("0") if relevant to the classification task. I collected 63 073 sentences in total. Class distribution is random, and the classes are not equally split. For all the models except for XLNet, 58 027 sentences were utilized for training and 5046 for testing. There are 29 099 "neutral" sentences and 28 928 "suicidal/depressed" sentences in the test set. There are 2530 "neutral" sentences and 2516 "suicidal/depressed" sentences in the test set. For the XLNet model, 62 173 sentences were utilized for training and 900 for testing. There are 31 178 "neutral" sentences and 30 995 "suicidal/depressed" sentences in the train set, 451 "neutral" sentences and 449 "suicidal/depressed" sentences in the test set.

Figure 13. XLNet results on Grant Sattaur and Waco negotiation data without a threshold and with threshold 0.9 applied (suicidal ideation detection task)



In Figure 13, the Grant Sattaur negotiation is compared to tape no. 215 (picked randomly) from the Waco negotiation. At the default threshold, the "suicidal/depressed" sentence predictions prevail in the text. The model found 603 sentences tagged as "suicidal/depressed," with the threshold set to 0.9 in the Grant Sattaur negotiation. For comparison, tape 215 from the Waco negotiation contains only 16 sentences identified as "suicidal/depressed" with the threshold set to 0.9, and sentences tagged as "neutral" prevail in the text at the default threshold (245 neutral sentences).

In the Grant Sattaur negotiation, the number of "suicidal/depressed" sentences starts to rise from the middle towards the end of the negotiation. Examples of Grant Sattaur sentences are "Just do not think anything least is going to help me," or "You know I had talked to the therapist the counselors, you know everybody -- I do not know it is going to help me." An example from the negotiator speech is "So killing yourself is going to make everything go away?". An example from the dispatch unit[18] is: "Okay? If it makes you feel better, I want you to cry because sometimes crying helps you know, makes you think better." These are the sentences with the highest probability of being indicative of suicidal thoughts/depression class according to the model.

5.11. Sentiment analysis with Google Natural Language API

The sentiment analysis was complemented by Google's Natural Language API, which calculates the overall mood or sentiment (positive, neutral and negative) and the magnitude of emotions. The software manufacturer's support website is available under this link: https://cloud.google.com/natural-language. As it is Google's proprietary service, little information about datasets utilized for training and quality metrics is present. However, from my tests, I believe this service is useful in identifying sentiment.

The sentiment is represented by numerical score and magnitude values (Google 2023). According to the documentation of the Google Cloud Platform Natural Language API, the score of the sentiment "ranges between -1.0 (negative) and 1.0 (positive) and corresponds to the overall emotional leaning of the text" (Google 2023). A high magnitude score indicates that the text is emotionally driven. Again,

[18] The very first minutes of the negotiation involve a dialogue between Grant Sattaur and the dispatch unit.

more information is needed by Google on how magnitude and score are calculated. Score: 0.0 and magnitude: 0.0 means no emotions, score: 0.7 and magnitude: 0.7 indicates positive sentiment, –0.7 and magnitude: –0.7 indicates negative sentiment, score: 0.7 and magnitude: 2.5 indicates positive sentiment and strong emotions, score: 0.0 and magnitude: 2.5 indicates strong mixed emotions, e.g., anger and joy. Google provides the following definition of magnitude:

"magnitude indicates the overall strength of emotion (both positive and negative) within the given text, between 0.0 and infinite. Unlike score, magnitude is not normalized; each expression of emotion within the text (both positive and negative) contributes to the text's magnitude (so longer text blocks may have greater magnitudes). (…) A document with a neutral score (around 0.0) may indicate a low-emotion document or may indicate mixed emotions, with both high positive and negative values, which cancel each out. Generally, you can use magnitude values to disambiguate these cases, as truly neutral documents will have a low magnitude value, while mixed documents will have higher magnitude values." (Google 2023).

The magnitude ranges from 0.0 to infinite and represents the overall strength of emotions (both positive and negative). The column score in Table 32 is the score of the whole Oceanside Police negotiation with Grant Sattaur. Scores close or equal to 0 represent a normal behavior in sentiment analysis classification when classifying the whole document instead of single sentences. The negotiator's calculated magnitude is 70.6667, which indicates the presence of strong emotions.

Table 32. Google's Natural Language sentiment analysis results on Grant Sattaur and the police negotiator speech

Score	**Magnitude**	**Interlocutor**
-0.2333	15.3667	Grant
0.0	70.6667	Negotiator
Number of "positive" sentences in the Grant Sattaur negotiaion	**Number of "negative" sentences in the Grant Sattaur negotiaion**	**Number of "neutral" sentences in the Grant Sattaur negotiaion**
156 (correctly classified as positive)	154 (correctly classified as negative)	1061 (correctly classified as neutral)

I also performed the analysis on the sentence level. I sought to verify manually if a given class is predicted well by Google Natural Language API. 58 sentences were misclassified (false positives and false negatives, I discarded them from Table 32), 156 were predicted correctly as positive, and 154 were predicted correctly as negative; the remaining sentences were neutral.

All the sentences were verified manually to check if they are representative of a give class. Among the mispredicted sentences, some sentences are classified as negative despite being positive: "I do not want anything to happen to you," a positive sentence, which indicates preoccupation with the subject's health and well-being, was classified as negative sentiment with score −0.6.

Words associated with sentences classified with negative sentiment score are shown in Table 33. Words associated with sentences classified with positive sentiment are shown in Table 34. Most negative word "problem" was found in the negotiator's sentence: "The problem is that you are getting angry and pissed off with everybody?." Most positive word "age" was found in the negotiator's sentence "That is a great age."

Table 33. Word-level classification (WCLS) on Grant Sattaur, most negative words in the sentences with the lowest sentiment score

Word	**Score**	**Magnitude**
"problem"	–0.9	0.9
"arrest"	–0.9	0.9
"heart"	–0.9	0.9
"mistakes"	–0.9	0.9
"coward"	–0.9	0.9
"violation"	–0.9	0.9
"restraining order"	–0.9	0.9

Table 34. Word-level classification (WCLS) on Grant Sattaur, most positive words in the sentences with highest sentiment score

Word	**Score**	**Magnitude**
"age"	0.9	1.8
"things"	0.9	1.8
"friends"	0.9	0.9
"job"	0.9	0.9
"car"	0.9	0.9

6. CONCLUSION

The goal of this work was a description of the language used during crisis interventions through artificial intelligence and linguistics. It was also carried out to respond to the need for research on the feasibility of combining automated text tools to analyze crisis intervention and negotiation text data based on real-life situations.

Ten automated natural language processing classifications were performed with machine learning methods on qualitative data, the Grant Sattaur negotiation from December 26, 2007[1]. Raw text was converted to automatically annotated sentences which allowed to highlight the characteristics of police language. Binary and multi-class sentence level (SCLS) classification method was performed. I highlighted the modern XLNet (Yang et al. 2019) deep learning method and results because that solution addresses several problems introduced by BERT (Devlin et al. 2018). The downside is the time required to train the model and calculate the inference, which is much higher than NB-SVM (Wang and Manning 2012), Logistic Regression, FastText (Joulin et al. 2016), BiGRU (Rana 2016), and BERT (Devlin et al. 2018) models tested in this work. These models converge faster and are relatively fast predictors too.

Since machine learning approaches are essentially quantitative, the applied methods were quantitative as well. Precision, recall, F1-score, macro average, and weighted average were calculated. The exploratory data analysis helped me understand the main features of the text, such as the interpretation of predictions, as well as the application of appropriate text-cleaning techniques and parameters to machine learning models, including minimum and maximum sequence length, the maximum number of features, or batch size. In addition, calculating class prediction probabilities and moving the threshold made it possible to discard irrelevant information from the negotiation test set.

Data mining methods and tools were also used to retrieve information from social media sources. Two custom English datasets were built: the suicidal ideation detection dataset and the hate speech and offensive language dataset. The bibliographic method, which enabled the separation and elaboration of sources, followed by an analysis and criticism of the current literature, allowed me to create

[1] The negotiation repents a dialogue between the negotiator and Grant Sattaur, and, in the first minutes, between the dispatch unit and Grant Sattaur.

appropriate categories. These categories (tags) act as a filter. They discard irrelevant information making data mining of Twitter a viable option. Reddit, Wikipedia and Steam were also mined. The above is intended to enrich the existing database with new sentence samples for binary and multi-class classification. The focus is on small to medium-sized datasets. Thus, I created custom datasets on suicidal thoughts, offensive language, and hate speech, making automatic recognition of this phenomenon in text possible. By gathering more data, I improved the "hate" class detection from precision=0.44 and recall=0.61 (Davidson et al. 2017) to precision=0.88 and recall=0.91.

The research shows that it is possible to train a model that highlights general text characteristics even with small to medium datasets and in a short time. To find more dissimilarities between the two texts, I utilized the "20 Newsgroups" dataset to train a model able to recognize religious sentences. I demonstrated that more instances of religious sentences, as compared to the Grant Sattaur negotiation, can be found in tape 215 of the Waco negotiation[2]. More instances of religious language use are expected in the Waco negotiation, where the interlocutor is a sect member. The religious sentence detection model was able to highlight text features related to symbolism and existentialism.

The XLNet deep learning model using emotion detection revealed the prevalence of the sadness emotion class and, using suicidal ideation detection, a high number of suicidal ideation/depression sentences in the Grant Sattaur negotiation. The Grant Sattaur negotiation was also compared to the Waco negotiation, tape 215, in which few suicidal ideation/depression sentences were predicted. Regarding the Grant Sattaur negotiation, a large quantity of rude/explicit language sentences was found in the negotiator's speech. The model found no real metaphors and just eleven sarcastic sentences, which is a correct result with few mistakes made. Results with sentiment analysis trained on Internet Movie Database (IMDb) dataset were inconclusive, but there are more negative sentences in the negotiator's speech, which represents a correct result.

The Grant Sattaur police negotiation was not only studied with natural language processing. Each sentence was tagged with the use of the Verbal Interactional Analysis in chapter one. Most sentences were assigned to the

[2] The negotiation repents a dialogue between the negotiator and the leader of the apocalyptic religious movement, David Koresh.

tranquilizing, trust-building, intelligence-seeking, and finessing tags. 43 squelching attempts were also made in which the negotiator uses reprimands, argues, or loses contact with the subject.

Quantitative and qualitative methods of crisis communication methods were utilized to find key patterns of the Grant Sattaur negotiation and the Waco negotiation. The linguistic analysis highlighted mistakes the negotiator made during the crisis negotiation, see chapter four. The subject felt manipulated, attacked and insulted. He also felt unsafe and adopted a defensive stance. As a result, the suspect refused to comply 117 times, as shown in the Verbal Interactional Analysis. Refusals can be considered rapport-challenging speech acts. Communication difficulties were found in the form of expressions such as "what?," "hear?," and "listen?." and in turn constructional units (TCUs) such as "I do not know." At the same time, there were many negotiator sentences with "care" and "help" words. The linguistic analysis shows that the Grant Sattaur police negotiation presents a mix of hard and soft negotiation strategies. Below, I discuss each chapter in more detail.

Main police negotiation tactics were discussed in chapter one. I found that crisis negotiation techniques share similarities, but they also demonstrate specific differences. A common strategy is to 1) identify a problem, 2) build a positive face, image or identity of the other side, 3) listen carefully, 4) be patient, and 5) build the trust necessary for relationship development. Active listening is used to minimize some of the stress and negative emotions. Listening to the other side makes it more likely to be heard and understood. Listening, empathy, and patience help the subject move from a state of high emotionality to rationality which entails a problem-solving and rational decision-making attitude. Most models and real crisis negotiation examples indicate that it is sometimes a lengthy process requiring small steps to be achieved first.

Regarding differences, The Substantive Demands, Attunement, Face, Emotion (SAFE) framework and the Behavioral Change Stairway Model (BCSM) have different focuses and address different questions. SAFE responds to the "why" question, e.g., why the subject shifts from one mindset to another. The BCSM responds to the "what" and "how" questions, e.g., what the negotiator can do to persuade someone or solve a problem. The BCSM assumes that the hostage taker will not be hostile at the beginning of the negotiation and that active listening can be immediately applied, which is unlikely to always be true. Some negotiation tactics, such as the Philip Gulliver Phase Model, are fit for a controlled simulation rather than an authentic hostage negotiation in which uncontrolled and unpredictable events may happen (including communication failures). The concept of securitology was also presented. The perception of subjective security is important, as the subject must feel secure to establish communication.

Negotiation was also compared to mediation, as these terms are used interchangeably. Again, many similarities and differences were observed. Similarly to negotiations, a mediation should not be treated as a battle but rather as a process where parties finally reach a satisfactory agreement. The key differences between mediation and negotiation include the presence of a third-party mediator who does not directly participate in negotiations. Thus, a key difference between negotiation and mediation is that a mediator is impartial and neutral. Mediations are also confidential.

The goal of mediation and negotiation is a common agreement between the conflicted parties; in both cases, a constructive discussion is a mean to reach this objective. The needs and wants of both parties must be taken into account for an agreement to be reached. However, during the hostage negotiation or police interviewing process, the goal reached can sometimes benefit only the negotiator or particular subjects. It should be added that each party to mediation has a sense of victory after reaching an agreement, which sometimes represents the key difference from negotiations.

As far as similarities are concerned, breaking the conflict down into building blocks during the mediation technique is equivalent to simplifying problems described in the Philip Gulliver Phase Model. In the case of a negotiation, face-saving and appreciation strategies are adopted. During a mediation, however, we can only appreciate parties' actions when adopting the summarization or paraphrasing technique. Different goals, types of parties involved, and judicial and legal aspects allow one to distinguish between the concepts.

In chapter two, I discussed police interviewing methods and tactics with a focus on language. Early interrogation techniques used force, misinformation, and deceit to elicit information and provoke unnecessary stress and negative emotions. Later techniques focused on building relationships, relaxing the subject, and providing information on the interview and all legal aspects, including reading the Miranda rights. Soft skills were improved through intense training and rehearsal. All interviewing methods provide interesting clues and descriptions of emotions, including reasons for their occurrence. In police interviews, more emphasis is put on deception detection. However, there appear to be no unequivocal signals of lying, and an external factor can impact the subject response. As we saw in chapter two, deception detection techniques are also criticized by Joe Navarro.

Many interviewing tactics share similarities with hostage negotiations. Staying calm and concentrated represents a common tactic that normalizes homeostasis and behavior and helps prevent the other side from making rushed decisions. Establishing rapport is another key element shared by both domains. Setting aims and goals beforehand is important to assess if the task is complete or if one is moving in the right direction. Both interviewing tactics and crisis negotiations emphasize special procedures when dealing with particular subjects; thus, planning and preparing are central to many discussed methods and lead to interview failure if ignored. One has to look for the right place and time, establish roles, and gather information and the right experts.

Another similar key component is "Listen more, talk less," as both hostage negotiations and police interviews focus on information gathering during the initial stage. Face-saving techniques are also recommended in both. In police interviews, those are used to achieve confession, while in hostage negotiations, they help the subject cooperate and thus achieve a positive outcome. Furthermore, both domains highlight the importance of open-ended questions, where the "why" questions are important when speaking with depressive subjects.

In chapter three, I discussed the main emotion theories of modern psychology, and I demonstrated how emotions are expressed with language. I chose to focus on discrete categorical emotions, as this type of classification is popular in machine learning and can produce good results. The downside of this method is that one has to choose what each class of emotion represents, and for that reason, many nuances between emotions and their intermediate states are lost.

I focused on emotions relevant to the negotiation process and discussed how they impact negotiations. Expressive behavior stems from the subject's need to unleash negative emotions and frustration, which can be addressed through active listening, as analyzed in chapter one. Intense emotional states, such as anxiety and fear, produce deficits in reasoning abilities. Several techniques, such as psychotherapy, were presented for curing and controlling behavior disorders. Psychodrama and sociodrama are excellent methods for training, practicing and rehearsing negotiations.

The impact of hate speech on the victims' psyche, analyzed in chapter four, is also significant because negative emotions are characteristic of victims of depression, and hate speech and offensive language can be considered one of the possible causes.

In chapter four, various branches of linguistics that are useful for crisis communication dialogue were analyzed. As we saw, much linguistic research is not strongly rooted within a particular approach. Language can be analyzed from different angles, and the boundaries between analytical theories are fuzzy. One theory has either its 1) foundation in another, 2) is useful to another, or 3) borrows elements from another. Critical discourse analysis (CDA) and action-implicative discourse analysis (AIDA), for instance, can highlight important issues that discourse analysis cannot, such as contextual and socio-cultural features. Psycholinguistics helps identify writing difficulties, such as dyslexia, which helps find a particular person behind the text, which is helpful in forensic linguistics. Similarly, sociolinguistics helps identify, in colloquial terms, where the subject comes from, his occupation, and what company he keeps.

Politeness theory and selected dialogue speech acts were also taken into account. Crisis negotiations do not constitute a separate language or system but present systemic tendencies and patterns that incorporate particular lexical items. Crisis negotiations share similarities with business negotiations in the strong presence of action verbs and the particular use of dialogue speech acts and persuasion. Crisis negotiations, however focus on solving relational problems rather than focusing on substantive issues. The study of dialogue speech acts in chapter four allowed us to identify what dialogue acts occur during a crisis. Chapter four also explains the role of various communication tropes, such as metaphorical terms and swear words. They can be used for expressing feelings, achieving a positive or negative impact on others, producing a pain or tension-lessening effect, imitating the subject’s language, reinforce an argument, persuading the subject to comply or switching the conversation to another topic.

Crisis communication was studied from a pragmalinguistic perspective. The most relevant dialogue speech acts identified are directive speech acts (questions, requests, proposals, invitations, and advice), denials, refusals, expressive speech acts (apology, compassion, greeting and complimenting), and commissive speech acts (threats and promises). Finally, hate speech, swear words and communication tropes were analyzed separately. Depending on the context, they may indicate a disruptive element, leading to bad communication flow.

A more detailed analysis of crisis negotiation language was performed in chapter four. Communication failures can be found in the form of expressions such as "what," "come again," "hear," and "listen." In the Waco Siege negotiation, this type of communication flow interruption happened, among other reasons, due to cultural differences, changing negotiators, and allowing other interlocutors to participate. On the one hand, in the Grant Sattaur negotiation, the interruptions were caused by technical problems as the negotiator and the subject could not hear each other well. The word listen was used to silence the suspect, e.g., by saying: "Grant you be quiet and listen to me." This happened nine times.

In chapter five, I analyzed police negotiation data in real life situations using automated methods. The linguistic approach was necessary during the collection phase of new data, the building phase of the dataset, and the evaluation of the results produced by the model.

A sentiment analysis trained on the IMDb movie reviews dataset consistently reveals positive or negative feelings, with a slight prevalence of the latter, and negative feelings after applying threshold moving. Interestingly, more negative feelings were observed in the negotiator’s speech. This can be attributed to the fact that the negotiator tried to explain to the subject what the consequences of his actions would be, e.g., "And evidently whatever happens one way or another killing yourself is not going to -- it is not going to make things better." or "It is not worth it Mac it is not worth it." The Google Natural Language model also revealed balanced results between the quantity of positive and negative sentences; most negative ones come from the negotiator.

In general, everyday texts have a prevalently neutral tone, and negative sentiments should occur rarely. That is why a high threshold was set in all the models. Google Natural Language model appears to be more accurate at predicting sentiment by default. Despite its prevalently neutral scores, the magnitude score indicates strong feelings and mixed emotions in the Grant Sattaur negotiation text.

Sentiment analysis returns the overall sentiment of a whole text document, which is sometimes not enough for understanding text data because people identify numerous phenomena as positive but use negative words instead. The magnitude score helps disambiguate that. For instance, Google's Natural Language sentiment analysis classified the sentence "I do not want anything to happen to you." as a negative sentiment with a score of −0.6. It is worth mentioning that researchers report that recognizing sarcastic sentences represents a challenge in sentiment analysis (Bharti, Naidu, and Babu 2020). That happens because a sarcastic sentence often contains "only positive words conveying a negative sentiment" (Bharti, Naidu and Babu 2020).

Emotion detection helps to focus on the subject's signs of discomfort and distress. For example, the XLNet machine learning model found two dominant negative emotions: sadness and anger. It is helpful at this point to remember Stan Walters's interpretations of anger and how it changes the communication flow. The third most frequent emotion was fear. Moving the threshold to 0.9, the model found 28 sentences correctly classified as "sad." As the class of sadness is dominant in the Grant Sattaur negotiation, I also performed a suicide ideation detection which found 603 sentences tagged as "suicidal/depressed" with the threshold set at 0.9.

The dataset on which the model trained was transformed to tag sentences that might contain lexical items related to "powerlessness," "boredom," "defeat," "loss of interest", and "entrapment." The subject was passive and demotivated. Examples of sentences are: "I just have not had any motivation to do anything lately," or "And why should I stick with anything that I do?." Given the large number of sentences indicated as "sad" as well as "suicidal/depressed," one can hypothesize that the subject was affected by some form of depressive disorder. When recalling events, depressed subjects would include more "negative material and events" (May 2013: 436), as their perception of the world is distorted. Grant Sattaur often recalled negative past experiences. More than that, resignation in a depressed subject can be misinterpreted as acknowledgment (Walters 2002).

Finding indicators of suicidal thoughts and depression is important for both hostage negotiations and police interviews. As we saw in chapter four, we cannot elicit complete and truthful confessions from a depressive subject (Walters 2002). A soft integrative negotiation approach is preferred when dealing with subjects affected by depression. Therefore, recognizing text patterns automatically through deep learning is key. Concerning religious sentence prediction, toxic comment classification, and detection of hate speech, offensive language, and persuasion, the results of these tasks are best seen in combination with the Verbal Interactional Analysis.

A manual linguistic analysis with the Verbal Interactional Analysis model revealed 292 finessing attempts, including manipulating and persuading the subject. In addition, the XLNet machine learning model calculated 457 persuasion attempts (197 with the threshold set at 0.9). Thus, many attempts at persuading the subject were made, which is to be expected in a crisis negotiation. For instance, 54 483 persuasions were made in the Waco dataset as calculated by the persuasion detection model (8 860 with the threshold set to 0.9). However, it can also be hypothesized that using swear swords and attacking the subject's face to force him to comply was counter-productive. When this strategy was adopted, the subject responded with an act of refusal, while he complied or even proposed a resolution to the situation when no such tactics were adopted. The subject exhibited a defensive response to provocation.

The negotiator demonstrated a lack of patience during the middle and final stages of the negotiation. As time passed, the negotiator used more swear words during persuasion attempts. This behavior was found in the toxic comment classification, the toxic question classification, and the hate speech and offensive language detection. The first two are the most reliable models for the identification of rude or offensive language. It must be noted that toxic question classification does not classifies only questions but tends to classify all rude comments but focuses on questions.

Hate speech and offensive language detection models tends to predict too many offensive sentences, and toxic comment and toxic question classifiers work better toward finding rude and aggressive text. For example, with the threshold set to 0.9, the toxic question classification model found 27 rude sentences, whereas the toxic comment classification found 61 rude sentences. Examples of rude or otherwise offensive sentences uttered by the negotiator include: "Is that right that they can not be in their own house because you are being stubborn and being a coward instead of being enough of a man to come outside," "You are just going to be a coward and kill yourself?," and "You shut up and listen to me, Grant." This behavior is surprising considering that the negotiator tried to extend the negotiation time, which is considered a good tactic. This was achieved by asking many questions and keeping the subject busy, as indicated by the large number of instances where the negotiator gathered information by asking questions (240 sentences in total).

Another counter-productive tactic was using a religious argument as a persuasive means. The negotiator asked about the result of the subject's plan to kill himself. Examples of sentences that contain the argument concerning religion include: "Where are you going to end up? What is going to happen to your soul," "You never know what is going to happen after you die," "do not know what is going to happen," "Is there a heaven? Is there a hell?" or "You may end up in hell." The religious argument did not produce any positive results identifiable in the text. Religious sentence detection shows that the sentence most probable to be religious in the Grant Sattaur negotiation is: "that is the truth. And you know what the truth is" (probability: 0.998). There are not many religious sentences in this negotiation, especially if one sets the threshold higher; with the threshold set to 0.9, there are 43 potentially religious sentences. For comparison, tape 215 from the Waco dataset contains 75 sentences identified as religious, with the threshold set to 0.9. As mentioned, tape 215 has three times fewer sentences than Grant's negotiation.

Regarding the predictions of figurative or metaphorical language, all the six older and newer classification algorithms that were applied performed poorly on the dataset features. Hence, one may infer that the chosen dataset is a poor predictor. Literary and non-literal predicted sentences were very close to the 0.5 threshold, meaning the artificial intelligence models were undecided about which classes to assign. The Grant Sattaur negotiation contains hyperbole, e.g., "the good times outweigh the bad times a million to one," and various instances of figurative language, but not typical metaphors that leverage comparisons. The BERT model found the most probable non-literal expression to be: "He is going to nurse the rights." Noteworthy results were produced by sarcasm detection, where the XLNet model found eleven sentences with the threshold set to 0.9. Sarcasm detection also captures jocularity, as sarcasm is a type of irony with the intent to mock.

After evaluating the Grant Sattaur negotiation with both machine learning and linguistic analysis, it can be safely stated that face-saving techniques were not adopted during the final stage of the negotiation. The negotiator made no apologies and did not initiate any repair tactics. Face-threatening acts and offensive words were used instead. Nevertheless, the negotiation proceeded well until the mid-stage and until the negotiator adopted this strategy. Therefore, it is important to see not only how the subject reacts to the negotiator's speech but also how the negotiator reacts to a lack of cooperation from the subject. People often have incentives to stop cooperating with those they find obstinate, unpredictable, abrasive, or untrustworthy.

In the discussed case, the negotiator lost patience due to the subject's refusal and adopted a more rude and aggressive language. As mentioned above, a good flow or "good vibe" between the negotiator and the subject is essential. When there is no understanding between the two, steps should be taken to improve communication. While untrained people have the natural urge to act, known as the action imperative, negotiators should act at the right moment or otherwise wait. In other words, negotiators or police interviewers should allow the subject to feel he has a choice and let him act on his terms.

The high number of persuasion attempts during the whole negotiation indicates that the negotiator rushed Grant's decisions. Negotiators usually buy time to replace emotions with reason. Thanks to this strategy, the subject is often ready to accept and implement the negotiator's suggestions, resulting in a crisis resolution. Crisis communication is about exchanging precise information and good communication flow and should also be composed of relationships based on trust. In the Grant negotiation, trust was not established between the suspect and the negotiator. The subject felt that the negotiator lied to him and that he was being manipulated. The subject felt unsafe, and, in the end, he was not treated with dignity and respect.

Recent developments in artificial intelligence bring new possibilities for studying the linguistic features of text by utilizing automated means. Generative Pre-trained Transformer (GPT) represents a move toward systems that can generalize over a wide range of tasks. These developments introduce important changes to interdisciplinary studies where artificial intelligence aids and complements linguistic analysis.

What makes text classification difficult is that it needs to consider a larger context, as we do not receive para verbal and non-verbal communication feedback. Emotions and other discrete categories are context-dependent, and the classification task utilized in this work does not extend past sentence boundaries. In addition, we should mention the temporal persistence of text classifiers. Languages evolve, and as time passes by, the terminology changes making these models gradually obsolete. Furthermore, we have yet to fully know and control all the features deep neural networks learn.

Many lexical units are grammatically ambiguous but semantically unambiguous to a human. Problems with machine learning models based on categories (tags) include lexical referential, narrative, and semantic ambiguity (polysemy). Furthermore, it is not always possible to accurately determine what tag should be assigned to every sentence, especially when analyzing emotions. This difficulty is encountered in the discrete classification of emotions in modern psychology, and it is also encountered by researchers when building datasets based on discrete tags for machine learning, where no unanimous agreement is reached on what each class represents. Text annotation, performed in this work on hate speech and offensive language and suicide ideation detection, was a subjective task, as I had to annotate the text myself.

I plan to improve the suicide ideation, hate speech, and offensive language detection dataset to be more accurate on police negotiation data. The model encounters difficulties when discerning between the hate speech class vs. the offensive language class, which is also difficult for humans. Religious sentence detection deserves further improvement, especially in the number of sentences utilized for training and testing. The academic language detection task would be helpful in Steve Schroeder's utterance analysis in the Waco negotiation. From a linguistic perspective, future research would include the creation of a dataset composed of dialogue speech acts that occur during a crisis negotiation useful for machine learning. This is a difficult task considering that dialogue speech acts are dependent on context. With the development of NLP, machine learning algorithms and the neural network, it is possible to conduct a more accurate and customized analysis of emotions, sarcasm, rude language, and depression in text.

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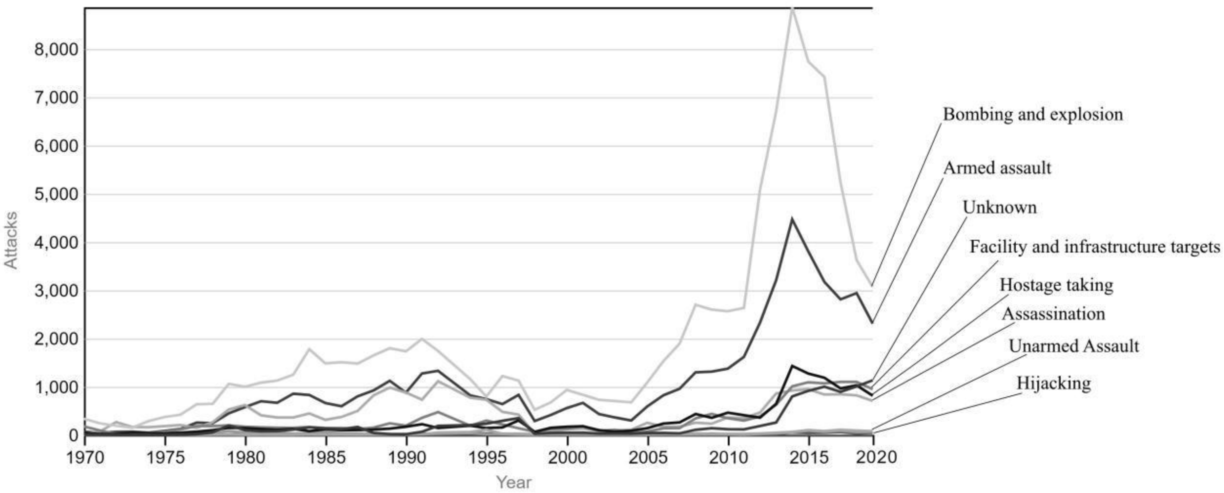
Charts:

Chart 1. Line chart of the total number of crisis incidents between 1970 and 2020 (Global Terrorism Database 2021: line chart)



Figures:

Figure 1. Seven layers of human security (Gierszewski 2017: 249)

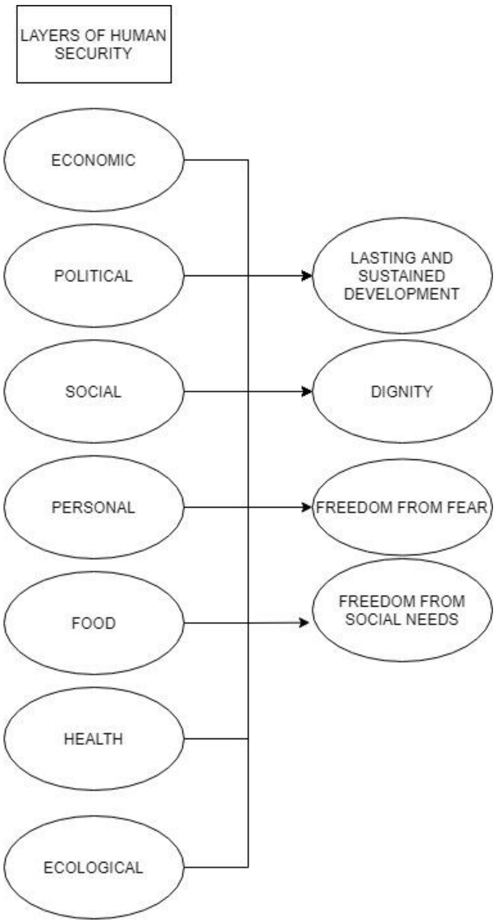


Figure 2. One-way communication between message sender and message receiver (Seong 2012)

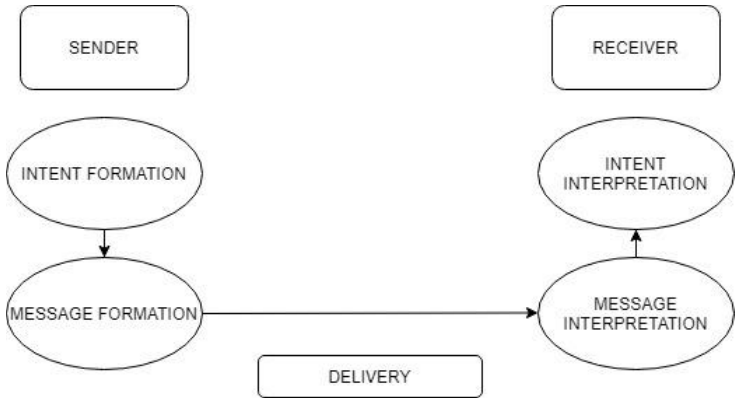
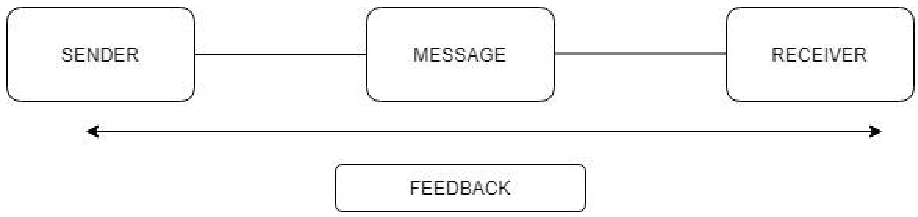


Figure 3. Two-way communication (based on image from MMRCSE 2018)



Tables:

Table 1. Airline Hijackings Worldwide by Decade (for years 1950-2014 see: Busch 2016: 23; for years 2015-2021 see Aviation Safety Network 2021)

Years	No. of hijackings	No. of fatalities
1950-1960	26	23
1960-1970	146	15
1970-1980	347	344
1980-1990	244	220
1990-2000	196	237
2000-2010	76	275
2010-2014	10	0
2015-2021	10	1

Table 2. Countries with most attacks on aid workers from 2004 to 2014 according to a report by "Statista" (Busch 2016: 26)

Country	No. of attacks	Country	No. of attacks
Afganistan	430	Syria	92
Sudan	219	South Sudan	84
Somalia	171	DR Congo	54
Pakistan	93	Sri Lanka	47
Kenya	43	Iraq	40

Table 3. Major attacks on aid workers by year: summary global statistics of killed and kidnapped between 1997 and 2020 (Aid Worker Security 2021)

Year	No. of killed	No. of kidnapped
1997	39	30
1998	35	18
1999	33	20
2000	57	11
2001	27	43
2002	38	24
2003	87	7
2004	56	23
2005	53	23
2006	88	65
2007	91	43
2008	127	60
2009	108	93
2010	73	93
2011	86	96
2012	71	91
2013	159	136
2014	123	121
2015	111	69
2016	109	87
2017	139	72
2018	131	131
2019	125	122
2020	117	125

Table 4. Total number of crisis incidents between 1970 and 2020 (Global Terrorism Database 2021: bar chart)

Armed Assault	54 069
Assassination	21 704
Bombing and explosion	98 739
Facility and infrastructure targets	15 506
Hijacking	773
Hostage taking (barricaded suspects)	1191
Hostage taking (kidnappings)	14 606
Unarmed assault	1265
Unknown	10 945

Table 5. Evaluation of suicidal patients with the SAD PERSONS Scale (Patterson et al. 1983)

Factors:	Points Assigned:
S=Sex (male)	1 (if not : 0)
A=Age (<19 or >45 years)	1 (if not : 0)
D=Depression	1 (if not : 0)
P=Previous suicide attempts	1 (if not : 0)
E=Ethanol abuse	1 (if not : 0)
R=Rational thinking loss	1 (if not : 0)
S=Social support lacking	1 (if not : 0)
O=Organized plan	1 (if not : 0)
N=No spouse	1 (if not : 0)
S=Sickness (chronic, debilitating disease)	1 (if not : 0)

Scores between 0 and 4 indicate low risks
Scores between 5 and 6 indicate medium risks
Scores between 7 and 10 indicate high risks

Table 6. Assessment of suicide potential by non psychiatrists using SAD PERSONS Score (Hockberger and Rothstein 1988)

Factors:	Points Assigned:
S=Sex (male)	1 (if not : 0)
A=Age (<19 or >45)	1 (if not : 0)
D=Depression or hopelessness	2 (if not : 0)
P=Previous attempts or psychiatric care	1 (if not : 0)
E=Excessive alcohol or drug use	1 (if not : 0)
R=Rational thinking loss	2 (if not : 0)
S=Separated/divorced/widowed	1 (if not : 0)
0=Organized or serious attempt	2 (if not : 0)
N=No social support	1 (if not : 0)
S=Stated future intent	2 (if not : 0)

Legend: Scores between 0 and 5 may indicate low risks and the subject may be safe to discharge. Scores between 6 and 8 indicates that the subject probably requires psychiatric consultation, and >8 scores indicate that the subject probably requires hospital admission
Table 7. Manchester Self-Harm Rule suicide risk assessment (Cooper et al. 2006)

1. History of self-harm
2. Previous psychiatric treatment
3. Benzodiazepine use
4. Any current psychiatric treatment

Table 8. The feelings of entrapment and defeat in depressed subjects (compare Griffiths et al. 2014: 55)

Sentence example:	Type of feeling (entrapment and defeat)
"I feel I'm in a deep hole I cannot get out of"	entrapment
"I would like to get away from who I am and start again"	entrapment
"I feel trapped inside myself"	entrapment
"I want to get away from myself",	entrapment
"I would like to escape from my thoughts and feelings"	entrapment
"I often have the feeling that I would just like to run away"	entrapment
"I often have the feeling that I would just like to run away"	entrapment
"I have a strong desire to escape from things in my life"	entrapment
"I can see no way out of my current situation"	entrapment
"I have a strong desire to get away and stay away from where am now but I cannot"	entrapment
"I feel trapped by other people"	entrapment
"I feel trapped by my obligations"	entrapment
"I would like to get away from other more powerful people in my life but I cannot"	entrapment
"I am in a relationship I cannot get out of"	entrapment
"I feel powerless"	defeat
"I feel completely knocked out of action"	defeat
"I feel that I have lost important battles in life"	defeat
"I feel powerless to change myself"	defeat
"I feel that I have sunk to the bottom of the ladder"	defeat
"I feel that I have lost my standing in the world"	defeat
"I feel down and out"	defeat
"I feel that I have given up"	defeat
"I feel there is no fight left in me"	defeat
"I feel defeated by life"	defeat
"I feel that my confidence has been knocked out of me"	defeat
"I am in a situation I feel trapped in"	defeat
"I feel that I am one of life's losers"	defeat
"I feel powerless to change things"	defeat
"I feel that life has treated me like a punch bag"	defeat
" I feel that I have not made it in life",	defeat
"I feel that I am an unsuccessful person"	defeat
"I feel unable to deal with whatever life throws at me"	defeat
"I feel that I am basically a looser"	defeat

Table 9. Anger, sad, happy, joy, fear, and hate categories (nouns), based on popular online dictionaries (the author's analysis based on Thesaurus, Merriam-webster, Lexico and Synonyms.com query)

anger (Thesaurus)	acrimony, animosity, annoyance, antagonism, displeasure, enmity, exasperation, fury, hatred, impatience, indignation, ire, irritation, outrage, passion, rage, resentment, temper, violence, chagrin, choler, conniption, dander, disapprobation, distemper, gall, huff, infuriation, irascibility, irritability, miff, peevishness, petulance, pique, rankling, soreness, stew, storm, tantrum, tiff, umbrage, vexation, blow up, cat fit, hissy fit, ill humor, ill temper, slow burn.
anger (Merriam-Webster)	angriness, birse, choler, furor, fury, indignation, irateness, ire, lividity, lividness, mad, madness, mood , outrage, rage, spleen, wrath, wrathfulness.
anger (Lexico)	annoyance, vexation, exasperation, crossness, irritation, irritability, indignation, pique, displeasure, resentment, hostility.
anger (Synonyms)	animosity, choler, displeasure, exasperation, fretfulness, fury, impatience, indignation, ire, irritation, offense, passion, peevishness, pettishness, petulance, rage, resentment, temper, vexation, wrath.
sad (Thesaurus)	bitter, dismal, heartbroken, melancholy, mournful, pessimistic, somber, sorrowful, sorry, unhappy, wistful, bereaved, blue, cheerless, dejected, depressed, despairing, despondent, disconsolate, distressed, doleful, down, down in dumps, down in the mouth, downcast, forlorn, gloomy, glum, grief-stricken, grieved, heartsick, heavy-hearted, hurting,in doldrums, in grief, in the dumps, languishing, low, low-spirited, lugubrious, morbid, morose, not happy, out of sorts, pensive, sick at heart, troubled, weeping, woebegone.
sad (Merriam-Webster)	bad, blue, brokenhearted, cast down, crestfallen, dejected, depressed, despondent, disconsolate, doleful, down, downcast, downhearted, down in the mouth, droopy, forlorn, gloomy, glum, hangdog, heartbroken, heartsick, heartsore, heavyhearted, inconsolable, joyless, low, low-spirited, melancholic, melancholy, miserable, mournful, saddened, sorrowful, sorry, unhappy, woebegone, woeful, wretched.
sad (Lexico)	sorrowful, dejected, regretful, depressed, downcast, miserable, downhearted, down, despondent, despairing, disconsolate, out of sorts, desolate, bowed down, wretched, glum, gloomy, doleful, dismal, blue, melancholy, melancholic, low-spirited, mournful, woeful, woebegone, forlorn, crestfallen, broken-hearted, heartbroken, inconsolable, grief-stricken, unhappy.
sad (Synonyms)	unhappy, sorrowful, dejected, regretful, depressed, downcast, miserable, downhearted, heavyhearted, down, despairing, disconsolate, out of sorts, wistful, tragicomic, tragical, doleful, melancholy, bittersweet, tragic, mournful, tragicomical, melancholic.

happy (Thesaurus)	cheerful, contented, delighted, ecstatic, elated, glad, joyful, joyous, jubilant, lively, merry, overjoyed, peaceful, pleasant, pleased, satisfied, thrilled, upbeat, blessed, blest, blissful, blithe, cannot complain, captivated, chipper, chirpy, content, convivial, exultant, flying high, gay, gleeful, gratified, intoxicated, jolly, laughing, light, looking good, mirthful, on cloud nine, peppy, perky, playful, sparkling, sunny, tickled, tickled pink, up, walking on air.
happy (Merriam-Webster)	fluky, flukey, fortuitous, fortunate, heaven-sent, lucky, providential.
happy (Lexico)	unhappy, sorrowful, dejected, regretful, depressed, downcast, miserable, downhearted, down, despondent, despairing, disconsolate, out of sorts, desolate, bowed down, wretched, glum, gloomy, doleful, dismal, blue, melancholy, melancholic, low-spirited, mournful, woeful, woebegone, forlorn, crestfallen, broken-hearted, heartbroken.
happy (Synonyms.com)	blessed, blissful, blithe, blithesome, bright, buoyant, cheerful, cheering, cheery, delighted, delightful, dexterous, felicitous, fortunate, gay, glad, jocund, jolly, joyful, joyous, lucky, merry, mirthful, pleased, prosperous, rapturous, rejoiced, rejoicing, smiling, sprightly, successful, sunny.
joy (Thesaurus)	amusement, bliss, charm, cheer, comfort, delight, elation, glee, humor, pride, satisfaction, wonder, alleviation, animation, delectation, diversion, ecstasy, exultation, exulting, felicity, festivity, frolic, fruition, gaiety, gem, gladness, gratification, hilarity, indulgence, jewel, jubilance, liveliness, luxury, merriment, mirth, prize, rapture, ravishment, refreshment, rejoicing.
joy (Merriam-Webster)	beatitude, blessedness, bliss, blissfulness, felicity, gladness, happiness, warm fuzzies.
joy (Lexico)	delight, great pleasure, joyfulness, jubilation, triumph, exultation, rejoicing, happiness, gladness, glee, exhilaration, ebullience, exuberance, elation, euphoria, bliss, ecstasy, transports of delight, rapture, radiance, enjoyment, gratification, felicity, cloud nine, seventh heaven, joie de vivre.
joy (Synonyms)	blessedness, bliss, cheer, comfort, contentment, delight, ecstasy, enjoyment, felicity, gaiety, gladness, gratification, happiness, merriment, mirth, pleasure, rapture, rejoicing, satisfaction, triumph.
fear (Thesaurus)	alarm, angst, anxiety, apprehension, awe, concern, despair, dismay, doubt, dread, horror, jitters, panic, scare, suspicion, terror, unease, uneasiness, worry, abhorrence, agitation, apprehensiveness, aversion, consternation, cowardice, creeps, discomposure, disquietude, distress, faintheartedness, fearfulness, foreboding, fright, funk, misgiving, nightmare, phobia, presentiment, qualm,

	reverence.
fear (Merriam-Webster)	alarm, alarum, anxiety, dread, fearfulness, fright, horror, panic, scare, terror, trepidation.
fear (Lexico)	terror, fright, fearfulness, horror, alarm, panic, agitation, trepidation, dread, consternation, dismay, distress, anxiety, worry, angst, unease, uneasiness, apprehension, apprehensiveness, nervousness, nerves, timidity, disquiet, disquietude, discomposure, unrest, perturbation, foreboding, misgiving, doubt, suspicion.
fear (Synonyms)	apprehension, solicitude alarm, fright, dread, terror, trepidation, dismay, consternation, misgiving, horror, timidity, awe.
hate (Thesaurus)	animosity, antagonism, dislike, enmity, hatred, horror, hostility, loathing, pain, rancor, resentment, revenge, venom, abhorrence, abomination, anathema, animus, antipathy, aversion, bother, bugbear, detestation, disgust, execration, frost, grievance, gripe, irritant, malevolence, malignity, nuisance, objection, odium, rankling, repugnance, repulsion, revulsion, scorn, spite, trouble, black beast, bête noire, ill will, mislike, nasty look, no love lost
hate (Merriam-Webster)	abhorrence, abomination, detestation, execration, hatred, loathing.
hate (Lexico)	loathing, hatred, detestation, dislike, distaste, abhorrence, abomination, execration, resentment, aversion, hostility, ill will, ill feeling, bad feeling, enmity, animosity, antagonism, antipathy, bitterness, animus, revulsion, disgust, contempt, repugnance, odium, rancour.
hate (Synonyms)	hatred, detestation, animosity, enmity, hostility, antipathy.

Table 10. Coding variables for crisis communication behavior derived from content analysis of crisis negotiation transcripts (based on: Taylor 2002: 41–44)

avoidance statements:	**definition:**	**utterance example:**
accuse	challenge an assertion made by the opposing, or fault the other party for performing or not performing a particular action	"Well you are never going to be ready"
avoid	attempt to move interaction away from the current issue, through either a direct request or a more subtle change to the focus of discussion.	"I do not want to talk about that"

denial	refusal to accept an accusation made by the other party. Such denials are not accompanied by an explanation of why the individual should be exonerated.	"No, no, you're lying. I didn't touch the girl"
inaction	failure to enter dialogue despite opportunity. Scored when an individual failed to respond to the other on three consecutive occasions	-
interrupt	continuous disruption of the opposing party. Scored as positive only after occurring twice over consecutive dialogue	-
negative reply	short retorts that have a negative or uncaring tone but were not necessarily in response to the other party's demands or offers	"Nah"
provoke	an overt attempt to aggravate the opposing party into taking some aversive action	"Take your damn choice Frank"
retract	clear withdrawal from a previously acknowledged agreement, regardless as to whether or not the speaker provides an explanation for their change in attitude	"Actually, no, I do not want to do that"
shift	termination of the discussion by communicating an issue different from that spoken in the previous utterance	"Well did you ask about the cigarettes?"
submissive attitude	show apathy, a lack of understanding, or an inability to cope with the events of the hostage crisis	"I do not know if they shot the cops or not"
distributive statements:	**definition:**	**utterance example:**
alternative	proposal of a concession or solution that has not previously been considered during the negotiation	"We cannot concede to those terms, but perhaps instead"
appeal	sincere request for the other party to reconsider altering his/her current attitude to comply with the individual's desire, with no suggestion of personal sacrifice	"Please, please, do not do anything stupid"
commitment	expresses a commitment to a particular issue or position	"I am sticking to my guns, they are not gonna recuperate me"
criticism	criticism of the opposing party's behavior or ability, where an explanation is given for the evaluation	"we cannot get no change out of you all man"
demand	forceful expression of a favor or concession wanted from the	"I want to talk to my wife"

	opposing party	
excuse	acceptance of wrongdoing that involves a pleading for forgiveness from the other party on account of extenuating circumstances. The negotiator may recognize that their behavior is negative, but denies ultimate responsibility for the event	"We, we tried Bill already, and ah, Bill does not have a phone and he is not at the house"
profanity	the use of obscene swearing or other indecent language	"Shit"
insult	degrading comment or scornful directed at the opposing party	"You sound a little bit immature to me"
justify	explanation of a previous or future action. This variable was coded when the negotiator admits responsibility, but rejects the idea that the behavior is negative. Note that justify and excuse are opposites in terms of admitting responsibility	"I am not real sure can get that through the window. That is a pretty big bag"
positive image of self	overt bragging about the superiority of personal ability or current situation in comparison to the ability of the other party	"I have not lied to you yet"
reject demand	refusal to comply with the other party's demands	"I am not going to do that"
reject offer	complete rejection of the other party's offer without considering an integrative compromise or alternative	"No, No, I do not want that"
threat action	threat to take punitive action if the opposing party does not comply. This variable was scored as present even if the threat was	"I will shoot another hostage if you do not comply in 45 minutes"
integrative statements:	**definition:**	**utterance example:**
accept offer	acceptance of a conciliatory offer from the opposing party	"Okay. Let me try working on that"
agree	express agreement with a statement made by the opposing party without making statements of personal assurance (promise) or compliance (comply demand)	"Well you are right"
allure	attempts to highlight how complying with demands will please other people, such as family members, and so lead to an increase in self-worth or personal satisfaction	"You do not just hurt yourself, you hurt all those that love you"
apology	direct regretful acknowledgement of previous actions	"I am sorry—I am sorry, I really and truly did not hear you"
common	allude to a similarity between self and the other party in terms of attitude, beliefs, or behavior	"at least we know that same way"
compliment	praise for the opposing party's attitude or behavior. This differed from the agreement variable as the	"You are doing a good job, too"

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	behavior explicitly commended the other party	
comply demand	active concession to the other party's demands or requests	"Yeah, ok, I will get you the food you want"
compromise	suggestion of a particular set of mutual concession as an alternative to directly accommodating the opposing party's offers or demands	"I am letting seven off, and then I will let seven afterwards"
confidence	expressions of trust in the others' ability to perform a particular action.	"I don't have to ask him, I know you for you"
discourage	attempts to discourage the other party from adopting a particular viewpoint or performing a particular action.	"There is no real crime if you don't do that"
empathy	sympathetic understanding for the explanations or feelings presented by the opposing party about their current situation	"I know you are tired you have been up for opposing party about their current awhile huh"
encourage	active encouragement of the opposing party to adopt a particular perspective or square meals a day, take a discussed action.	"you are gonna get three square meals a day, you would be warm"
humor	attempts to use humor to lighten the tone of the negotiations.	-
integrative	proposition of a solution or approach to interaction that is beneficial to both parties.	"I will let the woman go if you get me some beer and cigarettes"
negative image of self	a reflective criticism of personal behavior or ability. Often shown as an indirect realization of personal wrongdoing	"I have fouled it up"
offer	offering of goods or sentiments that precedes any request.	"Do you want me to see if I can get you an oxygen tank?"
promise	explicit and sincere assurance that a previous statement was valid, especially concerning the performance of a particular action	"I promise that my intention is not to harm the hostages"
reassurance	attempts to restore the other party's confidence or to confirm again a particular opinion or questionable fact about the current situation	"Helicopter will be here in just a few minutes"

Table 11. Refusal speech acts (RSA; compare Maróti 2016: 81–82)

Refusal strategies:	Examples:
Direct	
Performative verbs	"I refuse"
Non-performative statement	"No"
Negative willingness or ability	"I cannot" "I will not" "I do not think so"
Indirect	
Statement of regret	"I am sorry" "I feel terrible (…)"
Wish	"I wish I could help you…"
Excuse, reason, explanation	"My children will be home that night" "I have a headache (…)"
Statement of alternative	
I can do X instead of Y	"I would rather (…)" "I would prefer (…)"
Why don't you do X instead of Y?	"Why do not you ask someone else?"
Set condition for future or past acceptance	"If you had asked me earlier, I would have (…)"
Promise of future acceptance	"I will do it next time" "I promise I will (…)" "Next time I will (…)" – using "will" of promise or "promise"
Statement of principle	"I never do business with friends"
Statement of philosophy	"One cannot be too careful" "Better safe than sorry"
Attempt to dissuade the interlocutor	
Threat or statement of negative consequences to the requester	"I will not be any fun tonight" "I cannot go I look terrible" – to refuse an invitation
So-called guilt trip	"I cannot make a living off people who just order coffee" – waitress to customers situation "I cannot feed on scraps" "Researchers must eat too"
Criticize the request/requester or insult/attack	"Who do you think you are?" "That's a terrible idea"
Let interlocutor off the hook	"do not worry about it"
Self-defense	"I am trying my best" "I cannot do it without support" "It's too difficult" "That's impossible"
Request for help, empathy, and assistance by dropping or holding the request	
Unspecific or indefinite reply	-
Lack of enthusiasm	-
Avoidance:	
nonverbal	
silence	-
hesitation	-
do nothing	-
physical departure	-
verbal	
topic switch	-
joke	-

repetition of part of request	"Monday?"
indefinite postponement	"I will think about it"
hedging	"Gee, I do not know" "I am not sure" "Maybe"
request information	"I'd need to know more"
Setting expectations too high knowing that the other side will not accept them	"I can do it for 1000 euros" "I can do it but I need a year to finish it"