Partial automation of the data-collection process

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"He that comes to research must be in doubt, and must humble himself before the facts, earnestly desiring to know what they are, and what they signify"

- Lewis Fry Richardson

Introduction

Data is a prerequisite for scientific progress. Therefore, the development of new and better ways to collect data is an important and meaningful task. While the world is becoming saturated with information, this does not necessarily facilitate the production of useful data: As the volume of raw information increases, filtering and processing useful signals might actually become more diffcult. Innovation in data collection is important to handle the growing quantities of raw information.

The importance of collecting reliable and valid data effectively is the main motivation behind the present work. Lack of data creates "knowledge gaps", phenomena remain imponderable until they have been systematically and carefully observed. One such gap is created by the lack of systematic description of the phenomenon of *ceasefires*, which is a recurrent and presumably important part of many conflicts, and have been important components in many peace-processes. Despite this, the contingent effect of a ceasefire on a given conflict is unknown. Whether ceasefires facilitate peace in the long term will remain an open question until data has been collected and analyzed.

Data about ceasefires are certainly not lacking because they are trivial or uninteresting phenomena, rather, data-collection is limited by practicality. "Traditional" data collection is done through careful and patient treatment of raw information by trained human coders, a process that is costly both in terms of time and resources. This makes data a scarce resource. Improving the cost-efficiency of data collection processes might lead to much greater volumes of available data, which might then lead to more comprehensive understanding of important phenomena such as ceasefires.

The procedure that is proposed and tested here involves partial automation of the coding process: using computers to apply coding procedures to raw data. This is based on a proposed linkage between measurement as traditionally understood in scientific litterature, and statistical learning. Measurement, if treated as a process of estimating and applying measuring procedures to raw data, can be favourably enhanced by estimating the measuring procedures using statistical learning. This theoretical linkage is explored in chapters 2 and 5.

The great advantage of automatization is a substantial increase in cost-effectiveness: The computerization of the coding process leads to a great increase in speed, allowing for efficient and expedient production of new data. This will increase the range of problems that are analyzable, spurring theoretical development by making more hypotheses testable. In addition, I will also argue that there are substantial qualitative benefits to automating the data collection process, in terms

of both the validity and reliability of the resulting data:

Reliability is an obvious advantage of using computer algorithms: Computers are unimaginative in performing tasks, and will, even in cases requiring random number generation, be able to execute procedures in exactly the same way. This distinguishes computers from humans, that perform variably, especially tasks requiring sophisticated interpretation.

The validity of data is not directly improved by automatization, but is made easier to audit. Openness and replicability are facilitated by computerization, as computer algorithms can be made entirely public, and are reproducible. Human judgement, however strictly guided by coding instructions and guides, will never be as scrutable as computer procedures. This makes it possible to more fully assess the validity of automatically produced data in terms of the chain of procedures leading back to the raw information.

The technicalities of estimating and testing statistical learning systems on text data are presented in chapter 4 and 5. Using supervised learning necessitates the development of a corpus of text with which to train the model, and a thorough testing regime that evaluates different approaches. The corpus is presented in chapter 4, where I elaborate on the source, treatment and pre-classification of the data. In the 5th chapter I describe my classification methodology, defining key terms like supervised machine learning, and cross validation of classification schemes. I also explain the different techniques for transforming text into data, and the metrics used to evaluate the different classifier schemes.

While statistical approaches to data collection have been met with some skepticism (Schrodt and Van Brackle 2013: 37), Hanna (2017) has demonstrated that such approaches can be effective and accurate tools for producing data. I confirm these findings in chapter 6, where I evaluate several approaches, and present the results of a final evaluation on held-out data. These findings show that statistical learning is indeed a useful technique to apply in the process of coding data. With this thesis show that text classification based on statistical learning is indeed an interesting technology for facilitating effective data production within the political science domain.

Chapter 1

Ceasefires

The present system was designed to assist human coders in creating a dataset of ceasefires, by performing a "first pass" over raw text material, indicating what material is interesting to coders. The collection of data about ceasefires was motivated by a perhaps surprising lack of systematic knowledge about ceasefires, which despite this are often part of peace processes and conflict migitation work.

What is the effect of a ceasefire on a conflict? Do ceasefires facilitate further peaceful development, or are they detrimental to the prospect of lasting peace? Such stark contrast between competing, equally plausible hypotheses is testament to the lack of empirical validation of theories about ceasefires. This chapter outlines the ceasefire knowledge gap, and the way data production can contribute towards shedding light on the phenomenon.

The collection of new data drives theory development, a fact that has perhaps been underappreciated (Gleditsch *et al.* 2014: 301). Theory might proceed beyond the bounds of what has been, and can practically be observed, spurring further development beyond what is currently known, but any theory must eventually stand up to empirical scrutiny. This is only possible, after systematically and mindfully collecting data. Which is the foundational material with which theories can be made robust and trustworthy.

The serious nature of the context in which ceasefires exist makes it important to ensure reliable and valid data. While these qualities are always important, when the represented phenomenon affects human lives in such serious ways, its importance increases exponentially (Russett 1977: 95). This is obviously the case when collecting data about any kind of phenomenon relating to violent conflict. This is also true of ceasefires, that have the potential to save many lives, but might also prolong and exacerbate conflict.

Getting ceasefires right, both in terms of timing, talks and treaties, is vital. Therefore, understanding ceasefires, and consequently collecting high-quality data on ceasefires is an important task. In this chapter, I give a brief overview of the theoretical context of ceasefires, showing how the data that might result from the present work might contribute towards solving an urgent knowledge deficiency.

1.1 Ending Conflict

The study of conflict, specifically ending conflict, forms the theoretical backdrop of the work presented here. Conflict research is both the motivation for-, and the domain in which the data collection tool presented in the following chapter is situtated. To provide some context, I will first give a brief overview of the context of research on ending conflict, and how this relates to ceasefires.

Conflict arises when two parties are unable or unwilling to share a scarce resource. In this view, paraphrasing Clausewitz, violent conflict is indeed a continuation of politics by other means, a way of negotiating using the language of violence rather than words. The competing claim to the resource, which might be called an "incompatibility" (Wallensteen 2012: 15), lies at the heart of conflict, while its manifestation is violent action directed towards resolving the incompatibility in favor of either of the parties.

Bartering with weapons rather than words is almost always an inefficient way of achieving gains due to the extremely high costs of war (Fearon 1995: 383). Thus, prospects for negotiated peace should be present in almost any case. Central challenges to negotiations, however, include mutual distrust and suspicion, and faulty calculations about the prospects of military gain.

While decisive victory used to be the most predominant reason for conflict termination, it has been surpassed by other ways of ending conflict, and is now the least common category (Kreutz 2010: 246). This increase in peace agreements and ceasefires, negotiated endings, as a way of ending conflict makes it important to understand them.

At least in the case of civil wars, the way in which the war ends "greatly influences the duration of postwar peace" (Mason *et al.* 2011: 173) due to how different arrangements affect the post-war balance between the actors, and the desire to attain sovereignty (ibid.). A conflict is resolved when the parties to the conflict agree to a solution to their incompatibility, accept each other's continued existence as parties, and cease to use violent action as a means of negotiation (Wallensteen 2012: 8). In other words, conflict resolution involves a successful negotiation of terms that satisfy parties in the incompatible issue area. While victory and capitulation also end conflict, they do not necessarily resolve it.

Conflict resolution spans between a narrow and a broad conceptualization of peace; in the narrowest sense, conflict resolution is about ending violence, while in the broader sense, conflict resolution is also about creating justice (ibid. 11). This points towards the fact that resolving conflict does not simply mean ending it, but addressing issues and grievances, creating space for co-habitation between warring parties and securing the satisfaction with peace, compared with the prospects of war. Thus, while the end of violent action is a prerequisite for conflict resolution, it is not sufficient (Wallensteen 2012: 10).

The end of violent action can be brought about by a formal treaty, termed a ceasefire, defined as "an agreement between all of the main actors in a conflict that terminates military operations" (Kreutz 2010: 245). This is a prerequisite for traditional peacekeeping (Bellamy and Williams 2010: 173), which is primarily focused on

the cessation of violence and the facilitation of talks initiated by the parties themselves. The cessation of violence is obviously the most important part of conflict resolution (Wallensteen 2012: 9). A point of contention, however, is whether it is positive for the long-term prospects of peace, if a ceasefire precedes a more comprehensive, issue-resolving agreement between the parties.

A conflict with a ceasefire, but no issue resolution, might be called "frozen", in the sense that they are halted, but not resolved. Several "Frozen" conflicts attest to the persistence of issues that remain unsolved: DMZ lines separating warring parties, like in Cyprus and Korea, hold violence at bay, but might cement the dividing line between parties, certainly not facilitating negotiations and proper action towards solving the underlying incompatibility.

When talking about active involvement in ending conflict, it might be fruitful to distinguish between the concepts of conflict management and conflict resolution (Wallensteen 2012: 9). While managing a conflict by controlling the acts that constitute it might be both practically and morally necessary in many cases, management and resolution are not the same. While a conflict ends when it is resolved, and is thus managed, managing it does not necessarily mean that it is resolved. An interesting question thus becomes: How effective is conflict management, in a given case, in creating conflict resolution? In terms of interventions; when is it best to intervene, either to create lasting peace, or even just to avoid short-term atrocities?

Much scholarly attention has been given to the issue of how to understand the formulation and negotiation of claims on the part of the actors (notably Fearon 1995), while the effect and importance of simply ending the violence is more unclear. Many apparently have "strong opinions" (Wallensteen 2012: 45) about the merits of ceasefires, but a lack of empirical studies make them a persistently opaque phenomenon (ibid.).

Studying the "freezing" of conflict, simply committing to non-violent means while the cause for conflict remains is also an interesting case for understanding what essentially drives conflict; is it enough to simply handle the "symptom" of violence, or will the underlying "illness" of incompatibility manifest itself when ceasefires expire, are broken or declared void? While concrete actions constitute the conflict, some argue that they cannot be the sole focus if seeking a lasting resolution (ibid. 15).

1.2 Argument for ceasefires

There are several plausible arguments for why a ceasefire is an integral to building lasting peace. Achieving and enforcing a ceasefire halts the accumulation of further grief, makes the premises for further negotiation static and clear, and facilitates the inclusion of unarmed groups, which might be important actors when trying to reconcile and rebuild social trust.

Firstly, ceasefires are desirable for an obvious reason: They prevent further bloodshed and violence, saving lives and preventing devastation. While a mere ceasefire does not address the causes underlying the conflict, waiting for the issues to be resolved before stopping the violence might be morally unsustainable. It might take

a long time before parties reach an agreement (Mahieu 2007: 209); this period of violence might take a serious toll on the people affected by the conflict.

Secondly, ceasefires "lock" the conflict situation, making further gains or losses in using violent means impossible. This perhaps improves the prospects of negotiations, as the terms for negotiation are made less unpredictable: With a ceasefire, dramatic military gains cannot affect talks, which can proceed on clear terms. Clear public information reduces the probability of further violent action between two rational actors (Fearon 1995: 392), as the "transaction cost" of obtaining something through conflict is very high. Although ceasefires might provide clearer public information, however, they do not guarantee that furtive parties might still withhold information both about their capabilities, and their intent.

Thirdly, it is argued that the inclusion of non-armed groups in a peace-building process is much less likely before a ceasefire is in place (Wallensteen 2012). The violence deters anyone but those prepared to fight to resolve issues, which in turn demonstrably reduces the prospects for building robust peace (ibid.).

Fourth, unilateral ceasefires might be seen as signals of positive intent. Communication between parties through this kind of signaling is important for conflict resolution, because it can reduce mutual uncertainty. The more "costly" signals are, the more sincere they appear, and the stronger the effect (Fortna 2003: 344). Unilateral ceasefires show good will, perhaps also strength. Parties that announce that they do not have to fight desperately in order to win appear more amicable. Signaling that one is willing to forfeit further military gains, even exposing oneself to surprise attack, is surely costly enough to affect mutual trust positively.

1.3 Argument against ceasefires

While the immediate positive effect of a ceasefire gives a powerful incentive towards attaining and maintaining ceasefire in a conflict situation, conflicts are, as briefly discussed here, very complex processes. Balancing the short and long-term gains in terms of reconciliation and peace is important when seeking conflict-resolution, which makes it important to carefully assess the actions taken to establish peace.

Contrasted with sincere attempts at attaining lasting peace, the concept of "tactical pause" (Milton-Edwards 2017: 213) refers to a ceasefire based on tactical concerns, rather than a desire for further peace-building. The potential for ceasefires to be peace measures in disguise make them an ambiguous phenomenon. Mahieu (2007: 217) goes as far as to claim that he was unable to find only one case in which preliminary ceasefires were not "exploited by the parties to increase their preparedness for war".

Tactical ceasefires are driven by the interests of the military parties, to achieve zero-sum gains. If parties become militarily exhausted, and a stalemate is reached in the fighting, they might seek a ceasefire in order to recuperate and rearm (Wallensteen 2012: 45), and adjust strategies and tactics in relative peace (Schoon 2018: 492). Importantly, while these pauses might provide much-wanted relief for the civilian population, the recuperated and rearmed warriors might return in force, causing

much greater damage over the long run. Both decisive victory and holding out for parties to concede to negotiations, while being costly in the short term, removes the possibility of this kind of rearmed resurgence. The extension of conflict, increasing the overall toll of death and destruction (Mahieu 2007: 216), is important to avoid, but hard to anticipate.

A ceasefire becomes a kind of prisoners' dilemma, where both parties have incentive to defect (rearm and prepare for more conflict), but neither want both to defect as war is very costly. If they believe that sincere negotiations cannot provide them with the outcome they desire, or that the other party is likely in the process of "defecting", however, the chance of defection is high, as shown by (Mahieu 2007: 217). Fearon (1995) emphasizes the importance of this uncertainty, which arises when "one or more [parties] would have an incentive to renege on the terms" of an agreement for their own benefit.

1.4 Resolving the argument

So it stands that there are at least two plausible-sounding arguments about how ceasefires affect conflict. How do we determine which one is correct? Since all of these arguments can be formulated as falsifiable hypotheses, the answer is, of course, observing real ceasefires, and their effect on conflict.

What kinds of actors exploit ceasefires, and what kinds are more likely to be sincere in the pursuit of peace? Are there ways to tailor ceasefire interventions to specific conflict situations, factoring in the configuration of actors, their prospects, the conflict history, the development in the short and long term, and so on? These are all relevant questions for intevening parties seeking to establish peace (Mahieu 2007: 207).

By using granular, high quality data, it might be possible to answer these questions with some degree of confidence. Indeed, data collection must necessarily precede any serious effort to give general answers to these questions (Leng and Singer 1977: 92). The premise of data, given facts, lies at the base of any meaningful argument. While speculation, thinking that is based on logical deduction, is also a meaningful activity, at the end of the chain of deduction from which the argument proceeds must be some reference to the empirical world for the resulting argument to be interesting.

Data volume is desirable, as non-determinate interrelations can only be approximately observed through statistics performed on large numbers of cases. As a general rule, the less determinate the phenomena, the more data is needed (Richardson 1960 xvii). Useful data is not abundant, however. This is caused by multiple factors: Firstly, finding reliable documents and facts about war and conflict has always been very difficult. Large, complex and willfully opaque processes such as war will never become "favorable to the compilation of statistics" (Dumas and Vedel-Pedersen 1923: 21). Secondly, gathering high-quality data is a costly and difficult process.

War and conflict are certainly not simple determinate processes. Morgenthau (1948: 23) sardonically remarks that the empirical study of processes that are as complex as war and conflict is forfeit; there are simply too many factors that influence

outcomes, making the search for an objective, empirical science of war a fool's errand. This might be and overly pessimistic outlook today, however, as more and more raw data is being made available, and computerization is aiding researchers in gathering data.

1.4.1 Gathering data

The development of new sources of data is a very important factor furthering the development of theory: New data broadens the range of testable hypotheses (Salehyan 2015: 105), and spurs the development of theory in the wake of either refutative or confirmatory observation (Gleditsch *et al.* 2014: 301).

A salient example of this has been the development of the "tactical perspective" (ibid. 308) on civil war (Buhaug and Gates 2002). The correlation between geographically and temporally localized factors, such as natural resources, terrain and demographics and the outbreak of civil war is theorized, and partly demonstrated. However, the authors note that a strongly expected correlation, between rough terrain and conflict scope was not observed, likely because of "poor data" (ibid. 430). Further development of theory connecting localized factors with conflict patterns has been linked with the development of disaggregated event-data (Raleigh 2015: 87).

The perspectives on ceasefires discussed above indicate that there is a complex relationship between ceasefires and the conflict dynamic. The nature of this relationship, however, cannot be discerned without first making systematic observations, preferably of many cases of ceasefire. However, ceasefires have not yet been studied on the scale necessary for making robust inferences. Compiling data about ceasefires is a fundamentally important step towards better knowledge about them.

1.4.2 Challenge

If it is so important, why has data about ceasefires not already been created? This relates to two important facts about data creation: It is an expensive, and difficult process. As mentioned, data quality is paramount in such important contexts, but achieving good quality is extremely difficult, for several reasons. Frustratingly, data quality and cost are often mutually exclusive: To produce data of sufficient quality, more resources are needed in terms of hours spent coding, or spent developing useful tools and techniques.

Quality data relating to many interesting phenomena is, therefore, a scarce resource, a fact that determines the scope of scientific inquiry. This makes the development of techniques to remedy these two problems important, and is the motivation behind the work presented here.

How can the collection of data about ceasefires be improved by computerization? In the following chapters, I describe part of a pipeline through which raw information is transformed into data about ceasefires. The fact that this data does not already exist is testament to the great difficulty of conceiving and creating such data, as it is obviously needed, and would be a great boon for further development of theory surrounding the phenomenon.

Chapter 2

Data

The seemingly simple act of description in itself is perhaps understudied; some have even argued that the important process of data generation is one of the least developed skills in social science (Singer 1982: 212). While developing theories and formalizations of "mere observation" might not be the most salient of activities for social scientists, it is, arguably, the framework on which empirical study rests.

Being precise about what measurement is, how it is done, and what challenges are inherent in it, also makes it easier to see favourable similarities with processes such as statistical learning. This link is the foundation for the work presented here: The purpose of this chapter is to establish the theoretical background of the system that is presented in the subsequent chapters. By first describing what data is, and how it is made, I establish several formalizations that are used in the following chapters to describe a how computers can be applied to generated structured data.

While this chapter focuses on the basic definitions of data creation, the next chapter describes a specific process of coding data about ceasefires from newspaper data. While Holsti (1969: 94) emphasizes the importance of referencing some specific research question when discussing data creation methodology, I will nevertheless first attempt some nonspecific definitions of data, and the process of creating data, to ground the following discussion.

I will attempt to give some formal definitions of the component processes of data making, that will facilitate a structured discussion of the various kinds of data quality. The term "data quality" covers several aspects of how the data relates to the real world, and makes it possible to assess and compare different ways of producing data using a common standard. High quality is always desirable, but is very often difficult to attain. The core of my argument, and the motivation behind the work presented in the following chapters, is that the application of computers in data-creation makes it possible to maintain data quality while producing large amounts of data.

The nontrivial factor of cost is also a major driving factor behind automatization of processes in data collection. It was made clear in the previous chapter that important phenomena are also "data scarce", which prevents further study. This is in no small part due to the fact that the collection of high-quality data can be incredibly expensive and time-consuming. This makes the effectivization of data-collection a prerequisite for further development of theory and knowledge.

2.1 Definitions

A datum is essentially just a statement of something that was: An existential statement that refers to some state, condition or event that has existed Singer (1982). Datum is a Latin word, which originally means "a given". Data can thus be interpreted as "what is given" for an analysis, or rather, what is taken to be true; the premise for an argument. In this broad sense, any kind of perception or record, ephemeral or permanent, is data. Data is synonymous with information; perceived and recorded bits that refer to some fact, notion or state.

Reality, however, is an intractable mass of information, and the world is full of an infinite number of facts. When seeking knowledge about some particular phenomenon, it becomes necessary to make judgments about data relevance, to seek the "signal" in the "sea of noise" (Singer 1982: 196). This is called selection, and is the first of two necessary steps (Singer 1965: 69) from "raw" to structured data.

The next step is classification, or structured comprehension of the signal observations. In a sense, this is also a kind of selection process, as it involves choosing the set of *attributes* that will represent the phenomena: Once what we want to study has been defined, we also need to decide what it is about our objects of study that is relevant. A "data language", which denotes the relevant attributes and their significance, is the "Rosetta Stone" that mediates between the unstructured matter of raw observation and the structured matter of data (Krippendorff 2004: 150).

When combined, selection and classification of raw information creates structured data; a collection of bits of information that are curated and recorded according to a given set of procedures. This is a simplifying act (King *et al.* 1994: 42); some information is emphasized while the rest is discarded. This discrimination between signal and noise is one of the most difficult tasks in social science (ibid.).

The virtue of simplification, however, is that it facilitates analysis: Since the same procedures for structuring observations are applied to multiple cases, the resultant values can be compared in many useful ways. Data is purportedly connected to the world of concepts, and allows for structured reasoning, the testing of hypotheses and the observation of patterns relevant to the development of theory.

However, the "conceptual screening" (Singer 1965: 69) that is performed on raw information to produce data is certainly not neutral, a fact that in any case warrants critical assessment of data. Data should always be thought of as something more than mere facts: It is rather a combination of facts and scheme (Krippendorff 2004: 81). This means that auditing data, in terms of truthfulness and usefulness, is only possible through a detailed understanding of the scheme that links facts to structured data.

2.1.1 Data structure

Selected and classified observation make structured data: Information that has been registered according to a predetermined set of criteria. This is also a rather broad definition however; for the sake of simplicity, I will follow an influential definition of structured data that is more specific. This definition is attributed to Codd (1970):

Through what is termed the relational model, or relational theory (Date 2001: 5) of data, it is possible to define some basic properties and traits of structured data that serve as a practical foundation for further discussion.

The relational model states that structured data are organized into relations, which might also be called tables. A relation has columns, which Codd (1970) also call domains, and rows. Rows are distinct tuples containing one value from each domain. Importantly, columns hold a single significance, or meaning, representing some category or kind of information.

What is useful about Codds relational model of data, is that it emphasizes the relatedness of the observations *through* the information contained in the columns. This means that rows can be compared as similar but distinct instances having values in the same domains, meaning that they hold some value of information in the same categories, or rather, variables. The assumption of comparability and structured difference in terms of the variables makes the rows comparable: The relational data structure is a structure that, by design, facilitates comparative analysis.

The way in which the relational model facilitates analysis is clearer in the later specification of "Tidy data" (Wickham 2014), a special case of relational data that is further designed to easily yield itself to analysis. Tidy data is summarized through three principles that form a standard for how the semantics and the structure of data should be related (ibid. 4):

1. Each variable forms a column
2. Each observation forms a row
3. Each type of observational unit forms a table

The idea that observations can be seen as related through their traits requires an assumption of relatedness and difference. The segregation of observational units into separate tables (3) depends on the assumption of difference between the units, and the collection of values under a single given variable column (2) depends on the assumption of equality of the values in terms of the dimension that they express. In other words, the units are distinct, but comparable.

The reason for committing to this narrow model is analyzability, as Analyzability might be said to be the main motivation behind the difficult and costly enterprise of data-making in the first place (Krippendorff 2004: 146). While other kinds of structures, such as graphs or dictionaries are also analyzable, the readily analyzable form of unit-tables where the units can be compared in terms of a given set of variables is a useful ideal model to aim for when determining how the data should be structured before collection can begin. This makes the tidy model a useful point of reference when discussing both the merit, and the techniques of structuring data: While there are many kinds of structured data, I will only refer to the "tidy" tabular form in this thesis.

2.2 Making data

Scientific observation is, perhaps most of all, defined by systematicity. This is what sets data coding apart from "mere" observation. Coding, or "data-making" is thus defined as the application of rules to a set of observations. Furthermore, understanding the set of rules and the way they were applied is key to be able to reason about data.

Reasoning about data requires an understanding of both raw material, and the rules with which it was made. While a discussion of the raw information that is structured is specific to each data-gathering effort, data gathering schemes can be discussed more generally. Data creation can refer to a wide variety of methods, with the common element that information is recorded in some structured, predetermined way. The method applied in the following chapters is Content Analysis, defined as the systematic comprehension of *text* according to a given procedure (Holsti 1969: 5), but the terms and procedures discussed here are not exclusive to the analysis of text.

Adcock and Collier (2001: 530) discusses the relationship between concepts and observations in terms of four levels: From "background concept" to the application of indicators. These levels are linked by corresponding tasks, which link the world of concepts with empirical referents. Data making is the traversal of these levels in terms of the tasks: Conceptualization, operationalization, and scoring.

Conceptualization is a systematic formulation of some concept of interest (ibid. 529): The researcher starts with an interest in a "background concept" or domain, and must develop some systematic idea about how the concept is manifested in the form of empirical fact. Indeed, we must start with some idea of what we want to explain (King *et al.* 1994: 51), because we need to be able to discern between relevant and irrelevant facts about the objects we are looking at. This means that data collection is likely tied to the development of some theory about a concept or phenomenon of interest.

The outcome of data-making is the result of several acts that depend on prior assumptions; both the conceptualization and operationalization that define how the data relates to the realm of theory. While this is an inevitable fact about any kind of data; it must be handled cognizantly by those who admit the data in their analyses.

The codebook, instructions, coding guide or computer program used to process the raw information connects structured and unstructured data; linking the phenomena and the theoretical backdrop in which the data is framed. The creation of data starts with the definition of this material. Central elements are how the coding categories are defined, what the units of analysis are, and how the units will map to these to the categories (Holsti 1969: 94). This must all be established a-priori, before structured observations can be recorded (Neuendorf 2017: 18).

2.2.1 Truth and data

When discussing methodology, it is essential that key terms are disambiguated (Gerring 2008: 19). A potentially confusing term when discussing the process of data-making is "true". What might be helpful, is to discern between the "kinds" of truth

attainable through measurement:

The truth of some measuring procedure, given operationalization, or "test", is defined as the outcome of such a procedure administered to a given case exempt random errors of measurement (Allen and Yen 1979: 57). This truth is expressed by the concept of *reliability*. Deviations from this first truth are called "errors of measurement", and are assumed to be unsystematic. In this thesis, I will refer to this kind of "truth" as small t:

$$e := error$$
$$m := measurement$$
$$m = t + e$$

The *ideal truth* of the background concept, on the other hand, is what we approximate when we are conceptualizing, and reasoning about how and why to collect data (Adcock and Collier 2001: 531). How this kind of truth should be assessed, or even if there is such a thing as "ideal truths" about background concepts, are rather abstract questions which I will not go deeper into here: It should be said, however, that the collection of data is moot without properly defined analytical constructs (Krippendorff 2004: 89).

A third kind of truth in measurement might also be defined, relating to the term *validity*. Valid measurement means that each measure accurately reflects the concept as defined, or rather, that we are measuring what we are trying to measure (Adcock and Collier 2001: 529). In this sense, true measurements are not only free from random error, but are also a correct representation of the concept as defined.

The stages of truth might be thought of as hierarchical: It is not possible to attain a true measurement of a concept as it is operationalized, without attaining the truth of that operationalization. Similarly, it is not reasonable to think that one can approach the "real"truth of some concept as it actually is, without being able to measure correctly according to how it is understood. Put technically: Reliability is antecedent to validity, and validity is antecedent to "proper" understanding.

Holding the different kinds of discussion about the "truth" of a measurement separate is practical, as it also makes it possible to keep separate the discussion of validity, reliability, and the more foundational, philosophical arguments about the understanding of phenomena. Only the first two subjects are approached here.

2.2.2 Data quality

Considering the difficulty inherent in relating data to the truth of both a measurement procedure, and the intended concept, it should be clear that data-making is a process that involves both practical and conceptual challenges. Producing high-quality data, especially at scale, requires that much attention is put into developing the procedures and rules to be applied. Ensuring valid and reliable measurement is just as important as being able to produce data at scale: Without sound measurement, "big data" is nothing more than useless noise.

With more and more data being made available through the internet, being able to discern between good and bad data is of great importance (Simmhan *et al.* 2005).

Bad data corrupts and analysis or comprehension of it with false knowledge, yielding seemingly credible falsities. These "fake views" of the world are much more dangerous than other kinds of falsities in that they seem credible, and might yield themselves to statistical analysis that provides great rhetorical weight. "Cascading errors" is a term used by Chojnacki *et al.* (2012) to warn against the propagation of poor inferential quality from data to analysis.

Put simply; if the instructions are not public and explicit, the data cannot be admitted to an analysis with any degree of confidence (Singer and Small 1972: 14). If a researcher unwittingly admits data with errors, such as incorrect operationalizations, these errors "cascade", also affecting the result of any subsequent analysis (Chojnacki *et al.* 2012: 384).

Therefore, the single most important rule for data collection is to be diligent in recording details about the process and reasoning behind it, and to publish these details along with the data (King *et al.* 1994: 51). In fact, one might argue that the very idea of research "presupposes explicitness" (Krippendorff 2004: 81).

With open procedures, it is possible to carefully assess the quality of data. Data quality is often discussed using two key terms: Validity and Reliability. Together, the two measures are an expression of how well the data reflects whatever concept or idea. Valid and reliable data is data that accurately and reliably represents what it is purported to represent, and a prerequisite for any further meaningful analysis.

2.2.3 Measurement

Once the units of analysis and their attributes have been defined, and the schema of the data has been established, the process of data-making is a process of *measurement*. The term measurement covers the steps of *operationalization* and *scoring* (Adcock and Collier 2001: 530).

The classic definition of measurement is that it is "assignment of numerals to objects or events according to rules" (Stevens 1946: 677). While the term "numeral" might seem equivalent to "number", it might also simply mean "symbol" (Kerlinger 1973: 427): A numeral might hold quantitative meaning as a number, but can also simply serve as a label, like the numbering of football-players or billiard balls. Thus, measurement can either be a process of labelling or quantifying some phenomenon; the core process of data collection.

Measurement is a structured process, which is done according to a scale, which must be defined in advance. This means that what is observable is pre-defined as a "range"; a space of possible outcomes. Measurement, then, is a process of mapping a set of observations, termed the domain of the measurement, to this range, according to some given procedure, or "rule" (Kerlinger 1973: 428).

Measurement is analogous to the application of a function; the rule is a function of the observations, and produces a given range of outcomes. Firstly, A is defined as a given range, or "scale" in which the measurements will fall, or rather, the range of possible measurements as defined by the measurement scheme. I is a set of n length, $i_1 ... i_n$, that contain the attributes of a unit u. f is a rule for mapping these elements

to the scale A:

$$t_u = f(I_u) \tag{2.1}$$
$$t \in A \tag{2.2}$$
$$f(I_u) : I_u \to A \tag{2.3}$$

When talking about "real world" measurement, however, an important addition is needed to complete this formalization. A given measurement will, in any case, contain stochastic error, or e (Kerlinger 1973: 446). The error term, contains any kind of disagreement between what "should" have been measured, according to the rules of the measurement procedure, and what was actually measured. A more realistic formalization of the process, then, is:

$$g(I_u) = f(I_u) + e \tag{2.4}$$
$$m_u = g(I_u) \tag{2.5}$$
$$m_u \in B \tag{2.6}$$
$$g(I_u) : I \to B \tag{2.7}$$

The function g includes an error term, while the range of outcomes of g, B is a subset of the range of "true" outcomes on the scale A, meaning that the error term cannot make the score exceed the scale.

The properties of e under classical true score theory (Allen and Yen 1979: 56) are:

$$E(e) = 0 \tag{2.8}$$

Which means that the expected, or mean value of e is zero, and thus that the expected value of m is $f(I)$ (2.12) (Allen and Yen 1979: 57). This means that the measurement will, despite some variation, be a reasonable approximation of what we are trying to measure.

Whether this assumption holds for a given scheme, however, is an important question: Whether what we are trying to measure is actually what we are purporting to measure relates to the validity of the procedure.

Indication

What is measurement performed on, or rather, what does the set I contain? The question of what we actually observe when we attempt to measure some concept relates to the idea of indication, and a discussion of what validity and reliability is, and how to achieve them, starts with an account of how measurements relate to, or rather indicate the concepts we are trying to measure.

In general, we can say that measurement necessarily involves some kind of instrumentation, or medium. The distance between the observer and the observed phenomenon can vary greatly; from measuring the current temperature through a wall thermometer to measuring the level of discontent among the Russian working class in 1916, or the number of casualties that occurred during the battle of the

Somme. Obviously, the latter measurements are a great deal further removed from the actual phenomenon that is measured, than the former.

Whatever the distance, however, measurement is always done through indication; the observation of phenomena thought to be associated with the actual phenomenon of interest (Kerlinger 1973: 431). While temperature might be the object of a measurement when using an old thermometer, it is not directly observed; only indicated by the expansion and contraction of quicksilver, which is known to be correlated with temperature. Similarly, the phenomenon of war might be thought to be indicated by a given number of battle deaths, as is the case for the UCDP armed conflict data set (Gleditsch *et al.* 2002).

The activities, or "operations" deemed necessary and sufficient for observing a sought concept is called the "operationalization" of that concept (Kerlinger 1973: 432). The operationalization is related to the set I. Importantly, a concept can usually be operationalized in various ways, and the various operationalizations might vary both in their precision and reliability, but also in their accessibility and practicality.

Validity

The way data relates through real phenomena is through the "bridging" concept of indication. In this view, data is a bridge between an observed phenomena and the purported concept through an indicator. If the indication is sound, the measurement is "valid", meaning that we are actually measuring what we are trying to measure (Adcock and Collier 2001: 529). The term validity can be thought of as the soundness of the bridge between the observed phenomenon, and the referent world of concepts that we are seeking to observe (Singer 1982: 191).

The argument that a given indicator and operationalization is a good, or "valid" way of producing measurements of some concept must be thorough, and this is increasingly important the further away from the object the observer is. Like all other causal relationships, indication is hypothetical, a process of *inferring* from indicators to concept (Adcock and Collier 2001: 531). The argument behind the choice of operationalization must be sound, as it is the foundation of the validity of the data. Evidence put forth to support this hypothetical relationship between scores and indicators must be made clear.

A correspondence between a given measurement procedure and the "real" truth about some concept is termed the "isomorphism" between the procedure and reality (Kerlinger 1973: 431). Interestingly, this trait is not a part of the formal definition of measurement. Measurement without any assumptions about the truth value of the scores, as in 2.8, is simply a "game", its rules are only that some class of phenomenon should be mechanically mapped to a range of outcomes. Whether the game is played with rules that make sense in the real world is an entirely different question (ibid.), but it is of course of the utmost importance when making sense of the data.

When developing an operationalization, a balance must be struck between being specific and accurate, and including enough relevant cases (Sundberg and Harbom 2011: 92). There is always a tension between being too specific and too general. While the former means omitting cases, the latter means including too much.

The degree to which an operationalization is conceptually sensible is not easily verified. How can we be sure that a measurement procedure is well-defined, that $f(I)$ is a sound enough bridge between indicators and concept? In other words, how can we be sure that we are measuring what we are purportedly measuring, and producing valid data?

A way of reasoning about validity is through comparison with other measures. So called a measure can be validated by criterion, or rather, by comparison with some other, purportedly related concept (Allen and Yen 1979: 97). Given a set of measurements M' and M'', that supposedly measure the same thing, but are created using different measuring procedures, the variance of the two sets can be thought of as being composed by two component variances, *co* and $sp. The *common* variance *co* is the variance that is caused by a conceptual commonality between the measures, while the *specific* variance *sp* is specific to each measurement procedure (Kerlinger 1973: 470). A theoretical measure of validity, Val, is then defined as:

$$Val = \frac{co}{co + sp} \tag{2.9}$$

This measure can be reasonably approximated by comparing M' and M''. While such a comparison might be a reasonable, indeed compelling piece of evidence for the validity of some measure, especially given an established and trusted criterion measurement procedure (Adcock and Collier 2001: 537), it is, of course, not necessarily sufficient: Like all hypotheses, validity must be thoroughly and exhaustively argued, and can never be decisively proven. Laying bare the argumentation is necessary to enable conscious use of the data, again emphasizing the importance of openness.

Reliability

While considering validity is complex, indeed philosophical, Reliability is more easily estimated. The "reliability" of data is a measure of the extent to which repeated generation of the data using a given procedure would yield the same results. Although reliability is conceptually "simpler", it is antecedent to validity. A discussion of validity is moot without sufficient reliability: This is because validity is concerned with the conceptual meaning of $f(I)$ in 2.11, and if e dominates f in 2.4, validity is moot. An associational measure of reliability (Allen and Yen 1979: 73) can be defined as:

$$\rho^2_{mt} \tag{2.10}$$

Errors made in performing the measurement, recording the results, or during other related procedures generate e – error – and thus weaken the correlation between what "would have been" the score from the test proper, exempt these errors. Of course, the true score is not observable in itself. If it was, we would have simply used that for our measurement and avoided the e. In practice, however, we must assume that our measurements always contain some error. Further paraphrasing the definition of measurement within the framework of classical true score theory (ibid.), we expand

the formalization with the following:

$$E(m) = g(I) \tag{2.11}$$
$$E(e) = 0 \tag{2.12}$$
$$\rho_{em} = 0 \tag{2.13}$$
$$\rho_{e_1 e_2} = 0 \tag{2.14}$$
$$\rho_{e_1 m_2} = 0 \tag{2.15}$$

These are assumptions about how the measured true score relates to the other terms (Allen and Yen 1979: 73). 2.11 states that the expected value of a measurement is the result of the measurement procedure, and that the expected error is 0 2.12.

This is not the same as saying that the expected error is small, only that its mean value will be 0; $Var(e)$, the magnitude of error, cannot be assumed to be small or big. Assumption 2.12 does make it clear, however, that the true score t_u can theoretically be uncovered as the mean of an infinite number of independent, parallel measurements.

What generates random error, or rather, deviation from the procedure f? In practice, scores will be reliable if the collection is done strictly and precisely according to the rules laid out beforehand. Put formally, this would mean that $f(I)$ is followed strictly in 2.1, without admitting any additional variance.

Reliability increases or decreases as a function of the complexity of the coding rules, and the vagueness of the phenomenon being measured (Sundberg and Harbom 2011: 99). Simply put; the easier it is to measure a variable correctly, the more reliable measures will be attained. Reliability is affected by the "clarity, explicitness and precision" of the instructions (Singer 1982: 194); the less ambiguous the rules are, the more reliable the outcome will be.

If something is left implicit in the coding instructions for example, or if the observational matter is so complex or diverse that it cannot reasonably be "encapsulated" in the measurement scale, the measurements will be less reliable (Douglass and Harkness 2018: 192). When clerks assigned with collecting data encounter ambiguous situations where common sense must be applied to resolve between categories, or to determine the inclusion or exclusion of an observation, the decision made is not made within f, and thus creates an additional source of variance (Stone *et al.* 1966: 62).

However, it is important to be aware of the fact that simpler and more rigid rules will very likely result in less valid data (Sundberg and Harbom 2011: 99), especially in cases where the material to be structured is inherently complex, or ambiguous. A balance must be found in every case.

2.3 Computerization

A useful insight that is gained from the formalization of a data-making process as being a process of mapping inputs to some output using a pre-defined procedure is that data making is a process that is favourable to automation. Computers, unimaginative

and diligent, excel at performing such routinized operations, and have been considered for such task since the very early days of electronic computing (see Hunt *et al.* 1966).

Data quality largely depends on the definition and execution of the data-creation process. This raises the question: Do some approaches to data-creation inherently lead to higher data quality? Comparing approaches in terms of data quality reveals that there are salient differences that might greatly affect the quality of the data. In addition, practical differences, such as the time and resources per data point, are also important.

I will argue that computerizing a data-making process, that is, using a computer to perform part of, or the entire process of transforming information into structured data, will improve data quality, especially when compared to data-production processes involving human judgment as part of measurement process. I will attempt to demonstrate this in the final chapter of this thesis.

There are three facts about the way computers operate that drive this improvement in data quality: First, computers follow given algorithms unerringly. Second, computer algorithms can be scrutinized and reproduced post factum. Third, algorithms are executed extremely quickly.

2.3.1 Reliability

The measurement part of data-making is a schematic process of applying instructions to a given set of indicators to produce data. While it is certainly possible to perform high-quality coding using human coders, who follow instructions when comprehending information material, "coders are humans even when they are asked to act like computers" (Krippendorff 2004: 127). Human error is inevitable (Cioffi-Revilla 2017: 103), and is, as mentioned, exacerbated by complex and ambiguous instructions. The error-inducing effects of fatigue and boredom that arise from protracted coding of large amounts of data (Salehyan 2015: 108) are also avoided when using computers rather than people for the repetitive task of applying instructions to raw data.

When a computer applies a procedure to some raw data, the procedure is executed unerringly, yielding results with no random variation. This is a crucial difference between the way computers and humans cognize: For better or worse, humans inevitably err when following instructions, while the reliability of the execution of a computer program is nearly absolute (Stone *et al.* 1966: 12).

The fact that computers are thorough and unimaginative in performing tasks, while not making them particularly suited for developing typologies or reasoning about complex ideas, makes them ideal when it comes to the repetitive application of instructions. As I have shown here, data creation involves both kinds of reasoning; the development of concepts and operationalizations, and the schematic observations according to the operationalization. The latter task is ideally suited for automation, since it should involve little to no further abstract reasoning.

Traditionally, reliability is affected by the complexity of the coding instructions; the easier something is to measure and code, the more reliable the data will be (Sundberg and Harbom 2011: 99). Complex instruction that demand much of the coder creates fatigue, and the need for commonsensical disambiguation creates bias.

These "fluctuations" do not, however, enter into the process when a computer is used (Stone *et al.* 1966: 12).

For a computer, simple and complex instructions are equally difficult to execute, but not equally difficult to define. When using computers to code, one might say that the difficulty of measuring something instead affects the resultant validity, or rather, the chance of measuring a concept correctly. The development and scrutiny of the coding procedures, or rather the operationalization, for a computerized data-making effort, is very important.

2.3.2 Openness

While the schematic part of data-creation is suited for computerization, it is important to emphasize the importance of human intelligence in defining and managing the data-generating process. The importance of mindful and correct definitions and operationalization does not diminish with computerization, but arguably becomes even more important, as the volume of data that can be produced and disseminated is greatly increased. Thus, with the opportunities for creating vast amounts of data, ensuring operational validity and discussion about the concepts that underlie the data becomes extremely important.

While a justified critique of automated methods of information extraction is that they tend to sacrifice validity for high reliability (Bratberg 2017: 120), I would argue that the combination of efficiency and openness inherent in computing could rather facilitate the development of more valid, and importantly, validateable measures, since they allow for a much more detailed level of critique of data-creation projects:

While computers cannot help in defining correct operationalizations and conceptualizations, the fact that the operationalizations must be explicitly detailed (Stone *et al.* 1966: 12), and might also be made open, means that mindful use of data is made easier. The computer will not help with the development of operationalizations, but the detailed scrutiny of the operationalization, or even testing the effect of different operationalizations on the resulting data, and conclusions drawn from such data, might contribute positively to such discussions. This is made easier when coding with computers, since in addition to being open, the application of the procedures is extremely cost-efficient.

2.3.3 Resources

The running costs of a computerized data collection effort, both in terms of time and money, are very low. While the initial investment in hardware and in the development of software might be substantial, the result is extremely efficient. This has two important implications: Firstly, more data can realistically be produced, no longer limited by arbitrary financial boundaries. Secondly, data can be coded and recoded extremely quickly, making it more feasible to assess a given operationalization by comparison.

Experiences with automatic coding have shown substantial cost reductions: According to calculations by Schrodt and Van Brackle (2013: 26), coding 3 million

data points from 26 million records with the TABARI automated coder takes about 6 minutes, while the same work would require about 500 000 man-hours of manual coding. While the development of TABARI took a substantial amount of time and resources, once it is designed, the inclusion of new source material, and the continuous production of near real-time data is possible.

Chapter 3

News and conflict data

The system described in this thesis was written to assist coders in creating a structured data set based on newspaper text. The goal of the project is to create a comprehensive tabular data structure representing ceasefire episodes, defined in terms of a beginning and end date, and signatory parties. To create this data set, coders have to process enormous amounts of raw text. Thousands of news articles, filtered as containing some mention of ceasefires are downloaded per country, and must be read through in order to find the relevant information: When, where and between whom ceasefires have been signed.

The system that was designed and tested here assists the coders, by doing a first pass over the text data, rating each sentence in the newspaper articles as either relevant or irrelenvant for future coding. This first pass is meant to alleviate the information load on the coders, and speed up the process of converting thousands of raw reports to a handful of ceasefire occurrences. In formal terms, it is assumed that each message unit x has a hidden value y, denoting its relevance. The purpose of estimating y is to solve the "haystack task" (Hanna 2017: 7); the preselection of relevant documents that are likely to contain information that is deemed interesting or relevant for further information extraction.

In each case, the estimation of a hidden variable depends on some knowledge about the characteristics and idiosyncrasies of the kind of raw data one is working with. Working with text warrants a discussion of how its observable traits can be said to relate to unobservable information, and what processes affect this translation. In addition, the production and dissemination of text as an information source makes it necessary to be critical, and not blindly accept relayed information as true, even if it is presented as such.

3.1 Working with text

Text is not an unusual source of information for data collection efforts in political science: While many kinds of unstructured data might be interesting for political science research, the most relevant information is often expressed in the form of text. Language is central to the study of political conflict as the traces of political processes

are most often found in the form of language expressions (Grimmer and Stewart 2013: 1). Thus, the "raw material" of much of the coding work in political science is text.

This has also been the case for several successful efforts to gather event data and conflict data, from the very first such data sets (McClelland 1961), to later, large scale efforts utilizing computer coding (Schrodt *et al.* 1994; Hanna 2017; Osorio and Reyes 2017). Gathering facts about events at scale, seems to be best approached through the mass-analysis and coding of news data.

While text is often a useful source of information, the information it is meant to convey is nontrivial to extract. Furthermore, there are often issues of completeness and credibility, related to the sources of text. A third specific problem of text which is perhaps especially salient when using automated methods is the stochastic process through which information is conveyed using language symbols. All of these elements of data creation that proceeds from text are discussed in this chapter.

3.2 Text and information

Content analysis is the structured analysis of the content of language expressions (Stone *et al.* 1966: 5), also simply defined as the transformation of text into data (Holsti 1969: 2). Such analysis involves the collection and structured, systematic comprehension of text in terms its content. The assumption that lies at the heart of content analysis, is that it is possible to discern a meaningful picture of the *content* of a *message unit*, by examining its manifest features (Hunt *et al.* 1966: 151).

A message unit (Neuendorf 2017: 21) might be a document, a sentence or a paragraph, or some other conceivable unit of expression. A message unit contains language symbols; an expression of information that is a combination of the symbols and a language syntax. Together, the ordered symbols convey information, through their semantic relationship with meaningful concepts (Pustejovsky and Stubbs 2012: 12).

Systematically recording the semantic content of message units might variously be termed a process of description (Stone *et al.* 1966: 11), labelling (Pustejovsky and Stubbs 2012: 40) or information extraction (Benoit *et al.* 2009: 495). Although, while it might be philosophically interesting to discuss whether a text can be said to *contain* the information sought in any given case, warranting the use of the term "extraction", or whether the information only arises as a *combination* of what the observer expects, and what is contained in the text, warranting the use of the term "labelling", I will not go further with this discussion here. For the sake of parsimony. I have opted to use the term "extraction" throughout, which may also be taken as synonymous with "labelling" and "description".

The information to be extracted from each unit is the saliency for further coding, or rather, the relevance to a coding task. This information is initially unobservable: There is no given language symbol, present in every such relevant sentence, that will discern between relevant and irrelevant sentences. Instead, the basic assumption is that the information that the author intends to convey through a given text affects the symbol content of the text (Hunt *et al.* 1966: 159). The task, then is determining

how, or rather, estimating the function f that maps the set of symbols I to the variable y, which is the degree to which a sentence expresses information that is relevant to the coders.

To give a naïve, but clear example of how such a function might work, consider the sentences:

```
a <- "A ceasefire was declared at 20:00 this evening."

b <- "No ceasefire has been declared yet"
```

These sentences contain letters, which make up words, that are linked by syntax to form meaningful sentences. A useful starting point is to consider the sentences as sets of word-symbols:

```
[1] "A"         "ceasefire" "was"       "declared"  "at"        "20:00"
[7] "this"      "evening."
```

A human will easily be able to sort these two sentences as being either "relevant" or "irrelevant" when collecting data about the start of ceasefires. Sentence `a` contains a clear reference to the start of a ceasefire; while supplementary information must be collected to ascertain which parties were involved, it is clearly relevant. Sentence `b`, on the other hand, would not be relevant for coding the start of a ceasefire, as does not point to an event of interest. Given the task of sorting these two sentences as either "interesting" or "uninteresting" to coders on the basis of the set representations, sentence `a` will be labelled as `i`, and sentence `b` will be labelled as `u`.

What function $\hat{f}$ will effectively discern between sentences of type `i` and type `u`? From our meager "training" set we might infer a naïve decision rules that constitutes a mapping procedure from a given sentence to the information we seek. In pseudocode, this procedure might look like this:

```
f <- evaluate(sentence):

   if sentence.verb.conjugation is 3rd_singular_past:
      sentence is "i"

   otherwise:
      sentence is "u"
```

However, it should be clear that this procedure is entirely inadequate. A simple negation of the past participle "declared" in sentence `a`, while not changing the outcome of f, changes the semantic meaning of `a`:

```
a_neg <- "A ceasefire was not declared at 20:00 this evening."
```

This brief account shows that relating text symbols with manifest information is obviously quite complicated in most cases, as symbols or systems of symbols might

reasonably be related to several kinds of information at once (Bryder 1985: 24). The fact that there is no theory that can deterministically map the symbols of language to the information we seek makes the extraction of information from text a significant challenge: When something is expressed through language, there "is no theory to tell us what words will [necessarily] be used" (Stone *et al.* 1966: 10).

Instead, a given piece of information can be expressed through a very large number of distinct, conceiveable texts (Benoit *et al.* 2009: 497). Simplified, we might think of this as a process where the relayed information is altered by two stochastic processes; the process of formulation, and the process of interpretation. A given way of formulating a given piece of information, combined with a given scheme for interpreting this text, yields a piece of information that has been relayed through several potentially error-generating processes (Benoit *et al.* 2009: 498): Formulation, expression and understanding.

In other words; an author might not express the information clearly, and a reader might not properly understand the text. What this means in our case, is that there is no theory that could deterministically specify f. This is because, in formal terms, the function "generating" text from y, is partially stochastic, at least in practical terms.

The error term, or rather, the specific variance of each case must not be "included" in our function. This would lead to an "overfit" function, that will generalize poorly, due to the fact that random noise is used as information, rather than discarded. When estimating $\hat{f}$ in the following, avoiding such overfitting is very important.

3.3 Sourcing

The ceasefire dataset in production might aim to cover all ceasefires between 1989 and 2018. When considering how the data is collected, however, it becomes clear that this is not an entirely realistic assumption. It is very important to have an understanding of how text relates to the real world when using it as a medium to extract "real world" information (Oberg and Sollenberg 2011: 61). Problems of source coverage, and credibility, are unavoidable when coding from relayed information. These problems have been discussed since the very first data collection efforts in war and conflict research (Dumas and Vedel-Pedersen 1923: 21), and are arguably exacerbated in the age of massive flows of information from a great multitude of different sources.

Using a source rather than observing directly means that an intermediate element is present between the observer and the "real" world. An important question then becomes: Is the object of analysis, in this case episodes of ceasefires, accurately covered? Are some objects omitted from coverage, and is this done in a random or systematic fashion? Understanding how information is filtered through second-hand sources is important, because it has substantial effects on what the data can validly purport to be a representation of.

Using relayed information is ultimately a matter of trust. An important fact about trust is that it is transitive; if one is relying on information that is relayed through more than one link, for example in a newspaper article relating official reports of eyewitness accounts, one is essentially trusting several sources at once. A formalization

of such trust-chains in the concept of "data provenance" by Huang (2018: 2189) shows formally trustworthiness decreases significantly when these chains are long, and data is far-removed from the facts which they purportedly express. On the other hand, corroborating facts through several chains of trust increases trustworthiness.

Historians similarly distinguish between primary and secondary sources. Secondary sources are not as useful as primary sources for the same reason; they demand additional trust on the part of the recipient (Dulic 2011: 36). In the case of ceasefires, what is sought is essentially information about the actual events that constitute the ceasefire. Whether the source presenting such information was present when such an event occurred, or is relaying information from a correspondent, a local newspaper, a participant or a witness, affects the trustworthiness of the information. Journalists writing articles might sometimes be primary sources, but are mostly reiterating information they have received from third parties (Oberg and Sollenberg 2011: 49).

A basic assumption for collecting information relayed through text is that there is a "real" distribution of the phenomenon of interest, and that the relayed information will yield a subset or superset of this "real" distribution (Woolley 2000: 157). The underlying "true" distribution of objects is assumed as the set O. This set contains all the observations that are relevant to our data collection effort, or rather, that are covered by the typology. Another way of thinking about this is that O is the set of observations that "should" be available to us when coding data. However, what is conveyed in the source material, S, might either be a subset or superset of this true set: We might only be able to observe some true events, or we might observe reported events that did not in fact occur.

In the first case, $S \subset O$, it is important to reflect on the kind of selection that occurs when the distribution of true events is conveyed through source material. What determines whether something is reported? Only a small fraction of the events that happen on a given day end up in newspapers (Oberg and Sollenberg 2011: 53). When using certain source, it might be necessary to concede that its biases are imparted on the resulting data. Data that is produced using newspaper data, for example, will inevitably be more "newsworthy".

Newsworthiness can be defined in many ways, depending on the kind of information. In the case of protest events Wueest *et al.* (2013: 5) identifies three main factors: Firstly, violent and confrontational protests are more often reported than peaceful ones. Secondly, Events that are geographically closer to the offices of the agency are more often reported than distant ones. Thirdly, protests about issues or concerns that "resonate" more with general or salient concerns are more likely to be included.

In the case of conflict events, newsworthiness is also defined in terms of violence, and location. In addition, the feasibility of reporting creates a substantial bias: If a conflict area cannot be safely approached by reporters, its constituent events will be under-reported (Oberg and Sollenberg 2011: 55).

Inevitably, the target audience of a publication also governs what gets reported (ibid. 57); news producers are not always altruistic in their motives, but also exist to make money. If the audience is not interested in some particular conflict or area, it will receive less attention, because it will generate less revenue. This factor is magnified

by the fact that it is now possible for news agencies to gather detailed statistics about what gets read online, in terms of the number of views and the average time spent reading each article. Of course, the actual distribution O is not observable, and it is not possible to assess the true "completeness" of S (Wueest *et al.* 2013: 5).

Multi-source corroboration is an important way of handling source bias, however. Checking multiple sources, preferably sources with different geographical origin and political slant (Hanna 2017: 4) makes it less likely that the data will be seriously biased in one or the other direction, making the issue of source bias more manageable (Wueest *et al.* 2013: 1).

Corroboration, of course, will probably make it necessary to "merge" different accounts of the same "real" events, lest the set S will contain multiple observations that are in fact different "views" of the same entities in O (Huang 2018: 2186). If this issue can be handled efficiently, though, corroboration increases the chance of observing more of the units in O. Corroboration might also single out events that seem unlikely to be real, and thus increases the validity of the data: If an event is, for example, only reported by one less credible source, it might be flagged as less credible than if it was reported by multiple sources (Dulic 2011: 41).

In practice, however, data collectors have often had to focus on subsets of the raw material to code, which increases the chance of bias (Wueest *et al.* 2013: 7). This is due to issues of cost: With the enormous amounts of raw data available, several quintillion bytes of raw data produced each day (Cioffi-Revilla 2017: 103), attempting to extract data from everything at once is hardly possible for "traditional" coding efforts. Subsetting by excluding some sources of data, like certain newspapers or certain regions makes the "universe" of raw material more manageable, but less representative.

Ultimately, source bias must be accounted for in the typology. A data set generated on the basis of information relayed through the media will be a dataset of "newsworthy" information, even when corroborating the information through multiple news sources. For example, both the event data typology designed by Azar (1975: 2) and Leng and Singer (1977: 3) accounts for this explicitly, only purporting to cover *newsworthy* events, rather than *all* events. When this is explicitly stated, further analysis can account for the bias, rather than assuming that one is working with a representation of the full universe of events. A further delimitation of the unit of analysis is caused by the fact that only english-speaking media have been analyzed when creating the present data set.

However, the fact that ceasefires are deliberately publicized events is remedial when it comes to source problems. Events that are wilfully obscured, such as war crimes, will obviously be more seriously affected by source biases that ceasefires, which are announced publicly, and depend on mutual acknowledgement. This means that while sourcing problems are worthy of serious consideration in any case involving information extraction from relayed information, it might be considered less of a problem in the present case.

Chapter 4

Data methodology

The methods used to estimate functions that map attributes to outcomes in the following are based on supervised learning. Supervised learning is a clade of techniques within machine learning that are distinguished by the fact that they estimate functions on the basis of known attribute - outcome relationships. What this means is that the outcome function is based on an observed relationship in, preferably, many cases. This set of cases that "trains" the model forms the basis of the models' performance.

Producing training data means manually coding as much raw data as practically possible. Again, the quality of coding is extremely important: The validity of outcomes generated by the resulting function is directly linked with the validity of the manual labelling of the training data. This is because the function is an extrapolation of the relationship observed in the training cases: the quality of the training data thus determines the quality of the outcomes produced by the function. In addition to training, classifier testing must also be done on labelled data. This means that sufficient data must be developed, so that it can be separated into testing and training partitions.

In this chapter I describe the origin of the data used in the following chapters, as well as any selection and transformation procedures applied before classification. This makes it possible to make an informed assessment of the veracity of the results of the classification process, by examining the extended chain of information down to the source. In addition, the validity of the outcomes produced by the procedures in chapter seven is linked to the validity of the coding rules used to produce the data presented here.

4.1 Sourcing

The data used here was gathered from a variety of news sources through the news aggregator Factiva. This dataset is referred to as a "corpus"; a "collection of machine-readable texts that have been produced in a natural communicative setting" (Pustejovsky and Stubbs 2012: 19). The foundational corpus, which forms the basis of the data used I this thesis, is thus the entire Factiva database, consisting of millions of news articles from over 28 000 news sources (Oberg and Sollenberg 2011: 65).

The Factiva documents I had access to were downloaded in the context of a coding project, specifically for the task of coding ceasefires. These documents were pre-filtered using a search string, in order to facilitate the coding job, and all contained references to or mentions of the concept of ceasefire. This means that an initial pre-selection of the Factiva database was made, leaving only articles that contained one of several phrases referencing ceasefires. The documents were downloaded per-country, representing a second pre-selection. This was done to assist coders, as they worked on one country at a time. I selected documents from 19 countries whose PDF-files had been processed by human coders. This yielded 752 files containing approximately 100 news articles each.

The documents were in PDF-format, and had to be transformed into plain text for further processing. This was done by using command-line tools from the Xpdf-utils utility set. Text was extracted from documents containing the news articles, and split up into sentences. Finally, I performed a pre-filtering of the data, only including sentences that matched with this Regular Expression:

```
([Cc]ease-?fire|[Tt]ruce|[Aa]rmistice)
```

This resulted in a corpus of 111 965 sentences. A table showing the raw distribution of sentences and ceasefires for each country included in the analysis can be seen in the appendix (table 1). The number of ceasefires was retrieved from a dataset that is in production at PRIO / ETH.

The choice of sentences as the unit of analysis is based on an assesment of the practical value of the predictions. Text is essentially a stream of information, that can be unitized in many different ways. Defining a beginning and endpoint of each unit means demarcating this stream into separate units of analysis (Neuendorf 2017: 72).

In this case, the choice of sentences rather than paragraphs or whole news articles is based on two considerations: Firstly, the choice of whole articles would have been too coarse: An article might mention several ceasefires that have occurred, or might be exceedingly long, reducing the benefit of the pre-classification. Secondly, the choice of paragraphs, which might have been more ideal since it is a good middle-ground between the length of an article and the precision of a sentence, is difficult from a technical standpoint. Due to the way the articles are extracted from the source material, insufficient formatting information is retained. This means that the next feasible level of unitization below document-level is the sentence level with the present system and source materials.

4.2 Labelling

Supervised learning requires pre-classified data. This pre-classification will essentially outline the decision rule which is to be mimicked by the computer, and is vitally important to ensure good performance from the classifier, as no amount of statistical trickery can produce a good classifier from poor training data (Grimmer and Stewart 2013: 10). The estimation of these procedures are described in the following chapter.

The sentences were manually labelled as being either relevant or not irrelevant for the ceasefire-coders; 1 and 0 respectively. This means that while all the sentences used to train the model contain either the word "ceasefire", "truce" or "armistice", the model will be trained to discern between sentences that describe ceasefire violations, ceasefire discussions or other kinds of circumstances, and sentences that describe ceasefire announcements and the signing of ceasefire deals. This distinction will make further information extraction easier, since the coders are guided towards what is considered relevant.

I used two different strategies for pre-filtering sentences, before manually labelling them. These strategies were aimed at reducing the time needed to label, by increasing the probability that I would observe sentences of the respective class:

The first such strategy, focused on producing positive sentences, started with the dataset in production at the Peace Research Institute of Oslo (PRIO) and ETH Zürich. Data collection was done by several research assistants at PRIO and ETH Zürich during the fall of 2018 and winter of 2019, The assistants used the exact same collection of PDFs that were available to me. A column in this preliminary dataset contains "evidence text", a sentence or text snippet from a newspaper article. This text explicates the link between the text source material and the indicated ceasefire; this makes the sentences useful raw material for training the algorithm to recognize text that indicates the phenomenon of interest. This pre-selection yielded around 500 sentences.

The second strategy, focues on collecting negative, irrelevant sentences started with the entire corpus of news articles. To pre-filter the corpus before manually labelling the negative sentences, I attempted to filter out sentences referring to the ceasefires already retrieved from the ceasefires dataset. I used sentences from articles about the countries that had already been processed in the partial dataset used to retrieve the positive cases. The sentences from the articles gathered from these documents were then temporally filtered so that they did not overlap with any of the known ceasefires in each country within a period of one year. This reduced the chance of seeing the same sentences as I had seen when coding the positive cases.

The relevant sentences were labelled so that only sentences that unambiguously describe or indicate the start of a ceasefire get a value of 1. Even sentences that express strong intent from an actor towards signing a ceasefire, or a commentary assessment that gives a high probability of a ceasefire, are labelled as 0. This rule is based on the fact that the ceasefire-coders are attempting to capture actual events post factum, rather than intentions, and interpretations of circumstances. The negative sentences are in this sense negatively defined as those sentences that do not describe or indicate an actual event; speculation, discussion, and calls for ceasefires are all termed "irrelevant".

This resulted in 3067 sentences, with 979 sentences labelled as "interesting", and 2088 labelled as "uninteresting". 10 percent of these sentences were put aside as a "holdout" dataset, and reserved for a final evaluation of the classifier, while 90 percent will be used to understand the characteristics of the raw text, and to estimate and preliminarily evaluate methods of classification.

4.3 Description

A description of the training data helped guide the process of specifying the classification scheme. This is helpful, because processing the text in different ways might be a powerful way to improve classifier performance, but not in all cases. Different sources of text varies in different ways: The range of vocabulary, the length of paragraphs and sentences, and the use of words might differ between sources and genres. Therefore, intimate knowledge of the characteristics of the text material is important to be able to reason about techniques and procedures.

One of the most important questions is perhaps; are the texts belonging to either class sufficiently different to make classification viable? If so, in what way do they differ, and how can the difference between the sets be used best to construct the classifier. The training / development partition has some important characteristics for designing the classifier:

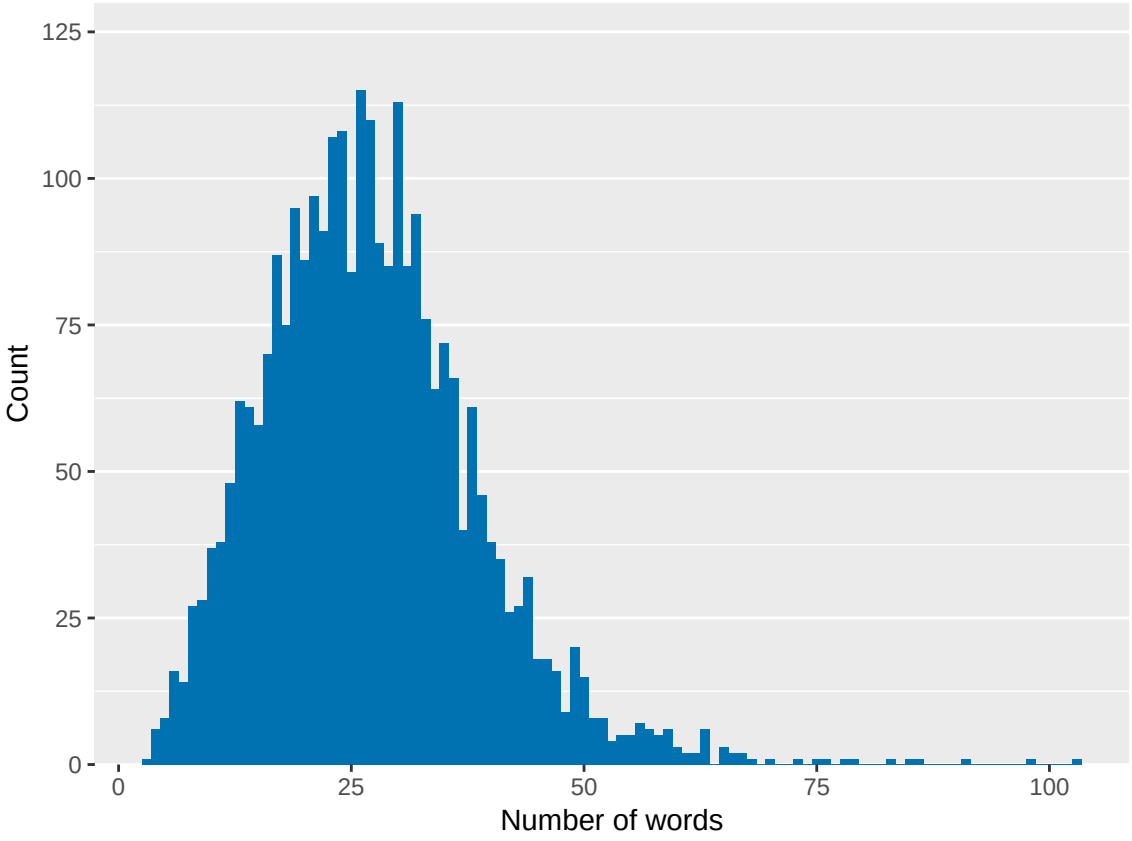


Figure 4.1: Length of sentences

The length is interesting, because it determines the chance that tokens are observed more than once for each unit. In the newspaper sentences, while some sentences are quite long, unique words very rarely appear more than once; the mean number of times each word appears in each sentence is 1.0187, meaning there is only a slim chance of observing a given word more than once. This has implications for how the

sentences should be vectorized. Various strategies for vectorization are described in the following chapter.

In addition to giving a description of the raw text as a whole, it is also important to make sure that the text associated with each class varies. This is important, because this variation will be used to train the classifier to recognize text as belonging to each class. As shown here, there seems to be some useful variation between the classes: relevant sentences very often contain the word "signed" and "agreed", while these words are not present as often in the irrelevant sentences.

This plot shows words word frequencies for each group of texts, as a percentage of total words. Since, as mentioned above, the sentences were selected as containing the words "ceasefire", "truce" and "armistice", these words are excluded from the plot. In addition, I excluded stopwords from the plot. Stopwords are grammatical words like prepositions and pronouns that occur very often in regular text (Bird *et al.* 2009: 60). The reason for excluding them here is that I am interested in the differences in the more semantically loaded words, like verbs and nouns. The exclusion of stopwords before classification might also improve classifier performance, an assumption which is tested in chapter 7. Note that both uppercase and lowercase words are shown; these count as discrete tokens, unless the text is normalized by lowercasing all words.

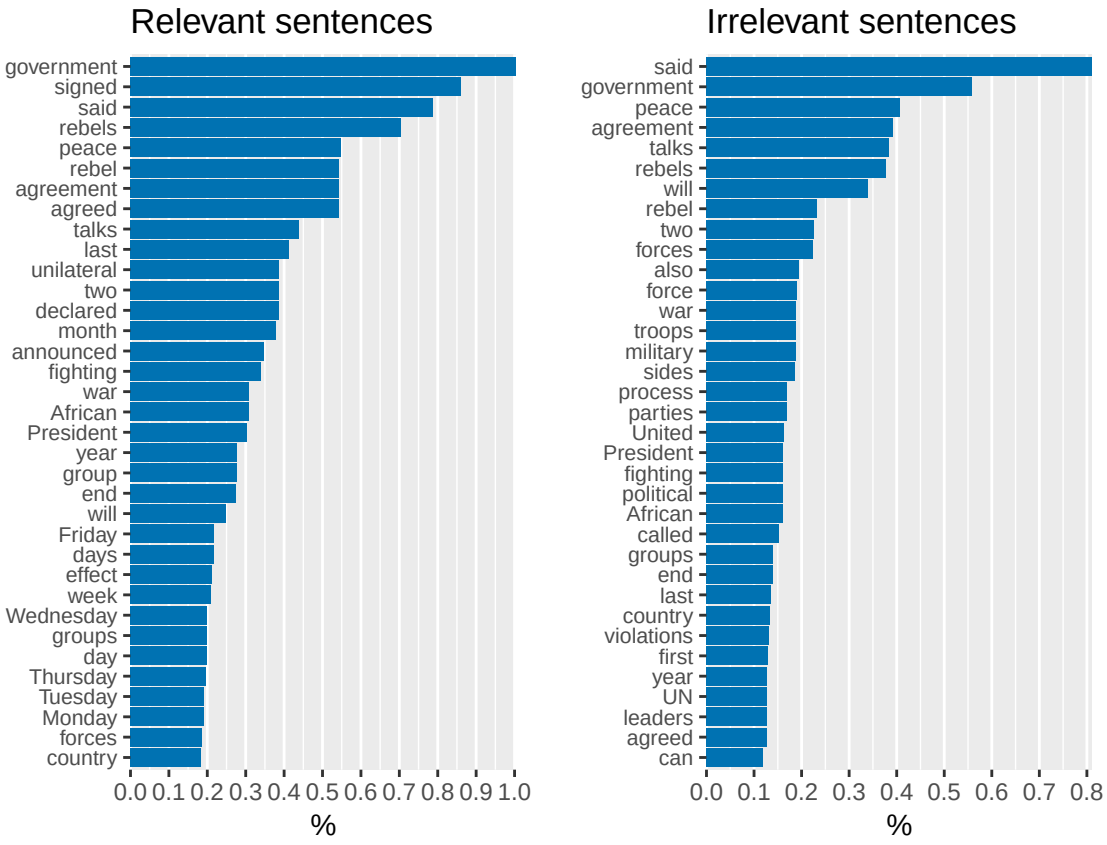


Figure 4.2: Word frequencies

	Training	Holdout
n	2761.00	306.00
Relevant sentences	870.00	109.00
Irrelevant sentences	1891.00	197.00
Mean number of tokens	26.02	26.55
Mean number of characters	164.57	167.71
Unique tokens	7367.00	2198.00

Table 4.1: Data characteristics

Chapter 5

Classification Methodology

Several steps are necessary to use statistical learning techniques to code outcomes similarly to human coders. The creation of structured data depends on two steps; selecting a set of attributes with which cases are represented, and classification based on these traits according to some given classifier function.

As mentioned in the previous chapter, I used supervised learning to estimate the classifier functions presented in the following chapter. This means extrapolating the decision rules from a set of coded data and applying these rules to new data. The estimation of the coding rule is done through the application of statistical techniques, that mimic the coding rule established in the training set.

In this chapter, I describe the technical methodology that was used to estimate and evaluate classifiers in the following. I begin with a brief, general overview of Machine Learning, defining key terms like *learning*, and drawing parallels to the previous discussion of systematic observation.

Since there is no predefined "best" classifier algorithm for any given problem, Thus, it is essential to test each algorithm using an evaluation scheme. This methodology is used to select classifier procedure that will be applied to a held-out partition of the labelled data, to give a final evaluation of the effectiveness of statistical learning methods in discerning between relevant and irrelevant sentences.

I then describe the procedures that are used to classify text in the following. Perhaps surprisingly, the classifier is not the focus variable that is tested. I opted to use a simple variant, while instead emphasizing different procedures related to the treatment and representation of text.

Finally, I give a brief overview of the implementation of the different steps. This description, along with links to the source code found in the appendix, makes it possible to reliably and accurately reproduce the work presented here, given a similar set of data.

5.1 Machine Learning

Machine learning is a term used to describe computer systems that infer functions from patterns in raw data. It can be considered a kind of "artificial intelligence"

(Pustejovsky and Stubbs 2012: 37) in the sense that it is able to "learn" its procedures from data, rather than having to be explicitly instructed. An agent can be said to "learn" if its performance is improved by way of observation (Russell and Norvig 2010: 693). A computer learns by way of statistical estimation, computing models of relationships between traits and outcomes that have been "observed".

Generally, learning, can be defined as the estimation of a procedure, or function of observed cases based on the association of their attributes and an outcome of interest. Thus, James *et al.* (2013: 36) describes statistical learning as an attempt to estimate a function f, where:

$$y = f(x) + \epsilon \tag{5.1}$$

This is done by observing cases expressed in terms of a vector of features. Recall that I defined measurement as $t = f(I)$ (2.1). In the definition of machine learning given above, the attempt to estimate the function $\hat{f}(x)$ behind measurements $y_1, y_2...y_i$ can thus be seen as an attempt to uncover $f(I)$ as a function of the set I of attributes $i_1, i_2...i_n$ of each unit of observation $u_1, u_2...u_i$.

There are two reasons for wanting to learn such a function from raw data (James *et al.* 2013: 17) : The first is to explore the coefficients in the function to learn more about the relationship between the variables, or rather, what has been learned about this relationship. This is usually the purpose of traditional regression analysis, where insight is gained from examining coefficients, that show statistical correlations between different indicators with various degrees of confidence.

The second reason is to use the learned function to predict new outcomes. This is extremely useful when an outcome of interest is more expensive or difficult to measure than the features (James *et al.* 2013: 28). Consider this in the case of text classification; observing manifest features of text is trivial, while measuring "hidden" information content, significance, or relevance is a much more difficult task. In the present case, it is not possible to measure outright whether a sentence is interesting or not to coders by, for example, testing whether a certain symbol, letter or word is present. Statistical learning, then, is used to create a procedure that infers the value of this attribute, based on what is observable: The symbol content of each sentence.

A basic dichotomy in machine learning is the distinction between supervised learning and unsupervised learning (Grimmer and Stewart 2013: 2). The difference between these rather different approaches, is that with supervised learning, the goal is to estimate a function of an outcome variable that is observed, while with unsupervised learning, a theorized number of outcomes are inferred from patterns in the data.

Supervised learning models are estimated using "training data", where the outcome variable is given, while unsupervised models are used to "discover" an outcome variable as a pattern in the independent variables. This process of "teaching" the model about the connection between indicators and the outcome variable y means that essentially, the outcome function f will be an imitation, or rather extrapolation of the coding function that "generated" the outcomes in the training data. This means that supervised learning and subsequent classification must proceed from a set of data that has been labelled (Grimmer and Stewart 2013: 3), as described in the previous chapter, and that the validity of the outcomes of the function is dependent

on the validity of the labelling of the training data. The algorithm "learns" how to classify documents, mimicking the assumed decision rule f applied by the human hand coders (Grimmer and Stewart 2013: 9).

It is clear from the definition given above that machine learning and formal measurement are analogous processes. The basic premise is estimating a function of a given set of traits, that will be used to infer some unobserved trait of interest. Machine learning models can thus be thought of as "measuring instruments".

Supervised models use the procedures and rules established in the training data to establish the measuring procedure. This means that a supervised learning model is a tool of *extrapolation*. It is thus very important to mindfully develop the rules with which the training data is classified: Valid training data is a prerequisite for valid outcomes using a trained model.

5.2 Evaluation methodology

There is no way to determine the ideal approach to estimating $\hat{y}$ a-priori. Measuring the performance of different approaches is the only way of determining which procedures perform well in a given context (Grimmer and Stewart 2013: 3). In addition to the classification step, different strategies for expanding each unit into a corresponding feature vector should also be considered.

Using flexible, powerful modelling techniques, it is possible to estimate a function $\hat{f}$ that will perfectly predict y for each training case. This will inevitably result in an *overfit* model, however: A model that does not generalize well to new, unobserved cases (James *et al.* 2013: 22). The term ϵ in the definition of statistical learning means that it must be assumed that the training data contains some specific variance in addition to the "common" variance that we are trying to model (see 2.9).

Fitting too flexible models to the data might lead to models that express the specific variance of the training set, a situation called "overfitting" where the classifier is trained to recognize the semantically trivial characteristics in the training data. These characteristics are not useful for classifying the phenomenon of interest more generally, but might be correlated with the phenomenon in the training data.

Recall from chapter 4 that information relayed through language is affected by the stochastic elements of language formulation; any given piece of information could be expressed in multiple ways. What this means is that each training case contains both uninteresting idiosynchrasies and information; in the terms used to discuss validity, we might say that each training case is affected by specific and general variance.

To handle this problem, evaluation strategies should be designed so that each procedure is tested on unseen data, that is not used to estimate the procedure. This is done by splitting the data into separate partitions, estimating the classifier using one partition, and applying it to an "unseen" partition. In addition, a final "holdout" partition can be used to give a definitive score using data that has not been used at all during preliminary evaluation of the development of the model. Because the data used to calculate the metrics are not used in estimating the model, the metrics give an indication of how well the model will generalize, thus avoiding overly specific,

overfit models.

Comparing y and $\hat{y}$, the predicted and actual classification of text in the unobserved data, it is possible to quantify model performance directly by calculating several metrics that favor different kinds of model performance. The choice of a performance metric affects the choice of models, therefore it is important to reflect on the characteristics of the different metrics.

5.2.1 K-fold cross validation

It is also important to consider different approaches to partitioning the data. If data is scarce, the testing partition might be too small to produce a useful metric. The partitioning of the data can be done in several ways. For example, one might sample a percentage of the data randomly, splitting it into two parts, training the model on one part, and evaluating it on the other. The randomness ensures that the model is representative of the whole data set.

However, if the data set is small, the respective partitions become to small to yield reasonable results. Classifier procedures perform better as the amount of training data increases. Training data is expensive to produce, and will in almost every case be a scarce resource. Therefore, it might be better to use a different strategy:

Resampling is a technique that involves estimating an equivalent model from multiple randomly created partitions of the same data. With multiple different random partitions, the resulting models will differ slightly. Calculating evaluation metrics for each model gives a more robust impression of how the modelling approach is performing.

One such approach is called K-fold cross validation (James *et al.* 2013: 181). This involves splitting the data into K partitions, called "folds". K models are then trained, excluding one part of the data in each case, thus each model is trained on $K - 1$ folds. Evaluating each model using the left-out fold gives a more robust and complete picture of how the modelling strategy is working on the whole of the data, as every data point is used for evaluation, yielding more generalizable results.

In addition to the K-fold validation procedure, ten percent of the data is "held out" from the process of specifying and testing the procedures. This data is unseen until the final evaluation, and will thus give a good indication of how well the classifiers generalize. This is a good strategy, because the results from development testing data might be biased towards good performance, since procedures are developed and selected using only this data (Jurafsky and Martin 2018: 77).

5.2.2 Metrics

When a classifier is used to predict scores for y where y is already known, its performance can be evaluated in terms of how often it classifies correctly. A Confusion Matrix (Fawcett 2006) is a way of presenting the performance of a classifier, and can be used to calculate additional performance measures.

In this matrix, the rows represent the hypothesized class of each case, and the columns represent the true case. Given two possible values of y, P and N, four

possible outcomes are possible: If the value of y is P, the classifier can either produce a "true" P, TP, or a "false" N, FN. Conversely, if the value of y is N, the classifier can either produce a TN, or a FP: While the Confusion Matrix is a useful tool for

	Actual N	Actual P
Hypothesized N	TN	FN
Hypothesized P	FP	TP
Total	N	P

Table 5.1: Confusion matrix illustration

evaluating classifiers up front, when comparing classifier specifications, it is often useful to express performance in terms of metrics, summarizing the matrix. From the Confusion Matrix, it is possible to calculate several such metrics, which summarize the performance of the classifier in various ways. Choosing to focus on a particular performance metric is an important decision when designing a classification scheme, as different metrics emphasize different kinds of performance.

A natural point of departure is to calculate the ratio of *correct classifications* to *total classifications*, called the *accuracy* of the procedure. The major diagonal of the confusion matrix represents correct decisions, while the minor diagonal holds erroneous decisions. From these, accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

However, while accuracy is desirable in any case, an accurate classifier is not necessarily useful. In a case where there are very few true positive cases, a procedure yielding only negatives will achieve a very high accuracy, while not being of much use in finding the positives (Jurafsky and Martin 2018: 74).

From these, and the column totals N and P, how many cases of $y = N$ and $y = P$ there are in total, it is possible to calculate:

$$Precision = \frac{TP}{TP + FP}$$
$$Recall = \frac{TP}{P}$$

Recall gives the ratio of *correctly classified* cases P, to *actual* cases P, while precision gives the measure of *correctly classified* cases P to *total classified* cases P. Recall thus reflects the degree of coverage, while precision reflects the credibility, or trustworthiness of predicted P.

In simpler terms, a more conservative classifier scores higher on precision than recall (Fawcett 2006: 863). Importantly, high precision and high recall tend to be mutually exclusive, (Chinchor and Diego 1992: 24). Thus, a choice must be made: If it is very important to catch all the positive cases, and some noise in the outcome is acceptable, recall should be prioritized. Conversely, if it is important that the cases classified as positive are not actually negative, precision should be prioritized (Hanna 2017: 13).

F1 and ROC

A "compromise" between these two statistics is the F statistic. The F statistic is calculated from precision and recall, and rewards models with equal, strong precision and recall while punishing models with low scores, or high but asymmetric scores in either statistic.

$$F = \frac{(\beta^2 + 1) \times Precision \times Recall}{\beta^2 \times Precision + Recall}$$

The balancing parameter β is used to determine the balance of the effect of Precision and Recall. The special case where $\beta = 1$, making F equal to the harmonic mean of Precision and Recall, is termed $F1$. "Weighting" the F score towards either Precision or Recall can be done based on considerations of the importance of credibitlity versus coverage.

For the specific task of classifying sentences as either "interesting" or not for the coders, one must consider the importance of either missing too many relevant sentences, or including too many irrelevant sentences. While it may seem logical to avoid missing as many potentially relevant sentences as possible, the system must also perform well in filtering the information, as that is its main function in the coding process. I therefore chose to weigh the measures equally, and to rank the models according to their F1-score.

Lastly, I also present some approaches as points in ROC-space. ROC-space is defined (Fawcett 2006: 862) as the two-dimensional space comprised of the evaluation metric dimensions Recall and Fallout. Fallout is a measurement of the number of cases with a true score of N, that have been classified as P.

$$Fallout = FP/N$$

When metrics calculated from a confusion matrix from a given procedure are mapped to ROC space, the point indicates the degree of coverage, Recall, versus what might be termed the "trustworthiness" of the procedure, represented as Fallout. More lenient models will produce more False Positives, but will also cover a larger array of the True Positives. More conservative models, on the other hand, will discard more True Positives as false, but will also produce fewer False Positives, as illustrated here:

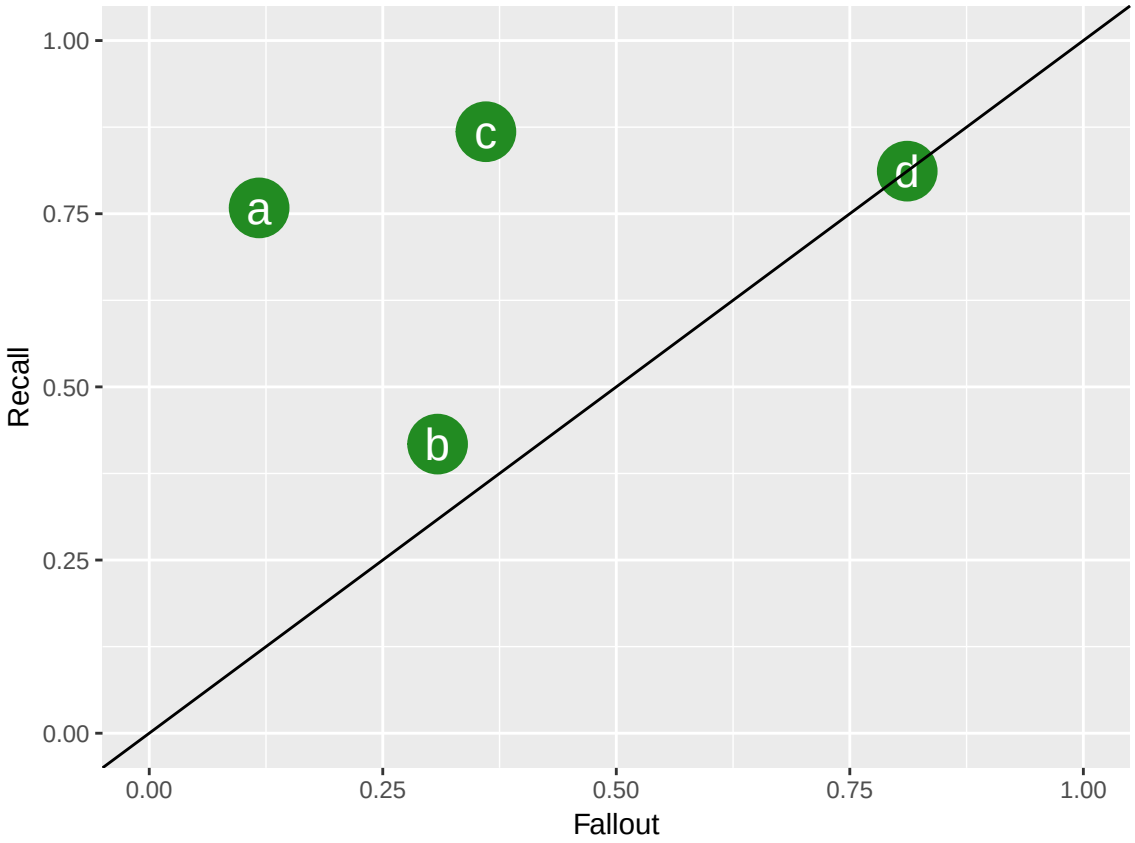


Figure 5.1: Example ROC graph

In this toy example, *a* is the model that combines a reasonable Recall without encurring too much fallout. *c*, on the other hand, correctly classifies more positives, but also wrongly classifies many negative cases as positives. Both *b* and *d* are dangerously close to the line between 0,0 and 1,1; These models do not perform much better than random guessing would.

The models *a* and *c* both perform well; choosing one of them involves a substantial choice: Is it more important to catch as many positives as possible, thus risking a less trustworthy set of predictions? Or is the trustworthiness of the predictions the most important element? This must be determined by considering the context in which the results will be used.

5.3 Procedure selection

Classifications are produced by sending the text through a pipeline of steps that might perform preliminary preprocessing, turns the raw text into a vector representation, and classifies it using some sort of classifier function. Any number of steps, algorithms and parameters could be tested, but a selection is made to facilitate testing.

The reason for limiting the range of procedure variants that will be considered is related to the exponential increase in variants that must be evaluated; The number of procedures that must be tested increases exponentially for each step that is con-

sidered. This makes it necessary to select a subset of steps to focus on; I have chosen to consider several preprocessing steps, instead of different classifiers.

Only two variants of the actual classification step will be considered here; a Support Vector Machine (Cortes and Vapnik 1995) with and without hyperparameter tuning. Support Vector Machines are a group of algoritms that are commonly used for supervised machine learning (Pustejovsky and Stubbs 2012: 39). SVM was chosen because it is considered one of the best range of classifiers "out of the box" (James *et al.* 2013: 337). The great advantage of SVM, along with the also common Logistic Regression and Naïve Bayes models, is that it balances simplicity with predictive power (Jurafsky and Martin 2018: 394), usually yielding adequate results. In addition, SVM models do not requiring long training cycles and complex tuning compared to more sophisticated approaches like Neural Networks. It would of course be very interesting to apply more advanced classification schemes to the task presented here, and compare the results, but for the sake of parsimony, I have chosen to only present results from using an SVM.

Support Vector Machine classifiers can be specified in several ways. Again, limiting the range for the sake of parsimony, i only use a linear kernel specification, which limits the range of hyperparameters to a single parameter: C. C determines the amount of error that will be tolerated by the separating hyperplane. Essentially, C determines the "slackness" of the separating rule; if C is small, the model is tightly fit to the data, potentially increasing the risk of overfitting. If C is large, on the other hand, the model might be underfit, and miss the relevant relationship.

C is treated as a tuning parameter (James *et al.* 2013: 347). This means that determining an a-priori value for C is not possible; several procedures must be estimated using cross-validation to determine which C-value yields the best results on testing data. In the presentation in the next chapter, the "tuning" step represents the inclusion of C-tuning; otherwise, C is set to 1, the default value in the implementation used here.

5.3.1 Text as data

"Raw" data like text, numbers and audio has no inherent vector representation, and must be given one through the measurement of some property or feature. This is called featurization. Featurization is essentially just a given way of measuring one or several attributes of an object to create an analyzable representation of it (Zheng and Casari 2018: 10).

Featurization is arguably the most important step when making a machine learning system, and might have a very strong effect on classifier performance (Bird *et al.* 2009: 224). This resonates with how we understand measurement, or indeed comprehension in general. What attributes we choose to look at, or ignore, determines what we are able to understand about some case. The procedures presented in the following chapter largely differ in terms of the way text is vectorized.

Featurization means that each case is given a feature representation $x_1 ... x_i$. Any structured measurement procedure, computerized or not, depends on some sort of "featurization", which is more or less rigid. In the case of using computers, however,

featurization must be entirely schematic, and predefined. While, as I argued, all measurement procedures can be more or less metaphorically viewed as mathematical functions, computer classifiers are actual mathematical functions that map vectors to outcomes. This means that all units must be given a numeric vector representation, which expresses some set of features that are determined to be relevant to the classification problem.

As briefly described in chapter 4, units of text such as sentences or documents can be expressed in terms of a set of symbols. A document-term-matrix (DTM) is a data set relation where documents are represented through *symbol occurrence*, with the word "term" used synonymously with "symbol" and "token". This means that the variables are symbols, and the values are how often terms occur in each document. This is an example of a basic representation of text, the "bag of words" approach.

	Original	i	read	reading	text	that
1	I read text	1	1	0	1	0
2	Read that text	0	1	0	1	1
3	Text I read	1	1	0	1	0
4	Reading text	0	0	1	1	0

Table 5.2: Vectorization example

Under this representation, texts are transformed into a dataset of count variables, expressing word occurrences. The values can either be expressed in terms of either-or occurrences, that are binary representations of whether a word occurs or not, or counts, that are numerical values that express how many times a word appears.

In addition, the more sophisticated Term-frequency-inverse-document-frequency transformation alters the "weight" of each word relative to their inverse document frequency, or rather, how rare a word is in terms of how many documents it occurs in. Common words are given less weight, while uncommon words are given more weight.

There are several strategies that attempt to improve the baseline bag of words approach. Each of these strategies aims to improve the performance of subsequent classification, by either normalizing the values, normalizing the data, or defining more complex features.

Content and utility words

One such strategy involves selecting certain features that are assumed to be more relevant than others. Only one set of such features is considered for this approach: Stopwords. Stopwords are words that might be expected to have little discriminatory power when classifying text. These include prepositions, conjugations of "to be", and pronouns like "them" and "he".

The importance of including stopwords might be said to be related to the required granularity of understanding necessary to discern between the classes of text. In some cases, it might be necessary to discern between texts using fine nuances in the way the author uses grammatical "utility words" like "the" and "on", but in other cases,

these words have no discriminatory value (Zheng and Casari 2018: 66). The list of stopwords used in the current implementation is included in the appendix.

Alternatively, instead of excluding stopwords, one might apply weights to the coefficients of each word, relative to their Inverse Document Frequency, or Term-Frequency-Inverse-Document-Frequency (Tfidf) transformation attempts to reduce the weight of utility words, since they appear in most documents, while retaining the weight of content words, which are rarer (Jurafsky and Martin 2018: 508).

Normalization

A second strategy involves normalization of symbols. The simplest normalization is treating words that are capitalized and uncapitalized as the same, by making all letters lowercase. If it is significantly important whether words are capitalized, warranting this distinction, lowercasing might be detrimental to performance, as it removes this information. In many cases, however, it is not.

The normalization of numbers relates to how numbers are featurized: Since each distinct number counts as a separate symbol, numbers increase the number of features disproportionately to their assumed predictive use. To handle this diversity, numbers can be transformed into a single token, such as `*number*`. This retains the information that a number is present, while collapsing the many distinct number-token columns into a single column. The discriminatory power of having any kind of number in a sentence is expectedly much greater than the discriminatory power of observing specific numbers, at least in the context of this classification problem.

Stemming is another kind of normalization that removes the distinction between symbols in a courser way. Stemmers reduce each word to a root stem, making distinct words with the same word stem appear the same. This means that the words “abstraction”, “abstracting”, “abstracted” and “abstract” would all be stemmed and represented by the symbol “abstract”. While collapsing several such words into single stems might significantly reduce the number of distinct symbols, and thereby reduce the dimensionality of the data, it is also a heavy-handed reduction of the information content of each text unit. The relevant question when considering to include stemming is; is the discriminatory value of suffixed words greater than stemmed words (Porter 1980). This is, in any case, a difficult question to answer. Here, it is answered empirically, by evaluating the effect of stemming on classifier performance.

N-gram featurization

A third strategy involves the featurization step: A perhaps striking fact about the bag-of-words representation of text is that it discards information that is often vital for human text comprehension: The sequence of symbols. Word sequence is an important syntactical component in many languages, that determines the semantic meaning of text. The tabular representation of texts in terms of symbol occurrence does not retain this information.

Thus, using a basic bag-of-words approach rests upon the assumption that the sequence of words is not useful for predicting y. It is worthwhile to evaluate this

assumption, by including procedures that vectorize the text in the form of n-grams. An n-gram is a representation of n number of words in sequence. Two such n-gram representations are considered here: Bigrams, and trigrams.

Since we are using statistical techniques to determine the significance of each feature, why not include as many features as possible and let the classifier sort them out? Again, this relates to the problem of overfitting (Bird *et al.* 2009: 225). If the classifier is allowed to "know too much" about the training data, it might start modelling idiosynchrasies rather than useful information. This makes the inclusion of more information, such as by using n-grams, a trade-off.

5.4 Implementation

In the following, all procedures were implemented using the software library Scikit-Learn 0.19.1 (Pedregosa *et al.* 2011). The SVM procedures included with Scikit-Learn use Libsvm (Chih-Chung and Chih-Jen 2011), a common implementation. In addition, some language processing, including stemming and stopword-removal, is done using Natural Language Toolkit 3.3 (Bird *et al.* 2009). The framework for building and testing classifiers was written in Python 3.6.5, and most of the code for handling and presenting data was written in R 3.4.4. The source code used to train and evaluate the models, as well as the source code used to render the thesis and produce the graphical content in this thesis can be found by following links in the appendix.

Chapter 6

Results

In this chapter, I present the results of two batches of tests. The first batch, where I test several algorithms on the training data using K-fold cross validation is used to select the "best" algorithm. This algorithm is then tested on the unseen held-out data, yielding a generalizable result. The results from testing the text classifier were positive. The best-performing specification achieved results that were quite positive.

In addition to these numerical results, preliminary trials from the data-making process at PRIO / ETH have also been quite positive. As an integral part of the process of gathering data about ceasefires, the classifier provides coders with an overview of the vast textual material, providing relevance-ranked overviews of the many thousands of sentences contained in the "raw" news material. Using these, coders have reportedly been able to work quicker, both producing more data, and auditing material that has already been gathered.

As part of the evaluation on the held-out data i also examine some errors made by the system. These discussions might be fruitfully considered when developing the system further, towards greater accuracy and coverage. I also outline some of the many possible ways in which the system can be improved by applying more sophisticated technologies. These suggestions for further research, building on the findings presented here, might lead to a more comprehensive automatic system for creating useful conflict data.

6.1 Procedure

Using the data described in chapter 5, several classifier algorithms were created. The modelling step in each of these procedures is an estimation of the "manual" procedure that was used to classify the message units as either relevant or irrelevant, $\hat{f}$, and is used to extrapolate this procedure to produce predictions of relevance for further coding work.

Determining what the ideal steps for processing and classifying the text would be a-priori is not possible (Grimmer and Stewart 2013: 3), and so, figuring out what steps to apply involves testing the performance of the algorithms on coded data. 13 configuration are presented below. The algorithm that performs best in the k-fold

evaluation step is then used to classify the held-out data, yielding a set of definitive metrics that indicate how useful supervised learning might be for relevance-classifying raw text in this specific problem domain.

What is a good score? This must, in any case, be defined in terms of the task. There exists no general standard of passable scores for either of the metrics presented here (Hanna 2017: 13). For this domain, however, I would argue that the results attained by the best approach are quite good, especially considering the relative simplicity of the classifier, preprocessing and featurization schemes.

An even more advanced featurization, or classification step might have yielded even better results, although the results clearly indicate that the attempts to improve performance through slightly more sophisticated procedures did not pay off in this case. The combination of parsimony and performance makes the top-performing procedure a good alternative for the task of ranking the relevance of sentences for coders, attaining an F1 score of 0.78.

6.2 Evaluation

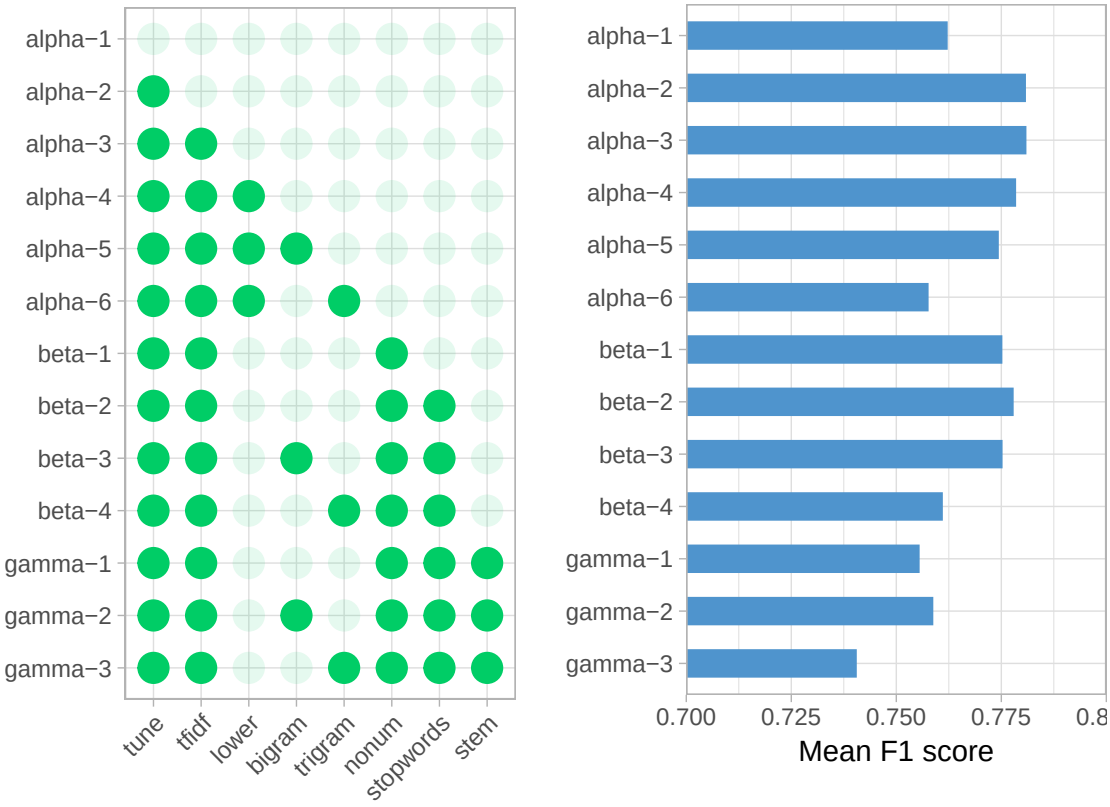


Figure 6.1: Procedure overview

13 different classifier configurations were evaluated. The number was, in part, limited by practicality: The total number of combinations of 8 different steps is 256 .

To facilitate the comparison, I chose to limit the configurations into 3 "families" of models.

Each procedure was evaluated using 10 folds, meaning the procedure was trained and tested ten separate times using different partitions for training and testing. The scores are therefore quite robust. In the table, the mean of these ten scores is show, for each procedure.

The Alpha family gradually introduces different steps, such as model tuning, Tfidf-normalization lowercasing, and n-gram featurization. The Beta family introduces number-word normalization and stopword removal, using the best-performing combination from Alpha. Finally, Gamma introduces stemming. Bigram and Trigram featurization is tested in all three groups.

What is immediately apparent from this comparison, is that the different approaches to modelling are quite similar in terms of performance. Note that the scale on which the F1 parameter is displayed is heavily compressed: The F1 parameter varies between 0 and 1, while F1 values displayed here range between 0.74 and 0.78.

Still, there are certainly interesting differences in performance. Most notably, the attempts to improve performance by including preprocessing and n-gram featurization are actually detrimental to the F1 score. This is not too surprising, considering the discussion of these steps in the previous chapter: more advanced preprocessing and vectorization steps might improve performance in some cases, but are not proven to be effective in all cases: Their effectiveness rests on certain assumptions about the text.

The best-performing model was selected from each of the model families, and situated in ROC space. The points in this graph represent separate scores, from each of the ten test folds. This plot shows that the performance detriment in the gamma-family seems to stem from the fact that the model yields slightly more false positives, while not gaining any significant new amount of true positives. This is penalized by the balancing parameter F1.

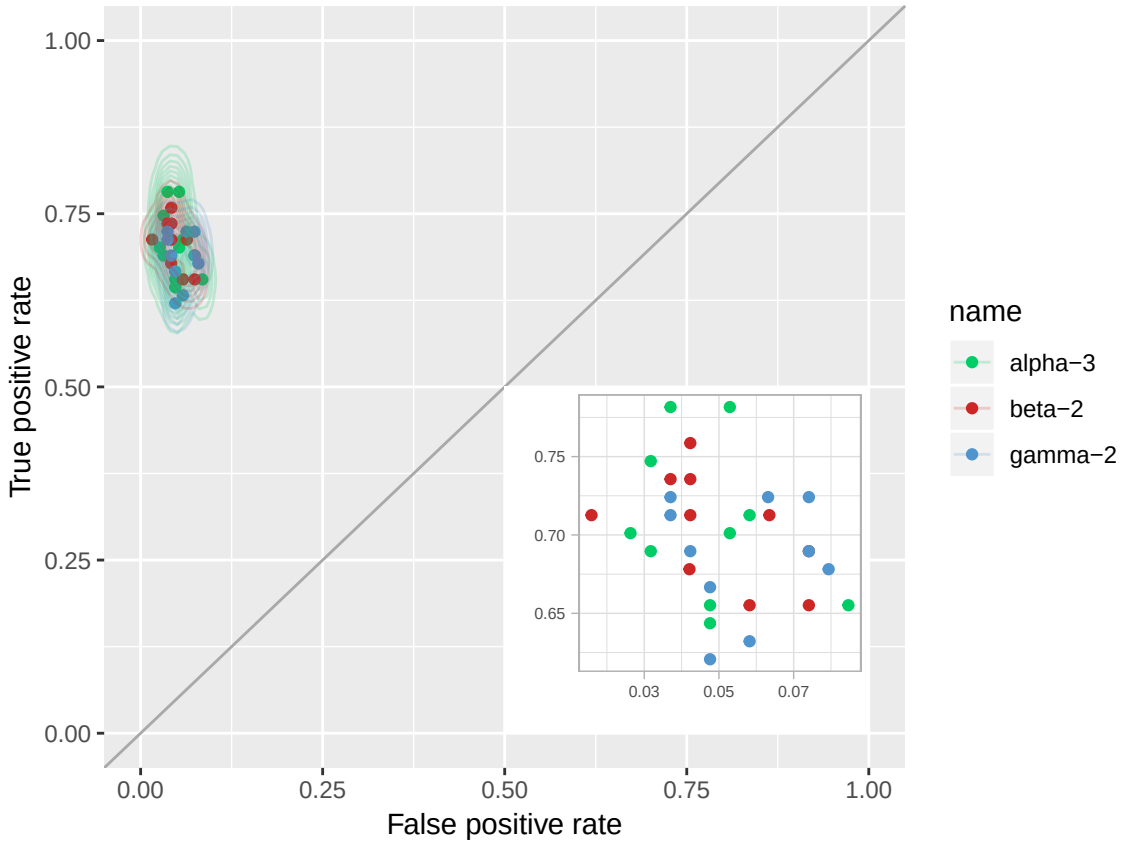


Figure 6.2: ROC procedure comparison

Again, it is quite clear that the models are not very different; in the full extent of ROC-space it is difficult to tell them apart. While it might be argued that the differences are so small that they are attributable to random error, this conclusion would still favour the best-performing procedure, alpha-3, since it is also the simplest procedure, involving fewer steps than beta and gamma.

The top performing classifier, with a mean F1 score of 0.78, was alpha-3.

alpha-3 thus seems to be the best $\hat{f}$ for predicting y that was attainable with the techniques attempted here, and the training data that was used. It should, however, be noted that the difference between the F1 value of the top performing classifier and the F1 value of the worst performing one, gamma-3, is only 0.0404.

It is certainly interesting that the procedure that yielded the best scores in the cross-validation evaluation was the simplest one. This is not easily interpretable, but should be considered in light of the discussion of these steps in the previous chapter. Feature selection might be excluding certain features that are actually relevant, symbol normalization like stemming and lowercasing might be removing important nuances of information from the normalized symbols, and n-gram vectorization seems to lead to an overproliferation of features, that the model is not able to utilize effectively. Model tuning and Term-frequency-inverse-document-frequency, however, yield slight improvements over the baseline model.

6.2.1 Holdout evaluation

To evaluate the generalizability of alpha-3, the procedure was subsequently tested on the held out data; data that has not been handled during the development and testing of the procedures. The results attained by attempting to classify the holdout data are more generalizable, since the data has not been used to create the classifier.

Since a majority of the cases in the holdout data are negative, meaning that they are uninteresting to coders, it might be a useful reference strategy to predict all the sentences as irrelevant, and calculate the accuracy: This gives an accuracy of 64.38%. Randomly guessing the class in every case, with evenly balanced probabilities of 50/50 for each class, gives an accuracy score of 0.53%. Using alpha-3, on the other hand, yields the following results:

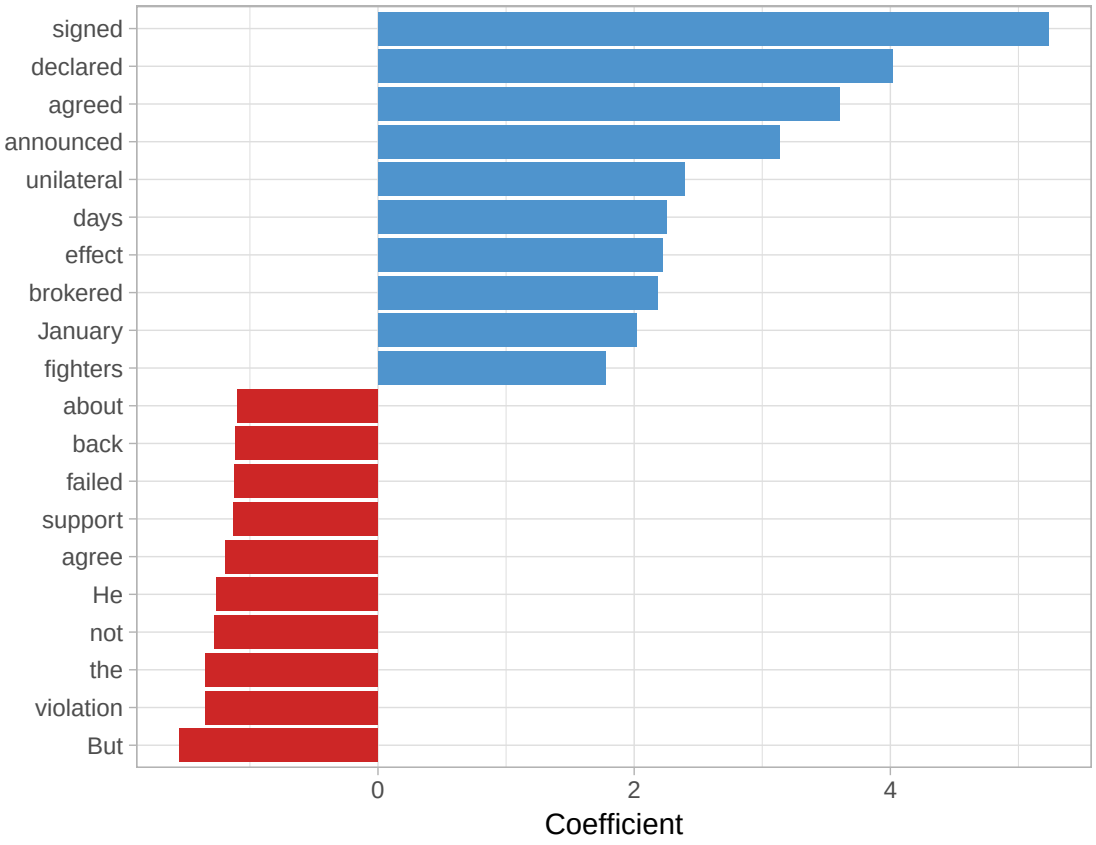
	Negative	Positives
Predicted N	186	11
Predicted P	28	81

Table 6.1: Holdout confusion matrix

This translates to a precision score of 0.74 , a Recall score of 0.88 , an accuracy of 87.25% , and an F1 score of 0.81. These scores seem to indicate that the information about whether a sentence is relevant or not for further coding yields itself quite well to classification; the proposed lower boundary for acceptable F1 values for a similar classification problem has been suggested as 0.65 (Hanna 2017: 13).

6.2.2 Holdout error analysis

The errors made by alpha-3 might inform future work improvements to the classifier. Browsing the sentences that were misclassified yields some interesting reflections on how the classifier works. Along with the coefficients estimated by the model, also called the feature weights, we might better understand the errors made by the model. These are the ten strongest coefficients in either direction:



The four verbs that are most strongly correlated with a sentence being interesting have much stronger coefficients than most other words, particularly, and perhaps expectedly, the word "signed".

The verb "to sign", specifically the conjugated form "signed" which corresponds to several conjugated forms of the verb, plays a significant role in discerning between the sentences. Both of the "false positive" sentences contain the salient conjugation, that strongly correlate with a sentence being interesting.

There were 28 false positive classifications. Two of these are:

- «A final and comprehensive ceasefire was to have been signed last month.»
- «In the first place, there was no cease-fire agreement signed in Windhoek»

Parsing the sentences, however, we see that the semantic meaning of both sentences does not, in fact, indicate that signing has taken place. The fact that "no cease-fire" has been signed is a sufficiently complex formulation to slip under the radar. Similarly, the complex verb construction "was to have been signed", subtly negating the verb, is not properly understood by the classifier. The passive-voice perfective construction "was to have been" only appears once in the holdout data, and does not appear in the training data.

Handling linguistic diversity is a matter of creating more training data, as sufficient amounts of training data would contain cases where the classifier is taught more advanced grammar than it is able to learn from the present data.

Another interesting false positive sentence is:

- «A 1999 peace accord signed in Lusaka set a timetable for a ceasefire, the deployment of U.N. peacekeepers and a transition to democracy, but it has not been implemented.»

This sentence was strongly predicted to be true, but was manually labelled as uninteresting. Figuring out how to handle this sort of sentence, however, is harder, because it must involve some disambiguation of the labelling rules: The sentence was labelled uninteresting because it does not directly indicate the start of a ceasefire, but an accord was signed. While it might be argued that this sentence should in fact had been labelled as "interesting", since it clearly indicates the signing of a peace accord, it might also be argued that focus should remain on the start of actual events. In the last case, the classifier can be made able to handle such ambiguous cases as this one, given more training data.

There were 11 false negatives:

- «Although Kabila and the rebels have accused each other of violating the ceasefire deal that went into effect on September 1, there has been a substantial reduction in fighting.»

The negative, irrelevant sentences include a lot of mentions of violations. Violation is strongly negatively correlated with a sentence being interesting, and this is presumably true of other forms of the stem "violat", like the above "violating". Despite mentions of violations, the sentence also mentions in passing when a ceasefire went into effect, rendering it interesting. This is overshadowed by the main content of the text, however.

- For that reason, Israel's Security Cabinet unanimously rejected a U.S. proposal for a ceasefire on Friday, though Israel agreed to a 12-hour pause for Saturday.

This is a very difficult sentence to get right by simply using word occurrence, since the rejection of a ceasefire proposal will almost certainly render a sentence "irrelevant", while the sentence also mentions a "12-hour pause", which was interpreted by the human coder as indicating the start of a 12-hour ceasefire.

- The cease-fire is reportedly for one week.
- They agree to a cease-fire.

These sentences were also, perhaps surprisingly, misclassified as negative, while they are labelled as positive. This perhaps reflects the detriment of using such short message units: Sentences of under ten words contain very little information with which to discern between positives and negatives. In addition to this, neither of these two examples contain words that strongly indicate that they are positive. In fact, the conjugation "agree" is quite negatively correlated with a sentence being interesting, while the past-tense form "agreed" is strongly positively correlated.

While some of these errors would have been very hard to avoid, owing to grammatical complexity, and lack of information due to brevity, the production of more training data would certainly help. In addition, it might be interesting to experiment with alternative vectorization strategies, such as Doc2Vec (Le and Mikolov 2014), that might facilitate better handling of unorthodox wording.

6.3 Further work

The classifier has already been "put to work" in the process of coding the PRIO ceasefire-dataset. While it is still necessary to manually code the details of each ceasefire, such as what the parties are, what conflict the ceasefire pertains to, and the concrete dates on which it begins and ends, the "reccomendation system" that has been implemented with this classifier helps coders skim through the material much more efficiently.

While no quantitative evaluation of the effect of the system on manual coding performance has been conducted yet, anectodal information from these first trials has been promising. Such an evaluation would require considerable time and resources, involving multiple passes over the same material to assess the effect of using the system, compared to not using the system. It would, however, be very interesting to quantify the alleged effect of using the reccommendations.

While these initial results have been promising, there are many interesting ways in which the classifier could be improved: The accuracy of the recommendations could be improved by adding more training data, or using more sophisticated technologies. In addition, the system could also be made to produce more information, in the form of partial coding, mapping each sentence to a particular conflict, set of actors, or similar contexts. This could lead to a more comprehensive automatization, finally leading to a completely automatic system for extracting interesting information from news data streams, such as has been demonstrated by Hanna (2017), Osorio and Reyes (2017) and Schrodt *et al.* (1994) among others.

Adding more training data is the most obvious way to increase performance of the relevance-rating step. Including data from more conflicts and countries would improve the generalizability of the classifier. Producing training data is laborious, but pays off in terms of model performance; strategies for producing useful training data, like using active learning (Rubens *et al.* 2015: 809) might be interesting to explore when creating more training data.

In addition, exploring the merit of more advanced vectorization and classification techniques would be interesting. Vectorizing text using sentence embeddings (Le and Mikolov 2014) would be particularly interesting to explore. In addition, promising results have been attained using Neural Networks (Beieler 2016) for the classification step; a much more advanced and computationally intensive classifier strategy.

Automating the coding process further would require the development of more sophisticated algorithms for parsing and processing the sentences, and extracting information. The system presented here is only a single step towards a fully automated coder, but discerning between relevant and irrelevant text units is an important first step in this process (Hanna 2017: 7). Stepping up the ladder towards fully automated information extraction, masses of unstructured information might be made intelligible, and open to analysis. In addition, such a system could be made to create the data in real-time, updating the data set continuously.

There are many problems inherent in full automatization, including include solving duplicate events (Schrodt and Van Brackle 2013: 30), resolving ambiguous or difficult language constructions, and avoiding semantically irrelevant material where

wording might trick automated systems. Sports reporting, where military metaphors are common, are a typical challenge (Schrodt *et al.* 2014: 4).

The approach demonstrated here, pairing human intelligence with machine prefiltering and recommendations is cost-effective and useful. Getting the best of both words, human intelligence paired with machine efficiency, the pairing manages to increase productivity while avoiding the problems inherent in full automatization. It should also perhaps be noted that the present system was developed in one year, by a single undergraduate student, including the production of training data. This means that development costs were negligible compared to the more comprehensive coder projects mentioned above, developed by professional scientists.

Chapter 7

Summary

In this thesis, I have argued for, and demonstrated the automatization of part of a data-creation process. Results seem to show that the system is a useful addition to such a process, yielding generally useful recommendations. The results show what kinds of procedures are most effective, among a selection of simple preprocessing and classifier configurations. The present system is a useful point of departure for future information extraction, using either manual or automatic techniques.

The work presented here proceeds from the idea that data is a necessary prerequisite for the development of scientific theory. Facilitating more efficent and precise data collection is an important part of expanding the scope of testable hypotheses. This helps theory development, by both enabling scrutiny of established theories, and perhaps also inspiring new, more accurate ones.

The development of more accurate theory about how ceasefires interact with conflict is the goal of the data collection program in which this project is embedded. Refining our knowledge about ceasefires makes it possible for policy-makers to design better interventions and mediation strategies, potentially migitating and preventing more conflict.

Improving the efficiency and quality of data-production is a powerful motivation, given the importance of achieving a better understanding of conflict related phenomena, such as ceasefires.

Data collection is difficult and expensive. Thus, useful data is a scarce commodity, requiring great investments of time and money to develop. This problem is exacerbated when observational material is ambiguous, requiring careful interpretation. Text is such an information source, being a conduit of information that imparts stochastic variance in the form of language idiosynchrasies, making the task of retreiving useful information from large corpora of text very challenging. In addition, in an age of information glut, ensuring the veracity of data is important, and increasingly difficult.

The complexity of text as a medium of information makes it difficult to develop data collection procedures. Using machine learning techniques, decision functions are learned previously labelled training-data rather than specified; this means that the careful interpretative wisdom humans apply when retreiving information from text can be learned, and subsequently applied by machines.

This is potentially a very effective way of approaching complex problems such as text-labelling. With the formalization of data-collection, and exposition of machine-learning theory, I hope to have shown that the process of data-collection can be seen as analogous to the process of estimating and applying machine-learning functions.

This was demonstrated and evaluated in the latter part of this thesis. Building and evaluating several relatively simple approaches to machine classifications, useful knowledge was gained about how to approach the particular problem of relevance rating.

The findings presented here show that the application of machine learning technology to the particular problem of discerning between relevant and irrelevant material for coding ceasefires is very useful. The primary issue of cost, which is prohibitive to data-collection, is effectively mitigated by the application of automatic tools with essentially no running cost. This also means that issues of data quality can be handled more effectively, since more resources and focus can be put into the development of sound procedures and algorithms rather than the drudgework of manual data collection.

While the present system can be improved and extended in many interesting ways, this proof of concept is a useful system in and of itself, already having yielded useful results in the process of making a dataset of ceasefires. The interdisciplinary approach, drawing on computer science, statistical learning theory, formal scientific methodology and conflict research which is demonstrated in this thesis is a powerful approach. With the further development of social science methodology leveraging the power and efficiency of computerized inference, one might hope that enough empirical data can be produced to enable researchers to gain comprehensive understanding of phenomena such as ceasefires, thus perhaps allowing for the resolution of more conflicts, preventing violence and devastation.

Appendix

Distribution sentences and ceasefires

	Country	Ceasefires	Sentences	Sentences per Ceasefire
1	Burundi	29	14949	515.48
2	Central African Republic	27	1390	51.48
3	Colombia	28	13729	490.32
4	Djibouti	5	670	134.00
5	El Salvador	3	2591	863.67
6	Guatemala	5	149	29.80
7	Guinea-Bissau	9	1249	138.78
8	Ivory Coast	11	12059	1096.27
9	Kenya	12	8458	704.83
10	Lesotho	1	263	263.00
11	Liberia	35	15038	429.66
12	Mexico	10	3045	304.50
13	Morocco	3	3983	1327.67
14	Mozambique	13	2799	215.31
15	Nicaragua	12	2163	180.25
16	Niger	11	1332	121.09
17	Senegal	10	594	59.40
18	Sierra Leone	15	9664	644.27
19	Uganda	24	17840	743.33

Coding of training sentences

Basic criterion:

- Sentence contains any of the words "([Cc]ease-?fire|[Tt]ruce|[Aa]rmistice)" In the following, "ceasefire" is understood as either "ceasefire", "truce" or "armistice"

Sentences containing any of the following are interesting:

- ceasefire was declared
- ceasefire was announced
- ceasefire was extended
- ceasefire went into effect
- *actor* is now observing ceasefire
- A peace deal includes a ceasefire
- ceasefire started/starts at *time*

Any of the following disqualify sentences as irrelevant:

- ceasefire provides for... (no time)
- *actor* calls to respect ceasefire
- *actor* calls for a ceasefire
- *actor* offers a ceasefire
- *actor* wants a ceasefire
- References to an ongoing ceasefire

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