Sentiment Analysis

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Abstract

Sentiment is a central topic for scholars of Political Communication. Despite its popularity, sentiment suffers from a lack of agreed-upon conceptualization and operationalization. The ambiguity and complexity is reflected in the applications of sentiment. Scholars have used sentiment as an analytical frame to describe and/or explain *tonality* of a (news) story, *outlook* or *perspective* in a (news) story, focus on *conflict or consensus*, focus on *incapability and misconduct*, as well as the *tone* towards actors and organizations in media, political, and public discourse. Sentiment has especially gained popularity in the “text-as-data" revolution due to the availability of data as well as computational text analysis methods. In this entry, we highlight the existing theoretical applications based on the core theories in political communication, as well as review the methodological toolkit to automatically measure sentiment. We thereby give an overview of the variety in approaches towards sentiment in political communication.

Key Words

Sentiment, Negativity, Tonality, Perspective, Affective Strategy, Automatic Text Analysis

Sentiment is a central topic for scholars of Political Communication (for overviews, see van Atteveldt et al. 2021; Lengauer et al. 2012). The concept has especially gained popularity in the “text-as-data" revolution due to the availability of data as well as computational text analysis methods (for overviews, see Grimmer et al. 2022; Baden et al. 2022). A search on the Web of Science database using the search string *sentiment* in the disciplines Political Science and Communication disciplines, selecting the top 25 journals, shows that since 2015, the amount of publications have tripled: From approximately 20 publications a year in 2015 to 60 since the 2020’s. Despite its popularity amongst scholars, sentiment – or any of the often co-occurring concepts, such as emotionality, negativity, polarity, subjectivity, tone, or valence – suffers from a lack of agreed-upon conceptualization and operationalization (Lengauer et al. 2012; Kleinnijenhuis 2008). Scholars have used sentiment as an analytical frame to describe and/or explain *tonality* of a (news) story, *outlook* or *perspective* in a (news) story (i.e. whether there is an optimistic or pessimistic future described), focus on *conflict or consensus* (including one-sided criticism, attacks, allegations as well as commendation), focus on *incapability and misconduct* (i.e. reflecting at least two-side), as well as the *tone* towards actors and organizations in media, political, and public discourses (for an overview, see Lengauer et al. 2012). These theoretically different notions potentially explain why off-the-shelf methods for sentiment analysis seem to measure vastly different things (van Atteveldt et al. 2021). For example, it matters if we think about sentiment as an outlook, investigating whether a news story focuses on hope versus despair, in which we are closer to the framing literature, or if we think about sentiment as a positive vs negative tone describing a political issue or actor. In this entry, we highlight the existing theoretical applications based on the core theories in political communication, as well as review the methodological toolkit to automatically measure sentiment. We thereby give an overview of the variety in approaches towards sentiment in political communication.

Applications of Sentiment

Sentiment analysis was originally developed to measure customer product feedback, using software to discern positive or negative sentiments in online reviews, aiding businesses and consumers alike (for an overview, see Sun et al. 2017). The objective was to extract opinions from texts, providing valuable insights without needing to read all the reviews. This proved very useful for theories of political communication, since many of them have sentiment at its core. At the same time, it has led the concept to appear in widely divergent manifestations, indicating both its complexity and ambiguity (van Atteveldt et al. 2021; Kleinnijenhuis 2008; Lengauer et al. 2012). The ambiguity and complexity of the concept is reflected in the application of sentiment as both *polarity* and *valence*. Polarity implies a dimension ranging from positive to negative, whereas valence implies a dimension from neutral to subjective (or emotional or value-laden). The ambiguity and complexity of the concept becomes also clear when thinking of the object to which sentiment is applied to.

When detecting *frames*, following Entman’s definition (1993), sentiment as an analytical framework is used to measure the promotion of a problem definition, the moral evaluation or recommendation. Looking at *agenda-setting*, however, sentiment is applied as an analytical framework to detect its second level (for an overview, see van der Velden and Loecherbach 2022). Testing these theoretical frameworks, scholars use sentiment analysis to measure what people think about political issues, parties, or particular politicians (i.e. second-level agenda-setting or effect of framing), as well as how these opinions diffuse, and change with different media channels or media usages. Scholars do so by conducting sentiment analysis on collected documents (e.g. (social) media posts), inferring political attitudes or predicting behaviors based on the sentiment measures. This technique has been widely used to assess public views on political candidates (Murthy 2015; Wang et al. 2012) and political issues like climate change (Dahal et al. 2019). In contrast to understanding citizens' perspectives, another application is concerned with the media's tone, still within the framework of framing or agenda-setting. This entails examining whether news coverage of political topics, parties, or politicians is positive or negative. Often, these analyses deal with the phenomenon of media negativity, a concept that describes the predominance of negative news over positive ones, the tone of media stories, and the extent of conflict or confrontation depicted in the news (Esser and Strömbäck 2012; Lengauer et al. 2012). Sentiment analysis has been used to study political media negativity in, among others, the Netherlands (van Atteveldt et al. 2008), the United States (Young and Soroka 2012; Soroka et al. 2018; Soroka et al. 2015), and the United Kingdom (Burscher et al. 2016).

That is not all. The concept of sentiment is also utilized to measure opinion leaders' endorsement of content, testing the *Two-Step Flow theory* (Katz 1957). More recently, with the emergence of social media, people have used sentiment as an analytical framework to study *selective exposure* (Sears and Freedman 1967), looking into norm-setting behavior of being selectively exposed to tonality on social media platforms (Tang and Fong 2013; Matalon et al. 2021). In addition, researchers found it a helpful analytical framework testing the *Elaboration Likelihood Model of Persuasion* (Petty et al. 1986), by researching questions such as "does negative content affect political attitudes (e.g. cynicism) or behavior (e.g. voting for anti-establishment parties)?" For example, sentiment analysis has been used to study negative campaigning, i.e. the phenomenon of politicians and parties criticizing or attacking each other instead of promoting their own policies. Recent studies apply a graded conceptualization of negative messages. Some sentiment analysis tools in political communication were developed for exactly that use case (Haselmayer and Jenny 2017; Rudkowsky et al. 2018). Studies applying sentiment analysis for the study of negative campaigning found that negative campaigning is relatively successful for challenger parties but not for incumbents (Lau and Pomper 2002), that voters get better informed when political candidates attack and raise doubt about each other (Geer 2006), and that coalition parties refrain from strong attacks against their coalition partners even if they criticize each other frequently (Haselmayer and Jenny 2018). In addition, female legislators are found to use less negative words in their debate contributions in parliament (Haselmayer et al. 2021).

Measuring Sentiment

The most commonly employed methods for sentiment analysis in quantitative text analysis include *lexicon-based* approaches and *machine learning* techniques (for overviews, see van Atteveldt et al. 2021; Baden et al. 2022). Lexicon-based methods rely on sentiment lexicons or dictionaries, where words are assigned sentiment scores and are aggregated to determine the overall sentiment of a given text (Taboada et al. 2011). These approaches offer simplicity and efficiency, making them easily interpretable and suitable for analyzing data. They also exhibit remarkable versatility by accommodating sentiment analysis in multiple languages (Mukhtar et al. 2018). However, lexicon-based approaches have ample limitations (for an overview of dictionary based sentiment, see van Atteveldt et al. 2021). In contrast, machine learning techniques have gained immense popularity in sentiment analysis due to their ability to capture nuanced sentiments and adapt to changing language trends (Alantari et al. 2022). Supervised learning algorithms like Naive Bayes and Support Vector Machines, as well as deep learning models such as Recurrent Neural Networks and Convolutional Neural Networks, have demonstrated exceptional performance in sentiment analysis tasks (Thakkar et al. 2022). These methods excel in handling the complex relationships between words and sentiments, making them suitable for sentiment analysis across various domains. By incorporating contextual information, machine learning techniques enable more accurate sentiment classification (Babu and Kanaga 2022). However, machine learning approaches come with their own set of considerations.

To mitigate these challenges, researchers in the fields of political communication and computational social science are continually exploring hybrid approaches that combine the strengths of lexicon-based methods and machine learning techniques (Frigau et al. 2023; Tesfagergish et al. 2022). These hybrid methods aim to leverage the interpretability and language versatility of lexicon-based approaches while harnessing the predictive power and adaptability of machine learning models. For example, Latent Semantic Scaling (LSS) (Watanabe 2021), which is based on a technique known as Latent Semantic Analysis (LSA), combines dictionary and word-embedding analysis. It estimates the semantic similarity of words based on their surrounding contexts and assigns them continuous polarity scores according to their proximity to seed words. LSS requires two human inputs: a feature that specifies the concept of interest and a set of seed words that define the dimensions of scaling (e.g., while ’migration’ might be a feature, positive-negative could be the dimensions of scaling determined by the seed words), which makes it suitable for topic-specific sentiment analysis (Rauh 2022; Umansky 2022). By integrating multiple methods, researchers can tackle the limitations of individual approaches and enhance the overall accuracy and robustness of sentiment analysis systems.

References

Alantari, Huwail J et al. (2022). “An empirical comparison of machine learning methods for text-based sentiment analysis of online consumer reviews.” *International Journal of Research in Marketing* 39.1, pp. 1–19.

Babu, Nirmal Varghese and E Grace Mary Kanaga (2022). “Sentiment analysis in social media data for depression detection using artificial intelligence: a review.” *SN Computer Science* 3, pp. 1–20.

Baden, Christian et al. (2022). “Three gaps in computational text analysis methods for social sciences: A research agenda.” *Communication Methods and Measures* 16.1, pp. 1–18.

Burscher, Bjorn, Rens Vliegenthart, and Claes H. de Vreese (2016). “Frames Beyond Words: Applying Cluster and Sentiment Analysis to News Coverage of the Nuclear Power Issue.” en. *Social Science Computer Review* 34.5, pp. 530–545.

Dahal, Biraj, Sathish A. P. Kumar, and Zhenlong Li (2019). “Topic modeling and sentiment analysis of global climate change tweets.” *Social Network Analysis and Mining* 9.1, p. 24.

Entman, Robert M (1993). “Framing: Toward clarification of a fractured paradigm.” *Journal of communication* 43.4, pp. 51–58.

Esser, Frank and Jesper Strömbäck (2012). “Comparing News on National Elections.” In: *The Handbook of Comparative Communication Research*.

Frigau, Luca et al. (2023). “Semi-supervised sentiment clustering on natural language texts.” *Statistical Methods & Applications*, pp. 1–19.

Geer, John G. (2006). *In Defense of Negativity: Attack Ads in Presidential Campaigns*. University of Chicago Press.

Grimmer, Justin, Margaret E Roberts, and Brandon M Stewart (2022). *Text as data: A new framework for machine learning and the social sciences*. Princeton University Press.

Haselmayer, Martin, Sarah C Dingler, and Marcelo Jenny (2021). “How Women Shape Negativity in Parliamentary Speeches—A Sentiment Analysis of Debates in the Austrian Parliament.” *Parliamentary Affairs*.

Haselmayer, Martin and Marcelo Jenny (2017). “Sentiment analysis of political communication: combining a dictionary approach with crowdcoding.” *Quality and Quantity* 51.6, pp. 2623–2646.

Haselmayer, Martin and Marcelo Jenny (2018). “Friendly fire? Negative campaigning among coalition partners.” *Research and Politics* 5.3, p. 205316801879691

Katz, Elihu (1957). “The two-step flow of communication: An up-to-date report on an hypothesis.” *Public opinion quarterly* 21.1, pp. 61–78.

Kleinnijenhuis, Jan (2008). “Negativity.” *The international encyclopedia of communication*.

Lau, Richard R. and Gerald M. Pomper (2002). “Effectiveness of Negative Campaigning in U.S. Senate Elections.” *American Journal of Political Science* 46.1, pp. 47–66.

Lengauer, Günther, Frank Esser, and Rosa Berganza (2012). “Negativity in political news: A review of concepts, operationalizations and key findings.” *Journalism* 13.2, pp. 179–202.

Matalon, Yogev et al. (2021). “Using sentiment analysis to predict opinion inversion in Tweets of political communication.” *Scientific Reports* 11.1. Number: 1, p. 7250.

Mukhtar, Neelam, Mohammad Abid Khan, and Nadia Chiragh (2018). “Lexicon-based approach outperforms Supervised Machine Learning approach for Urdu Sentiment Analysis in multiple domains.” *Telematics and Informatics* 35.8, pp. 2173–2183.

Murthy, Dhiraj (2015). “Twitter and elections: are tweets, predictive, reactive, or a form of buzz?” *Information, Communication & Society* 18.7, pp. 816–831.

Petty, Richard E et al. (1986). *The elaboration likelihood model of persuasion*. Springer.

Rauh, Christian (2022). “Supranational emergency politics? What executives’ public crisis communication may tell us.” *Journal of European Public Policy* 29.6, pp. 966–978.

Rudkowsky, Elena et al. (2018). “More than Bags of Words: Sentiment Analysis with Word Embeddings.” I*Communication Methods and Measures* 12.2-3, pp. 140–157.

Sears, David O and Jonathan L Freedman (1967). “Selective exposure to information: A critical review.” *Public Opinion Quarterly* 31.2, pp. 194–213.

Soroka, Stuart, Lori Young, and Meital Balmas (2015). “Bad News or Mad News? Sentiment Scoring of Negativity, Fear, and Anger in News Content.” *Annals of the American Academy of Political and Social Science* 659.1, pp. 108–121.

Soroka, Stuart et al. (2018). “Negativity and Positivity Biases in Economic News Coverage: Traditional Versus Social Media.” *Communication Research* 45.7, pp. 1078–1098.

Sun, Shiliang, Chen Luo, and Junyu Chen (2017). “A review of natural language processing techniques for opinion mining systems.” *Information fusion* 36, pp. 10– 25.

Taboada, Maite et al. (2011). “Lexicon-based methods for sentiment analysis.” *Computational linguistics* 37.2, pp. 267–307.

Tang, Jie and Acm Fong (2013). “Sentiment diffusion in large scale social networks.” *2013 IEEE International Conference on Consumer Electronics (ICCE)*. ISSN: 2158-4001, pp. 244–245.

Tesfagergish, S. G., Kapočiūtė-Dzikienė, J., & Damaševičius, R. (2022). “Zero-shot emotion detection for semi-supervised sentiment analysis using sentence transformers and ensemble learning.” *Applied Sciences* 12.17, p. 8662.

Thakkar, Ankit et al. (2022). “Improving the performance of sentiment analysis using enhanced preprocessing technique and Artificial Neural Network.” *IEEE transactions on affective computing* 13.4, pp. 1771–1782.

Umansky, Natalia (2022). “Who gets a say in this? Speaking security on social media.” *New Media & Society*, p. 14614448221111009.

Van Atteveldt, Wouter, Mariken A.C.G. van der Velden, and Mark Boukes (2021). “The validity of sentiment analysis: Comparing manual annotation, crowd-coding, dictionary approaches, and machine learning algorithms.” *Communication Methods and Measures* 15.2, pp. 121–140.

Van Atteveldt, Wouter et al. (2008). “Good News or Bad News? Conducting Sentiment Analysis on Dutch Text to Distinguish Between Positive and Negative Relations.” *Journal of Information Technology & Politics* 5.1.

Van der Velden, Mariken ACG and Felicia Loecherbach (2022). “Content Analysis in the Research Field of Political Coverage.” In: *Standardized Content Analysis in Communication Research: Ein Handbuch-A Handbook*. Springer, pp. 85–97.

Wang, Hao et al. (2012). “A System for Real-time Twitter Sentiment Analysis of 2012 U.S. Presidential Election Cycle.” *Proceedings of the ACL 2012 System Demonstration.*, pp. 115–120.

Watanabe, Kohei (2021). “Latent semantic scaling: A semi-supervised text analysis technique for new domains and languages.” *Communication Methods and Measures* 15.2, pp. 81–102.

Young, Lori and Stuart Soroka (2012). “Affective News: The Automated Coding of Sentiment in Political Texts.” *Political Communication* 29.2, pp. 205–231.