Section A

1. Background reading

1.1. Introduction

Sentiment analysis is a technique that extracts attitudes, opinions, perspectives, and emotions from various sources such as text, voice, and tweets using natural language processing (NLP) technologies such as machine learning and deep learning (Wankhade et al., 2022). The process involves text pre-processing, feature extraction, sentiment classification, and evaluation and optimization, (Gao *et al*,2019). Sentiment analysis helps businesses to monitor brand reputation, examine customer feedback, predict stock prices, and examine public opinion on political issues (Nisar & Yeung ,2018; Wankhade *et al*.,2022). It also has the potential to improve customer experience, enable audience comprehension, reputation management, and provide meaningful insights about products and services (Shaya *et al*., 2018). Sentiment analysis is also used to identify potential crises and patterns in public sentiment, allowing policymakers to make informed decisions and respond to public concerns in a timely manner, (Ghoe & Ipeirotis, 2019; Sánchez-Rada & Iglesias ,2019). Moreover, sentiment analysis helps to track online conversations and spot potential risks to public safety, such as hate speech or terrorist activities. (Barti & Malhotra, 2016).

The importance and applications of sentiment analysis

Sentiment analysis can provide real-time insights into public opinion and sentiment on social and political issues, brand reputation, and public perception (Ghose & Ipeirotis,2019). One of its main benefits is its potential to enhance customer experience by analyzing customer feedback, social media posts, and reviews (Liu, 2012). In order to identify client demands and track brand and product sentiment in customer feedback, firms frequently employ sentiment analysis to examine text data (Wankhade et al., 2022). Sentiment analysis has the potential to transform how businesses and organizations interact with their customers and stakeholders, resulting in improved assistance outcomes and customer experiences that foster loyalty and retention (Liu,2012). It also helps monitor brand reputation and identify potential crises, enabling businesses to address negative sentiment proactively. Sentiment analysis can identify trends and patterns in public sentiment, allowing policymakers to respond to public concerns in a timely manner, (Hu *et al*, 2013). Additionally, it can be used to track online conversations, (Gupta & Kaur,2018), and identify potential risks to public safety, such as hate speech or terrorist activities.

Sentiment analysis can also help businesses improve their brand messaging and interact with customers more effectively on social media. By analyzing user interactions and content preferences, businesses can determine when and how to engage with their customers, (Liu,2012). Monitoring social media mentions can also help businesses quickly address criticism (Wang *et al*, 2019). Given the significant impact that social media can have on businesses, it is essential to compete effectively to attract potential customers. Sentiment analysis accuracy can aid businesses in assessing how they are perceived and identifying any weaknesses in their branding and business strategies that need to be addressed promptly (Fombelle *et al*, 2018; Goh *et al*, 2019).

Potential Challenges

Although sentiment analysis can provide valuable insights, it also comes with challenges and limitations that need to be addressed. One of the major challenges is the complexity of natural language and the difficulty of accurately interpreting human emotions and expressions. Sentiment analysis algorithms may struggle to accurately classify text data that contains sarcasm, irony, or other forms of figurative language, leading to inaccurate results, (Rashid *et al*., 2019). Additionally, analyzing sentiments and emotions with NLP can be challenging since machines need to be trained (Cambria *et al*., 2013). Although machine learning algorithms are effective tools for making precise predictions, their conclusions may still be influenced by the human biases present in the training dataset (Bolukbasi *et al*., 2016); Gao *et al*., 2020).

Determining the tone in written text can be difficult, particularly when analyzing a large volume of data that may include subjective and objective responses. Machine learning algorithms may struggle to understand figurative language, such as sarcasm and irony, and to accurately interpret the context of negative sentiment expressed through comparative expressions or negation (Gao *et al*., 2020). As a result, sentiment analysis techniques may produce incorrect results if the algorithms do not consider the context of words and phrases within the text. For instance, the presence of negation in a sentence does not necessarily indicate a negative sentiment, and negative statements can pose a challenge to machine learning models (Pang & Lee, 2008).

Another challenge is that sentiment analysis algorithms can be biased, leading to unfair or incorrect results. This can happen when a sentiment analysis algorithm is trained using data from a specific demographic group, and then applied to data from a different demographic group (Kiritchenko & Mohammad, 2018). Translating expressions from one language to another can also lead to a loss of meaning and inaccurate analysis. Emojis can also pose a challenge as they cannot be reliably categorized in sentiment analysis methods that rely on written sentences. Despite these challenges, sentiment analysis can revolutionize how businesses, organizations, and policymakers interact with their stakeholders and respond to public opinion. As the field of natural language processing advances, we can anticipate more advanced sentiment analysis algorithms that can manage the complexity of human language, resulting in more accurate and less biased findings.

Section B

Analysis

The limitations of using lexicons in sentiment analysis, which are predefined lists of happy and sad words, mean that this approach may not always give accurate results and should be used with caution, (Mohammad, & Turney, 2013). Although lexicon-based analysis is an uncomplicated method for sentiment analysis, it may not be as precise as more intricate techniques (Sadia *et al*., 2018). For instance, a sentence can include positive words but meaning may imply something else and that will confuse the classifier (Sadia *et al*., 2018). More advanced approaches such as machine learning or deep learning models can help address the limitations, (Ghosh & Veale., 2016; Zhang *et al*., 2018). According to Socher *et al*., 2013, “richer supervised training and evaluation models are required for sentiment detection”, (Socher *et al*., 2013). One of the limitations of using lexicons is that they have a limited vocabulary and may miss more complex emotions or sentiments that are not captured by those lists, (Gao & Huang, 2018). Additionally, people communicate their emotions in a variety of ways, which makes relying solely on lexicons limiting, (Balahur & Turchi, 2018). For example, terms or words may elicit various emotions in different contexts, (Mohammad & Turney, 2013). According to Mowlaei *et al*.,2020, existing aspect-based techniques perform less well because broad lexicons are not effectively adjusted to the context of aspect-based datasets (Mowlaei *et al*., 2020).

Moreover, the limitation of the sentiment analysis approach is that it does not consider the context in which words are used, which can lead to incorrect analysis when words are used sarcastically (Mowlaei et al., 2020). Another limitation of the approach used is that it does not account for negation, which can completely change the meaning of a sentence. Additionally, the approach may struggle to recognize idiomatic expressions or figures of speech that convey a sentiment different from the literal meaning of the words used (Sadia et al., 2018). When analyzing sentiments, the approach may face challenges in recognizing irony and sarcasm, which could result in incorrect classification of sentiments (Gao *et al*., 2020). Moreover, it may not consider the tone or emotion conveyed in the tweet, leading to the misclassification of sentiments, even if the language used is neutral but is expressed in an angry tone (Barbieri & Saggion, 2014). To address the limitations of the current sentiment analysis approach, a machine learning model can be used, which involves training on a large dataset of tweets with labelled sentiments, to learn the patterns and relationships between words and sentiments

(Sadia *et al*., 2018). In addition, the approach could also benefit from incorporating advanced natural language processing techniques, such as dependency parsing, entity recognition, and named entity recognition, to better understand the structure and meaning of the text (Balamurali *et al*., 2017; Socher *et al*., 2013). This could help the approach to recognize idiomatic expressions and figures of speech that convey sentiments different from their literal meanings. Additionally, while they may be more computationally expensive, machine learning algorithms such as decision trees, random forest, naïve bayes, logistic regression, stochastic gradient descent, support vector machine, logistic regression, and deep learning methods including simple recurrent neural network (RNN) model can provide a higher level of accuracy and flexibility for sentiment analysis tasks, (Ghiassi *et al.*,2018; Rodrigues *et al*., 2022).

Language limitation can be addressed by using multilingual sentiment analysis which is used to analyze sentiments in different languages, in order to expand the scope of the approach beyond English (Nakamura & Nagata, 2010), this can be particularly useful for businesses that operate in multiple countries and need to understand how their brand is perceived in different regions. To overcome the limitation of tone and emotion, the sentiment analysis approach can be enhanced by integrating methods to identify emotional states, such as anger, fear, joy, or sadness, and take them into account during the analysis (Kouloumpis *et al*., 2011). Additionally, the approach can be improved by frequently refreshing the lexicons and models with new and pertinent terms to keep up with the dynamic and changing language and jargon used in social media (Zhang *et al*., 2018).

Questions that could be asked given a list of tweets.

- What are the most common hashtags used in the tweets?
- Which twitter users are being mentioned the most?
- What is the average length of the tweets?
- What is the sentiment distribution across different hashtags or user mentions?
- What are the most frequently occurring words or phrases in the tweets?
- Are there any patterns or themes in the tweets based on the time of day or day of the week?

Investigating a list of tweets can provide valuable insights beyond just sentiment analysis. By asking questions such as, "What are the most common hashtags used in the tweets?", one can gain an understanding of the popular topics or conversations that are currently happening (Iqbal *et al*., 2018; Rashid *et al*., 2019). This information can be employed by businesses or organizations to tailor their content or marketing strategies to reach their target audience. Similarly, identifying the Twitter users that are mentioned the most can provide valuable information about the key influencers in a particular conversation or topic. Another question that could be asked is "what is the average length of tweets", which can also reveal information about the communication style of users. For example, shorter tweets may suggest that users are more concise in their messaging, while longer tweets may suggest that users are more detailed or expressive in their writing or that longer tweets tend to be more polite and formal, while shorter tweets are more informal and conversational. (Danescu-Niculescu-Mizil *et al*., 2013). Analyzing the sentiment distribution across different hashtags or user mentions can reveal patterns or insights about the sentiment of specific audiences or communities. For example, a particular hashtag or user mention may consistently generate positive or negative sentiment (Iqbal *et al*., 2018). Finding the most frequently occurring words or phrases in the tweets can provide insight into the language and terminology used by users, which can be useful to identify trends and patterns in sentiment analysis. (Ramesh *et al*., (2018). Finally, analyzing patterns or themes in the tweets based on the time of day or day of the week can reveal insights into the behaviour or preferences of social media users (Lerman & Ghosh, 2010; Liu *et al*., (2017).

To get the shape of sentiment over time

To get the shape of sentiment over time, tweets must be examined from a specific time range, rather than a single moment in time (Badawy *et al*., 2019). One approach is to gather tweets over a period, and then perform sentiment analysis on each of the tweets, and record the sentiment score along with a timestamp (Badawy *et al*., 2019; Kim & Hovy, 2014). This approach can be extended to include real-time sentiment analysis by continuously collecting tweets and analyzing them as they are posted, and to get the shape of sentiment over time, the sentiment scores for each time can be aggregated for example, hourly or daily, (Kim & Hovy, 2014).

Adding a time-based analysis to the sentiment analysis program can supply insights into how sentiment changes over time and can help identify patterns or trends in sentiment that may be useful for businesses or organizations to understand their audience or customers, (Kim & Hovy, 2014; Liu, 2012). Tweets can be grouped by period, such as by hour, day, week, or month, depending on the level of granularity desired (Agarwal *et al*., 2011). The sentiment score is calculated for each period, based on the percentage of happy and sad tweets in that period, and plot the sentiment scores over time on a graph (Pak & Paroubek, 2018).

The two-category classification (happy and sad) used in sentiment analysis is often over-simplistic, as human emotions are complex and multidimensional (Mohammad *et al.*, 2018). However, despite its limitations, this approach can still be useful for certain applications. For example, or product development, knowing whether a customer is happy or sad about a product or service can be useful in finding areas for improvement or targeting marketing efforts, (Agarwal *et al*., 2011). In customer service, identifying negative sentiment can help companies quickly respond to customer complaints and resolve issues. The two-category classification is just a starting point, and more sophisticated sentiment analysis techniques, such as multi-class classification or emotion analysis, may be necessary for more understanding of human emotions, (Poria *et al.*, 2017).

Sentiment analysis in other languages and for tweets that are in a mix of languages can be more challenging than for tweets in a single language (Kiritchenko & Mohammad, 2018). Hence, it is important to first determine the language of the tweet which using language detection algorithms that can detect the language of the text. Once the language of a tweet is determined, sentiment analysis models are trained for each language to account for language-specific complexities in language use and sentiment expression (Liu, 2012; Nguyen *et al*., (2017),). Also, when examining tweets that are in a mix of languages, it is important to account for code-switching, where users switch between languages in a single tweet, (Kouloumpis *et al*.,2011). This can be done using techniques such as language identification at the word or phrase level, or by training models that can manage mixed-language text (Lai *et al*,2018).

Sentiment analysis in other languages and for mixed-language tweets requires additional steps and considerations. Sentiment analysis models for other languages can be more challenging than for English due to a smaller dataset size and diversity in language use (Arun & Srinagesh, 2020). As such, collecting and labelling large and diverse datasets can be critical to improving the accuracy of sentiment analysis models for other languages (Kiritchenko & Mohammad, 2018).

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