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ABSTRACT

Communication plays a central role in how crisis events evolve. The huge collection of today's digital available content from actors such as organizations, news media, and the public provides scholars with the opportunity to analyze large-sized collections of crisis-related communication and provide supplementary evidence for previous findings from smaller scaled research. However, the massive costs and complexity of analyzing these large-scaled data sets have hindered their use within the field of crisis research. This paper aims to provide an overview of how automated content analysis can potentially simplify and complement the analysis of these large collections of texts. Computational methods have long been used in the field of computer science and are currently gaining momentum within the field of crisis communication. This paper discusses the dictionary method, supervised method, and the unsupervised method as potential useful tools for analyzing crisis communication.

1. Introduction

Organizational crisis situations[1] and their societal consequences repeatedly occupy our news screens. Correspondingly, organizations report that they frequently face a crisis (Verhoeven, Tench, Zerfass, Moreno, & Verčič, 2014). This omnipresence of crisis situations and the potential negative societal effects of these critical situations have increased the scholarly attention for crisis management. Crisis management has become a key element of crisis research, mainly because multiple stakeholders, and the organization itself, will suffer when the management regarding a crisis fails (Coombs, 2007). Within crisis management, communication and the interaction with multiple involved actors is acknowledged to be a fundamental factor; when the communication is inefficient, so will be the crisis management efforts (Coombs, 2015). It can even be stated

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[1] Crisis is a broad term, frequently used by both academics and practitioners to refer to a wide variety of events and issues. In general, it refers to a breakdown in a system, creating shared stress (Perry, 2007). In the context of crisis management, Coombs (2015) divides crisis in disaster and organizational crisis. Disasters refer more to disrupting events that pose great societal danger, while organizational crisis mainly refers to the threating effects of an unpredictable event on important expectations of stakeholders and the negative consequences for the organization. This study makes no explicit difference between crisis and disaster. It needs to be acknowledged that there are significant differences in communication and how social media is used between different crisis types. These differences might have implications for the applications of automated content analysis. Nevertheless, it is assumed that the different computational methods are useful for studying communication in the context of all types of crises and disasters. The methods can be used to categorize all types of communication based on different starting points or research questions related to crisis research. The final results of the analysis, and the extent to which they are theoretically interesting, depend on the cases that are studied, however, the practical application of the methods remains comparable.

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that, although crises have real origins, they are constituted in the communicative interplay between several actors, whose perceptions produce real consequences (Kleinnijenhuis, Schultz, & Oegema, 2015).

Due to the far-reaching consequences of communicative efforts during a crisis, a significant body of research and numerous cases about crisis communication exist today. Scholars and practitioners aim to understand the flow of communication in times of crisis and how the communicative interplay can affect outcomes such as public panic (e.g., Liu & Kim, 2011; Van der Meer & Verhoeven, 2013), crisis escalation (e.g., Seeger, 2002), post-crisis organizational reputation (e.g., Coombs & Holladay, 2008), or financial markets (Kleinnijenhuis, Schultz, Utz, & Oegema, 2013).

The increasing body of crisis research in the field of communication has adopted multiple methodological approaches to unravel the dynamics of crisis communication. So far, crisis literature is dominated by studies applying experimental designs to understand public responses towards organizational crisis communication (Coombs, 2007; Kim & Cameron, 2011). Additionally, case studies are still the majority of the extant crisis research. For example, multiple scholars have analyzed, under different conditions, the effectiveness of the crisis-response strategies for specific cases as a way to minimize or avoid post-crisis damage. Based on Benoit's (1997) speculative image restoration strategies, Coombs (2007) categorized several response strategies as denial, diminish, and rebuild. Extensive empirical research has demonstrated how these strategies, for various crisis situations, differently affect several outcome variables such as the organization's post-crisis reputation (e.g., Coombs & Holladay, 2008) and secondary crisis communication (Schultz, Utz, & Göritz, 2011).

The digital age has brought substantial changes to the field of crisis research. In general, crisis situations set in motion a large amount of messages from various actors (Thelwall & Stuart, 2007). The shift towards online publication and archiving of different news outlets – e.g., online news websites and online archiving of newspapers – and organizations – e.g., online press releases and organizational statements on corporate websites – provides crisis researchers with new opportunities to study large amounts of crisis communication data. Furthermore, social media has become an integral part of crisis situations (Madden, Jansoke, & Briones, 2016; Ott & Theunissen, 2015; Van der Meer & Verhoeven, 2013), increasing the accessibility of public crisis communication via online platforms such as blogs, Facebook, or Twitter. Analysing the huge collection of content and understanding the complex dynamics of this contemporary media landscape in the context of organizational crisis situations requires a larger scale of analysis. Therefore, an emerging research avenue in the field of crisis communication applies forms of automated content analysis to study the communicative processes and effects using large amounts of crisis data. As scholars have recognized that much of the crisis is constructed and formed within the discourse of communication among different domains or actors (Kleinnijenhuis et al., 2015; Van der Meer, Verhoeven, Beentjes, & Vliegenthart, 2014), the use of automated content analysis provides opportunities to enrich the body of crisis literature using large data sets. In other words, this automated approach can help to provide supplementary evidence for what crisis scholars so far have suspected based on qualitative or small-scale quantitative research.

Academics in crisis research, just like academics from other social sciences, have just started to recognize the opportunities of (newly) available automated content analysis. The general aim of these computational methods, which commonly find their origin in computer science, is to automatically identify or classify certain patterns within large amounts of texts with reduced costs and time (Flaounas et al., 2013). With the use of computer-assisted methods, this classification becomes more replicable and is (likely) to be without bias due to subjective interferes of the researcher (Riff, Lacy, & Fico, 2014).

This paper aims to map the available and applicable automated content approaches for the field of crisis research. An overview of such techniques is provided to gain practical understanding of what computational methods can be used for within crisis research, guided by the overview paper of Grimmer and Stewart (2013) in the context of political communication. Both deductive and inductive computational approaches will be discussed. Deductive approaches are mainly used to analyze content based on a priori defined categories or taxonomies while inductive approaches can be applied to explore (new) patterns in text. Therefore, these different methods can serve different purposes, for example confirmatory analysis of expectations regarding content or consequences of communication based on existing theory and smaller scale analyses or more exploratory objectives aiming to further build theory based on population samples. Additionally, for each method an example will be provided of a study that applied this approach to gain insights in how these techniques can be used to answer questions related to crisis research.

2. Principles of automated content analysis

Before discussing the potential useful automated content methods, some principles need to be addressed (Grimmer & Stewart, 2013). First, automated content analyses are, of course, not free from drawbacks. Automated methods are not equivalent to manual methods. The computer-aided part makes these methods more systematically reliable and therefore more replicable, however, it cannot replace human augment. Due to the complexity of language, automated content analysis might only amplify careful reading of text. Most automated content analysis rely on the *bag of words* approach where word frequencies are used as features of text and word order does not inform the analysis (e.g., Hellsten, Dawson, & Leydesdorff, 2010; Miller, 1997). All these automated methods might fail to provide an accurate account to actually process texts. Therefore, it is argued that automated content analysis should be solely used to help researchers to content analyze large amounts of text where careful thought, reading, and interpreting the output is still essential and should be guided by the researcher.

Within the analysis of text, a wide range of different research questions and designs should lead to the use of different methodological and statistical approaches. Therefore, there is no guarantee that certain methods will be applicable to each study design. In some cases, the output of such methods may be simply wrong or misleading. Even if a specific automated content analysis is applicable to answer or test certain research questions of hypotheses, it is still not guaranteed that the method will return theoretically interesting results. The applicability of a method is therefore context and data dependent. For that reason, the validation of these techniques needs to be tested to evaluate the applicability in the context of a study design. The validation of the use of automated methods can take multiple forms, dependent on the type of method (Grimmer & Stewart, 2013). When certain categories are already known in advance, researchers should evaluate whether the automated methods are capable of replicating the human coding. However, when categories are not known, researchers should come up with a combination of theoretical, experimental, or statistical evidence to demonstrate that the output of the method is conceptually accurate and valid (Budge & Pennings 2007; Slapin & Proksch, 2008). Therefore, it is important for researchers who plan to apply computational methods to consider the link between the research objective and type of automated content analysis.

3. First steps

Prior to conducting the automated content analysis, the data need to be acquired. Within crisis research, scholars have sparsely applied these automated methods across a diverse set of texts, including archives of media content about an organizational crisis (e.g., Schultz, Kleinnijenhuis, Oegema, Utz, & Van Atteveldt, 2012), press releases of the organization that is experiencing a crisis from the website of the organization or a media archive (e.g., Van der Meer, 2014), social media manifestation of online public such as blogs or twitter data (e.g., Van der Meer & Verhoeven, 2013), or transcription of the communication among crisis emergency response personnel (Netten & van Someren, 2006). The rapid movement to electronically stored and distributed text documents often enables easy access to required data. For example, certain online databases as Lexis Nexis or ProQuest facilitate the option to download multiple text files of newspaper or press wires at once. However, other types of data are harder to acquire. Sometimes text needs to be transcribed first, for example in the case of television news regarding a crisis or the communication among emergency response personnel. Additionally, text stored on websites can be difficult to access as websites do not provide an option to batch download text files. Automated scraping techniques (e.g., Jackman, 2006) can make acquiring texts on websites easier – for example press releases from an organizational website.

After acquiring the data, the text needs to be simplified and transformed into quantitative data before it can be automatically analyzed. In order to effectively analyze text, certain textual information needs to be discarded that is either unhelpful or too complex for statistical methods. Certain freely available software can help in simplifying these texts. The most common pre-processing steps are discussed below.

The first pre-processing steps relates to the *bag of words* approach. As mentioned before, this approach discards the order in which words occur in documents and focuses on the (co-)occurrence of words within texts. It is assumed that a simple list of words can be sufficient to convey the general meaning of the text of analysis (Jurafsky & Martin, 2009). However, certain word pairs or triples can be retained. Second, the vocabulary of the words in the text needs to be simplified. Stemming or lemmatization can be used to reduce the total number of unique words in the data set. These approaches reduce the complexity of the words that refer to the same basic concept by removing the end of the words or reduce the words to their base forms (Manning, Raghavan, & Schütze, 2008). Additionally, things as punctuation and capitalisation are typically removed. Third, using a stop words list, function words that do not convey meaning but primarily have a grammatical function are deleted from the text. Additionally, by removing, for example, words that appear in more than 99% of the documents and in less than 1%, other very common words and uncommon words are removed (Hopkins & King, 2010; Quinn, Monroe, Colaresi, Crespin, & Radev 2010). An additional option, sometimes applied by researchers, is to weigh the words in the document. TF-IDF weighted word frequencies can be applied to evaluate the power of a word to discriminate between articles (Manning et al., 2008). If a word is rare, it is assumed to be more distinguishing. A word gets assigned the number of times it occurs in the document (TF), weighted by the frequency of articles in the dataset containing the word (IDF). Finally, the texts are transformed into a document-term matrix, indicating how often words occur in each text of analysis. This matrix is often the input for the different types of automated content analysis.

Several options of freely available software exist that can help with these pre-processing steps. For example, JFreq software, made available by Will Lowe (Lowe, 2011), and the software programs made available by Loet Leydesdorff (Vlieger & Leydesdorff, 2011), can read large amounts of texts to create documents in which each word in the texts is a row and each text is a column (i.e., document-term matrix). Additionally, this type of software also allows using word stems as opposed to whole words and deleting stopwords. For those academics familiar with programming language, they can use, for example, Python where multiple modules are available for these pre-processing steps such as stemming, lemmatizing, TF-IDF, and creating document-term matrices.

4. Automatically categorizing text

Within the field of crisis research, as well as in other social and communicative fields, assigning texts to categories is the most common application of automated content analysis. The categorizations of texts, which are identified by the analysis, are often interpreted as the topics or frames used in the texts of analysis. In general, the concept of framing refers to an emphasis in salience of different aspects of an issue (De Vreese, 2005). In the context of crisis research, framing refers to how a crisis situation is presented. The basis of a frame is formed in the meaning of the words (Hellsten et al., 2010). More specifically, these types of methods build upon the similarity in occurrence patterns of words (Hellsten et al., 2010). The word (co-)occurrences of related words can specify the construction of crisis meaning and represent a higher-order structure of texts (Leydesdorff & Hellsten, 2006). Co-word analysis maps the strength of associations between key words in texts, which enables to identify clusters or frames embedded in the text. Therefore, content analyzing the distribution of words and their (co-)occurrences can help to automatically identify which frames are used within a certain bulk of text (Leydesdorff & Hellsten, 2006).

The computational methods used to categorize text in order to identify frames can help crisis researchers to answer multiple questions. How a crisis is framed can determine whether it will escalate or not and also alter the severity of its impact. Accordingly, public relations efforts and crisis management tend to be regarded as successful when the framing of organizational press releases resonates as intended in the news and hereby affects also stakeholders' perceptions (Schultz et al., 2012). Therefore, fundamental questions in crisis research relate to how a crisis situation is presented or framed by different actors. For example, how does the news media frame the crisis? Or is the frame provided by the organization that is undergoing the crisis adopted by the news media and the public? Ergo, the theory of framing in combination with automated content analysis can play a key role in crisis research to provide insights in how the situation is understood and framed and to what extent the framing of different actors is comparable or different.

The remainder of the paper addresses different types of automated content analysis. An overview is given of the following approaches: Dictionary methods, supervised methods, and unsupervised methods. Each approach generally aims to describe the large dataset of text files with fewer dimensions by automatically mapping a group of correlated words or text that together form a distinctive and meaningful classification. However, the computational methods serve multiple research objectives. The techniques differ in terms of being either deductive or inductive. In some cases the classification (of words) is a priori defined and other techniques aim to inductively identify issue specific categories in order not to overlook meaningful concepts (Van Atteveldt, Kleinnijenhuis, & Ruigrok, 2008). The deductive approaches relate more to confirmatory research designs while the inductive approach is more appropriate for exploratory research. For each technique discussed below an example is given how it has been applied within the context of crisis research.

5. Dictionary methods

Dictionary methods are most in line with manual content analysis where scholars detect certain categories – e.g., frames – in text based on a deductive or taxonomy based-coding strategy using for example a codebook with indicators questions (e.g., Semetko & Valkenburg, 2000). The dictionary methods aims to automate this process by apply advanced search strings. In this sense, dictionary methods are the most intuitive and straightforward automated method to apply (Grimmer & Stewart, 2013). The basis behind this approach is counting how often certain words occur, words that determine a category a document could belong to. Thus, the dictionary approach uses the rate at which key words appear in the text of analysis to measure to what extent the text belongs to a particular predefined category.

A frequently used categorization, to classify text using dictionary approach, is whether a text conveys information positively or negatively. When the goal is to measure tone or sentiment, a list of words with attached tone scores are used to measure a text's tone based on the relative rate at which these specific words occur (e.g., Eshbaugh-Soha, 2010). Sentiment analyses are, for example, commonly used within the field of marketing to assess how organizations and their brands are evaluated by the public online (Mostafa, 2013). The dictionary approach to analyze sentiment in text is continuously developing and improving to obtain a valid tool to automatically assess the tone and sentiment in text for all languages. For example, a more powerful algorithm called SentiStrength does not only count the number of words with attached tone but also involves other features of the text such as negation or punctuation (Thelwall, Buckley, Paltoglou, Cai, & Kappas, 2010).

Tone or sentiment is just one type of text categorization that can be performed with a dictionary approach. Dictionaries can relatively easy be applied across different categories or issues. One needs to identify the words that separate a certain category and measure how often those words occur in the text of analysis. There are some techniques to find these separating words. A variety of widely applied dictionaries already exist that provide key words for particular categories (e.g., Hart, 2000; Pennebaker, Francis, & Booth, 2001; Turney & Littman, 2003). Moreover, certain scholars have identified how well words actually separate already identified categories (Diermeier, Godbout, Yu, & Kaufmann, 2011; Taddy, 2010).

However, the dictionary methods should be used with caution. Previously applied dictionaries may not apply in other contexts or domains. For example, a word can have a positive connotation in one context and refer to something negative in another situation. The domain specificity forces scholars to evaluate if word lists created in another context are indeed applicable to their field of research or if a new context-specific dictionary needs to be created. Again, the importance of validation in automated methods needs to be emphasized. Researchers could evaluate whether the automated clustering of text using dictionary methods is comparable with human coding of the same texts. Unfortunately, measures from dictionaries are rarely validated by researches (Grimmer & Stewart, 2013).

5.1. Example of dictionary method

An illustrative example of how dictionary methods can be applied within the field of crisis research is the study by Schultz and colleagues (2012). In this paper, Schultz and colleagues investigated the communicative interplay between public relations and the news media during the BP oil spill crisis in the Gulf of Mexico. More specifically, via an automated content analysis they examined frame differences between BP's public relations and UK and US news regarding the BP crisis. Using a dictionary method, the salience of actors and the use of frames was recorded.

For their analysis, Schultz and colleagues collected 126 press releases from the website of BP and used LexisNexis to obtain 1.376 articles from American newspapers and 2.355 articles from UK newspapers about the BP crisis. Several steps were taken in order to develop a keywords list with descriptors and concrete search strings to identify the actors and frames used in text. First, two of the authors read a sample of the texts to gain insights into the central actors within the crisis and how the crisis developed. Second, earlier related studies were consulted to gain understanding of what could be relevant keywords for the categories of actor type and different frames. Third, via a list of the most frequently used words, the list with keywords was reworked to select the most important descriptors of the actors and frames. Finally, based on a sample of the texts, an iterative test of these keywords was used to filter out mistakes of the first and second degree. The authors provide an Appendix with the final set of search strings that was used, making it easier for other researchers to replicate the study.

The list of the main actors within the BP crisis consisted of BP, the White House, politics, the court, and environmental protests actors. Based on the exploration of the text and theory regarding diagnostic and prognostic framing, keywords were used to find the categories cause, solution, consequences, and oil spill problem. Via the use of AmCat (Amsterdam Content Analysis Toolkit), a document database and management system, keyword-based analyses were conducted to measure the attention for actors and the use of frames in each text file. In the results, the mentioning of actors and use of frames was compared among the press releases and the newspaper articles of the different outlets. Additionally, the frames were visualized in figures were associations between actors and the frames were plotted.

6. Supervised methods

Supervised methods offer a useful alternative of automated content method for assigning texts to predetermined categories (Russell & Norvig, 2002). Rather than dictionary methods, supervised methods do not require researchers to identify keywords and search strings that separate different categories to deductively code text. However, this more advanced automated content analysis does require a relatively high degree of initial manual labour. The idea of supervised learning methods is relatively simple. Based on a set of texts that human coders categorize by hand, a computer algorithm learns how to sort texts into the predetermined categories (Burscher, Odijk, Vliegenthart, De Rijke, & De Vreese, 2014). So the algorithm identifies certain characteristics, or the lack of certain characteristics, that separate certain categories in order to code the text into the correct category. Thus, this technique can be used for coding latent or implicit variables in a dataset so large that it is not feasible to hand code every article.

The method starts with setting up a codebook for the manually coding of a training set based on a sample of the entire dataset of texts. As this type of supervised learning method is often used for coding latent or implicit categories the reliability of the manual coding scheme is essential. Therefore, it is suggested to iteratively develop a codebook that will guide the coders how to categorize the text of analysis. When a reliable codebook with sufficient intercoder reliability (Krippendorff, 2004; Neuendorf, 2002) is developed, the coding of the training set can begin. The more articles of the entire dataset are coded, the more reliable the automated coding will be. The researchers should determine how large their random sample of the entire dataset should be for manual coding. One rule of thumb states that one hundred texts for the training set should be enough in case of a total of 500 texts (Hopkins & King, 2010). When the manual coding is completed, the labelled texts are used to train the supervised learning machine. This method can either provide the proportion of a category for each text or assign individual texts into the different categories. Basically, the learning algorithm assumes that there is a (unobserved) function that can be used to describe the relationship between the words in texts and the categories. The learning method attempts to learn this relationship in order to reproduce the manual coding. Different types of supervised methods exist, for an overview see the article by Grimmer and Stewart (2013).

A clear advantage of supervised methods over the dictionary approach is that they are easier to validate with statistical indicators. The algorithm can be used to redo the coding that was already done manually. If the supervised learning method performs well, the manual coding will be replicated (Burscher et al., 2014). The comparison of the output of the machine coding and the hand coding provides a clear evaluation that is free from researchers' subjectivity.

6.1. *Example supervised method*

In the context of framing research, the application of supervised learning methods have, for example, been tested for news articles (Burscher et al., 2014) and policy issues (Burscher, Vliegenthart, & De Vreese, 2015a). Burscher and colleagues (2014) explored the application of supervised machine learning to code generic frames. They focus on four of the generic news frames as defined by Semetko and Valkenburg (2000): conflict frame, economic consequences frame, human-interest, and morality. These generic frames are also occasionally used to explore the framing of organizational crisis (e.g., Kuttschreuter, Gutteling, & de Hond 2011). An indicator-based and holistic approach to modelling the frame coding process were compared to a random baseline model.

Burscher and colleagues (2014) collected front-page news articles of three national Dutch newspapers between 1995 and 2011 about political issues via the LexiNexis database. Based on 11 dichotomous indicator questions of frame indicators, 30 trained coders categorized 6030 articles to measure the extent to which one of the four frames appeared in a text.

The automated coding performance was evaluated in terms of classification accuracy, receiver operating characteristics, and Krippendorff's Alpha between human classifications and computer-based classifications. The final results indicate high coding performance for all four generic frames, concluding that supervised learning methods are suitable for frame coding. Furthermore, the authors show that the performance differs between frame types and that an increase in the number of training texts can significantly improve the computer-based classification.

Besides automatically coding frames, supervised methods can also be of practical help in times of emergency or crisis. Netten and van Someren (2006) investigated the application of supervised learning to improve the distribution of information between emergency response personnel involved in crisis situations. This method may help to encounter the occurrence of communicative errors that might results in mistakes and subsequently lead to more damage to the situation. In the midst of a crisis, where much information is passed by means of speech among different relevant actors, the classification becomes a difficult task. The authors found a way to use supervised machine learning techniques to classify the information in order to help dynamic information distribution and optimize the information flow among collaborating actors. The unsupervised method learns from a collection of texts that is manually labelled as relevant or irrelevant to classify texts accordingly. Furthermore, a prototype system for information distribution was developed, called Task-Adaptive Information Distributor.

To test their prototype system they focused on a crisis case where a fire broke out in a church. Due to several mistakes in the information distribution between emergency personnel, three firemen died. The information that the police went inside the church and did not find anyone was not communicated to the fire truck team. If this had been communicated, the firemen would not have gone inside at their arrival. The study focuses on actors such as control rooms of the police, regional fire department, and fire-truck team.

For training the machine learning methods, transcribed simulated scenarios of communication among emergency personnel in crisis management operations are labelled. Thus, the input format to the system is unstructured text. They used the context features of task descriptions, location information, and emergency phase to determine whether information should be labelled relevant for each actor. After the training phase the system was able to classify new information, in combination with context information, accordingly to relevance for actors. Finally, the Task-Adaptive Information Distributor would than actually distribute the message to the designated actor(s) that have a particular role for which the message is relevant. The scenario indicated that the machine learning method is actually able to correctly identify which information is relevant for which actor and hence support the information flow during a crisis.

7. Unsupervised methods

Contrary to dictionary based and supervised automated content analyses, unsupervised methods inductively identify word clusters in text. In other words, rather than searching for predefined categories such as frames, unsupervised methods provide the researcher with information about which categories can been found in the texts that are analyzed. This inductive method is mainly used to explore texts when little previous empirical research or theory is available to formulate clear expectations. Thus, this type of method can be useful when a set of categories is difficult to derive beforehand, as is often the case for specific issues or when the aim is to derive issue-specific frames from texts. Moreover, inductively identifying clusters can be valuable because it can identify organizations of text that are theoretically useful but still understudied or previously unknown (Grimmer & Stewart, 2013).

In short, unsupervised learning methods are a technique that automatically learns the underlying features of text without explicitly imposing certain categories beforehand. Modeling functions and properties of the text of analysis are used to estimate a set of categories and assign texts to those categories. This unsupervised automated method looks for word repertoires or latent patterns of words co-occurrence that form the underlying contexts which enables to highlight how a certain issue can be categorized. In other words, the (co-)occurrences of related key words in text specify the construction of meaning and represent a higher-order structure of texts that can be identified as, for example, a frame (Leydesdorff & Hellsten, 2006).

Two broad classes of relevant unsupervised learning methods for the classification of text can be distinguished: Single membership and mixed membership models. Both methods are considered Fully Automated Clustering approaches. First, single membership models are clustering models that estimate texts into mutually exclusive and exhaustive categories or clusters. Groups of texts are clustered, representing an estimate of a category (Grimmer & Stewart, 2013). These texts score the highest on a cluster of words – i.e., words that highly correlated with each other in and among texts. The groups of correlated words form a distinctive meaningful classification within the text of analysis. These word groups or clusters represent the higher-order structure in texts (Leydesdorff & Hellsten, 2006). Amongst the most common Fully Automated Clustering approaches are Principal Component Factor Analysis (Vlieger & Leydesdorff, 2012) and the K-Means algorithm (Burscher, Vliegenthart, & De Vreese, 2015). In general, these algorithms tend to identify a partition of the text that minimizes the distance within the cluster. Each text gets assigned to the cluster for which its distance to the cluster center is the smallest. These types of cluster analysis have frequently been used to identify issue-specific frames in text. Second, mixed membership models assume that each text is a mixer of different categories or clusters, there for each text exhibits multiple topics in different proportions (Grimmer & Stewart, 2013). The models share a basic hierarchical structure. Topic models have been proposed as the method of including this structure (Blei, Ng, & Jordan, 2003; Řehůřek & Sojka, 2010). The most widely used topic model is the Latent Dirichlet Allocation (LDA). So far, LDA has, for example, been used to identify important news items (Krestel & Mehta, 2010).

7.1. Arbitrary steps

Despite that most steps within the unsupervised methods are automated, the researcher is still required to guide the analysis. This guidance holds that parts of the method are still arbitrary and a result of subjective decisions.

First, although one of the main advantages of unsupervised methods is that no a priori coding schemes need to be supplied, these tools often do require setting the number of clusters in a model. For example, for both the K-Means clustering and the LDA topic modeling the number of clusters or topics in the final clustering must be determined beforehand. However, no clear or default rule exists for determining the number of clusters. The trade-off is to describe the data with fewer categories than are actually present, but with sufficient categories so all relevant information is included. Some statistical equations attempt to eliminate this decision by estimating the number of clusters (Frey & Dueck, 2007). For example, the perplexity measure (Blei et al., 2003) and alpha hyperparameter (Kim, Kim, & Oh, 2014) are statistical indicators that can be used for this purpose. However, the estimated number of clusters are found to be strongly model dependent. Additionally, having mathematically estimated the number of categories does not say anything about the interpretability of the produced categories (Grimmer & Stewart, 2013). In social science in general, the categories are used to answer substantial theoretical questions about the texts of analysis. Therefore, the interpretability of the categories is considered more important than providing the best prediction of the data. In conclusion, it is stressed that the statistical parameters to determine the amount of categories should only be used to make an initial selection of models and the interpretability should be decisive for the amount of categories.

Second, not relying on pre-defined categories leaves more room for identifying new or unexpected frames. These generated clusters need to be labelled in order to facilitate the communication of results and answering certain research questions (Van der Meer et al., 2014). This labelling is an interpretive and subjective process based on the words and/or the documents that form the clusters. This subjectivity may come with the danger of the fallacy of misplaced concreteness.

Third, the validation of unsupervised methods is not as clear and straightforward as it is for supervised methods. The best way of proving validity of Fully Automated Clustering techniques is still under discussion (DiMaggio, Nag, & Blei, 2013; Ramirez, Brena, Magatti, & Stella, 2012; Quinn et al., 2010). Scholars are advised to start using statistical parameters to gain an indication of the amount of clusters, and then manually inspect how many of the clusters are meaningful. Afterwards, manual coders can check whether the automated coding was done correctly for a subsample of all texts. Additionally, if a cluster is actually valid, then external events should explain sudden increases in attention to a cluster (Grimmer, 2010). For a more elaborate review of validity and Fully Automated Clustering models, see DiMaggio et al. (2013) and Quinn et al. (2010).

7.2. Example unsupervised methods

The unsupervised method approach enables to highlight frame development over time and compare framing among different domains (Leydesdorff & Hellsten, 2005). For example, Jonkman and Verhoeven (2013) investigated the public debate in The Netherlands regarding third-party airport risk using unsupervised methods. To explore how the discourse regarding the airport evolved over time, the content of two quality newspapers from May 1992 to May 2009, a total of 579 relevant news articles, was content analyzed. Different periods were identified within the data based on previous research on third-party airport risk and the publicity pattern detected in the data set. To study the development of discourse and frames over time, the news articles were analyzed for each research period separately. An unsupervised method was applied to obtain the frames that were used in each period. With the open source software from De Vlieger and Leydesdorff (2011) document-word matrices, based on the 75 most frequently used words in text, were constructed for each period. Principal Component Factor analyses were run on the matrices to find a maximum of six word clusters per period. These word clusters were interpreted as the implicit frames used in the newspapers that formed the discourse regarding the airport risk. The clusters were provided with a frame label so the frame could be compared between the different time periods. Moreover, the frames were visualized in word networks or clouds using Pajek software based on a cosine-normalized matrix (see e.g., Leydesdorff & Hellsten, 2005). In the two-dimensional word network each node represented a word and the size of the node was proportional to the frequency of the word. The lines in the pictures represented the correlation among the words. Each word in the network was assigned a different colour depending on the frame it belongs to. The central conclusion of the study was that the economic frame dominated the third-party airport discourse. In 1990s these economic frames were flanked by accidents and risk frame and in the 2000s by accidents and safety frames.

Other researchers in the field of crisis research applied a comparable unsupervised method to explore the interplay between different domains. Van der Meer and colleagues (2014) investigated whether the crisis frames of the domains public relations of the organization experiencing the crisis, news media, and the public aligned over time. The authors collected press releases, newspaper articles, and public social media messages of four organizational crisis cases to compare the frame usage over time. To explore the development of implicit framing over time, the data were analyzed separately for several research periods: Initial phase, period of extensive communication, and final crisis phase. Using the software from De Vlieger and Leydesdorff (2011) and Principal Component factor analysis, unsupervised learning methods were used to obtain twelve frames for each actor, time period, and crisis situation. To obtain a statistical indicator of frame alignment among the different actors, the application of factor analysis was further elaborated on the level of the words that form the clusters. In a factor analysis each word gets a factor loading assigned which indicates its substantive importance to the given cluster or frame. Hence, the factor loadings are interpreted as the extent to which a specific word represents a frame. To statistically assess the level of frame alignment among domains, the factor loadings of mutual-used words by the separate domains are compared. This process provided the research with the level of frame alignment among the domains PR, news media, and the public in each crisis period for each crisis case. The overall results documented the dynamic character of crisis framing over time among actors. First, in the initial crisis phase, the frames generally varied across the domains. Second, in the phase of extensive communication the frames of the domains actually did align. However, this level of frame alignment was only temporary as in the final crisis phase the framing de-aligned.

8. Conclusion and discussion

This article provides a brief overview of recent automated tools to analyze crisis communication. The discussed automated techniques can help researchers in the field of crisis communication and management as a valuable tool in any large-scale content analysis project. As a lot of data is becoming available online, the tools can help to understand the evolvement of crisis communication and how to manage the flow of communication. Thus, these automated methods will make possible inferences that were previously impossible. If crisis researchers are capable to effectively use large-scale content analysis in their inferences, then many substantial research questions are likely to be answered (Grimmer & Stewart, 2013).

The automated approach to content analysis provides a wide range of tools to answer diverse questions within the field of crisis research. The available tools actually extend beyond the methods discussed in this paper. However, this overview provides a first outline of what is broadly available and potential useful for crisis researchers. The dictionary method, supervised method, and unsupervised method provide especially interesting tools for classifying texts and identifying frames within crisis communication. However, it needs to be emphasized that the selection of these tools is context specific. The selection of an automated tool should depend the input data that will be used as well as on the initial interest and questions of the researcher. Therefore, a debate of which automated method is the "best" is considered a misplaced debate (Grimmer & Stewart, 2013). For example, a debate existed that casted unsupervised and supervised method as competitors (e.g., Hillard, Purpura, & Wilkerson 2008; Quinn et al., 2010). However, both methods have different objectives and should rather be seen as complementary methods. Practically, supervised methods are most applicable when predefined categories exist for the texts that need to be categorized. If no categorization scheme is available beforehand, unsupervised method are useful by inductively finding new categories. In some cases a combination between these methods can be insightful, especially for new research projects with recently collected data. For example, unsupervised methods could complement supervised methods by contributing to new coding schemes, while supervised methods could validate and generalize the findings of unsupervised methods.

Besides the input data, the initial research objective should guide the selection of the type of computational method. The deductive methods, the dictionary method and supervised method, are mainly applicable when researchers have clear indications of what to expect. It can be used to confirm how often different actors use certain predefined categories in crisis communication. For example, the supervised method used in the discussed article by Burscher and colleagues (2014) can be used to confirm what generic frames different actors or media outlets use when communicating about different types of crisis. Furthermore, in the other discussed article Schultz and colleagues (2012) used previous theory and a qualitative analysis of the text to come up with multiple categories that were than used to categorize text with the help of a dictionary method. Accordingly, these deductive methods are also highly applicable for validating findings based on small-scale and qualitative research. The inductive unsupervised method is mainly useful for the purpose of exploring new areas or complement existing findings. The discussed articles (Jonkman & Verhoeven, 2013; Van der Meer et al., 2014) show how this method can be applied to explore crisis communication processes when little clear-cut assumption can be formulated beforehand.

Because most computational methods addressed in this paper are related to the concept of framing, its theoretical limitations need to be mentioned. Framing has emerged as one of the most popular research areas in communication science. Yet despite the popularity of framing theory, the conceptualization has arguably become less clear over the years. The framing literature is characterized by considerable disagreement over the exact constitution, both in terms of theoretical and methodological operationalization, and a strong overlap exists with other conceptual models such as agenda-setting and priming (Cacciatore, Scheufele, & Iyengar, 2016; Scheufele & Iyengar, 2014). Academics who use the automated content analysis to identify frames in texts should acknowledge these limitations and place their studies along the lines of existing framing traditions (e.g., psychology-rooted or sociology-rooted framing and equivalency framing or emphasis framing). Despite the theoretical limitations of framing, the use of computational methods (in combination with framing theory) is still considered a valuable approach to automatically categorize large-sized collections of texts and understand what is emphasized within the communication of crisis events.

The suggested automated methods also have their limitations. The tools are consistently being improved and researchers look for new ways to statistically analyze texts. For example, one could argue that the *bag of word* approach, that forms the basis for all discussed methods, has its limitations. By assuming that text documents are a bag of words, the word order does not inform the analysis. Only looking at word (co)occurrences significantly reduces the amount of information. The *bag of word* approach is commonly found to infer substantively interesting properties of texts (Hopkins & King, 2010), however; there are certain other approaches that are capable of taking more elements of language into account. For example, techniques such as part of speech tagging and named entity recognition can take the syntactic structure into account. Van Atteveldt and colleagues (2008) build a model to automatically code semantic relationships and disentangle the syntactical function of the elements of a sentence. This type of methods, developed in the field of computational linguistics, might help to advance the current automated analysis to categorize and understand content. In the end there will always be room for improvement if it comes to using algorithms to understand texts. Therefore, for automated content analysis to become a standard tool for crisis research, academics have to contribute to the development of new computational methods and ways to validate the findings of computer-assisted analyses. However, the automated content analyses as discussed in this paper do seem to serve their purpose at this point. Hopefully this brief overview provides understanding of how automated tools can be applied within the field of crisis research and inspires researchers to apply them to large-scale data sets.

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