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Survey on sentiment analysis: evolution of research methods and topics

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Abstract

Sentiment analysis, one of the research hotspots in the natural language processing field, has attracted the attention of researchers, and research papers on the field are increasingly published. Many literature reviews on sentiment analysis involving techniques, methods, and applications have been produced using different survey methodologies and tools, but there has not been a survey dedicated to the evolution of research methods and topics of sentiment analysis. There have also been few survey works leveraging keyword co-occurrence on sentiment analysis. Therefore, this study presents a survey of sentiment analysis focusing on the evolution of research methods and topics. It incorporates keyword co-occurrence analysis with a community detection algorithm. This survey not only compares and analyzes the connections between research methods and topics over the past two decades but also uncovers the hotspots and trends over time, thus providing guidance for researchers. Furthermore, this paper presents broad practical insights into the methods and topics of sentiment analysis, while also identifying technical directions, limitations, and future work.

Keywords Sentiment analysis · Keyword co-occurrence analysis · Evolution analysis · Research methods · Research topics

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1 Introduction

Web 2.0 has driven the proliferation of user-generated content on the Internet. This content is closely related to the lives, emotions, and opinions of users. Therefore, analysis of this user-generated data is beneficial for monitoring public opinion and assisting in making decisions. Sentiment analysis, as one of the most popular applications of text-based analytics, can be used to mine people's attitudes, emotions, appraisals, and opinions about issues, entities, topics, events, and products (Cambria et al. 2022a, b, c, d; Injadat et al. 2016; Jiang et al. 2017; Liang et al. 2022; Oueslati et al. 2020; Piryani et al. 2017). Sentiment analysis can help us interpret emotions in unstructured texts as positive, negative, or neutral, and even calculate how strong or weak the emotions are. Today, sentiment analysis is widely used in various fields, such as business, finance, politics, education, and services. This analytical technique has gained broad acceptance not only among researchers but also among governments, institutions, and companies (Khatua et al. 2020; Liu et al. 2012; Sánchez-Rada and Iglesias 2019; Wang et al. 2020b). It helps policy leaders, businessmen, and service people make better decisions.

The majority of user-generated content data is unstructured text, which increases the great difficulty of sentiment analysis. Since 2000, researchers have been exploring techniques and methods to enhance the accuracy of such analysis. The popularity of social media platforms has brought people around the world closer together. With the continuous advancement of technology, the research topics, application fields, and core methods and technologies of sentiment analysis are also constantly changing.

Comparing and analyzing papers from specific disciplines can help researchers gain a comprehensive understanding of the field. There have been many surveys on sentiment analysis (Nair et al. 2019; Obiedat et al. 2021; Raghuvanshi and Patil 2016). However, there is a lack of adequate discussion on the connections between research methods and topics in the field, as well as on their evolution over time. In 1983, Callon et al. proposed co-word analysis (Callon et al. 1983). It can effectively reflect the correlation strength of information items in text data. Co-word analysis based on the frequency of co-occurrence of keywords used to describe papers can reveal the core contents of the research in specific fields. An evolutionary analysis of the associations between core contents is helpful for a comprehensive understanding of the research hotspots and frontiers in the field (Deng et al. 2021). It can provide guidance for researchers, especially those who are new to the field, and help them determine research directions, avoid repetitive research, and better discover and grasp the research trends in this field (Wang et al. 2012). To fill in the gap in existing research, we conduct keyword co-occurrence analysis and evolution analysis with informetric tools to explore the research hotspots and trends of sentiment analysis.

The main contributions of this survey are as follows:

- Using keyword co-occurrence analysis and the informetric tools, the paper presents a survey on sentiment analysis, explores and discovers useful information.
- A keyword co-occurrence network is constructed by combining the paper title, abstract, and author keywords. Through the keyword co-occurrence network and community detection algorithm, the research methods and topics in the field of sentiment analysis, along with their evolution in the past two decades, are discussed.
- The paper summarizes the research hotspots and trends in sentiment analysis. It also highlights practical implications and technical directions.

The remainder of this paper is organized as follows: In Sect. 2, we summarize and analyze the existing surveys on sentiment analysis and present the research purpose and methodologies of this paper. Section 3 details the survey methodology, including the collection and processing of scientific publications, visualization, and analysis using different methods and tools. In Sect. 4, we analyze the results obtained from the keyword co-occurrence analysis and evolution analysis, along with the research hotspots and trends in sentiment analysis identified through the analysis results. Finally, in Sect. 5, we summarize the research conclusions as well as the practical implications and technical directions of sentiment analysis. We also clarify the limitations of this paper and make suggestions for future work.

2 Existing surveys on sentiment analysis

Sentiment analysis is a concept encompassing many tasks, such as sentiment extraction, sentiment classification, opinion summarization, review analysis, sarcasm detection or emotion detection, etc. Since the 2000s, sentiment analysis has become a popular research field in natural language processing (Hussein 2018). In the existing surveys, the researchers mainly conducted specific analyses of the tasks, technologies, methods, analysis granularity, and application fields involved in the sentiment analysis process.

2.1 Surveys on contents and topics of sentiment analysis

When research on sentiment analysis was still in its infancy, the contents and topics of surveys mainly focused on sentiment analysis tasks, analysis granularity, and application areas. Kumer et al. reviewed the basic terms, tasks, and levels of granularity related to sentiment analysis (Kumar and Sebastian 2012). They also discussed some key feature selection techniques and the applications of sentiment analysis in business, politics, recommender systems and other fields. Nassirtoussi et al. explored the application of sentiment analysis in market prediction (Nassirtoussi et al. 2014). Medhat et al. analyzed the improvement of the algorithms proposed in 2010–2013 and their application fields (Medhat et al. 2014). Ravi et al. analyzed the papers related to opinion mining and sentiment analysis from 2002 to 2015. Their study mainly discussed the necessary tasks, methods, applications, and unsolved problems in the field of sentiment analysis (Ravi and Ravi 2015).

Existing surveys of the applications of sentiment analysis have focused more on the domains of market research, medicine, and social media in recent years. Rambocas et al. examined the application of sentiment analysis in marketing research from three main perspectives, including the unit of analysis, sampling design, and methods used in sentiment detection and statistical analysis (Rambocas and Pacheco 2018). Cheng et al. summarized techniques based on semantic, sentiment, and event extraction, as well as hybrid methods employed in stock forecasting (Cheng et al. 2022). Yue et al. categorized and compared a large number of techniques and approaches in the social media domain. That study also introduced different types of data and advanced research tools, and discussed their limitations (Yue et al. 2019). In the context of the COVID-19 epidemic, Alamoodi et al. reviewed and analyzed articles on the occurrence of different types of infectious diseases in the past 10 years. They reviewed the applications of sentiment analysis from the identified 28 articles, summarizing the adopted techniques such as dictionary-based models, machine learning models, and mixed models (Alamoodi et al. 2021b); Alamoodi et al. also conducted a review of the applications of sentiment analysis for vaccine hesitancy (Alamoodi et al. 2021a). Researchers also reviewed the application of sentiment analysis in the fields of election prediction (Brito et al. 2021), education (Kastrati et al. 2021; Zhou and Ye 2020) and service industries (Adak et al. 2022).

Quite a number of research works investigated sentiment analysis works in non-English languages. Sentiment analysis in Chinese (Peng et al. 2017), Arabic (Al-Ayyoub et al. 2019; Boudad et al. 2018; Nassif et al. 2021; Oueslati et al. 2020), Urdu (Khattak et al. 2021), Spanish (Angel et al. 2021), and Portuguese (Pereira 2021) were conducted. They mainly reviewed the classification frameworks of the sentiment analysis process, supported language resources (dictionaries, natural language processing tools, corpora, ontologies, etc.), and deep learning models used (CNN, RNN, and transfer learning) for each of the languages involved.

2.2 Surveys on methods of sentiment analysis

Before machine learning technology became mature, researchers were particularly concerned about feature extraction methods. For example, Feldman summarized methods for extracting preferred entities from indirect opinions and methods for dictionary acquisition (Feldman 2013). Asghar et al. reviewed the natural language processing techniques for extracting features based on part of speech and term position; statistical techniques for extracting features based on word frequency and decision tree model; and techniques for combining part of speech tagging, syntactic feature analysis, and dictionaries (Asghar et al. 2014). Koto et al. discussed the best features for Twitter sentiment analysis prior to 2014 by comparing 9 feature sets (Koto and Adriani 2015). They found that the current best features for sentiment analysis of Twitter texts are AFINN (a list of English terms used for sentiment analysis manually rated by Finn Årup Nielsen) (Nielsen 2011) and SentiStrength (Thelwall et al. 2012). Taboada sorted out the characteristics of words, phrases, and sentence patterns in sentiment analysis from the perspective of linguistics (Taboada 2016). Besides, Schouten and Frasinar conducted a comprehensive and in-depth critical evaluation of 15 sentiment analysis web tools (Schouten and Frasincar 2015). Medhat et al. (2014) and Ravi et al. (Ravi and Ravi 2015) also analyzed the early algorithms for sentiment analysis.

In the study by Schouten et al., the authors focused on aspect-level sentiment analysis, combing the techniques of aspect-level sentiment analysis before 2014, such as frequency-based, syntax-based, supervised machine learning, unsupervised machine learning, and hybrid approaches. They concluded that the latest technology was moving beyond the early stages (Schouten and Frasincar 2015). As research into sentiment analysis became more and more popular and there was important progress made in the development of deep learning technologies, researchers started to pay more attention to the techniques and methods of sentiment analysis. Deep learning methods in particular became the focus of discussions among researchers.

Prabha et al. analyzed various deep learning methods used in different applications at the level of sentence and aspect/object sentiment analysis, including Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-term Memory (LSTM) (Prabha and Srikanth 2019). They discussed the advantages and disadvantages of these methods and their performance parameters. Ain et al. introduced deep learning techniques such as Deep Neural Network (DNN), CNN and Deep Belief Network (DBN) to solve sentiment analysis tasks like sentiment classification, cross-lingual problems, and product review analysis (Ain et al. 2017). Zhang et al. investigated deep learning and machine learning techniques for sentiment analysis in the contexts of aspect extraction and categorization, opinion expression extraction, opinion holder extraction, sarcasm analysis, multimodal data, etc. (Zhang et al. 2018). Habimana et al. compared the performance of deep learning methods on specific datasets and proposed that performance could be improved using models including Bidirectional Encoder Representations from Transformers (BERT), sentiment-specific word embedding models, cognitive-based attention models, and commonsense knowledge (Habimana et al. 2020). Wang et al. reviewed and discussed existing analytical models for sentiment classification and proposed a computational emotion-sensing model (Wang et al. 2020b).

Some researchers also discussed web tools (Zucco et al. 2020), fuzzy logic algorithms (Serrano-Guerrero et al. 2021), transformer models (Acheampong et al. 2021), and sequential transfer learning (Chan et al. 2022) for sentiment analysis.

2.3 Overall survey methodology

With the increase in the popularity of sentiment analysis research, more related research results began to accumulate. Researchers needed to systematically organize and analyze results from a large number of publications to perform literature reviews. They used different survey methodologies to conduct surveys of a large number of papers.

Content analysis is a powerful approach to characterizing the contents of each study by carefully reading its content and manually identifying, coding, and organizing key information in it. A literature review is formed as a result of the repeated use of this approach (Elo and Kyngäs 2008; Stemler 2000). Content analysis has been used for different studies and systematic reviews (Qazi et al. 2015, 2017). For example, Birjali et al. have studied the most commonly used classification techniques in sentiment analysis from a large amount of literature and introduced the application areas and sentiment classification processes, including preprocessing and feature selection (Birjali et al. 2021). They conducted a comprehensive analysis of the papers, discovering that supervised machine learning algorithms are the most commonly used techniques in the field. A complete review of methods and evaluation for sentiment analysis tasks and their applications was conducted by Wankhade et al. (2022). They compared the strengths and weaknesses of the methods, and discussed the future challenges of sentiment analysis in terms of both the methods and the forms of the data. Although this method can review the research contents and penetrate into the cores of the papers most systematically, it requires a considerable amount of manpower and time for in-depth literature reading.

The systematic literature review guideline proposed by Kitchenham and Charters has gradually attracted the attention of researchers (Kitchenham 2004; Kitchenham and Charters 2007; Sarsam et al. 2020). This review process is divided into six stages: research question definition, search strategy formulation, inclusion and exclusion criteria definition, quality assessment, data extraction, and data synthesis. Researchers can eliminate a large number of retrieved papers by using this standard process and finally conducting further analysis and research on a small number of papers. Kumar et al. reviewed context-based sentiment analysis in social multimedia between 2006 and 2018. From the 573 papers retrieved in the initial search, they finally selected 37 papers to use in discussing sentiment analysis techniques (Kumar and Garg 2020). This approach was also used by Kumar et al. in their research on sentiment analysis on Twitter using soft computing techniques. They selected 60 articles out of 502 for follow-up analysis (Kumar and Jaiswal 2020). Zunic et al. selected 86 papers from 299 papers retrieved in the period 2011–2019 to discuss the application of sentiment analysis techniques in the field of health and well-being (Zunic et al. 2020); Ligthart et al. followed Kitchenham's guideline and identified 14 secondary studies. They provided an overview of specific sentiment analysis tasks and of the features and methods required for different tasks (Ligthart et al. 2021). Obiedat (Obiedat et al. 2021), Angel (Angel et al. 2021) and Lin (Lin et al. 2022) also all followed this guideline to select literature for further analysis. This method can reduce the amount of literature that requires in-depth reading, but in the case of a large amount of literature, more effort is still required to search and screen the material than in traditional literature review methods (Kitchenham and Charters 2007).

There are also a few authors who have used informetric methods to review papers. Piryani et al. conducted an informetric analysis of research on opinion mining and sentiment analysis from 2000 to 2015 (Piryani et al. 2017). The authors used social network analysis, literature co-citation analysis, and other methods in the paper. They analyzed publication growth rates; the most productive countries, institutions, journals, and authors; and topic density maps and keyword bursts, among other elements. To a certain extent, they interpreted core authors, core papers, areas of research focus in this field, and the current state of national cooperation. In order to explore the application of sentiment analysis in building smart societies, Verma collected 353 papers published between 2010 and 2021 (Verma 2022). Using a topic analysis perspective combined with the Louvain algorithm, the author identified four sub-topics in the research field. Similarly, Mantyla et al. employed LDA techniques and manual classification to explore the topic structures of sentiment analysis articles (Mäntylä et al. 2018). The informetric methods use natural language processing technologies to intuitively conduct topic mining and analysis of a large number of papers. Through topic clustering, the literature is organized and analyzed, which reduces the time researchers spend on reading the literature in depth. These methods are suitable for exploring research topics and trends in the field.

2.4 Summary of advantages and disadvantages of the existing surveys

In the following, we discuss the advantages and disadvantages of the existing surveys from a number of different points of view.

2.4.1 From the point of view of the contents and topics of sentiment analysis

As summarized in Table 1, the researchers organized the literature and conducted depth investigations of the contents and topics of sentiment analysis. They reviewed the tasks of sentiment analysis (e.g., different text granularity, opinion mining, spam review detection, and emotion detection), the application areas of sentiment analysis (e.g. market, medicine, social media, and election prediction), and different languages for sentiment analysis, such as Chinese, Spanish, and Arabic (Adak et al. 2022; Al-Ayyoub et al. 2019; Alamoodi et al. (2021a, b); Alonso et al. 2021; Angel et al. 2021; Boudad et al. 2018; Brito et al. 2021; Cheng et al. 2022; Hussain et al. 2019; Kastrati et al. 2021; Khattak et al. 2021; Koto and Adriani 2015; Kumar and Sebastian 2012; Ligthart et al. 2021; Medhat et al. 2014; Nassif et al. 2021; Nassirtoussi et al. 2014; Oueslati et al. 2020; Peng et al. 2017; Pereira 2021; Rambocas and Pacheco 2018; Ravi and Ravi 2015; Schouten and Frasincar 2015; Sharma and Jain 2020; Yue et al. 2019; Zhou and Ye 2020). They summarized the methods and application prospects of sentiment analysis under different contents and topics. As the field

Table 1 Advantages and disadvantages of the existing surveys

Existing surveys	Advantage	Disadvantage or limitations
From the point of view of the contents and topics of sentiment analysis Adak et al. (2022), Al-Ayyoub et al. (2019), Alamoodi et al. (2021a, b), Alonso et al. (2021), Angel et al. (2021), Boudad et al. (2018), Brito et al. (2021), Cheng et al. (2022), Hussain et al. (2019), Kastrati et al. (2021), Khattak et al. (2021), Koto and Adriani (2015), Kumar and Sebastian (2012), Ligthart et al. (2021), Medhat et al. (2014), Nassif et al. (2021), Nassirtoussi et al. (2014), Oueslati et al. (2020), Peng et al. (2017), Pereira (2021), Rambocas and Pacheco (2018), Ravi and Ravi (2015), Schouten and Frasincar (2015), Sharma and Jain (2020), Yue et al. (2019), and Zhou and Ye (2020)	The existing surveys conducted in-depth investigations of the contents and topics of sentiment analysis. They reviewed the tasks of sentiment analysis (e.g., different text granularity, opinion mining, spam review detection, and emotion detection), the topics of application areas of sentiment analysis (e.g. market, medicine, social media, election prediction, etc.), and different languages for sentiment analysis, such as Chinese, Spanish, and Arabic, etc. The existing surveys provided useful insights. They also summarized the techniques and application prospects of sentiment analysis under different contents and topics.	The existing surveys cover a short time range, and there has not been a survey dedicated to the evolution of research contents or topics of sentiment analysis. There have also been few survey works analyzing the connections between topics and methods, and their evolution (e.g., how the contents and topics of sentiment analysis change over time).
From the point of view of the methods of sentiment analysis Acheampong et al. (2021), Ain et al. (2017), Alamoodi et al. (2021a, b), Asghar et al. (2014), Chan et al. (2022), Cheng et al. (2022), Feldman (2013), Habimana et al. (2020), Koto and Adriani (2015), Kumar and Sebastian (2012); Medhat et al. (2014), Prabha and Srikanth (2019), Ravi and Ravi (2015), Schouten and Frasincar (2015), Serrano-Guerrero et al. (2021), Taboada (2016), Wang et al. (2020b), Yue et al. (2019), Zhang et al. (2018), and Zucco et al. (2020)	The existing surveys analyzed different methods of sentiment analysis. Sentiment analysis methods based on lexicons, rules, part of speech, term position, statistical techniques, supervised and unsupervised machine learning methods, as well as deep learning methods like LSTM, CNN, RNN, DNN, DBN, BERT and other hybrid approaches have been analyzed and discussed. The advantages and disadvantages of each method have also been analyzed by the existing surveys.	Even though the existing surveys analyze different methods of sentiment analysis, there have been few survey works on the evolution of research methods. In addition, the connections between topics and methods of sentiment analysis, and their evolution over time, have not been studied.

Table 1 (continued)

Existing surveys	Advantage	Disadvantage or limitations
From the point of view of the overall survey methodology		
Angel et al. (2021), Birjali et al. (2021), Kitchenham and Charters (2007), Kumar and Garg (2020), Kumar and Jaiswal (2020), Ligthart et al. (2021), Lin et al. (2022), Mäntylä et al. (2018), Obiedat et al. (2021), Piryani et al. (2017), Qazi et al. (2015, 2017), Sarsam et al. (2020), Verma (2022), Wankhade et al. (2022), and Zunic et al. (2020)	The existing surveys have mainly used the content analysis method, Kitchenham and Charters' guideline, and the informetric methods. The use of the content analysis method and Kitchenham and Charters' guideline enables in-depth analysis of literature contents. The use of informetric methods can reduce the time researchers spend on reading the literature in depth, and is suitable for exploring research methods, research topics, and the evolution of the field over time.	When there is a large amount of literature to be surveyed, the use of the content analysis method and Kitchenham and Charters' guideline requires more time and manpower. The evolution of research methods and topics of sentiment analysis over time has not been studied while using informetric methods. There have also been few survey works leveraging keyword co-occurrence analysis and community detection to analyze the connections between research methods and topics, and their evolution over time.

has grown, new topics have emerged, and knowledge from other fields has been gradually integrated into it. In recent years, the popularity of social media has aroused increasing interest in sentiment analysis research, and the number of papers published, especially those related to different topics of sentiment analysis, has grown rapidly. However, the existing surveys cover a short time range, and there has not been a survey dedicated to the evolution of research contents or topics of sentiment analysis. There have also been few survey works analyzing the connections between topics and methods, or their evolution (e.g., how the contents and topics of sentiment analysis have changed over time).

2.4.2 From the point of view of the methods of sentiment analysis

Some researchers reviewed different techniques and methods of sentiment analysis in different application areas and tasks. They analyzed and discussed sentiment analysis methods based on lexicons, rules, part of speech, term position, statistical techniques, supervised and unsupervised machine learning methods, as well as deep learning methods like LSTM, CNN, RNN, DNN, DBN, BERT, and other hybrid approaches (Acheampong et al. 2021; Ain et al. 2017; Alamoodi et al. 2021b; Asghar et al. 2014; Chan et al. 2022; Cheng et al. 2022; Feldman 2013; Habimana et al. 2020; Koto and Adriani 2015; Kumar, Akshi and Sebastian 2012; Medhat et al. 2014; Prabha and Srikanth 2019; Ravi and Ravi 2015; Schouten and Frasincar 2015; Serrano-Guerrero et al. 2021; Taboada 2016; Wang et al. 2020b; Yue et al. 2019; Zhang et al. 2018; Zucco et al. 2020). These researchers also compared the advantages and disadvantages of each method. As summarized in Table 1, even though existing surveys analyze the techniques and methods of sentiment analysis, providing good insights, there has not been a survey that analyzes the evolution of research methods over time. There have also been few survey works that focuses on the connections between topics and methods of sentiment analysis, and their evolution over time.

2.4.3 From the point of view of the overall survey methodology

The survey methods used have mainly been the content analysis method, Kitchenham and Charters' guideline, and the informetric methods. As summarized in Table 1, the content analysis method can effectively analyze the contents of research papers in depth, but it does not address the issue of the evolution of the research methods and topics (Bengtsson 2016; Birjali et al. 2021; Elo and Kyngäs 2008; Krippendorff 2018; Qazi et al. 2015, 2017; Wankhade et al. 2022). Although the number of papers that need to be read in depth can be reduced by following Kitchenham and Charters' guideline, more effort is needed to search and screen literature than in traditional literature review methods (Angel et al. 2021; Kitchenham 2004; Kitchenham and Charters 2007; Kumar and Garg 2020; Ligthart et al. 2021; Lin et al. 2022; Obiedat et al. 2021; Sarsam et al. 2020; Zunic et al. 2020). The informetric methods are best suited to investigating the research methods and topics of sentiment analysis (Bar-Ilan 2008; Mäntylä et al. 2018; Piryani et al. 2017; Santos et al. 2019; Verma 2022). There are three surveys using informetric techniques and tools that are well suited for analysis of a large number of papers over many years (Mäntylä et al. 2018; Piryani et al. 2017; Verma 2022). However, the evolution of research methods and topics of sentiment analysis over time has not been studied with informetric methods. There have also been few survey works that leverages keyword co-occurrence analysis and community detection to analyze the connections between research methods and topics, and their evolution over time.

Therefore, to address the gaps in the existing surveys, this study presents a survey on the research methods and topics, and their evolution over time. It combines keyword co-occurrence analysis and informetric analysis tools to reveal the methods and topics of sentiment analysis and their evolution in this field from 2002 to 2022.

The following section, Sect. 3, describes our proposed survey methodology in detail.

3 The proposed survey methodology

This section describes our proposed survey methodology, including collection of scientific publications, processing of scientific publications, as well as visualization and analysis using different methods and tools. The overall scheme of this survey (Fig. 2) is also presented in the end of Sect. 3 to better visualize and summarize the proposed survey methodology in this research.

3.1 Collection of scientific publications

We collected research data from the Web of Science platform. We used keywords such as "sentiment analysis," "sentiment mining," and "sentiment classification" to search for relevant papers as data samples. In examining the retrieved papers, we found that some paper topics, paper types, and publication journals were not related to sentiment analysis, so we excluded them. The papers we included were mainly related to the sentiment analysis of texts. We excluded papers on sentiment analysis related to image processing, video processing, speech processing, biological signal processing, etc. Therefore, the retrieval strategy was as follows:

Topic Search (TS) = ("sentiment analy*" or "sentiment mining" or "sentiment classification") And Abstract (AB) = "sentiment" NOT TS = ("face image*" or "speech recognition" or "speech emotion" or "physiological signal*" or "music emotion*" or "facial feature extraction" or "video emotion" or "electroencephalography " or "biosignal*" or "image process*") NOT Title = ("facial" or "speech" or "sound*" or "face" or "dance" or "temperature" or "image*" or "spoken" or "electroencephalography" or "EEG" or "biosignal*" or "voice*" not AB = "facial."

The results in conferences are given the same relevance as journal papers. We chose four databases in the Web of Science: two conference citation databases (Conference Proceedings Citation Index—Social Sciences & Humanities [CPCI-SSH], and Conference Proceedings Citation Index—Science [CPCI-S]), and two journal citation databases (Science Citation Index Expanded [SCI-Expanded] and Social Sciences Citation Index [SSCI]). Given the various forms of words such as "analyzing" and "analysis," a truncated search technique (marked with an asterisk) was used to prevent the omission of relevant papers. The time frame of the retrieved papers was from January 2002 to January 2022, and the publication types of the papers included "article," "conference paper," "review," and "edited material." A total of 9,714 papers were obtained from the four databases above. These included 3,809 articles, 5,633 proceeding papers, 267 reviews, and 5 pieces of editorial material from 2002 to 2022. Overall, there were 104 papers from January 2022. The number of papers each year from 2002 to 2021 is shown in Fig. 1.

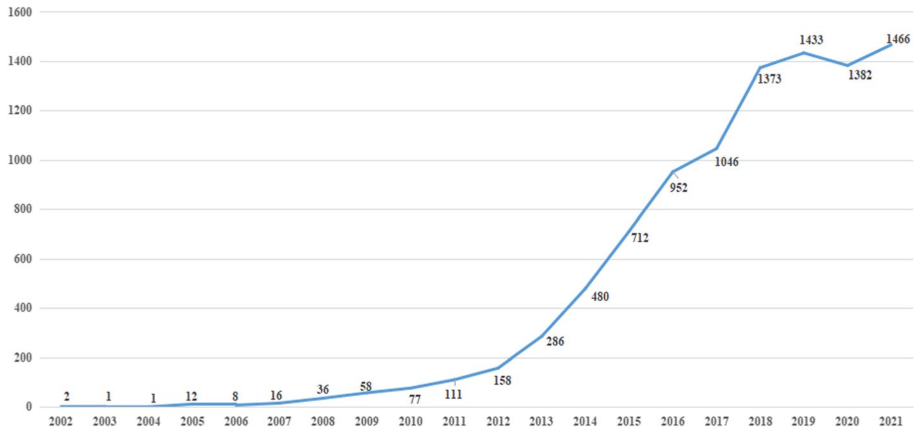


Fig. 1 The number of papers each year from 2002 to 2021

3.2 Processing of scientific publications

In this process, our purpose was to extract the key contents of the papers, which are used to analyze the research methods and topics in the field of sentiment analysis. Due to their limited number, the author keywords in each paper often cannot fully represent the key content of the paper. We found that combining the title and abstract could better reflect the core information. Therefore, we synthesized the title, abstract, and author keywords of each paper to extract keywords that represented the main research method and topic of the paper involved using KeyBERT[1]. KeyBERT is a keyword extraction technique that uses BERT embedding to create keywords and key phrases that most closely resemble document content (Grootendorst and Warmerdam 2021). The specific keyword extraction process was as follows:

First, we used KeyBERT to extract 8 keywords and eliminated keywords with a weight lower than 0.3. We then combined the extracted keywords with the author keywords and removed duplicates. After that, we standardized the whole collection of keywords and merged synonyms. Finally, we counted the number of keywords and removed meaningless terms like "sentiment analysis," "sentiment classification," and "sentiment mining."

After statistical analysis, we obtained 41,827 keywords with a total word frequency of 88,104. As there were 9,714 papers and 41,827 keywords, we found that most of the keywords with word frequency below 10 were not representative of the research contents of sentiment analysis. As a result, a total of 685 representative keywords were reserved for subsequent analysis. These keywords appeared a total of 30,801 times. Table 2 shows the keywords with word frequency in the top 50.

High-frequency keywords generally represent research hotspots. We therefore extracted high-frequency keywords to serve as the basis for the subsequent analysis. We found that most of the keywords with word frequency 18 and lower, such as "ranking," "mask," "experience," "affect," "online forum," and so on, were not relevant to sentiment analysis. Therefore, the keywords with a word frequency higher than 18 were reserved for analysis. These

[1] https://github.com/MaartenGr/KeyBERT.

Table 2 Keywords with word frequency in the top 50

Rank	Keywords	Frequency	Rank	Keywords	Frequency
1	Twitter	1393	26	Online review	202
2	Opinion mining	1177	27	Text analysis	200
3	Natural language processing	1098	28	Review	189
4	Machine learning	883	29	Covid-19	183
5	Social medium	834	30	Latent Dirichlet Allocation	171
6	Text mining	704	31	Feature selection	169
7	Deep learning	668	32	Product review	146
8	Sentiment lexicon	472	33	Prediction	146
9	SVM	464	34	Supervised learning	145
10	Social network	461	35	Attention mechanism	140
11	User review	458	36	Semantic	139
12	Word embedding	425	37	Semi-supervised learning	136
13	Topic model	422	38	Arabic language	135
14	Long Short-term Memory	370	39	Arabic sentiment analysis	133
15	Convolutional neural network	354	40	Aspect extraction	131
16	Big data	350	41	Text sentiment	129
17	Microblog	323	42	Aspect-based sentiment analysis	126
18	Text classification	309	43	Domain sentiment	125
19	Naive bayes	291	44	Lexicon-based	124
20	Aspect-based	286	45	Chinese language	119
21	Mining sentiment	283	46	Chinese text	115
22	Neural network	228	47	Domain adaptation	110
23	Data mining	228	48	Word2vec	107
24	Recurrent neural network	226	49	Transfer learning	106
25	Feature extraction	213	50	Polarity classification	100

keywords appeared 25,429 times in the collected data, accounting for close to 83% of all the keywords. We obtained 275 keywords, which were used to analyze the main methods and topics of sentiment analysis.

3.3 Visualization and analysis using different methods and tools

3.3.1 Analytical methods

Keywords are the core natural language vocabulary to express the subject, content, ideas, and research methods of the literature (You et al. 2021). Keywords represent the topics of the domain, and cluster analysis of these words can reflect the structure and association of topics. Keyword co-occurrence analysis counts the number of occurrences of a set of keywords in the same document. The strength and number of associations between research contents can be obtained through keyword co-occurrence analysis. Dividing research methods and topics into sub-communities helps researchers to analyze hotspots and trends in methods and topics, as well as to obtain sub-fields of sentiment analysis research (Ding et al. 2001).

3.3.2 Visualization and analysis tools

BibExcel[2] is a software tool for analyzing bibliographic data or any text-based data formatted in a similar way (Persson 2017). The tool generates structured data files that can be read by Excel for subsequent processing (Persson et al. 2009). Our processing steps are as follows. First, we imported the standardized bibliographic data into BibExcel. This tool can help structure the data. Second, we checked and corrected the data and used BibExcel to count the number of co-occurrences of keywords.

We then used Pajek[3]software to visualize the keyword co-occurrence network and divided the sub-communities. Pajek is a large and complex network analysis tool (Batagelj and Andrej 2022; Batagelj and Mrvar 1998). It can calculate certain indicators to reveal the state and properties of the network involved. In addition, Pajek's Louvain community detection algorithm can help divide the keyword co-occurrence network into sub-communities, which represent sub-fields of sentiment analysis (Blondel et al. 2008; Leydesdorff et al. 2014; Rotta and Noack 2011). The Louvain community-detection algorithm unfolds a complete hierarchical community structure for the network. It has an advantage in subdividing different areas of study: multiple knowledge structures and details can be shown in one network (Deng et al. 2021).

After that, we applied VOSviewer[4] to optimize the visualization of sub-communities (Van Eck and Waltman 2010; VOSviewer 2021; Perianes-Rodriguez et al. 2016; Waltman and Van Eck 2013; Waltman et al. 2010). VOSviewer can help display the core keywords in each sub-community and the correlation between keywords. It can also reflect the closeness of the association between sub-communities. Finally, we used Excel to count the frequency of keywords for each year and to map the evolution of research methods and topics in the field of sentiment analysis.

3.3.3 Graphical representation of the overall scheme of this survey

This paper proposes and conducts a new research survey on sentiment analysis. The graphical representation of the overall scheme of this survey is shown in Fig. 2. The main scheme includes four modules: Module A, Collection of scientific publications; Module B, Processing of scientific publications; Module C, Visualization and analysis through different methods and tools, and Module D, Result analysis and discussions based on various aspects.

In Module A, scientific publications are collected from the Web of Science (WOS) platform, as has been detailed in Sect. 3.1 Collection of scientific publications above. Module B, Processing of scientific publications, has been detailed in Sect. 3.2 above. It performs a data processing procedure to obtain key information, which includes all the representative keywords and high-frequency keywords. The title, abstract and keywords of the papers are used to extract such key information using KeyBERT (Grootendorst and Warmerdam 2021). Such key information is analyzed and visualized through different methods, including different visualization tools, as introduced in Sect. 3.3 (Module C), Visualization and analysis using different methods and tools, above.

[2] https://homepage.univie.ac.at/juan.gorraiz/bibexcel/.

[3] http://mrvar.fdv.uni-lj.si/pajek/.

[4] https://www.vosviewer.com/.

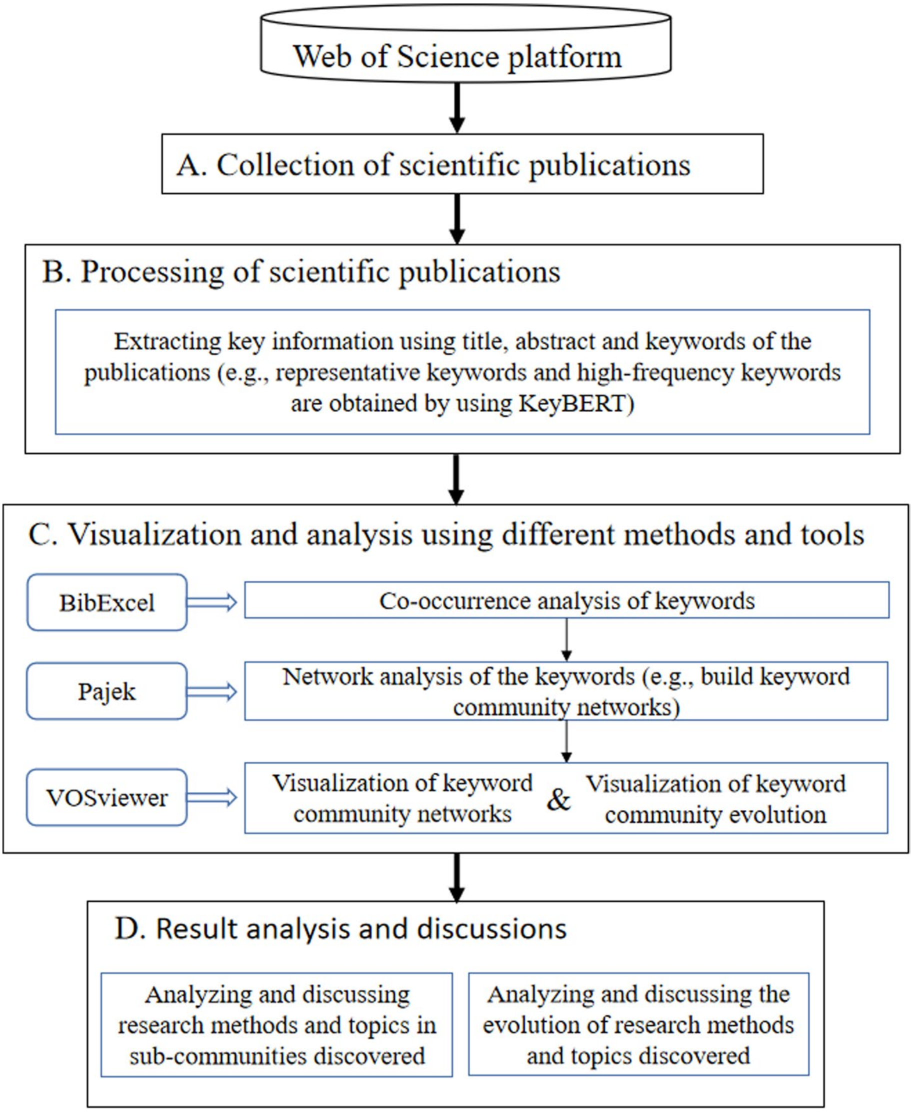


Fig. 2 Graphical representation of the overall scheme of this survey. Module A: Collection of scientific publications; Module B: Processing of scientific publications; Module C: Visualization and analysis using different methods and tools; Module D: Result analysis and discussions considering various aspects

In Module C, the number of co-occurrences of keywords is obtained using BibExcel (Persson 2017), the co-occurrences of keywords are analyzed and visualized using Pajek (Blondel et al. 2008; Leydesdorff et al. 2014; Rotta and Noack 2011) and VOSviewer (Van Eck and Waltman 2010; VOSviewer 2021; Perianes-Rodriguez et al. 2016; Waltman and Van Eck 2013; Waltman et al. 2010). The keyword community network and the keyword community evolution are analyzed and visualized using these tools, as described in Sect. 3.3 (Module C), Visualization and analysis using different methods and tools.

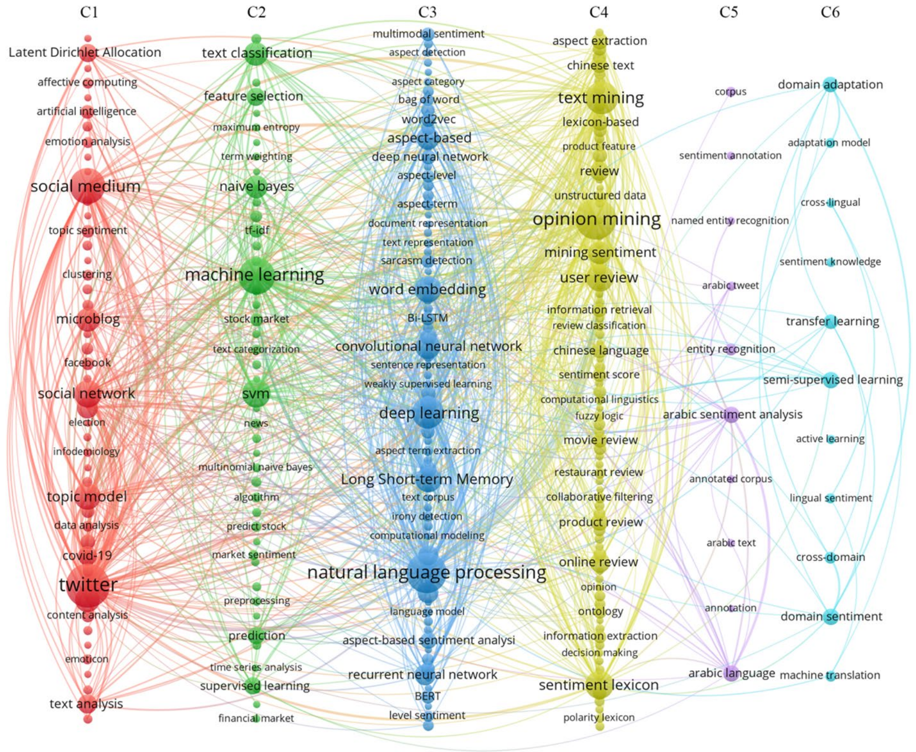


Fig. 3 Keyword community network

According to the visualization and analysis results obtained in Module C, Module D, Result analysis and discussions, will be detailed in Sect. 4.

In the following section, Sect. 4 (Module D), results are analyzed and discussed considering various aspects, including the research methods and topics of sentiment analysis in each community, the evolution of research methods and topics along with the research hotspots and trends over time.

4 Results and analysis through various aspects

4.1 Research methods and topics of sentiment analysis

4.1.1 Overall characteristic analysis

The high-frequency keywords were presented in Table 2. These keywords can be regarded as the main research contents in the field of sentiment analysis. "Twitter" ranks at the top. It is followed by "opinion mining," "natural language processing," "machine learning," and so on. The high-frequency keywords cover the topics of the studies, the contents of the studies, and the techniques and methods used. Based on these keywords, we used Pajek's Louvain method to construct a keyword co-occurrence network to

Table 3 The top 20 keywords in each community

Community	Keywords
C1	Twitter, social medium, social network, topic model, big data, microblog, data mining, text analysis, covid-19, Latent Dirichlet Allocation, emotion, artificial intelligence, topic sentiment, Facebook, emotion classification, content analysis, social medium analytics, data analysis, crowdsourcing, emotion analysis
C2	machine learning, svm, text classification, naive bayes, feature selection, prediction, supervised learning, tf-idf, stock market, random forest, genetic algorithm, algorithm, logistic regression, news, ensemble learning, predict stock, investor sentiment, text categorization, market sentiment, artificial neural network
C3	natural language processing, deep learning, word embedding, Long Short-term Memory, convolutional neural network, aspect-based, neural network, recurrent neural network, feature extraction, attention mechanism, semantic, text sentiment, aspect-based sentiment analysis, word2vec, deep neural network, task analysis, Bi-LSTM, attention network, multimodal sentiment, short text
C4	opinion mining, text mining, sentiment lexicon, user review, mining sentiment, online review, review, product review, aspect extraction, lexicon-based, Chinese language, Chinese text, polarity classification, movie review, sentiment dictionary, information retrieval, recommender system, sentiment score, sentiwordnet, unsupervised learning
C5	Arabic language, Arabic sentiment analysis, entity recognition, corpus, Arabic tweet, named entity recognition, Arabic text, annotated corpus, sentiment annotation, annotation
C6	semi-supervised learning, domain sentiment, domain adaptation, transfer learning, cross-domain, machine translation, lingual sentiment, adaptation model, sentiment knowledge, cross-lingual, active learning

Table 4 Global network characteristics of sub-communities

Community	Links between or within the communities						Nodes
	C1	C2	C3	C4	C5	C6	
C1	466	535	742	991	101	87	47
C2	535	386	710	821	86	94	47
C3	742	710	1134	1306	143	246	74
C4	991	821	1306	1205	159	193	86
C5	101	86	143	159	25	19	10
C6	87	94	246	193	19	41	11
Global network							275

represent the research methods and topics as shown in Fig. 3. The keyword co-occurrence network is divided into six communities. The research methods and topics of the six communities include social media platforms (C1), machine learning methods (C2), natural language processing and deep learning methods (C3), opinion mining and text mining (C4), Arabic sentiment analysis (C5), and others, such as domain sentiment analysis and transfer learning, etc. (C6).

In Fig. 3, the size of the node represents the number of keywords. The thickness of the line between the nodes represents the number of collaborations between keywords. The top 20 keywords in each community are sorted in descending order, as shown in Table 3. The keyword co-occurrence network features of the six sub-communities are described in Table 4. The number of nodes shows the number of keywords in each community, and the number of links shows the correlations between the keywords.

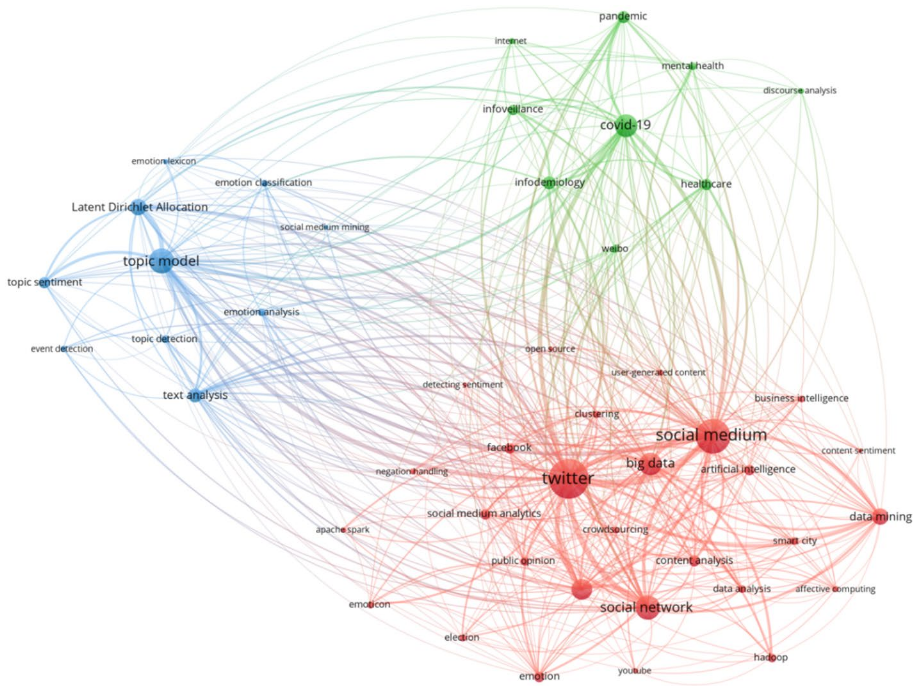


Fig. 4 The keyword co-occurrence network for the C1 community

As shown in Table 4, we can see from the number of links between sub-communities that there is a strong correlation between them, especially the link between C3 and C4, which has 1306 lines. The reason may be that the research methods of C4 focus on "opinion mining" and "text mining," while those of C3 focus on "natural language processing" and "deep learning," and C3 provides more technical support for C4 research. In C5 and C6, the research methods and topics are scattered. Their internal links are also low, but the connections with C3 and C4 are relatively high. The contents of C5 and C6 may include some emerging research methods and topics. We will present a specific analysis on the methods and topics of each sub-community in the next subsection.

4.1.2 Analysis on research methods and topics of sub-communities

4.1.2.1 Analysis on research methods and topics of the C1 community Figure 4 shows the keyword co-occurrence network of the C1 community. The research methods and topics of the C1 community focus on three areas: "social media," "topic models," and "covid-19." In the context of big data, web 2.0 technology provides users with a way to express reviews and opinions of services, events, and people. Various social media platforms, such as Twitter, YouTube, and Weibo, have a large amount of users' emotional data (Momtazi 2012). Compared to traditional news media, information on social media spreads more quickly, and people are able to express their feelings more freely. It is important to analyze the emotions generated by the information shared and published on social media (Abdullah and Zolkepli 2017; Wang et al. 2014). Researchers have been extracting text data from social

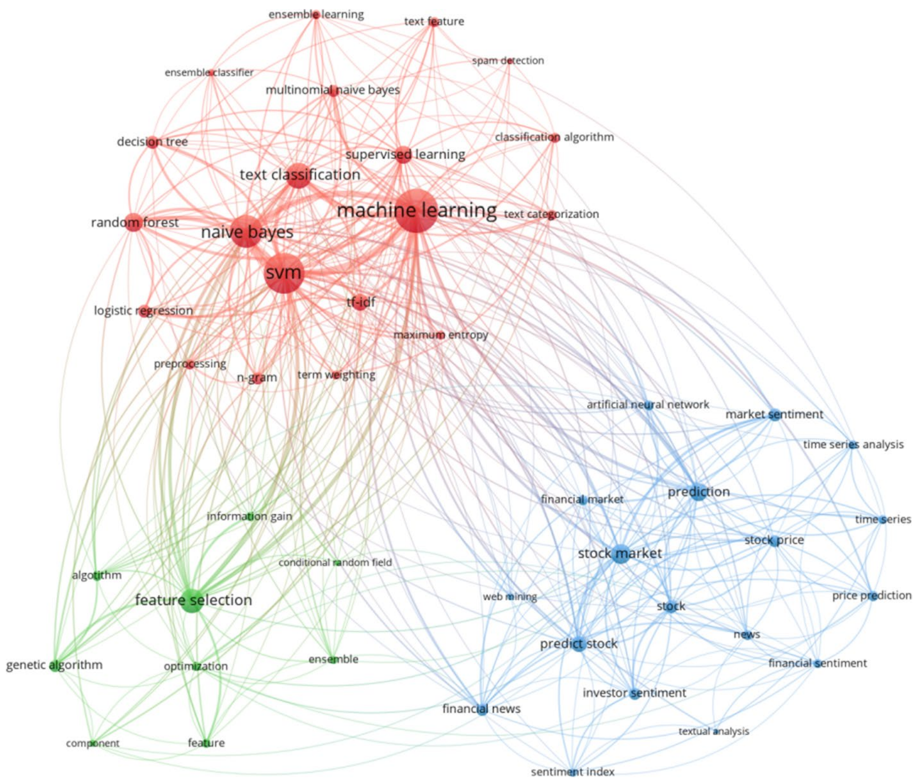


Fig. 5 The keyword co-occurrence network for the C2 community

media platforms for years to detect unexpected events (Bai and Yu 2016; Preethi et al. 2015), improve the quality of products (Abrahams et al. 2012; Isah et al. 2014; Myslin et al. 2013), understand the direction of public opinion (Fink et al. 2013; Groshek and Al-Rawi 2013), and so on.

Users' sentiments are often associated with the topics, and the accuracy of sentiment analysis can be improved through the introduction of topic models (Li et al. 2010). Among them, the Latent Dirichlet Allocation (LDA) method is cited most frequently. Previous studies found that the LDA method can be effective in subdividing topics and identifying the sentiments of the contents. This method is quite general, and there are also many improved models based on this one that can be applied to any type of web text, helping to enhance the accuracy of sentiment polarity calculation (Chen et al. 2019; Liu et al. 2020).

As the COVID-19 pandemic has unfolded, a large number of individuals, media and governments have been publishing news and opinions about the COVID-19 crisis on social media platforms. This has resulted in a lot of sentiment analysis studies focusing on COVID-19-related texts exploring the impact of the epidemic on people's lives (Sari and Ruldeviyani 2020; Wang, T. et al. 2020a), physical health (Berkovic et al. 2020; Binkheder et al. 2021) and mental health (Yin et al. 2020), and so on. Therefore, we can see many related keywords, such as "infodemiology," "healthcare," and "mental health."

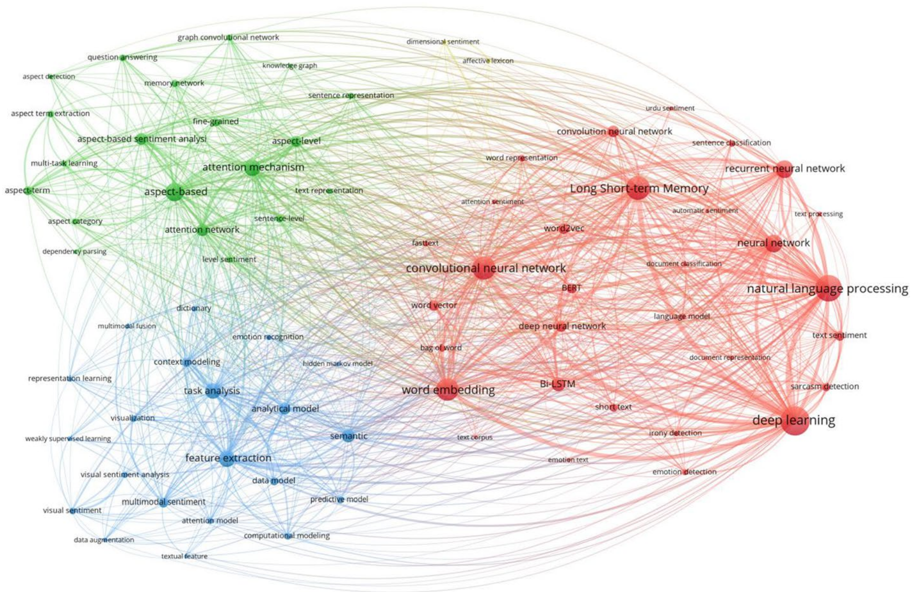


Fig. 6 The keyword co-occurrence network for the C3 community

4.1.2.2 Analysis on research methods and topics of the C2 community The contents of the C2 community mainly focus on "machine learning," "text classification," "feature extraction," and "stock market" (see Fig. 5). Most keywords are related to the research methods of sentiment analysis. Machine learning approaches have expanded from topic recognition to more challenging tasks such as sentiment classification. It is very important to explore and compare machine learning methods applied to sentiment classification (Li and Sun 2007). Methods like Support Vector Machine (SVM) and Naive Bayes models are widely used (Altrabsheh et al. 2013; Dereli et al. 2021; Shofiya and Abidi 2021; Tan et al. 2009; Wang and Lin 2020) and are used as benchmarks for the comparisons of models proposed by many researchers (Kumar et al. 2021; Sadamitsu et al. 2008; Waila et al. 2012; Zhang et al. 2019). Many algorithms, such as random forest (Al Amrani et al. 2018; Fitri et al. 2019; Sutoyo et al. 2022), tf-idf (Arafin Mahtab et al. 2018; Awan et al. 2021; Dey et al. 2017), logistic regression (Prabhat and Khullar 2017; Qasem et al. 2015; Sutoyo et al. 2022), and n-gram (Ikram and Afzal 2019; Singh and Kumari 2016; Xiong et al. 2021) are used to enhance the accuracy of machine learning, as shown in Fig. 5.

The trading volume and asset prices of financial commodities or financial instruments are influenced by a variety of factors in the online environment. Machine learning and sentiment analysis are powerful tools that can help gather vast amounts of useful information to predict financial risk effectively (Li et al. 2009). Research on the relationship between public sentiment and stock prices has always been the focus of many scholars (Smailović et al. 2014; Xing et al. 2018). They have used machine learning methods to explore the influence of sentiments on stock prices through sentiment analysis of news articles, and then predicted the trend changes in the stock market (Ahuja et al. 2015; Januário et al. 2022; Maqsood et al. 2020; Picasso et al. 2019).

4.1.2.3 Analysis on research methods and topics of the C3 community The contents of the C3 community also mainly focus on the methods for sentiment analysis, like "natural language processing", "deep learning," "aspect-based sentiment analysis," and "task analysis" (Fig. 6). Sentiment analysis is a sub-field of natural language processing (Nicholls and Song 2010), and natural language processing techniques have been widely used in sentiment analysis. Using natural language processing technology can help to better parse text features, such as part-of-speech tagging, word sense disambiguation, keyword extraction, inter-word dependency recognition, semantic parsing, and dictionary construction (Abbasi et al. 2011; Syed et al. 2010; Trilla and Alías 2009). With the rise of deep learning technology, researchers began to introduce it to sentiment analysis. Neural network models like LSTM (Al-Dabet et al. 2021; Al-Smadi et al. 2019; Li and Qian 2016; Schuller et al. 2015; Tai et al. 2015), CNN (Cai and Xia 2015; Jia and Wang 2022; Ouyang et al. 2015), RNN (Hassan and Mahmood 2017; Tembhurne and Diwan 2021; You et al. 2016), and some combination of these, as well as other models (An and Moon 2022; Li et al. 2022; Liu et al. 2020a; Salur and Aydin 2020; Zhao et al. 2021), have received significant attention.

Sentiment analysis granularity is subdivided into document level, sentence level, and aspect level. Document-level sentiment analysis takes the entire document as a unit, but the premise is that the document needs to have a clear attitude orientation—that is, the point of view needs to be clear (Shirsat et al. 2018; Wang and Wan 2011). Sentence-level sentiment analysis is intended to perform sentiment analysis of the sentences in the document alone (Arulmurugan et al. 2019; Liu et al. 2009; Nejat et al. 2017). Aspect-based analysis is a fundamental and significant task in sentiment analysis. The aim of aspect-level sentiment analysis is to separately summarize positive and negative views about different aspects of a product or entity, although overall sentiment toward a product or entity may tend to be positive or negative (Rao et al. 2021; Thet et al. 2010). Aspect-level sentiment analysis facilitates a more finely-grained analysis of sentiment than either document or sentence-level analysis (Liang et al. 2022; Wang et al. 2020c). The traditional levels of analysis, such as sentence-level analysis can only calculate the comprehensive sentiment polarity of paragraphs or sentences (Wang et al. 2016; Zhang et al. 2021). In recent years, the aspect level has become more and more popular, and with the application of deep learning technology, it has become better at capturing the semantic relationship between aspect terms and words in a more quantifiable way (Huang et al. 2018). The process of sentiment analysis involves the coordination of multiple tasks, and the subtasks include feature extraction (Bouktif et al. 2020; Lin et al. 2020), context analysis (Yu et al. 2019; Zuo et al. 2020), and the application of some analytical models (Tan et al. 2020).

4.1.2.4 Analysis on research methods and topics of the C4 community The C4 community mainly shows keywords related to the research methods and topics of "opinion mining" and "user review," which is the largest of the six sub-communities (Fig. 7). With the popularity of platforms like online review sites and personal blogs on the Internet, opinions and user reviews are readily available on the web. Opinion mining has always been a hot field of research (Khan et al. 2009; Poria et al. 2016). From Table 4, we can see that the link between C3 and C4 has 1306 lines. In opinion mining, researchers use many text mining methods to discover users' opinions on goods or services, and then help improve the quality of corresponding products or services (Da'u et al. 2020; Lo and Potdar 2009; Martinez-Camara et al. 2011). In addition, scholars have found that the consideration of user opinions can help improve the overall quality of recommender systems (Artemenko et al. 2020; Da'u et al.

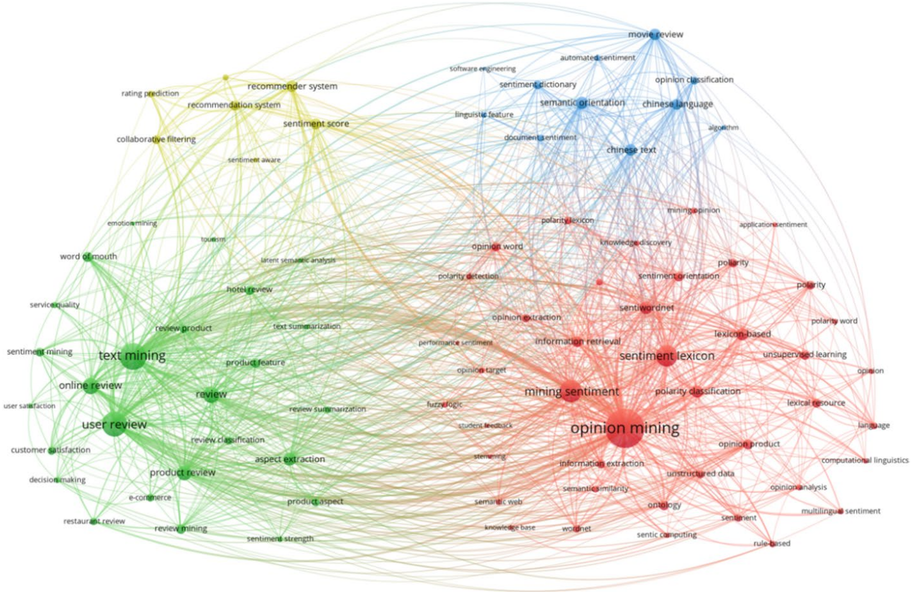


Fig. 7 The keyword co-occurrence network for C4 community

2020; Garg 2021; Malandri et al. 2022). Therefore, "recommendation system" has a strong correlation with "opinion mining."

Evaluation metrics for quantifying the existing approaches are also a popular topic related to opinion mining. There is a keyword named "performance sentiment" in the C4 community. Precision, recall, accuracy and F1-score are the most commonly used evaluation metrics (Dangi et al. 2022; Jain et al. 2022; JayaLakshmi and Kishore 2022; Li et al. 2017; Wang et al. 2021; Yi and Niblack 2005). Some researchers have also used runtimes to calculate the model efficiency (Abo et al. 2021; Ferilli et al. 2015), p-value to statistically evaluate the relationship or difference between two samples of classification results (JayaLakshmi and Kishore 2022; Salur and Aydin 2020), paired sample t-tests to verify that the results are not obtained by chance (Nhlabano and Lutu 2018), and standard deviation to measure the stability of the model (Chang et al. 2020). There have also been researchers who have used G-mean (Wang et al. 2021), Pearson Correlation Coefficient (Corr) (Yang et al. 2022), Mean Absolute Error (MAE) (Yang et al. 2022), Normalized Information Transfer (NIT) and Entropy-Modified Accuracy (EMA) (Valverde-Albacete et al. 2013), Mean Squared Error (MSE) (Mao et al. 2022), Hamming loss (Liu and Chen 2015), Area Under the Curve (AUC) (Abo et al. 2021), sensitivity and specificity (Thakur and Deshpande 2019), etc.

4.1.2.5 Analysis on research methods and topics of the C5 & C6 communities Both subcommunities C5 (Fig. 8) and C6 (Fig. 9) are small in size. The C5 community has 25 nodes and the C6 community has 41 nodes. The core content of the C5 community is "Arabic sentiment analysis." Before 2011, most resources and systems built in the field of sentiment analysis were tailored to English and other Indo-European languages. It is increasingly necessary to design sentiment analysis systems for other languages (Korayem et al. 2012), and researchers are increasingly interested in the study of tweets and texts in the Arabic language

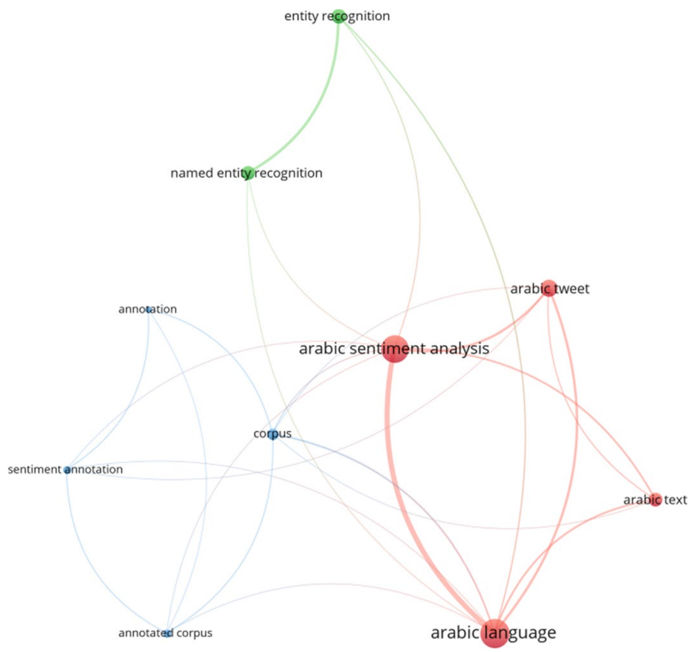


Fig. 8 The keyword co-occurrence network for the C5 community

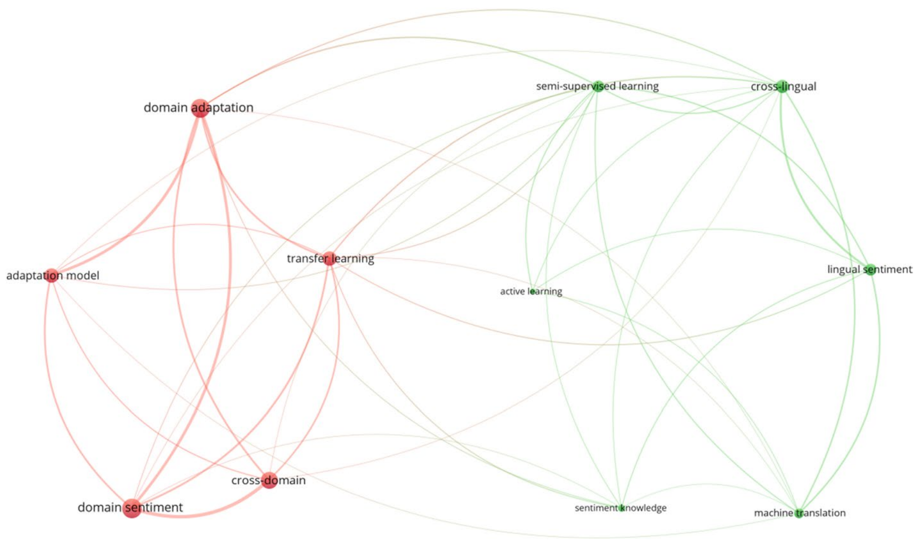


Fig. 9 The keyword co-occurrence network for the C6 community

(Heikal et al. 2018; Khasawneh et al. 2013; Oueslati et al. 2020). They use technologies such as named entity recognition (Al-Laith and Shahbaz 2021), deep learning (Al-Ayyoub et al. 2018; Heikal et al. 2018), and corpus construction (Alayba et al. 2018) to enhance the accuracy of sentiment analysis.

The contents of the C6 community are not very concentrated. From the size of the circle, we can see that the keywords "domain adaptation"(Blitzer et al. 2007; Glorot et al. 2011), "domain sentiment," and "cross-domain" appear more frequently. Cross-domain sentiment classification is intended to address the lack of mass labeling data (Du et al. 2020a). It has attracted much attention (Du et al. 2020b; Hao et al. 2019; Yang et al. 2020b). Advances in communication technology have provided valuable interactive resources for people in different regions, and the processing of multilingual user comments has gradually become a key challenge in natural language processing (Martinez-Garcia et al. 2021). Therefore, some keywords related to "lingual" have appeared. Other keywords, such as "transfer learning," "active learning," and "semi-supervised learning," are mainly related to sentiment analysis technologies.

4.2 Evolution of research methods and topics of sentiment analysis

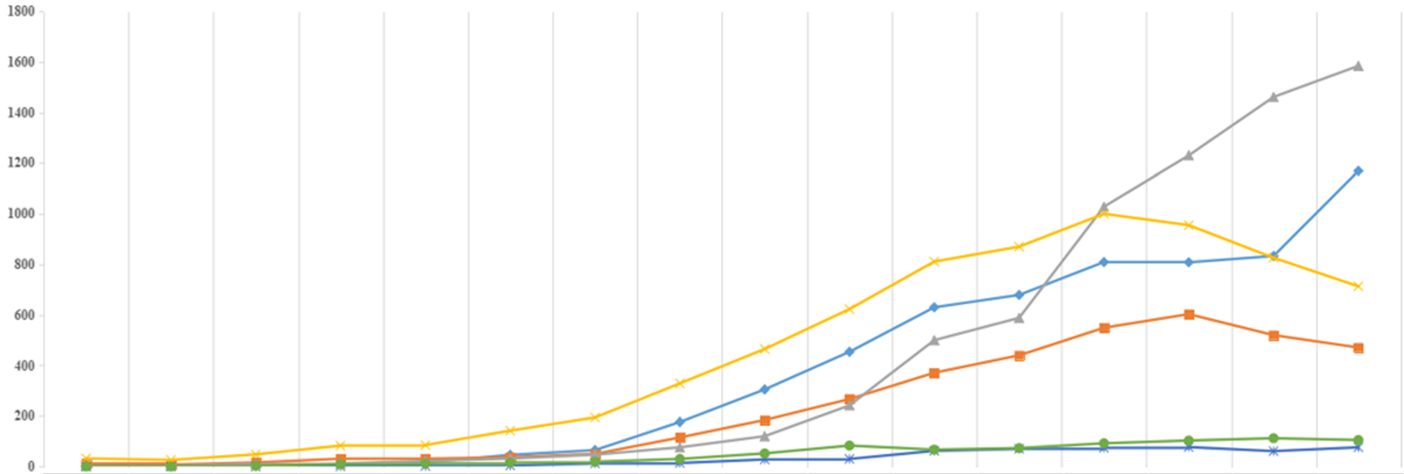
4.2.1 Overall evolution analysis

Annual changes in keyword frequency in sentiment analysis research can reflect the evolution of research methods and topics in this field. Based on the keyword community network (Fig. 3), we counted the frequency of keywords in each sub-community for each year. The keyword community evolution diagram is shown in Fig. 10. Since there were fewer papers published before 2006, we combined the occurrences of keywords from 2002 to 2006. We can see that the C1 community and the C3 community have shown a significant growth trend. The C2 community was in a state of growth until 2019, and the frequency of keywords decreased year by year after 2019. The frequency of C4 community keywords continued to increase until 2018 and declined after 2018. The number of keywords in the C5 community and in the C6 community both had a slow growth trend, but the trend was not obvious.

4.2.2 Evolution analysis of sub-communities

We selected the high-frequency keywords under each category and plotted the change of word frequency in each year, as shown in Figs. 11 and 12. In the C1 community, "social medium," "Twitter," "social network," "covid-19," "Latent Dirichlet Allocation," "topic model," and "text analysis" all had significant increases in word frequency, and the growth trend in 2021 was obvious. "Covid-19" appears in 2020, and the word frequency increased rapidly in 2021. Social media platforms have always been the focus of researchers' attention. Under the influence of COVID-19, more people express their emotions, stress, and thoughts through social media platforms. Sentiment analysis on data from social media platforms related to COVID-19 has become a hot topic (Boon-Itt and Skunkan 2020). We believe that due to the impact of COVID-19, the widespread use of social platforms in 2020–2021 has led to a surge in the number of C1-related keywords.

The C2 community focuses on the method of "machine learning," and the C3 community focuses on the methods of "deep learning" and "natural language processing." The keywords in the two communities are mainly related to the techniques and methods of sentiment analysis. We have found that before 2016 (Fig. 10), the frequency of keywords in



	2002-2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
C1	4	2	4	10	17	46	65	176	305	454	630	679	809	808	833	1169
C2	12	8	16	31	31	37	50	115	184	267	371	440	549	603	520	471
C3	3	4	10	12	22	31	47	76	120	242	500	588	1028	1230	1461	1584
C4	32	26	48	83	85	142	194	329	465	623	811	870	1000	955	826	713
C5	0	0	0	1	2	4	12	14	28	30	62	70	74	77	61	76
C6	0	0	3	9	12	16	19	30	52	83	67	73	92	103	112	105

Fig. 10 Keyword community evolution diagram

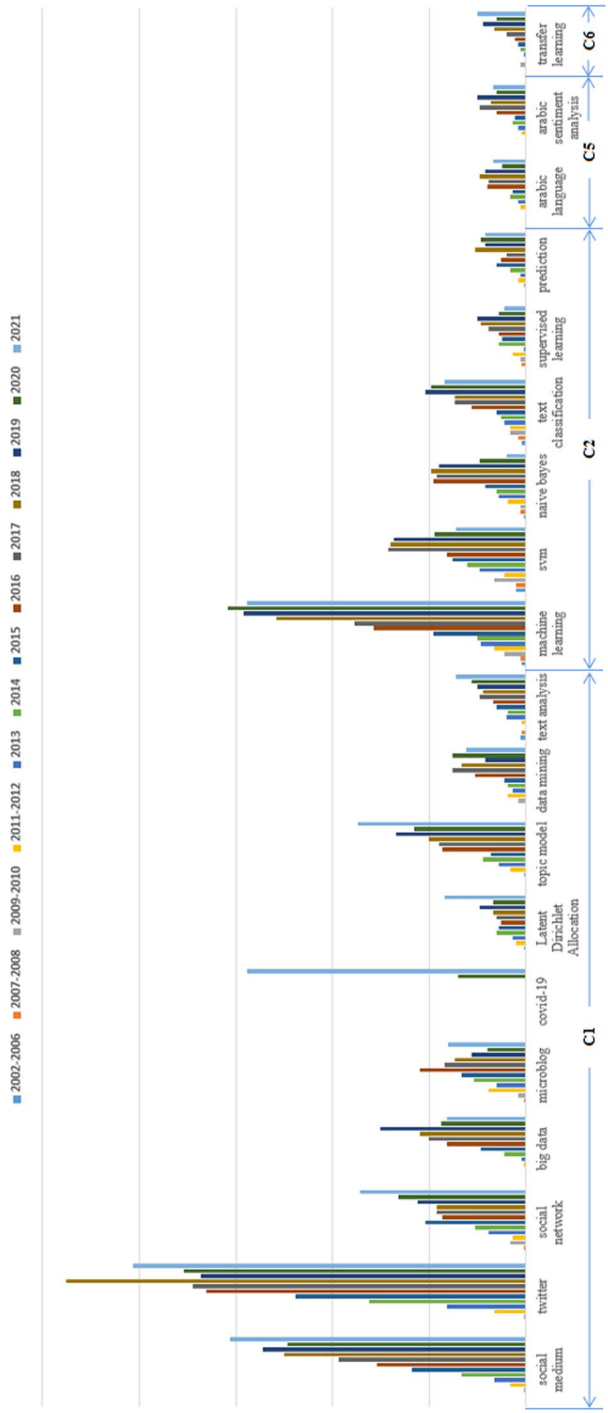


Fig. 11 C1, C2, C5, C6 communities: High-frequency keyword evolution diagram

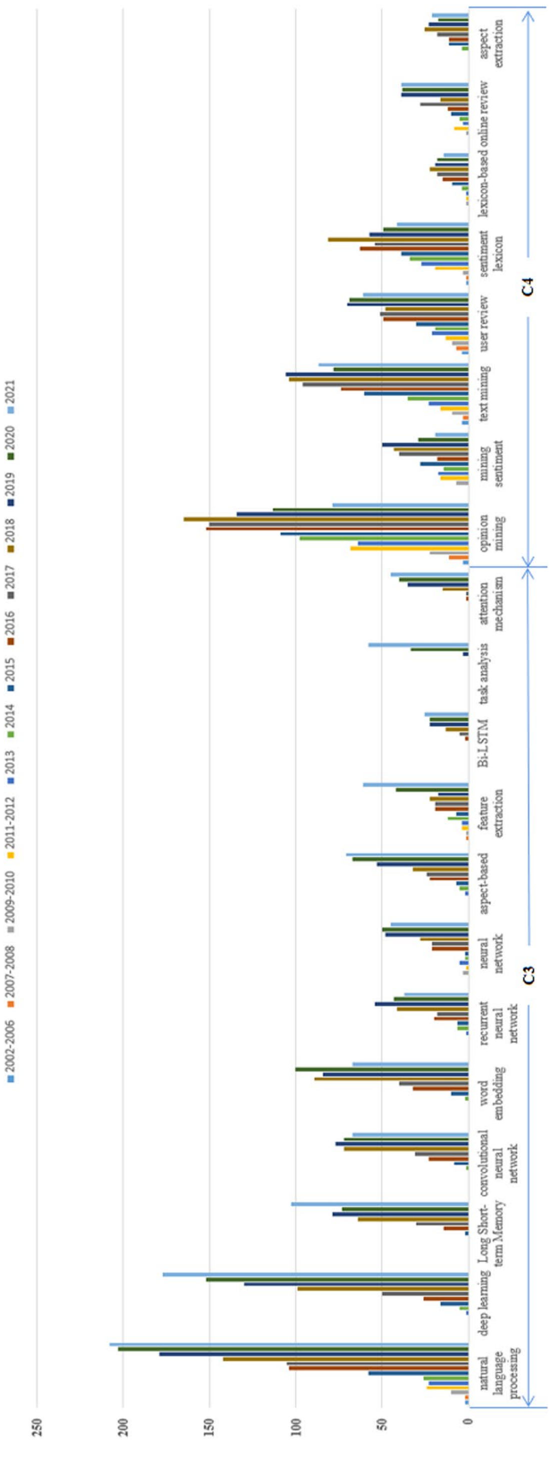


Fig. 12 C3, C4 communities: High-frequency keyword evolution diagram

the C2 community was higher than that in the C3 community, and in 2016 and later, the frequency of keywords in the C3 community gradually accounted for a larger proportion of the total. This reflects the fact that deep learning-related technologies and methods have become a research hotspot, and the attention given to SVM, Naive Bayes, supervised learning, and other technologies in machine learning has declined. In addition to deep learning models such as Bi-LSTM, Long Short-term Memory, and recurrent neural network in the C3 community, the number of "aspect based" and "feature extraction" keywords have also been growing, which shows that researchers now pay more attention to the aspect level of text granularity in the field of sentiment analysis.

Among the keywords found in the C4 community, the word frequency of the "opinion mining" keyword has decreased since 2018. This shows that in the field of sentiment analysis, researchers have begun to reduce the attention they give to sentiment analysis of opinions on product or service quality, while still maintaining a certain degree of attention to "user review" and "online review." In addition, the number of keywords for "sentiment lexicon" and "lexicon-based" has declined. It may be because, in the context of the widespread application of deep learning technology in recent years, the lexicon-based method requires more time and higher labor costs (Kaity and Balakrishnan 2020). However, its accuracy still attracts attention due to the high involvement of experts, especially in non-English languages (Bakar et al. 2019; Kydros et al. 2021; Piryani et al. 2020; Tammina 2020; Xing et al. 2019; Yurtalan et al. 2019).

The high-frequency keywords in the C5 and C6 communities are "Arabic language," "Arabic sentiment analysis," and "transfer learning." Arabic has 30 variants, including the official Modern Standard Arabic (MSA) (ISO 639–3 2017). Arabic dialects are becoming increasingly popular as the language of informal communication on blogs, forums, and social media networks (Lulu and Elnagar 2018). This makes them challenging languages for natural language processing and sentiment analysis (Alali et al. 2019; Elshakankery and Ahmed 2019; Sayed et al. 2020). Transfer learning can solve the problem by leveraging knowledge obtained from a large-scale source domain to enhance the classification performance of target domains (Heaton 2018). In recent years, based on the success of deep learning technology, this method has gradually attracted attention.

5 Research hotspots and trends

Through the analysis in Sects. 4.1 and 4.2, we found that the research methods and topics of sentiment analysis are constantly changing. The keyword topic heat map is shown in Fig. 13. From this map, we can see that in the past two decades, research hotspots have included social media platforms (such as "social medium," "social network," and "Twitter"); sentiment analysis techniques and methods (such as "machine learning," "svm," "natural language processing," "deep learning," "aspect-based," "text mining," and "sentiment lexicon"), mining of user comments or opinions (e.g., "opinion mining," "user review," and "online review"), and sentiment analysis for non-English languages (e.g., "Arabic sentiment analysis" and "Arabic language").

With the popularity of digitization, a large amount of user-generated content has appeared on the Internet, where users express their opinions and comments on different topics such as the news, events, activities, products, services, etc. through social media. This is especially so in the case of the Twitter mobile platform, launched in 2006, which has become the most popular social channel (Kumar and Jaiswal 2020). However, online

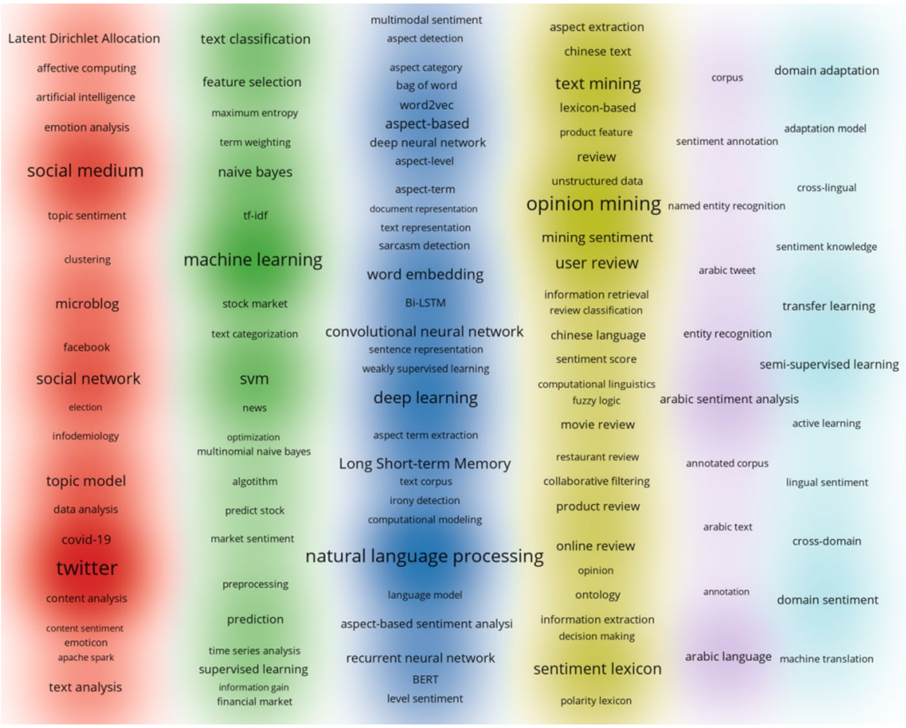


Fig. 13 Keyword topic heat map

text data is mostly unstructured. In order to accurately analyze users' sentiments, the research methods for sentiment analysis, such as natural language processing technology, and automatic sentiment analysis models have become the focus of researchers' works. From Fig. 11, we can see that early technologies and methods are dominated by machine learning and that SVM and Naive Bayes have always been favored by researchers. This has also been confirmed in studies by Neha Raghuvanshi (Raghuvanshi and Patil 2016), Harpreet Kaur (Kaur et al. 2017), and Marouane Birjali (Birjali et al. 2021). With the improvement of neural network and artificial intelligence technology, deep learning technology has been widely used in sentiment analysis, and has resulted in good outcomes (Basiri et al. 2021; Ma et al. 2018; Prabha and Srikanth 2019; Yuan et al. 2020). However, deep learning technology still has room for improvement, and the hybrid methods combining sentiment dictionary and semantic analysis are gradually becoming a trend (Prabha and Srikanth 2019; Yang et al. 2020a).

The granularity of sentiment analysis ranges from the early text level to the sentence level and finally to the aspect level, which is currently gaining strong attention. The granularity of sentiment analysis is gradually being refined, but the method is immature at present, and further research work in the future is needed (Agüero-Torales et al. 2021; Li et al. 2020; Trisna and Jie 2022).

Early sentiment analysis was mainly in the English language. In recent years, non-English languages such as Chinese (Lai et al. 2020; Peng et al. 2018), French (Apidianaki et al. 2016; Pecore and Villaneau 2019), Spanish (Chaturvedi et al. 2016; Plaza-del-Arco et al.

2020), Russian (Smetanin 2020), and Arabic (Alhumoud and Al Wazrah 2022; Ombabi et al. 2020) have attracted more and more attention. Furthermore, cross-domain sentiment analysis technology is in urgent need of research and discussion by researchers (Liu et al. 2019; Singh et al. 2021).

6 Conclusion and future work

6.1 Conclusion

Judging from the increasing number of papers related to sentiment analysis research every year, sentiment analysis has been on the rise. Although there are many surveys on sentiment analysis research, there has not been a survey dedicated to the evolution of research methods and topics of sentiment analysis. This paper has used keyword co-occurrence analysis and the informetric tools to enrich the perspectives and methods of previous studies. Its aims have been to outline the evolution of the research methods and tools, research hotspots and trends and to provide research guidance for researchers.

By adopting keyword co-occurrence analysis and community detection methods, we analyzed the research methods and topics of sentiment analysis, as well as their connections and evolution trends, and summarized the research hotspots and trends in sentiment analysis. We found that research hotspots include social media platforms, sentiment analysis techniques and methods, mining of user comments or opinions, and sentiment analysis for non-English languages. Moreover, deep learning technology, with its hybrid methods combining sentiment dictionary and semantic analysis, fine-grained sentiment analysis methods, and non-English language analysis methods, and cross-domain sentiment analysis techniques have gradually become the research trends.

6.2 Practical implications and technical directions of sentiment analysis

Sentiment analysis has a wide range of application targets, such as e-commerce platforms, social platforms, public opinion platforms, and customer service platforms. Years of development have led to many related tasks in sentiment analysis, such as sentiment analysis of different text granularity, sentiment recognition, opinion mining, dialogue sentiment analysis, irony recognition, false information detection, etc. Such analysis can help structure user reviews, support product improvement decisions, discover public opinion hotspots, identify public positions, investigate user satisfaction with products, and so on. As long as user-generated content is involved, sentiment analysis technology can be used to mine the emotions of human actors associated with the content. The improvement of sentiment analysis technology can help machines better understand the thoughts and opinions of users, make machines more intelligent, and make better decisions for policy leaders, businessmen, and service people. However, most of the current sentiment analysis methods are based on sentiment dictionaries, sentiment rules, statistics-based machine learning models, neural network-based deep learning models, and pre-training models, and have yet to achieve true language understanding in the sense of comprehension at the deep semantic level, though this does not prevent them from being useful in certain practical applications.

As an important task in natural language understanding, sentiment analysis has received extensive attention from academia and industry. Coarse-grained sentiment analysis is increasingly unable to meet people's decision-making needs, and for aspect-level sentiment analysis and complex tasks, pure machine learning is still unable to flexibly achieve true language understanding. Once the scene or domain changes, problems such as the domain incompatibility of the sentiment dictionary and the low transfer effect of the model involved keep appearing. At present, the accuracy of sentiment analysis provided by machines is far less than that of humans. To achieve human-like performance for machines, we believe that it is necessary to incorporate human commonsense knowledge and domain knowledge, as well as grounded definitions of concepts, in order for machines to understand natural language at a deeper level. These, combined with rules for affective reasoning to supplement interpretable information, will be effective in improving the performance of sentiment analysis. Future research in this direction can be strengthened to achieve true language understanding in machines.

6.3 Limitations and future work

There are some research limitations in this paper. First, we only studied papers written in English and searched from the Web of Science platform. We believe there are papers in other languages or other databases (e.g., Scopus, PubMed, Sci-hub, etc.) that also involve sentiment analysis but that were not included in our study. In addition, the keywords we chose to search in the Web of Science were mainly "sentiment analysis," "sentiment mining," and "sentiment classification." There may be papers related to our research topic that do not have these keywords. To track developments in sentiment analysis research, future studies could replicate this work by employing more precise keywords and using different literature databases.

Second, we selected the main high-frequency keywords for analysis, and some important low-frequency keywords may have been ignored. In future work, we can analyze the changes in each keyword in detail from the perspective of time and obtain more comprehensive analysis results.

Third, the results show that the themes of sentiment analysis cover many fields, such as computer science, linguistics, and electrical engineering, which indicates the trend of interdisciplinary research. Therefore, future work should apply co-citation and diversity measures to explore the interdisciplinary nature of sentiment analysis research.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest or competing interest in this article.

Research involving human participants or animals This article does not contain any studies with human participants or animals performed by any of the authors.

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