Article

Australasian Marketing Journal
2024, Vol. 32(4) 367–380

DOI: 10.1177/14413582231217126
journals.sagepub.com/home/anz
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Simplifying Sentiment Analysis on Social Media: A Step-by-Step Approach

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Abstract

This tutorial presents a systematic guide to performing sentiment analysis on social media data, designed to be accessible to researchers and marketers with varying levels of data science expertise. We prioritise open science by providing comprehensive resources, including self-collected data, source code and guidelines, facilitating result reproduction. For marketing and business researchers without programming experience, this tutorial offers a robust resource for conducting sentiment analysis. Experienced data scientists can use it as a reference for evaluating cutting-edge approaches and streamlining the sentiment analysis process. Our work stands out in its unique perspective on the challenges and opportunities of sentiment analysis within the social media data domain. We delve into the potential of sentiment analysis for social media marketing, offering practical guidance and best practices for enhancing brand reputation and customer engagement. Notably, this tutorial advances beyond previous studies by comprehensively comparing a wide range of sentiment analysis methods, including state-of-the-art transfer learning approaches, filling a critical gap in the existing literature. Our commitment to transparency underscores our contribution, as we provide all necessary resources for result reproducibility. We make our resources available at the following address: https://tinyurl.com/SentimentTutorial.

Keywords

big data analytics, sentiment analysis, marketing decisions, social media data

Date received: 7 August 2023; accepted: 6 November 2023

Introduction

The past few years have seen significant growth in social media platforms, where users freely express their opinions and thoughts. These platforms have attracted over 7.6 billion users globally, with 53% being active users (Alantari et al., 2022; Hartmann et al., 2019, 2023; Shaw, 2018; Vermeer et al., 2019). The advent of social media has led to the evolution of traditional word-of-mouth (WOM) into a new form known as electronic word-of-mouth (eWOM), which spreads more quickly and efficiently (Bu et al., 2021; Y. Zhang et al., 2022). eWOM stands for 'electronic word-of-mouth', which is a form of textual data that online users use to share their opinions, recommendations and experiences about products, services and brands. eWOM encompasses a wide range of online activities, such as social media posts, online reviews, forums, blogs and other forms of user-generated content. In the realm of marketing, eWOM is considered an essential source of information for customers, which has a significant impact on a company's reputation, sales and customer loyalty. As a result, many businesses are monitoring and analysing eWOM to gain consumer insights and inform their marketing strategies. The sheer volume of firm-related eWOM on social media has made it challenging for marketers to measure and monitor their marketing initiatives in virtual communities. Data analytics is crucial for gaining insights from eWOM, enabling firms to identify new opportunities and optimise their performance. Sentiment analysis is a useful eWOM data analytic tool, allowing marketers to understand public opinion and customer emotions associated with certain products or services.

Despite the great opportunities, the utilisation of social media sentiment analysis for business purposes presents various challenges. *Challenge 1*: Domain dependence in social media sentiment analysis is a prevalent issue. While a substantial body of research has focused on sentiment analysis in other domains (e.g., online reviews and news articles), it is challenging to directly apply these approaches to the social media domain due to their unique characteristics. For instance, Twitter text often includes linguistic irregularities and informal idioms, making it dynamic with the frequent formation of new expressions and hashtags. *Challenge 2*: Although some methods have shown promising results, it can be challenging for marketers without a data science background to fully reproduce and apply them to their research, creating a reproducibility challenge. *Challenge 3*: Selecting the most appropriate technique based on multi-criteria

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Table 1. The Difference Between Existing Works on Sentiment Analysis in Marketing and This Article.

Article	Main contributions	Social	LX(1)	ML(2)	TL(3)	Script	Data	Code	How-to
Ordenes et al. (2014)	• Adopt a holistic approach to feedback analysis • A more in-depth examination of customer experiences		✓						
Homburg et al. (2015)	• A community-matched measure of consumer sentiment • Diminishing returns to extensive firm engagement can negatively impact consumer sentiment	✓	✓						
Mian et al. (2018)	• Measure investor sentiment in the stock market • Explore the effect of sentiment on advertising expenditure		✓						
Kauffmann et al. (2019)	• Propose an advanced application of sentiment analysis in making more informed decisions. • Incorporate product feature selection and extract supplementary information from online reviews.			✓					
Hartmann et al. (2019)	• Compare the performance of lexicon-based and machine learning approaches • Conduct on various social media datasets	✓	✓	✓					
Vermeer et al. (2019)	• Compare the performance of lexicon-based and machine learning approaches • Conduct on various social media datasets	✓	✓	✓					
Saura et al. (2022)	• Utilise a machine learning approach to conduct sentiment analysis • Validate the results using Twitter datasets	✓		✓					
Alantari et al. (2022)	• Propose an empirical framework for sentiment analysis • Focus on online consumer reviews		✓	✓	✓	✓			
Hartmann et al. (2023)	• Propose an empirical framework for sentiment analysis • Focus on online reviews and social media data	✓	✓	✓	✓				
This article	• Propose a step-by-step guide on conducting sentiment analysis on social media data • Make available all the necessary information for researchers and marketers to reproduce the results.	✓	✓	✓	✓	✓	✓	✓	✓

Note. LX(1) = lexicon-based approaches; ML(2) = machine learning approaches; TL(3) = transfer learning approaches.

decision-making is another critical challenge among the available approaches. For instance, in some cases, firms require high accuracy to precisely predict negative opinions in response to a reputational crisis, while in other cases, rapid processing time is necessary to avoid scalability issues.

Existing studies on sentiment analysis techniques are limited in addressing these challenges. Table 1 presents a comparison of existing studies on sentiment analysis techniques for marketing research as well as the difference between these works and this article. We examine eight design principles for effective sentiment analysis research in social media data, as proposed by Cambria et al. (2016); Ravi and Ravi (2015). These principles include: *Social data*: the ability of a sentiment analysis research to handle and process data from various social media platforms; *LX*: enabling lexicon- based sentiment approaches which involve using pre-built dictionaries or lexicons of words associated with positive or negative sentiment; *ML*: enabling machine learning sentiment analysis approaches which involve training a model on a dataset of labelled text; *TL*: enabling transfer learning sentiment analysis approaches which allow the model to leverage the knowledge it has gained from pre-training on large amounts of text; *Script*: providing an executable script that can be run directly, making it easier for users to use and integrate the sentiment analysis tool or platform into their research works; *Data*: providing necessary data for the tutorial, ensuring that users can follow along with the tutorial and replicate the results; *Code*: providing necessary source code for the tutorial, enabling users to implement the sentiment analysis tool or platform themselves and customise it to their specific use case; and *How-to*: providing necessary step-by-step guidance for the tutorial.

Previous studies on sentiment analysis in marketing have primarily concentrated on a single class of sentiment analysis methods. For example, Ordenes et al. (2014) developed a lexicon-based method for sentiment analysis to assess customer feedback and investigate the customer experience. Similarly, Homburg et al. (2015); Mian et al. (2018) proposed a lexicon-based approach to improve the effectiveness of advertising expenditure and discover potential relationships between the financial market and social media sentiment. More recent studies have focused on developing a machine learning approach for sentiment analysis of online reviews (Kauffmann et al., 2019) and social media data (Saura et al., 2022). Hartmann et al. (2019) was one of the first to compare sentiment analysis techniques for marketing, but it only focused on lexicon and machine learning techniques and did not include transfer learning approaches, which are now considered state-of- the-art. Similarly, Vermeer et al. (2019) followed the same paradigm with the work by Hartmann et al. (2019) by including social data from the Facebook platform but also did not address transfer learning. Hartmann et al. (2023) provided a comprehensive comparison of state-of-the-art transfer learning approaches but focused on online reviews rather than social media data. Alantari et al. (2022) also conducted a comparative study and proposed a pre-trained model, but the proportion of social data used was limited and may not generalise to the broader social data domain. Moreover, another limitation of existing studies is the lack of transparency, as they do not provide data, source code or tutorials for reproducing their results.

In this paper, we overcome these limitations by designing step-by-step guidance that allows researchers – with little or no background in data science – to conduct research on sentiment analysis with state-of-the-art approaches. First, we study the unique challenges social media sentiment analysis faces and review the relevant literature to see how existing methodologies have addressed the sentiment analysis problem in social media data (to address challenge

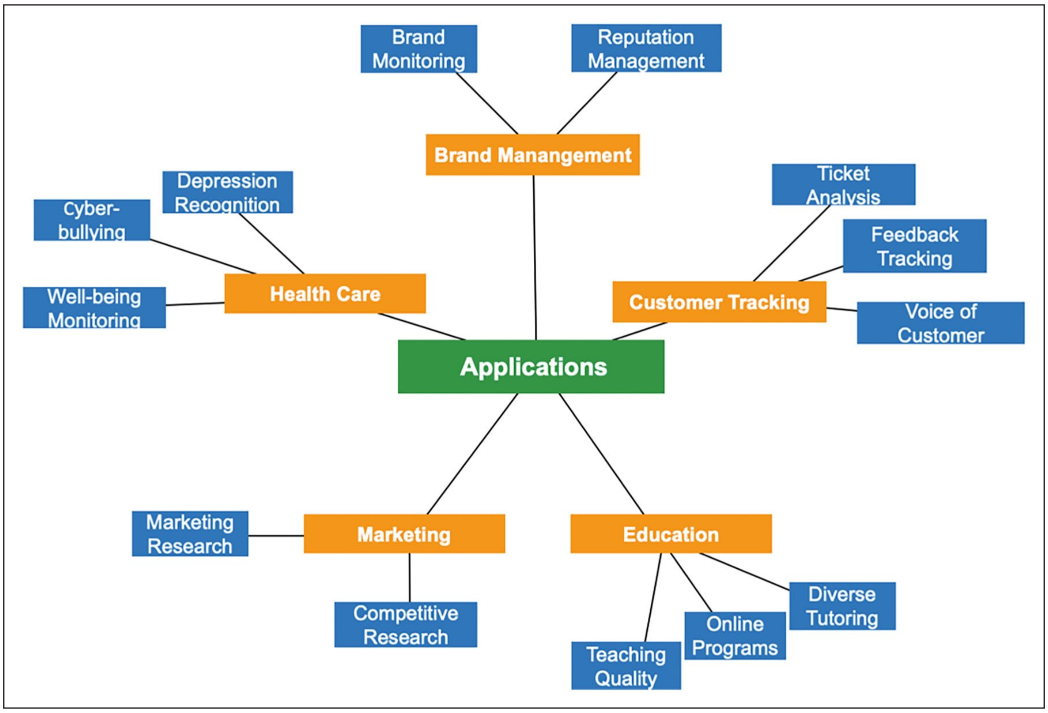

Figure 1. Applications of social data sentiment analysis.

1: domain dependence). Second, this tutorial can serve as a standalone guideline for marketing and business researchers to conduct sentiment analysis using state-of-the-art approaches in data science because the results can be fully reproduced via step-by-step guidance (to address challenge 2: reproducibility). The final contribution of this study is to provide a comparative performance of state-of-the-art approaches using social media data. These findings shall help firms select the most appropriate sentiment analysis approach for each business use case, considering a wide range of performance indicators (to address challenge 3: decision-making support).

With the spirit of open science, we public all necessary material (i.e., data, source code, guidelines) through which researchers and marketers can fully reproduce the results. By utilising this tutorial, a researcher who has not previously conducted digital quantitative research can adopt data science into their research journey. To this end, we focus on the research questions: *RQ1*: What are the critical steps in conducting sentiment analysis?; *RQ2*: What are the essential methods used in sentiment analysis?; and *RQ3*: How can we validate the quality of analytic results? The remainder of this paper is structured as follows. Section 2 provides a comprehensive review of sentiment analysis state-of-the-art approaches. Section 3 depicts our step-by-step guide to sentiment analysis, including data acquisition, pre-processing, feature extractions, approaches, evaluation metrics and interpretations of the analytical findings and comparative study of state-of-the-art approaches. Section 4 discusses the implications of our findings, acknowledges the study's limitations and suggests future research. Section 5 concludes this article.

Sentiment analysis: State-of-the-art approaches

Applications of social data sentiment analysis

Sentiment analysis using social data has numerous applications, including enhancing brand comprehension, complementing customer service and monitoring brand reputation. For instance, Airbnb uses sentiment analysis to monitor customer feedback on social media and improve its customer service. The company's social media team tracks mentions of the company on social media using a sentiment analysis tool and categorises them as positive, negative, or neutral. The team then uses this data to identify customer pain points and respond to complaints or issues promptly and effectively.

Another example is Domino's Pizza, which uses sentiment analysis to monitor customer feedback on social media and improve customer service. The pizza chain's social media team tracks mentions of the company on social media using a sentiment analysis tool, and then, the team uses this data to identify customer pain points and respond to complaints or issues quickly. Figure 1 depicts a few of the most commonly used applications of social data sentiment analysis. The following are some of the most significant domains and industries where social data sentiment analysis is applied:

- *Brand management*: When users encounter a problem, they rely on the Internet to find assistance and solutions. Therefore, it is crucial to maintain a brand's reputation to serve as a useful reference to winning the loyalty of an online audience. Using a sentiment analysis tool is a great way to boost brand monitoring and reputation management activities, offering customers timely and necessary support.
- *Customer tracking*: Customer complaints are unavoidable when running a business. Tracking and resolving customer complaints promptly shall help firms win back their customers and improve their experience. Sentiment analysis can help to achieve this goal by applying different aspects of customer tracking, including the voice of the customer tracking, review tracking and feedback tracking.
- *Education*: Utilising sentiment analysis techniques to understand students' feedback is essential to improving learning experiences. In addition, sentiment analysis can be leveraged to improve teaching quality, online programs and diverse tutoring.

- *Marketing*: Sentiment analysis is a potent marketing technology that enables marketers to comprehend the feelings of consumers in marketing initiatives and the process of value co-creation (Peltier et al., 2023). It is also an essential factor in marketing and competitive research because, by understanding consumer psychology, marketers can fine-tune the roadmaps of launching or promoting their products and services.
- *Health care*: Sentiment analysis allows healthcare providers to quantify patients' experiences and identify areas of improvement. A recent study (Kennedy et al., 2017) shows that most physicians agreed that listening to a patient's voice was essential for improving patient care. In addition, sentiment analysis is also beneficial for monitoring well-being, identifying cyberbullying and recognising depression.

Overview of key approaches

In the literature, sentiment analysis approaches can be categorised into four different distinct classes (Giachanou & Crestani, 2016): (i) lexicon, (ii) machine learning, (iii) hybrid, and (iv) transfer learning approaches. Figure 2 reveals these classes of approaches, and here, we discuss each class in detail.

Lexicon approaches. Lexicons are a collection of tokens, each of which is assigned a predefined score (Chowdhary, 2020) indicating the sentiment orientation nature underlined the text (i.e., neutral, positive or negative). Figure 3 presents a typical working mechanism of the lexicon approaches. In the first stage, the document input is divided into single-word tokens. Next, the separated tokens are assigned to a score based on polarity, such as {−1, 0, 1} for *positive, neural*, and *negative* sentiment, respectively. In some approaches, the score of tokens is continuously sampled from a range from [−1, 1]. In these cases, the score represents the intensity of polarity, in which 1 is the highest level of positive; and similarly, −1 is the highest level of negative. In the final stage, the final score of the document is aggregated from individual scores.

The critical advantage of lexicon approaches is that they do not require training data; therefore, they are easily approachable and highly feasible in applied research. Another advantage is that these approaches count the number of word occurrences and classify each text based on the relative frequency of positive or negative words, resulting in interpretable results. The main disadvantage of this class of approaches is that words can have multiple meanings, depending on the domain and context used, so a positive term in one domain may be negative in another. For example, the same 'small' word appears in the following two sentences: (1) *The screen of the cell phone is very small*, and (2) *the printer is very small and convenient*. While the 'small' word in sentence (1) carries a negative orientation, its sense in sentence (2) is positive. This problem can be solved by changing an existing vocabulary with sentiment vocabulary specific to a particular domain. Due to the simplicity of the approaches, lexicon approaches often could yield a moderate performance in sentiment analysis.

One of the most well-known lexicon approaches developed for social media data analysis is SentiWordNet (https://github.com/aesuli/SentiWordNet) – a lexical resource for sentiment analysis based on the WordNet database. Ghose et al. (2012) employ sentiment analysis as a feature extractor to develop a recommender system that suggests to consumers which products are the best value for their money. To quantify the underlying brand sentiment, Schweidel and Moe (2014) model the sentiment represented in social media posts as well as the venue format as two interconnected processes. Utilising social media data from two diverse industries, the authors enable the post's content and brand emotion to influence both processes. Peng et al. (2015) intend to determine if and how different emotions influence the stock market's response to American Customer Satisfaction Index (ACSI) data (https://www.theacsi.org/). A direct sentiment index is used to look at how investors' positive, neutral, and negative feelings affect the above relationship. Similarly, Mian et al. (2018) employ an investor sentiment index (Baker and Wurgler, 2006) to track their work on investor sentiment and advertising spending. Their findings show that when investor sentiment is low, firms reduce their advertising spending, even though the effectiveness of advertising is higher.

To facilitate decision-making, Nave et al. (2018) utilises text mining and sentiment analysis to structure internet reviews and put them on a decision support system. Vermeer et al. (2019) apply the sentiment analysis technique and demonstrate that it may not be optimal for identifying relevant information required for engagement in web care. To understand the preferences of customers on search engines, Ghose et al. (2019) presents a structural econometric model to enhance the user experience in unstructured social media (Zahrai et al., 2022). The authors in the work (Singh et al., 2021, 2022) apply SentiWordNet to analyse online reviews to investigate how consumer-perceived negativity associated with the supply chain spreads over time and impacts automobile sales. Similar to sentiment analysis on social media data, a wide range of lexicon approaches

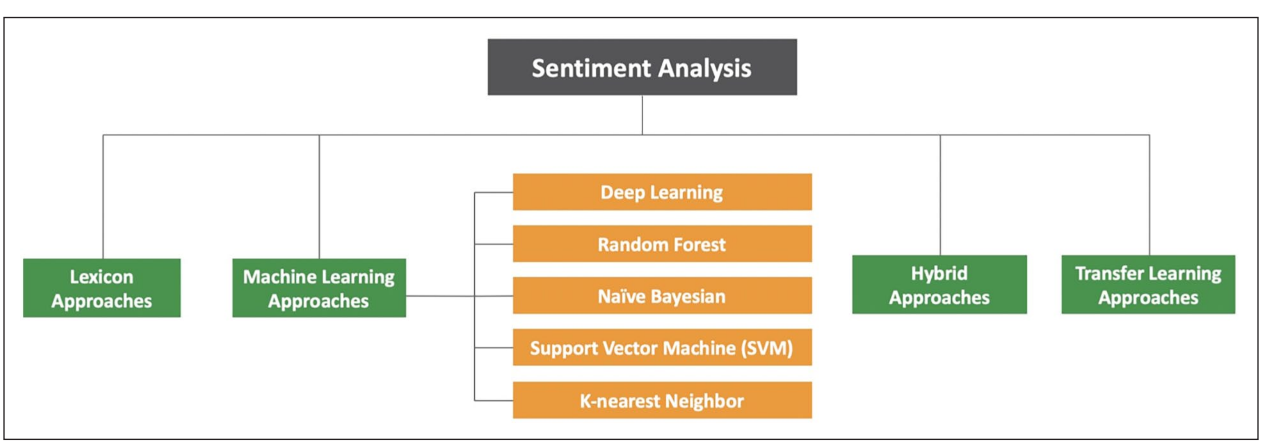

Figure 2. Classes of sentiment analysis approaches (Giachanou & Crestani, 2016).

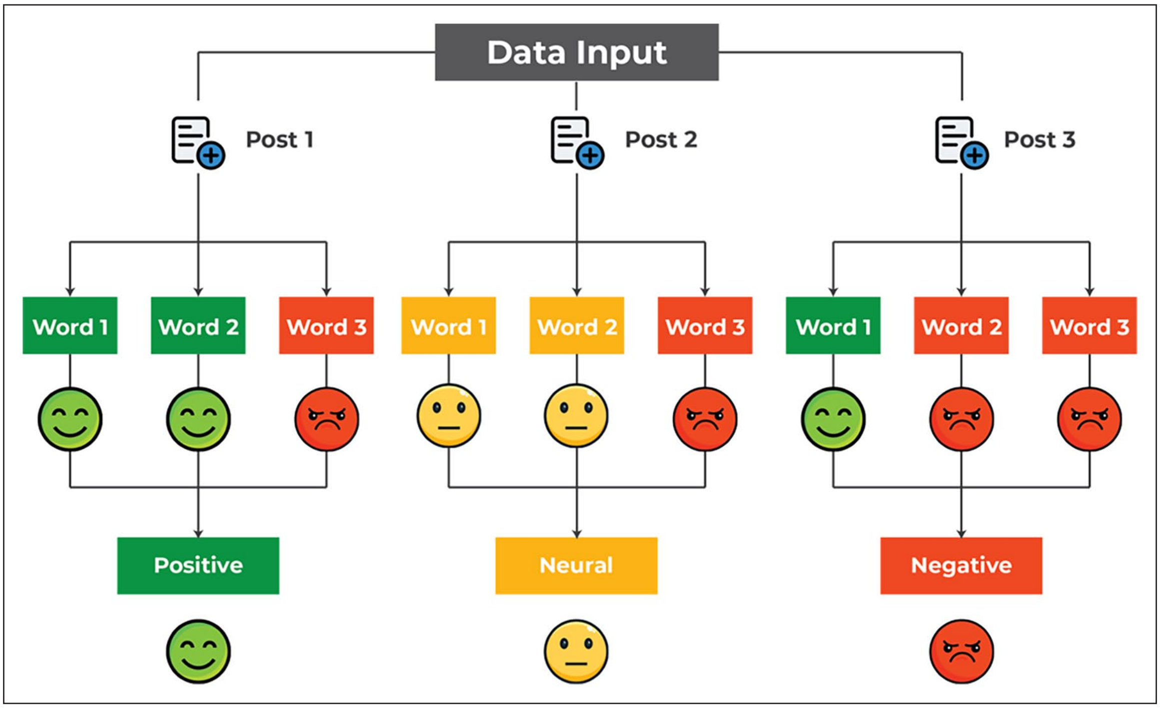

Figure 3. A typical working mechanism of the lexicon approaches.

(Chen, 2017; Goes et al., 2014; Ludwig et al., 2013; Ransbotham et al., 2019; Sridhar and Srinivasan, 2012; Van Laer et al., 2019) have been proposed to perform sentiment analysis online reviews (Robertson et al., 2021; Villarroel Ordenes et al., 2017) to monitor online customers' opinions.

Machine learning approaches. Most machine learning approaches utilise a classifier that is trained on various textual features to perform social data sentiment analysis. Standard sentiment analysis classifiers in the social data domain are *k-nearest neighbour, support vector machine (SVM), Naïve Bayes, deep learning* and other approaches. A typical machine learning algorithm for sentiment analysis treats the problem as a classification problem, which is demonstrated in Figure 4. Machine learning techniques require labelled documents for training, where the labels are typically class-level labels (i.e., positive, neutral and negative). The learning process involves two stages: *training* and *prediction* stage. During training, a data set with labels is fed into the classification algorithm, which outputs a learned model. The test data is then fed into the learned model, which predicts the sentiment orientation.

Machine learning approaches have the main advantage of automatically capturing dataset-specific word and sentiment associations based on labelled data. This line of approaches is often capable of handling complicated meanings and provides the organisation with a great deal of classification flexibility. As a result, using supervised machine learning improves not only efficiency but also reproducibility (Feng et al., 2021; Ma & Sun, 2020). In addition, classifiers can be trained once and can be reused in multiple contexts. The most significant limitation of machine learning approaches is the lack of interpreting predicted results. However, this limitation can be addressed by hybrid approaches (Section 2.2.3), which combines the interpretable capability of lexicon approaches and the efficiency of machine learning approaches. Here, we discuss a variety of different machine learning approaches as follows:

Support vector machine (SVM). SVM algorithms are non-probabilistic supervised learning algorithms commonly employed for classification applications (Zhou, 2021). The fundamental goal of SVM is to identify a hyperplane that most effectively separates the data into discrete classes. Homburg et al. (2015) design a personalised community-matched measure of customer sentiment and analyse consumer messages from 10 online forums. This study investigates how consume respond when corporations actively participate in online consumer-to-consumer conversations. Villarroel Ordenes et al. (2019) conducted a text mining analysis on many social media data by well- known companies to study the effects of mixed messages on customers' message spreading. Many comparative studies have included SVM as the primary machine learning technique (Hartmann et al., 2019; Tirunillai & Tellis, 2017; Vermeer et al., 2019) compared with other competing baselines.

Naïve bayes. This is a machine learning approach that is based on Bayes' theorem (Zhou, 2021). In this approach, probabilities are assigned to words or phrases, thereby classifying them into distinct labels. The work by Ghose et al. (2012) develops a recommender system that promotes products that deliver the best value for customers' expenditure. The key concept is that products with a more significant surplus should be prioritised to recommend in consumer inquiries. By using the content and link structure of consumer blogs, Tirunillai and Tellis (2017) perform sentiment analysis of online chatter using a variety of different metrics. By employing an extensive microblogging data set, Kim et al. (2022) investigate how consumer sentiment is affected by hot news in sales and the stock market. Their work is based on a prior work (Sprenger et al., 2014), which applied the Naïve Bayes social data sentiment analysis technique. Airani and Karande (2022) study how hashtag position, user anonymity and the bandwagon effect impact consumer sentiments on social media. Recent benchmark works (Hartmann et al., 2019;

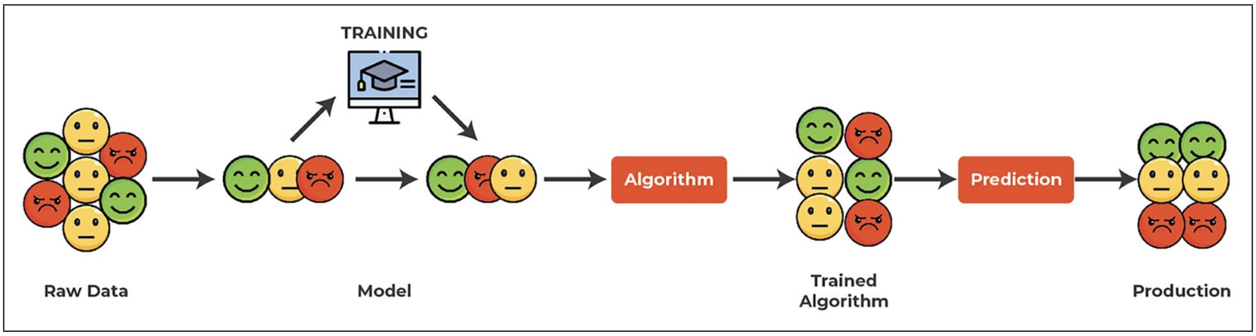

Figure 4. A typical working mechanism of machine learning approaches.

Vermeer et al., 2019) also employ Naïve Bayes in their framework to evaluate its performance for sentiment analysis in various domains.

Deep learning. Deep learning is the most emerging field of machine learning, which aims to simulate human perception problems such as image and natural language understanding (Goodfellow et al., 2016). In sentiment analysis research, Jena (2020) propose to use deep learning techniques – convolutional neural network (CNN), recurrent neural network (RNN) and doc2vec algorithm – to extract views of value to potential consumers, marketers and practitioners. Chakraborty et al. (2022) propose a framework to overcome two main difficulties in obtaining fine-grained, attribute-level sentiment analysis from online text. First, they design a hybrid deep learning model to capture the linguistic structure and then address the issue of missing attributes in the text. The motivation behind this is that reviewers often write about a subset of attributes while remaining silent on others. Based on user-generated content (UGC) on Twitter, Saura et al. (2022) recognise challenges and opportunities for remote work using digital platforms and online technologies.

Other sentiment analysis approaches. Logical regression (Goodfellow et al., 2016) is a machine learning technique that multiplies an input value by a weight value. It is a classifier that discovers which input features are most practical in distinguishing between positive and negative classes in sentiment analysis problem (Vermeer et al., 2019). *Decision tree* (Zhou, 2021) classifier is a supervised learning technique in which a tree is constructed using the training example to classify the underlying text's sentiment orientation. By adopting the decision tree technique, Matalon et al. (2021) investigate the opinion inversion phenomenon by proposing to use politically-oriented findings related to Israel's conflict. The *k-nearest neighbours* (KNN) algorithm (Zhou, 2021) is not widely used in sentiment analysis, but it has been shown to produce good results when properly trained (Hartmann et al., 2019).

Hybrid approaches. The hybrid approaches refer to the sentiment analysis techniques that combine lexicon with machine learning approaches. These approaches provide a sweet spot trade-off between accuracy and interpretability, which overcomes the limitation of component approaches. The cost for these gains is a potential decline in the prediction performance. In work by D. Zhang et al. (2015), the authors combine word2vec and SVM as a joined model to classify sentiment. The authors first cluster related features to demonstrate word2vec's capacity to capture semantic characteristics, then train and categorise the comment texts using the SVM algorithm. The work by Alantari et al. (2022) summarise text data topics with linear discriminant analysis (LDA) (Chowdhary, 2020) and use rating data to predict complicated models of purchase decisions (Khodabandeh & Lindh, 2021), consumer consideration (Mulcahy et al., 2021) and the overall experience (Lim et al., 2021). Other works investigate a practical combination of TF-IDF and SVM, and they can produce impressive results (Hartmann et al., 2019, 2023). Such hybrid approaches have gained much attraction, and they play an essential role in various sentiment analysis applications.

Transfer learning approaches. Transfer learning (Goodfellow et al., 2016) is one of the advanced techniques in Artificial Intelligence (AI) (Mogaji et al., 2020), where the knowledge learned by one model can be transferred to another. We consider an intuition of the transfer learning sentiment approach in Figure 5. In the figure, we see that model A is already trained on massive data and can accurately classify sentiment orientation. This way, model A (the source task) is referred to as a pre-trained model because it has already gained knowledge from a large amount of data and can perform the prediction task with fewer mistakes. Suppose we have model B (the target task) and want to inherit all the knowledge from model A with some modifications as the training resources, or the computation power is limited. Similar strategies are frequently used in sentiment analysis to transfer the sentiment prediction power from one domain to another.

Although transfer learning appears to be a simple concept, it is a powerful tool. Transfer learning will enable deep learning tasks with fewer data and resources. Using an appropriate pre-trained model shall improve accuracy and accelerate the training process. The primary disadvantage of transfer learning is that it results in a decline in the new model's performance. This phenomenon, known as *negative transfer*, is the most significant limitation (Goodfellow et al., 2016) of transfer learning approaches. The reason is that transfer learning works best when the initial and the target models are sufficiently similar. When the target domain for the new task is too much different from the domain of the original task, the pre-trained models become obsolete and may perform worse than expected. Furthermore, regardless of how similar these two domains are, transfer learning might not always guarantee a successful transfer between the two. There are currently no specific standards or algorithms to determine which tasks are related, making it challenging to find optimal solutions to negative transfer.

Transfer learning has been emerging in recent decades because of its ability to produce high accuracy while not requiring large training data (Goodfellow et al., 2016). The work by Piñeiro-Chousa et al. (2016) uses a pre-trained natural language processing toolkit (Manning et al., 2014) to evaluate stock-related posts of online micro-blogging. The work by Kauffmann et al. (2020) provides a method to automatically analyse user reviews and convert them into

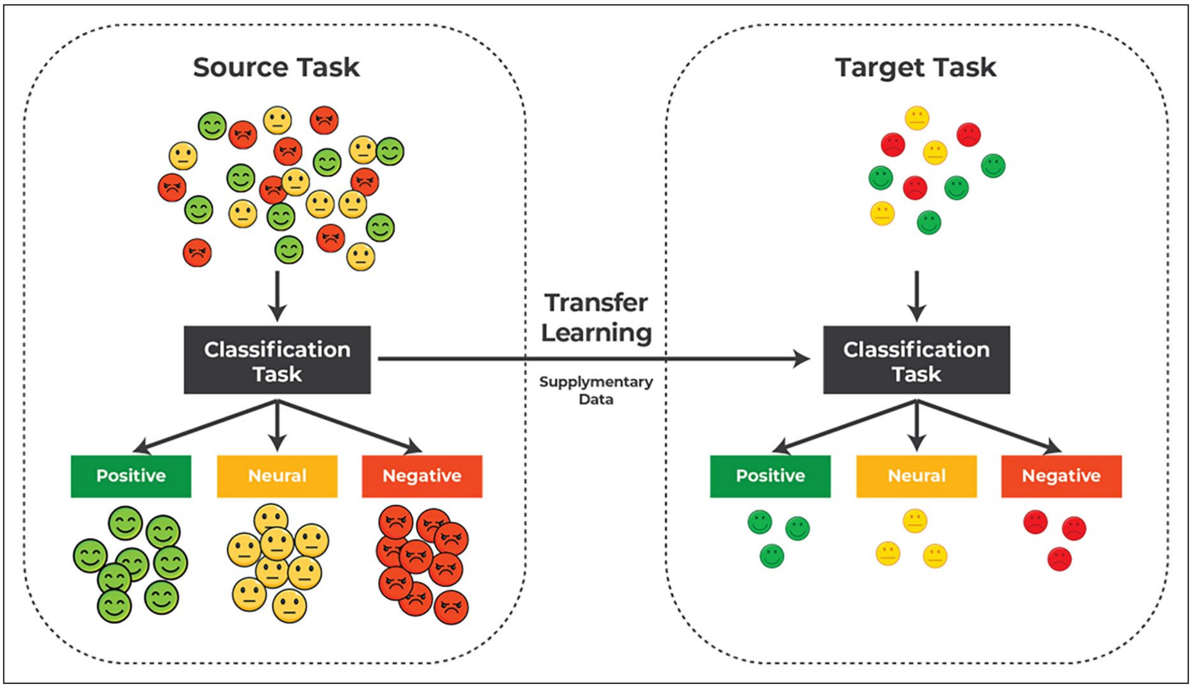

Figure 5. A typical working mechanism of transfer learning approaches.

a quantitative score. The work by Hartmann et al. (2023) provides a pre-trained sentiment analysis model that can be deployed to the online review domain as similar to an off-the-shelf dictionary.

A step-by-step guide of sentiment analysis

Sentiment analysis in social media involves the process of determining the emotional tone behind a social media post. Here, we use a flowchart to illustrate the process involved in social media sentiment analysis (Figure 6), and the process typically consists of the following five steps:

- *Step 1: Data collection*. Collecting the relevant social media data, such as posts, tweets, and comments, either through Application Programming Interfaces (APIs) or publicly achieved datasets. Details of this step are provided in section 3.1.
- *Step 2: Data pre-processing*. Cleaning and pre-processing the collected data to remove irrelevant information, such as URLs, hashtags and stop words. Details of this step are provided in section 3.2.
- *Step 3: Feature extraction*. Converting the text into a numerical format that can be processed by computer algorithms. Details of this step are provided in section 3.3.
- *Step 4: Sentiment approach*. Determining the sentiment expressed in each social media post using techniques such as lexicon-based, machine learning-based or transfer learning-based approaches. Details of this step are provided in section 3.4.
- *Step 5: Evaluation*. Evaluating the results of the sentiment analysis using various performance indicators. The evaluating process includes determining the overall sentiment, identifying trends and patterns and drawing conclusions about the attitudes and opinions expressed in the social media data. Details of this step are provided in section 3.5.

Step 1: Data collection

Data collection refers to gathering information from various sources and storing information for further analysis. Data collection is critical in conducting research or making informed business decisions, and the quality of the data collected directly impacts the accuracy of the analysis and insights generated from it. Data from social media can be collected in several ways, including:

- *Social media APIs*. API stands for Application Programming Interface, a set of rules and protocols for accessing a web-based software application or web tool. Accessing the data might be available through the APIs provided by social media platforms, such as Twitter, Facebook or Instagram. APIs provide a way to programmatically access a platform's data, allowing users to build applications that interact with the platform's data.
- *Public datasets*. Public datasets are collections of data that are freely available for anyone to use for research purposes. These datasets are often created and shared by research institutions or private companies and can be used for various research purposes.

To facilitate the adoption of the tutorial, we provide our self-collected data as a public dataset. Users can directly apply it as the data input for the subsequent steps, which are revealed next.

Step 2: Data pre-processing

Data pre-processing is an important step in sentiment analysis which helps clean and transform raw data into a format that can be effectively analysed. Data pre-processing for social media sentiment analysis typically involves the following steps: (i) *data cleaning*, (ii) *data improvement* and (iii) *data normalisation*.

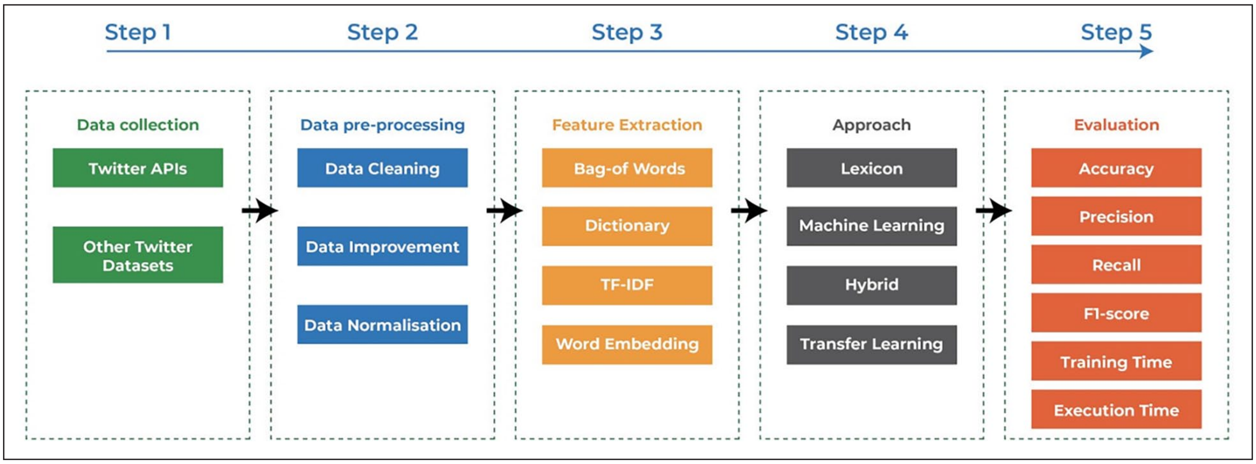

Figure 6. The basic workflow of the sentiment analysis process.

Data cleaning. In sentiment analysis, data cleaning refers to the process of preparing text data for analysis by removing irrelevant information. This is an important step in ensuring that the sentiment analysis model is able to effectively identify and analyse the sentiment of the text. Some common data-cleaning tasks for social media sentiment analysis include:

1. *Stopwords removal*: Stopwords are common words that frequently appear in sentences. As they contribute nothing to the analysis, we can eliminate them without the concern of losing crucial information.
2. *Hashtags, URLs, and usernames removal*: Prior works (Symeonidis et al., 2017) showed that hashtags, URLs and usernames contribute nothing to the opinion analysis. Therefore, we exclude them to avoid an excessive number of unnecessary terms in the dataset.
3. *Word stemming*: The practice of reducing word variants to their root form is called stemming. Preliminary research indicated that stemming approaches considerably improve results; hence, we include these strategies in this data processing step.

Data improvement. Data improvement in sentiment analysis refers to the process of adding additional information to a text data set in order to enhance the accuracy and insights of sentiment analysis models (Schreiner et al., 2021; Toan et al., 2018). In this work, the data improvement phase for social media sentiment analysis typically involves the following steps:

1. *Emoticons replacing*: Emoticons like ':-)' and ':)' communicate naturally good emotions. Therefore, instead of considering these emoticons to be worthless and eliminating them, we counted them as contextual perspectives of positive emotions and replaced them with the word 'happy'. Similarly, we substituted the word 'sad' for ':(' and ':-('to communicate negative context-based thoughts.
2. *Spell correction*: Recently, a new trend has emerged on social media – posting repeated words or characters to emphasise their emotions (Schreiner et al., 2021). As an alternative to 'like', a user may choose 'likkkkke' or 'likeeee' to reflect the intensity of their emotions. In order to accurately analyse the emotion of the data, it is required to eliminate such duplications by applying spell correction techniques.

Data normalisation. The normalisation stage makes the data more organised and comparable across various data sources. As our study entails extracting opinions from various social media data channels, we use the following transformations:

1. *Lowercase transforming*: Combinations of lowercase and uppercase characters are used in online posts and reviews. We transform all data to lowercase to enable case-insensitive comparisons and simplify the analysis process.
2. *Tokenisation*: Tokenisation is the process of converting a string of text into a list of words, which can be used as input for other computer algorithms. Tokens are typically words, punctuations or subwords that retain semantic meaning for the text being processed.

Step 3: Feature extraction

Feature extraction is a crucial step in sentiment analysis where distinguishable and relevant information is extracted from the raw text data to represent it in a numerical form suitable for further analysis. Some common approaches to feature extraction for sentiment analysis include:

- *Bag of words model*. Bag of words model – `BOW (Chowdhary, 2020) in short—involves converting text into a matrix representation, where each row corresponds to a document and each column represents a unique word in the corpus, and the value at each cell represents the frequency of the word in the document.
- *Dictionary*. These approaches (Baccianella et al., 2010; Hutto & Gilbert, 2014) involve using a pre-existing dictionary of words that have been labelled as positive or negative. The sentiment score of a text is calculated by counting the number of positive and negative words in the text and taking the difference.
- *TF-IDF*. TF-IDF (Chowdhary, 2020) stands for 'Term Frequency-Inverse Document Frequency', which help represent the importance of a word in a document relative to an entire corpus of documents. It calculates the relevance of a word in a document by multiplying its frequency in the document by its rarity in a corpus of documents.
- *Word embedding*. Word embedding (Chowdhary, 2020) is a method of mapping words from a vocabulary to a continuous

vector representation in a high-dimensional space that captures the semantic meaning and relationships between words. More precisely, these vectors are learned from a large collection of documents to ensure that words with similar meanings shall have similar vectors.

Step 4: Select an approach

Social media sentiment analysis is a specific application of sentiment analysis that involves analysing the sentiment expressed in social media posts, such as tweets, Facebook posts and other types of user-generated content. We integrate into our tutorial some common categories of sentiment approaches for social media sentiment analysis (presented in Table 2), which are outlined below:

- *Lexicon*. This involves using pre-defined dictionaries and rules to classify the sentiment of social media posts. These approaches can be simple and fast, but they can be limited by the quality and coverage of the dictionaries and rules used.
- *Machine learning-based approaches*. This involves using machine learning algorithms to learn patterns in annotated social media data and use that knowledge to classify the sentiment of new social media posts. These approaches can be more flexible and accurate than rule-based approaches, but they require a large annotated training dataset.
- *Transfer learning*. This involves using pre-trained deep learning models, such as BERT Sanh et al. (2019), to classify the sentiment of social media posts. These models have been trained on large amounts of text data and can be fine-tuned for specific domains, such as social media text, to improve their accuracy.

Step 5: Evaluation and findings

Evaluation metrics. Evaluation metrics for sentiment analysis refer to measurements used to evaluate the accuracy and effectiveness of sentiment analysis models. In this section, we review popular metrics used to evaluate sentiment analysis methods and their acceptable ranges in the literature.

(1) *Accuracy*. This indicator assesses the model's ability to accurately classify the sentiment of a text, and is calculated as the ratio of correct predictions to total predictions.
(2) *Precision*. Precision measures how often the model correctly identifies a positive or negative sentiment. A high precision suggests that the model produces accurate predictions, whereas a low precision shows that the model is making more inaccurate predictions.
(3) *Recall*. Recall quantifies the model's ability to recognise all positive and negative cases in the dataset. A high recall score shows that the model accurately identifies all positive and negative cases within the dataset.
(4) *F1 score*. This is the harmonic mean of precision and recall, providing a balanced view of the model's performance.

Acceptable ranges for accuracy, precision, recall and F1-score are context-dependent. In the literature, it is common to see sentiment analysis models achieving a performance of around 0.7 to 0.8, which indicates that the model is acceptable and able to correctly identify sentiment in the data around 70 to 80% of the time, and a performance of over 0.8 is considered excellent (Alantari et al., 2022; Hartmann et al., 2019, 2023; Saura et al., 2022; Vermeer et al., 2019). In order to evaluate the performance of the reviewed methods comprehensively, we compare their performance using the employed evaluation metrics, as presented Table 3. As the number of instances in each class of

Table 2. Description of Sentiment Analysis Approaches.

Category	Method	Feature
Lexicon	SentiWordNet (Baccianella et al., 2010)	Dictionary
	Vader (Hutto & Gilbert, 2014)	Dictionary
Machine learning	SVM (Zhou, 2021)	Word embedding
	Naive Bayes (Zhou, 2021)	TF-IDF
	Logistic Regression (Zhou, 2021)	TF-IDF
Transfer learning	DistilBERT (Sanh et al., 2019)	Word embedding
	BERT (Sanh et al., 2019)	Word embedding
	RoBERT (Sanh et al., 2019)	Word embedding

Table 3. End-to-End Comparison.

Category	Methods	Precision		Recall		F1 micro		Accuracy
		Micro	Macro	Micro	Macro	F1 micro	F1 macro	
Lexicon	SentiWordnet	0.393	0.44	0.393	0.444	0.393	0.382	0.393
	Vader	0.259	0.591	0.259	0.39	0.259	0.241	0.259
Machine learning	SVM + TF-IDF	0.724	0.673	0.724	0.663	0.72	0.67	0.724
	SVM + Word2Vec	0.698	0.634	0.698	0.603	0.698	0.614	0.698
	Naive Bayes	0.707	0.696	0.707	0.558	0.707	0.578	0.707
	Random forest	0.717	0.673	0.717	0.628	0.717	0.646	0.717
	Logistic regression	0.653	0.613	0.653	0.595	0.653	0.598	0.653
Transfer learning	distilBERT	0.793	0.755	0.793	0.776	0.793	0.763	0.793
	BERT	0.82	0.775	0.82	0.791	0.82	0.783	0.82
	roBERT	0.833	0.79	0.833	0.806	0.833	0.796	0.833

sentiment is an imbalance, we provide the average measure in both individual classes (i.e., micro average) and across classes (i.e., macro average) to provide more insight views (Goodfellow et al., 2016; Zhou, 2021) about how stable the evaluated approaches are.

The results of our evaluation show that transfer learning approaches outperform other approaches in all metrics used, and roBERT is the best method. This finding is consistent with previous research (Alantari et al., 2022), and the improvement comes from the ability to leverage the knowledge learned from the massive amount of data in the pre-trained model (Goodfellow et al., 2016). Within the transfer learning class, roBERT performs the best and consistently achieves the highest overall performance. This finding is valuable to marketing stakeholders as they can use it as a reference for the state-of-the-art approach in sentiment analysis of social data. Among the other approaches, machine learning methods outperform vanilla lexicon approaches. We found that there is little difference between machine learning approaches, such as SVM, Naïve Bayes, Random Forest, and Logistic Regression, with accuracy ranging from 0.653 to 0.724, with the highest performance achieved by SVM. Lexicon approaches perform the worst among all classes, highlighting issues with the lexicon algorithm when applied to sentiment analysis of social data. Furthermore, the micro view results show higher performance than the macro view in all cases due to the imbalance nature among sentiment groups in social data sentiment analysis.

(5) *Training time*. Training time refers to the duration required to train a model on a given dataset. The training time can vary significantly depending on the complexity of the method, the size of the dataset and the computational resources available.

The acceptable range for training time depends on the specific requirements and constraints of the application. In time-sensitive scenarios or when quick model deployment is crucial, shorter training times are preferred. However, in research or offline analysis settings where time is less critical, longer training times may be acceptable to attain higher accuracy or accommodate larger datasets. We conducted a comparison of the training process for all the reviewed approaches, and the results are presented in Figure 7, with the training time measured in seconds. As expected, transfer learning approaches require significantly more training time compared to other classes. Specifically, roBERT, BERT and distilBERT require 713, 690 and 365 seconds, respectively, to train the models. This trade-off between accuracy and computation time is well-known. Lexicon approaches, on the other hand, have a straightforward working mechanism and do not require model training, but they produce poor accuracy (as discussed in the previous section). Machine learning approaches fall somewhere in between, requiring more time than lexicon approaches but less than transfer learning approaches. Our results suggest that machine learning approaches could be a suitable trade-off approach, particularly in the early stage of adopting social media monitoring, as the implementation time is relatively fast, and the accuracy is reasonable.

(6) *Execution time*. Execution time refers to the duration it takes for a sentiment analysis method to process and analyse a given input text, resulting in sentiment predictions. In essence, this metric measures the speed at which a sentiment analysis method can generate predictions in real-world applications.

Acceptable execution time ranges are highly dependent on the application context. Real-time applications, such as social media

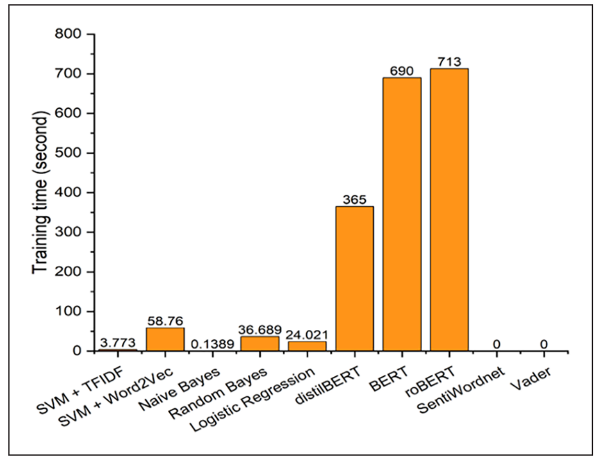

Figure 7. Comparison of training time.

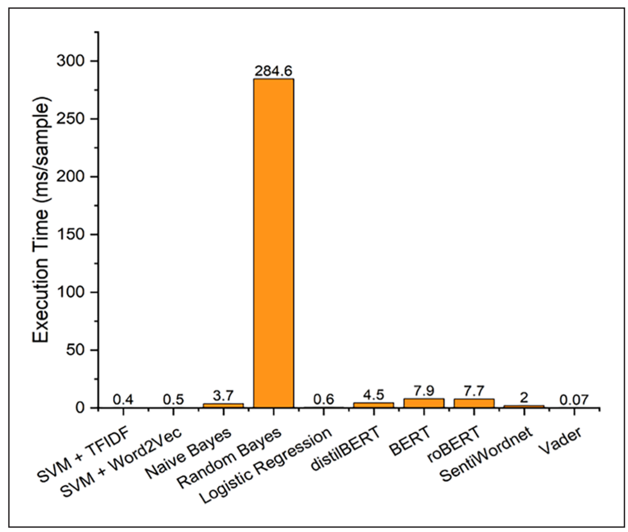

Figure 8. Comparison of execution time.

monitoring or customer service chatbots, require fast sentiment analysis methods to provide quick responses. In contrast, offline analysis tasks or batch-processing scenarios may have more flexibility in terms of execution time. We conducted a comparison of the execution time for all the reviewed approaches, and Figure 8 illustrates the execution time per sample, measured in milliseconds. Among the reviewed methods, Random Forest exhibits the longest processing time per sample, which could pose scalability challenges when dealing with large volumes of social data. In contrast, the other methods demonstrate significantly shorter execution times, all below 7.9 milliseconds per sample. Notably, roBERT, BERT and distilBERT, the transfer learning approaches, achieve the highest accuracy while maintaining processing speeds of 7.7, 7.9 and 4.5 milliseconds per sample, respectively. The lexicon approach demonstrates the fastest execution time at 0.07 milliseconds per sample, but its lower accuracy may limit its suitability for many marketing use cases. Within the machine learning category, SVM+TF-IDF processes a sample in just 0.4 milliseconds, approaching the accuracy of transfer learning approaches while delivering nearly 10 times faster execution per sample.

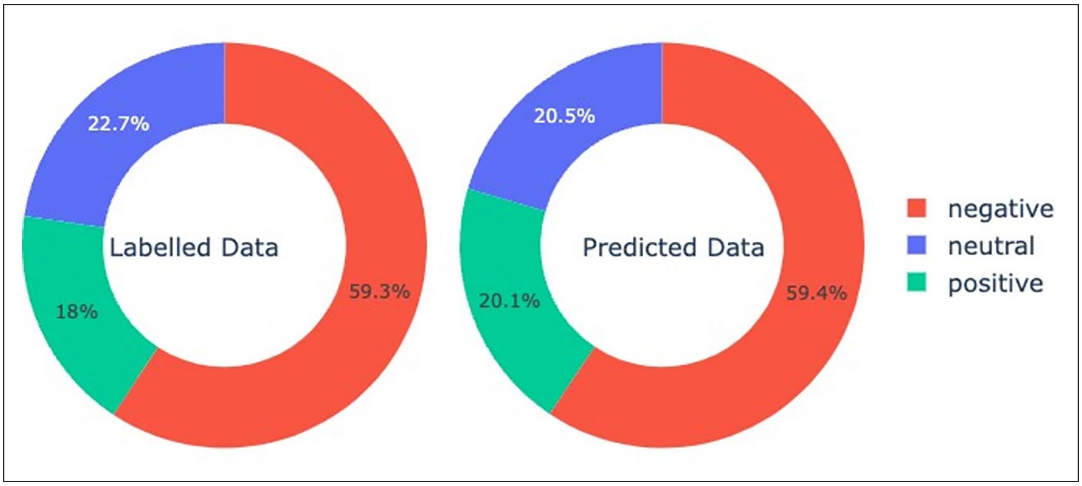

Figure 9. Comparison of labelled and predicted sentiment distribution of the best method.

Interpret the findings

Interpret the effectiveness. To provide a comprehensive assessment of the effectiveness of the best method, roBERT, we conducted a thorough analysis comparing the labelled sentiment results with the predicted sentiment results using roBERT. The findings are visually presented in Figure 9, showcasing two pie charts representing the distribution of labelled sentiments and predicted sentiments, respectively.

The results of roBERT for sentiment classification exhibit a high degree of similarity compared to the ground truth labelled data. The proportions of negative, positive and neutral sentiments obtained through roBERT closely align with those in the ground truth dataset, as depicted in the pie chart. This indicates that roBERT effectively captures and classifies sentiments, demonstrating its effectiveness in sentiment analysis tasks for business and marketing applications. The minor discrepancies in sentiment proportions can be attributed to inherent challenges in sentiment analysis, but overall, roBERT shows reliable and valid performance, providing valuable insights into customer opinions, market trends and brand perception.

Interpret the limitations. To gain a deeper understanding of the limitations of alternative approaches, we conducted an extensive analysis of their predictions for each sentiment category in comparison to the actual ground truth. Our analysis highlights that transfer learning approaches closely approximate the ground truth within each sentiment group, presenting compelling evidence of their exceptional performance in terms of accuracy and other evaluation metrics. In contrast, the predictions of lexicon-based approaches notably fall short in the positive and negative sentiment groups, indicating a higher rate of incorrect predictions that adversely affect their overall accuracy. On the other hand, machine learning approaches demonstrate a reasonable estimation in comparison to the ground truth, which helps elucidate why their accuracies remain at a moderate level.

Research implications

Unravelling some key insights from the technology blackbox

Social media is the primary platform through which customers express their thoughts and emotions, providing valuable data for researchers and marketers to extract practical knowledge and understand customers' experiences. With modern analytics solutions and services, marketing initiatives can be largely automated, freeing up marketers to focus on their core tasks (Chau et al., 2023). While commercial systems can help marketers achieve their goals, these systems are often considered 'black boxes' (Pitt et al., 2023), making it challenging to investigate their correctness and improve results when faced with a problem. To address this limitation, this paper provides a step-by-step tutorial for researchers without a background in data science to perform sentiment analysis using social media data. Additionally, researchers with limited programming knowledge can customise the published algorithms, metrics and data to enhance their work. Finally, the findings of this study provide firms and brands with a benchmark for the performance of state- of-the-art approaches, allowing them to identify the most suitable sentiment analysis approach for their business use case and marketing activities (Figure 10).

Simple guide for researchers/practitioners without data science background

In recent years, sentiment analysis has become increasingly popular for analysing social media data, as it allows firms to monitor large volumes of textual messages and listen to online conversations about their brands and competitors in real time (Quach et al., 2021). In this study, we demonstrate how to perform multiple sentiment analysis approaches and evaluate their performance using various metrics, all without requiring a background in data science. We achieve this by publishing our self-collected data alongside a code repository that business researchers can use with step-by-step examples. The primary contribution of this study to the body of knowledge is the presentation of a comparative study that can serve as a standalone tutorial for researchers and marketers with minimal programming experience. Our research has important implications for the expanding social media monitoring industry (Vahdat et al., 2021) and for comprehending consumer responses (Schamp et al., 2023).

In addition, we offer further guidance and recommendations for business researchers and practitioners. Firstly, the techniques and software we have described and built for this tutorial should be sufficient for basic research and for exploring the most interesting topics in greater qualitative depth. However, practitioners should remember that while adopting the sentiment analysis pipeline through detailed guidelines may be straightforward, it can be resource-intensive

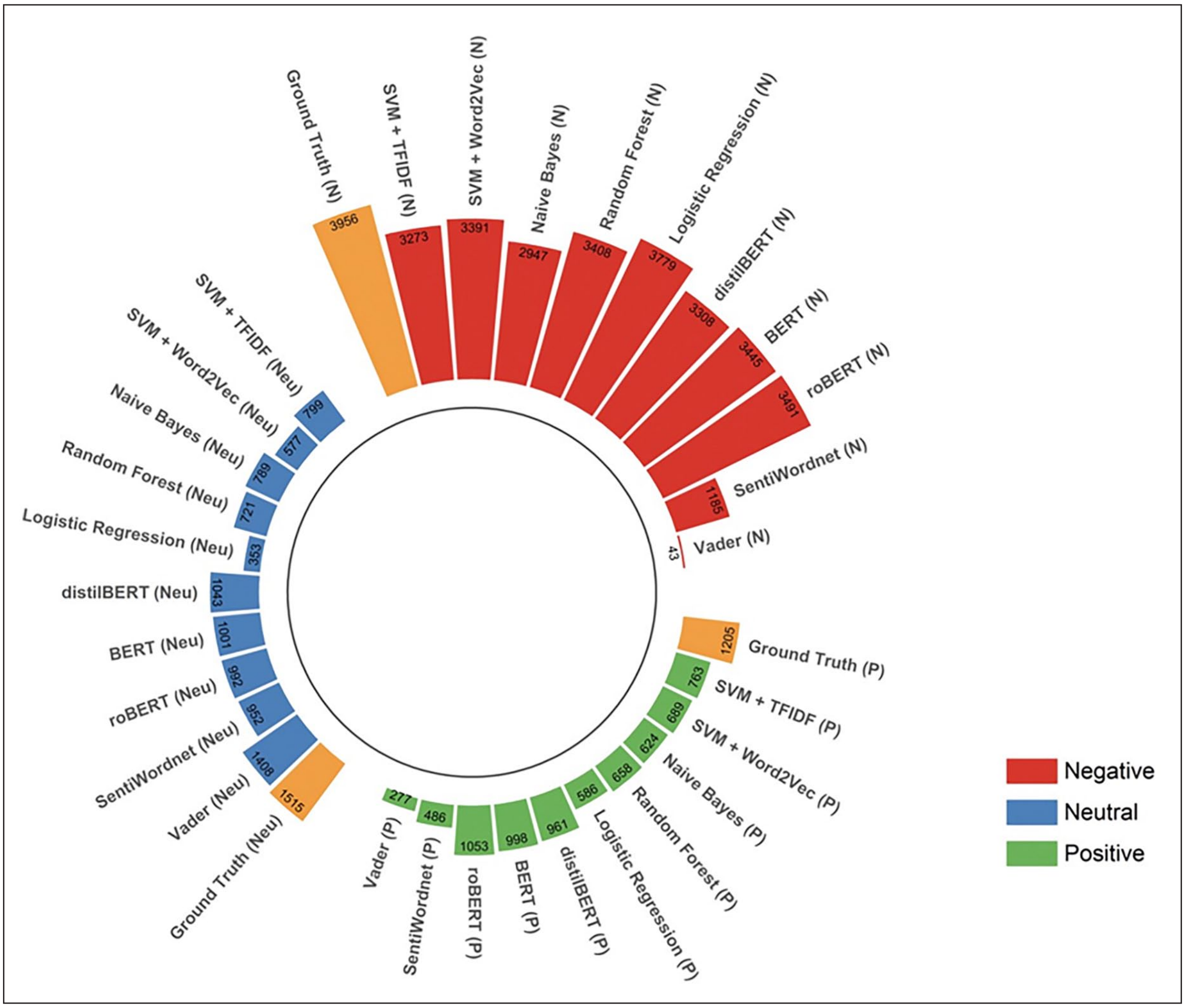

Figure 10. Interpretability of the sentiment result.

for extensive datasets, particularly those requiring high training time. Secondly, while the findings suggest that transfer learning can be a more effective technique for sentiment analysis than other approaches, researchers should carefully consider the data distribution between domains to avoid negative transfer effects. Finally, since no single approach is suitable for all firms, this study provides various options with sufficient analysis and findings from multiple perspectives to help firms identify the most suitable solutions. Based on this, firms may choose the approaches that best suit their context in terms of technical capability, resources and available information.

Limitations and future research directions

While this tutorial provides valuable insights, we acknowledge several limitations that future research could address. The primary limitation is that this study's data and findings focus solely on Twitter data. However, social data come in various formats, including text messages, forum posts, blog entries and social networking site feeds (Weismueller et al., 2020). Integrating these data sources into future research could yield insights into customers' opinions, social media communities and online communications (Humphreys & Wang, 2018). Secondly, state-of-the-art approaches like transfer learning lack the ability to explain prediction results, which is referred to as explainable AI (Zhou, 2021), and hold enormous potential for future research. Thirdly, the detailed guidelines provided in this study will help marketing researchers and practitioners select appropriate techniques for evaluating sentiment revealed in social data. Future studies can build on our efforts in these specific directions. Finally, due to space constraints, we only discuss some of the most commonly used approaches in the three classes. Each class of approaches has many potential extensions, and future research is necessary to go beyond this study.

Conclusion

This tutorial provides a comprehensive overview of sentiment analysis using social media data, evaluating prevalent state-of-the-art approaches. Our primary objective is categorising and comparing these approaches for sentiment analysis on social data. We introduce common application domains and present detailed guidelines for the sentiment analysis process, covering critical operations such as data acquisition, pre-processing, feature selection, approach selection and evaluation metrics. Through extensive experiments, we compare various sentiment analysis approaches using metrics including precision, recall, F1 score, accuracy, training time and execution time. The comparative findings highlight that recently proposed transfer learning approaches offer more accurate estimations than those previously utilised in marketing publications.

While insightful, our tutorial has limitations. First, it predominantly uses Twitter data, but social data exists in various forms. Future research should integrate diverse sources for deeper insights. Second, current state-of-the-art methods, like transfer learning, lack explainability (explainable AI), warranting further exploration. Third, our guidelines assist marketing professionals in sentiment analysis, but future studies can expand on these directions.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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Supplemental material

Supplemental material for this article is available online.

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