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The many applications of sentiment analysis: a literature review

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Abstract

Sentiment Analysis (SA) is a rapidly growing subset of Natural Language Processing (NLP) that provides a powerful tool to researchers and decision-makers alike across various disciplines. As SA is a growing field, little research has been done to comprehensively present the current contributions in this field. This work utilized a semi-systematic literature review to identify current research (defined as within the last ten years) as well as gaps in the literature on the subject. The literature review uncovered three themes in current SA research: applications, experiments, and vulnerabilities, with vulnerabilities as an emerging theme calling for further research in this area.

Keywords: sentiment analysis, opinion mining, text mining

Introduction

Sentiment Analysis (SA) is becoming a popular subset of Natural Language Processing (NLP). NLP seeks a holistic computational understanding of natural language by combining social sciences, natural sciences, and engineering (Siebers et al., 2022; Liu et al., 2022). This is no easy feat as language can be confusing and varying. This undertaking requires a computer to understand each component of language such as structure, meaning, and relationship to other words within a language. NLP tasks seek to answer these challenges (Siebers et al., 2022). SA is an NLP task that extracts opinions and categorizes them as either positive, negative, or neutral from a given sample of text (Gupta & Sandhane, 2022). One of the common usages of SA is in the field of marketing. By leveraging the massive amount of data available on social media networks, researchers can apply SA to gain valuable information for merchants, political pollsters, and stock traders, just to name a few (Devika et al., 2016). Additionally, SA can be utilized to gain an understanding of individuals' perceptions on various topics such as COVID-19 and climate change (Feizollah et al., 2022; Taufek et al., 2021). These applications make SA an increasingly powerful tool for decision-making (Hussein, 2018).

SA is a rapidly accelerating field. This can make it difficult to stay at the forefront of research on this topic as well as to assess the collective contribution of the research in this field. Studies utilizing literature review as its methodology can combat this problem. (Snyder, 2019). Currently, there is a lack of research that comprehensively details the various uses of SA within the body of knowledge. A semi-systematic literature review on the subject can bridge this gap.

This study aimed to identify key articles and themes in the discipline of sentiment analysis to determine and consolidate the current state of research. Consistent with the purpose of this study, the research sought to answer the following research question.

RQ1: *What are the themes and applications that can be identified from the current state (last 10 years) of research on sentiment analysis?*

Review of the Literature

Utilizing humans to code research qualitatively has long been a useful practice in the sociological analysis of text data. However, this approach can be limited in its ability to scale to large bodies and can have low intercoder reliability when dealing with subtle themes. Computational content analysis (such as NLP) can remove some of these limitations (Rozado et al., 2022). SA, a subset of NLP, examines an individual's attitudes, opinions, and emotions toward an entity (Medhat et al., 2014). Researchers have further defined sentiment analysis into finer-detailed subjects such as polarity analysis, subjectivity analysis, and opinion mining (Cobos et al., 2019). For simplicity's sake, in this work, these terms will be collectively referred to as SA. Some of the most utilized sources for SA datasets are blogs, social media posts, and comments from movie and product reviews (Truică et al., 2021).

Levels

Typically, SA takes place at three main levels: document, sentence, and word/term or aspect level (Hussein, 2018; Devika et al., 2016). Document-level sentiment analysis seeks to determine whether the document has an overall positive or negative sentiment. This method considers the entire document as the basic information unit. It also assumes that the document expresses an opinion about a single entity or topic. This type of analysis is not typically employed in the context of news articles, discussions, or blog posts, as these documents frequently discuss multiple entities within the text (Amina & Azim, 2019). Instead, this analysis works better with social media posts such as a tweet that contains the writer's feelings at a particular moment in time, or product reviews of a particular item (Cao et al., 2022). This analysis can be done as a binary classification (positive or negative) or on a numerical scale (Zhang et al., 2017).

Sentence-level SA utilizes sentences as the basic unit of text. This method then extracts individual words and analyzes their polarity to determine the sentiment of a given sentence (Li et al., 2021). However, each sentence cannot be assumed to have an opinion or polarity (Zhang et al., 2017). This type of analysis can be more complicated, particularly if the sentences are of shorter length or full of colloquial language (Mutinda et al., 2021). Additionally, this type of approach does not work well for comparative sentences where there may be multiple entities and associated sentiments discussed. For example, the sentence "Tacos taste better than pizza" is a comparative sentence that discusses two different entities as well as two different opinions for both. These challenges are better served by utilizing a finer-grained technique such as aspect-level analysis (Amina & Azim, 2019).

Word/term-level, more commonly referred to as aspect-level SA, looks at the individual word or term as the unit of text. Many analysis methods do not consider word placement or ordering. Typical use cases include blog posts or product reviews that are comparing multiple products/aspects of those products. This can be ineffective as it can change the sentiment of a sentence (Engonopoulos et al., 2011). Compared with other analysis methods, aspect-level analysis has a much finer granularity. This analysis consists of extracting and summarizing individual opinions and aspects/features within the data being examined (Li et al., 2021). This is particularly useful in the case of product reviews, where there might be different sentiments based on distinctive features of the product. For example, in a smartphone evaluation, the reviewer might express positive opinions about voice quality, but negative opinions on battery life (Zhang et al., 2017).

Another example where aspect-level analysis can be useful is in extracting best practices and lessons learned from military after action reports, as these documents can contain multiple opinions based on the aspect being discussed (Mestric et al., 2020).

Approaches

There are many approaches to SA, but most fall under three common methods: rule-based, lexicon-based, and machine learning-based. Rule-based approaches utilize rules and dictionaries containing words and their associated sentiments (Devika et al., 2016; Sudhir & Suresh, 2021). There are many pre-built dictionaries and rule packages available. Researchers can also choose to define their own dictionaries and rules to solve specific problems (Wang et al., 2020). One example of an NLP task that can make up the rules utilized is Part of Speech (POS) tagging. POS tagging annotates the types of words associated with text. Typical POS tags are noun, verb, and adjective, but can also be finer-grained (Siebers et al., 2022). Rules-based approaches are typically simple as they do not consider the sequential merging of words, but approaches can vary in complexity as more rules are utilized. In turn, these implementations will require frequent maintenance and fine-tuning as rules are added. While an advantage of rules-based approaches is that training data are not required, there can be disadvantages of lower-recall and extra work in the tediousness of defining rules (Sudhir & Suresh, 2021).

Lexicon-based approaches look at the structure of words within a text to calculate the sentiment polarity (Iqbal et al., 2019). There are many lexical-based resources available to assist in sentiment detection or classification such as WordNet-Affect, WordNet, or Senti-WordNet. These tools help detail the semantic relationships between words as well as categorize words based on emotion (Chen et al., 2018). Typically, these tools include a dictionary of positive and negative words with each word also having a numerical sentiment polarity value assigned. Once sentiment values are assigned to the words within the corpora, sentiment is then calculated based on the semantic orientation of words within the given dataset (Li et al., 2021). One simple way of doing this is by adding up the individual words' sentiment weights. A final positive numerical value indicates an overall positive sentiment for the given corpora, while a negative value indicates an overall negative sentiment (Kochmar, 2022).

Machine learning-based approaches do not utilize pre-defined rules, but rather machine learning procedures. The task of sentiment analysis is normally described as a classification problem, where the given text needs to be classified as positive, negative, or neutral. This approach utilizes models that are trained based on training data to generate a machine-learning algorithm that generates prediction tags to determine sentiment (Sudhir & Suresh, 2021). The crucial aspect of utilizing a machine learning approach is in selecting the most appropriate text features to aid in sentiment classification. Some examples of text features are emoji polarity, sentiment word frequency, and use of negation words. Then the model is trained using machine learning methods (Liu et al., 2022). Supervised methods are typically based on classifiers such as conditional random fields (CRFs) and support-vector machines (SVM) while unsupervised methods are typically based on frequency analysis or word dependencies (Ali et al., 2021). It is important to note that SA applications often utilize multiple levels and approaches making the study of SA quite complex. However, combining various levels and approaches of SA provides more granularity in solving a given research problem.

Methodology

This study conducted a semi-systematic literature review to answer the research question. Literature reviews can synthesize the current state of research as well as create or inspire agendas for future research. (Snyder, 2019). A semi-systematic literature review was chosen due to the large amount of research on the topic, and the various modalities of SA, which made a systematic literature review unfeasible. Articles were identified by searching the Institute of Electrical and Electronics Engineers (IEEE) Explore Database. Searches were limited to full-text works published in peer-reviewed journals. As the field of SA is a relatively new research area, a ten-year inclusion period was selected to ensure articles from the beginning of the research were captured. Inclusion criteria were articles detailing SA and/or its application in practice. Exclusion criteria were articles that were literature reviews or did not discuss textual SA or its applications. The article selection process was carried out following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines which seek to provide transparency in the selection process (Page et al., 2021). Figure 1 details the workflow of record selection. Zotero was utilized as a citation manager to manage articles chosen for inclusion and to prevent duplication. The only automated tool utilized by Zotero was citation generation. Microsoft Excel was utilized to assist with chart generation (Figures 2 and 3) and qualitative coding.

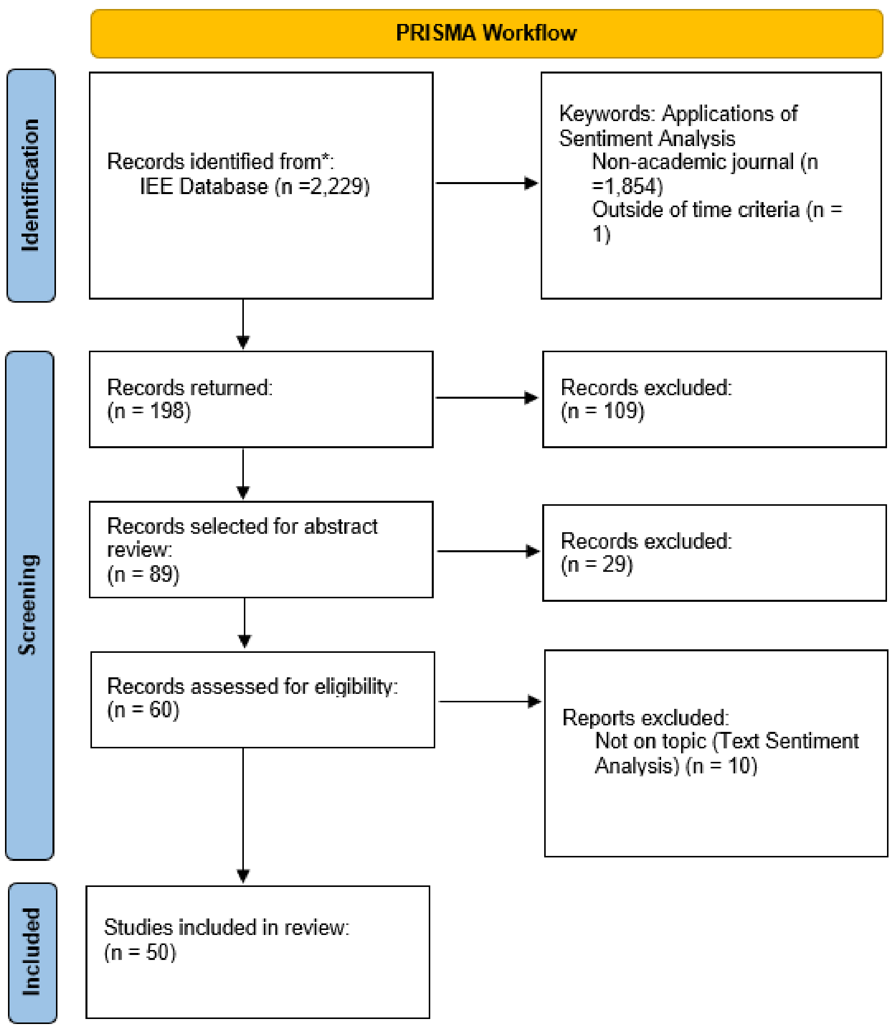

Figure 1- PRISMA Workflow

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Results

Excel was utilized to generate charts showing descriptive statistics of the articles included in the review. Figures 2 and 3 depict the descriptive statistics from the researcher's qualitative coding. There were no articles before 2016 that met the inclusion criteria for this study. The bulk of the articles reviewed were published in 2019 with the number of articles published in the following years declining from 2019 levels (See Figure 2). With the review conducted in early January 2023, it is too early to determine if publishing trends will continue to decline in 2023.

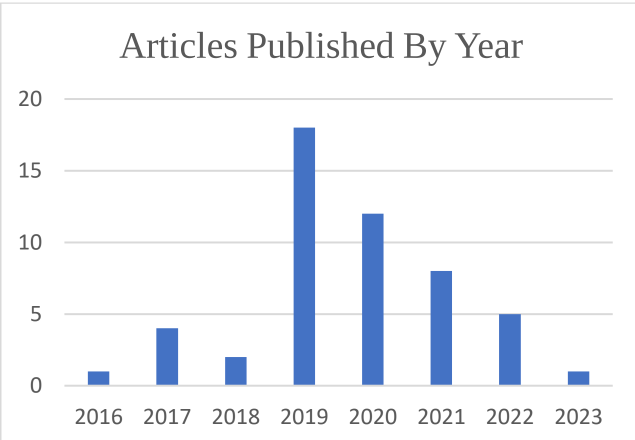

Figure 2- Articles Published by Year

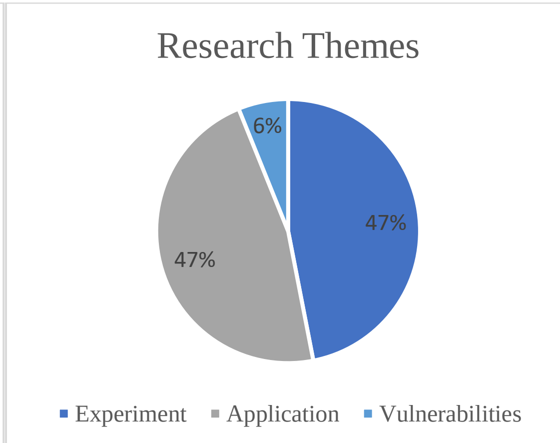

Figure 3- Research Themes

Regarding the research question, the literature review concluded that there are three overarching themes to the current state of research on sentiment analysis (See Figure 3). The first is the practical applications of SA, most commonly in the fields of social media, finance, public opinion/sensing, e-commerce, and education. The second theme discovered in the review was experimented with utilizing SA techniques or models. The final theme discovered regarded vulnerabilities within common SA technologies and models utilized. The themes extracted were not surprising considering SA is an advancing field that is growing rapidly. There is a crossover between themes as many experiments proposing advancements to SA are also the first of their kind in the application/domain to which they are being applied. Therefore, the researcher determined the theme based on the majority of content within the article.

Applications

Understanding consumer reviews is a popular application of SA. SA can support thematic analysis to help e-commerce application developers to understand user concerns and experiences (Olagunju et al., 2020). Product reviews are known to impact product brand and sales promotion which makes accurate analysis of product reviews crucial. Recent studies propose various methods for taking full advantage of the product reviews available (Huang et al., 2019; Yang et al., 2020). Further, an accurate sentiment understanding of product reviews can assist models in providing better alternate product ranking suggestions on e-commerce applications (Awajan et al., 2021). New forms of media such as Danmaku can help researchers infer customer sentiments on products or movies based on comments left on video content (Bai et al., 2019).

Another prominent application of SA is in the financial domain, particularly in stock prediction and understanding investor behavior. Lein Minh et al. (2018) utilized S&P 500 index stock prices alongside financial news articles to create a model that predicted stock prices with higher accuracy than previous models. Ren and Wu (2020) proposed an inventive analysis to detect investor herd behavior within the Chinese stock market, finding that there was a stronger tendency to herd on negative emotions. Grgic & Podobnik (2021) combined Twitter analysis and psychology concepts (VAD) to analyze risk behavior in the cryptocurrency market.

SA has also been utilized to sense public opinion for political or public health applications. Recent studies show how political decision-makers can utilize the analysis to get a feel for citizen reactions to news and political policy implementation (Amina & Azim, 2019; Wang et al., 2019*)*. This can be useful for climate monitoring of heatwaves or other adverse weather conditions (Murakami et al., 2016; Kamal et al., 2019). Integrating time data into the analysis can help policymakers understand citizen sentiment at a given point in time and provide a richer analysis (Li et al., 2019).

Public opinion/sensing applications of SA are also utilized within the educational domain to utilize course evaluation data (Zhai et al., 2020). Cobos et al. (2019), utilized SA to create a content analysis system for online courses, which allows instructors to see in real-time the effect of their course content. One novel application of SA was Chen et al's (2018), research which utilized SA to build a tool for language learning. This tool assists students in learning English emotion words. Another innovative application was a human resources system that utilized SA to classify text and implement an unbiased performance review for employees (De Oliveira Góes & De Oliveira, 2020).

Experiments

Many of the articles reviewed contained experiments to propose an advancement to the field of SA. All experiment articles reviewed utilized machine learning approaches or a combination of lexicon and machine-based approaches. Most of the articles reviewed that detailed experiments or proposed advancements were in the field of aspect-level analysis. Jiang et al. (2019) utilized a transformer to extract long-text features. Additionally, the study implemented emotion questions related to the target instead of averaging word vectors as seen in most other studies.

Shams et al. (2020) detailed a language-independent model for aspect-based sentiment analysis. This model appears to be the first of its kind that had promising results on both English and Persian datasets. Ali et al. (2021) proposed a bidirectional-gated recurrent unit (GRU) model that outperformed seven other common aspect-level models while having excellent efficiency.

Document-level analysis was the second most common level of SA experiment seen in the literature. Hameed & Garcia-Zapirain (2020) posed a bidirectional long short-term memory (BiLSTM) model with acceptable efficiency to be recommended for real-time applications. Cao et al. (2022), injected user identity into pre-trained language models which increased accuracy. Nguyen et al. (2022), implemented a novel approach to obtain group-level emotion analysis of Twitter data. Their work classified overall emotion but also was able to predict six different emotions versus simply positive or negative emotions.

A popular focus of SA experiments dealt with the natural challenges given the complexity of language. Son et al. (2019) utilized soft attention-based Bi-LSTM with a convolution network to address the complexities of sarcasm detection within SA. Wu et al. (2022) detailed a two-level LSTM and flipping model to address the polar flipping of words within a sentence. Polar flipping is when a word can display multiple sentiments based on the given sentence. For example, the word 'heavy' could have a positive polarity in the context of a fish that was caught but a negative polarity when discussing the weight of a phone. Masood et al. (2020)

proposed a context-aware sliding window algorithm that accumulates sentiment from past tweets to help determine the sentiment of current tweets.

Vulnerabilities

As with all technologies, SA is not without its vulnerabilities or potential for attacks from adversaries. Three articles in the review discussed various vulnerabilities or solutions to adversarial attacks in the process of SA about systems based on a deep neural network (DNN). All articles focused on adversarial text being injected within the text classification step of SA. Dai et al. (2019) implemented a sophisticated backdoor attack against LSTM-based classification models through data poisoning. The research showed that the trigger sentence could be placed in positions that were contextually correct to visually conceal its purpose. Additionally, the poisoning data had little impact on model performance to further hide the attack. Wang et al. (2021) proposed *TextFirewall*, a system defending against adversarial texts in sentiment classification that performed with 90% accuracy on internet movie database (IMDB) reviews and over 96% accuracy on Yelp datasets with promising potential for future experiments.

Less research has been done on the vulnerabilities of SA within Chinese datasets. Semantic and syntactic differences in the Chinese language make SA and text analysis more complicated than in other languages. Nuo et al. (2020) presented *WordChange,* an adversarial generation approach for Chinese text classification. *WordChange* accurately and efficiently reduced the accuracy of the LTSM model by 45% and 48% in its presented experiments. With the increasing utilization of SA in varying applications, the consequences of adversarial attacks increase as well.

Discussion

The literature review uncovered three themes in current SA research: applications, experiments, and vulnerabilities. Most of the literature reviewed fell within applications and experiments, which is not unusual given that SA is a growing field with many new technologies being created to support its advancement. The literature review showed there is a current gap in the research discussing the vulnerabilities of SA technologies. There was significantly less research being done in this area compared to research being done on the application and experimentation of SA. As SA is increasingly utilized in various fields and applications, the consequences of vulnerabilities being exploited could be devastating. While the exploitation of vulnerabilities within an SA context of e-commerce does not seem that consequential, having inaccurate data when utilizing SA to implement public policy or determine performance reviews is.

While it is believed that SA is still an increasing branch of research, the data uncovered in the literature review shows that the number of publications seemed to peak in 2019, with decreasing numbers of publications in the following years. At the time of the research (January 2023), it is too early to see if that trend will continue in 2023. The research may continue to decrease in SA in favor of other NLP technologies or processes. Regardless, further research should continue to take place to bridge the gap in knowledge of vulnerabilities. Further research in this area would not only add to the body of knowledge in SA but would contribute to applications and the body of knowledge in NLP as well (Wang et al., 2021).

Conclusion

This research sought to determine the current articles and themes from the current research in sentiment analysis (SA). Three themes were identified: applications of SA, experiments utilizing SA, and vulnerabilities of SA. The findings related to applications and experiments utilizing SA were expected, given the relative newness of the field. The findings revealed a current gap in the body of knowledge on vulnerabilities within SA and its associated technologies, and further research should be done in this area. While many state the research in SA is growing, the results of this study indicated that research has been steadily decreasing, possibly in favor of multi-modal SA or other NLP technologies (Siebers et al., 2022).

This study was not without limitations, further research could expand on this study by utilizing more databases for source articles as well as expanding the criteria to include multi-modal SA which includes looking at video and speech data as opposed to only text data as was done in this study (Seng & Ang, 2019). Future studies should also look at determining if the field of SA is declining or being absolved into other NLP tasks.

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