Global Transitions Proceedings 2 (2021) 157–162

Contents lists available at ScienceDirect

Global Transitions Proceedings

journal homepage: http://www.keaipublishing.com/en/journals/global-transitions-proceedings/

Insights of strength and weakness of evolving methodologies of sentiment analysis

M.B. Nasreen Taj[a,*], G.S. Girisha[b]

[a] Dayananda Sagar University, Kudulugate, Karnataka, India and Department of Information Science and Engineering, GMIT, Davanagere, Karnataka, India
[b] Department of Computer Science and Engineering, Dayananda Sagar University, Kudulugate, Karnataka, India

ARTICLE INFO

Keywords:
Lexicon
Machine learning
Mining
Sentiment analysis
Text analysis

ABSTRACT

With every business process and organization being more concerned about adopting the latest technology towards understanding the success rate and risk associated with the product/service launch, they need to understand the intention and review of their prospective customer. Sentiment Analysis is one such advanced technology to analyze and perceive the behavior of a consumer. However, many challenges hinder analyzing precise sense of sentiments and locating the appropriate sentiment divisions. There has been a significant amount of work being carried out in this direction since the last decade. Furthermore, with the evolution of big data technologies, new methodologies have been introduced to improve sentiment analysis with various evolving applications. This paper provides a comprehensive study on sentiment analysis to provide valuable insight into sentiment analysis approaches and related fields. The paper discusses various essential information associated with the dataset, a new arena of application and methodologies, upcoming research methods, study findings, and further contributing to the ultimate study and research gap.

1. Introduction

After globalization, the world has seen economic liberalization. Any brand from any country became free to produce anywhere and sell anywhere if they follow the business compliances and global standards. An illustration of the business process and its impact on consumer behaviors is given in Fig. 1. The time before globalization is defined as pre-globalization and the time after as post-globalization. In the pre-globalization, there used to be limited local brands for every product and service. Therefore, the consumers had limited options.

The limited brands pose a compulsion for the consumer to choose out of the available brand. Thus, it creates a market of monopoly and an industry-driven market. In an industry-driven market, what exactly the consumers are saying does not impact the business. However, the synergy in post-globalization is entirely different as the corporates face tough competition because almost all the world brands are available in every market for each product and service. Therefore, consumers have many options for a product or a service to choose from brands. Thus it creates a consumer-driven market in consumer-driven market; what consumers are saying about a brand matter a lot for a brand owner. Thus, every brand owner needs to monitor their brand reputation closely. In this regard, the corporates or the brand owners maintain an open platform of the feedback system. Consumers can openly provide their opinion and express their experiences with the brand. Most of the time, a new prospect takes their purchase based on the sentiments expressed in their feedback.

The digital eco-system of collaboration provides many collaborative network platforms where people collaborate and build networks to share their thoughts and experiences and discuss common interest topics. These discussions may have a broad set of topics from different domains, including discussions about a company. The sentiments of the discussion may show a direct impact on the stock value of that company. Therefore, in the stock, performance prediction mainly depends on the septimates expressed in the topic discussion about the company or a product.

In the competitive market, digital platforms are also extensively used to campaign for the product or the services as a marketing effort by the corporates. The expressions against or pro to this campaigning and their analysis helps the brand-owners to be decisive about their strategies to take their further actions. In the business process, the corporates undergo many litigations, where they need to deal with a large corpus of the data and search an evidential proof in their favor. The appropriate tagging of the sentiments plays an essential role in the cost effect and speedy compliance monitoring. In all the above-discussed use-cases, the core function is to collect the data and develop a computational model that can effectively measure the degree of sentiments expressed through

* Corresponding author.
E-mail addresses: NASREENTAJMB.res-soe-cse@dsu.edu, nasreent@gmit.ac.in (M.B. Nasreen Taj), girisha-cse@dsu.edu.in (G.S. Girisha).

https://doi.org/10.1016/j.gltp.2021.08.059
Received 28 May 2021; Accepted 28 June 2021
Available online 12 August 2021

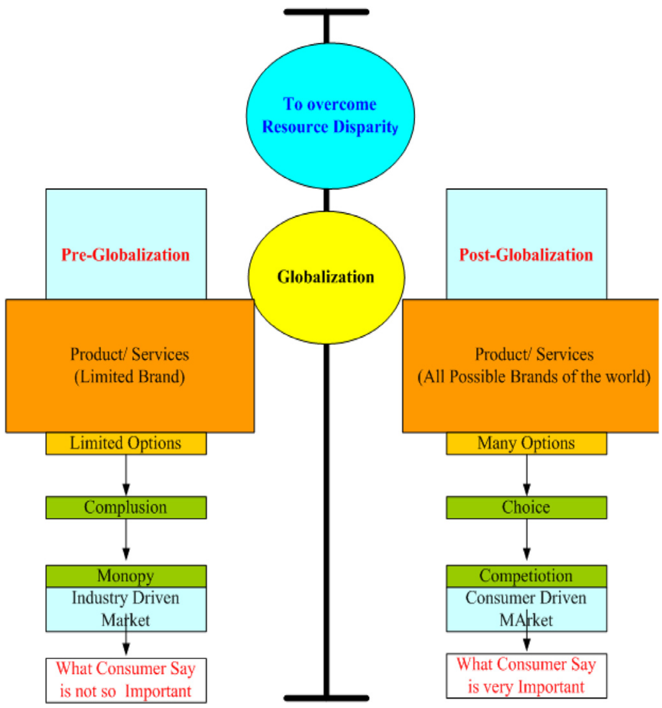

Fig. 1. An impact of the globalization.

the expressions by the participants, which is popularly known as "Sentiment Analysis. "However, there are research studies where sentiment analysis is done on images [1], videos [2], and voice data [3], too. In contrast, this paper deals with the textual data of simple to complex and heterogeneous formats.

This paper discusses various evolving methodologies in recent times in sentiment analysis. The paper's organization is as follows: Section 2 presents related work followed by the methodologies considered and dataset used in sentiments analysis approaches, while Section 3 discusses the taxonomy of research and upcoming trends in Sentiment analysis research methods. Section 5 presents discussion and study findings are, while Section 6 summarizes the contribution of the paper.

2. Related work

The proposed system collects research papers published in IEEE Xplore, Springer, and Elsevier to draft this manuscript. The inclusion criteria for drafting this paper are mainly all recently published journals, and the exclusion criteria are all theoretical. While collecting the research paper, the core keyword used is "sentiment analysis," published between 2015-to-2021 in IEEE Xplore digital library to find 4655 conference papers, 481 journals, 81 magazines, and 69 early access materials. A nearly similar trend is also found in other reputed publishers. This manuscript further performs more filtering to review 66 research articles to write this paper. The papers are selected with a criterion of inclusion of innovative methodology.

2.1. About dataset

The existing research implementation associated with sentiment analysis is always carried out considering a standard dataset which mainly uses textual contents with various representation. Amazon product data is one of the most extensive datasets consisting of 143 million reviews associated with Amazon products/services, e.g., brand, price, category information, ratings, feedback, etc. [4]. Another variant of this dataset has reviewed between 1 to 5 scores obtained from Amazon [5]. Existing research techniques have also witnessed using another large movie dataset called the IMDB movie review dataset consisting of 50,000 reviews [6]. The sentiment scoring is given between 1-10, where the score less than '4' is considered harmful while more than '7' is considered positive. The Stanford dataset's next standard dataset consists of 10,000 data obtained from reviews of Rotten Tomatoes [7]. This dataset has rated sentiments between 1 to 25 values representing negative and positive values.

Existing studies have also found that a dataset constructed from social media platforms is highly helpful. One such dataset is constructed from Twitter called Sentiment140, which utilizes the categorized outcome constructed by applying machine learning algorithms [8]. They are mainly meant for purchase planning, polling, brand management, etc. Furthermore, the Twitter dataset was also used for analyzing the sentiment associated with the airline of the United States [9]. Finally, another dataset is Paper Reviews associated with feedback of conferences and informatics [10].

The dataset has a 1-5 score for sentiments. Language-based analysis of sentiment is carried out for 81 language datasets generated using graph propagation based on real-world objects [11]. The Lexi coder also uses the existing dataset, a dictionary with 1709 positive sentiment and 2859 negative sentiment words [12]. The final dataset for sentiment analysis in this paper is the Opin Rank dataset, consisting of 42,230 reviews of cars aggregated from Edmunds and Trip Advisor [13]. It also has a collection of 2 59 000 reviews of hotels. This dataset mainly collects the information of 10 prominent cities of the world with international ranking.

The dataset mentioned above is reportedly used in recent studies, with unique methodologies and techniques discussed in the next section.

2.2. New arena of applications & methodologies

There are various areas of application where sentiment analysis is utilized, unlike the conventional approaches reported in [14]. There has been an increasing demand to use sentiment analysis in various applications with the advancement of technologies. This also leads to the evolution of novel methodologies. This section briefs about the latest arena of applications with the briefing of methodologies used.

- *Social Media Monitoring*: There are a vast amount of data being aggregated and processed over social media in the form of text. Sentiment analysis is applied to this final data to extract some meaning and logical inference from this massive, scattered and distributed social media data. The work carried out towards social media are carried out by Alattar and Shaalan [15], Amin et al. [16], and Cotfas et al. [17], considering some recent topic.
- *Automobile / Vehicle-based Services: The automotive sector is another booming sector that attracts many crowds* with the availability of the large number of information associated with choices of vehicle, its features, its sales, its diagnostic, sentiment analysis assists in narrowing down the inference associated with this prime information. The work carried out by Asensio et al. [18], Jena [19], and Pai et al. [20] have presented simplified techniques of sentiment analysis for analysis and forecasting purposes.
- *Product / Service Review*: This is the most conventional and highly deployed application of sentiment analysis. Different variants of methodologies are applied to analyze the feedback or review associated with certain products or services. For example, the work carried out by Ali et al. [21], Basiri et al. [22], Kastrati et al. [23] have carried out the analysis of review of educational data, drug-related data, and transportation service data, respectively.
- *Travel / Tourism-based Services*: Both tourist and tour-service operators primarily use travel and tourism-related data. The information is collected to understand varied sentiments associated with places and the classification of tourism places. The work carried out by Kirilenko et al. [24], Chen et al. [25], and Yu et al. [26] have presented

Table 1
Summary of Recent Approaches of Sentiment Analysis.

Topic	Authors	Problem areas	Methodologies	Advantage	Limitation
Social Media	Alattar and Shaalan [15]	Formulating actions for decision-makers	Filtered LDA model	Autonomous identification of sentiment	Deals with homogeneous data
	Amin et al. [16]	Identification of disease from social media post	Word embedding, Long Short-Term Memory	Higher accuracy	Consumes higher length of duration for analysis
	Cotfas et al. [17]	Opinion dynamics for COVID-19 vaccination from tweets	Deep learning, machine learning	It can be used for long term	Domain-specific analysis
Automobiles	Asensio et al. [18]	Analyzing sentiment for electric car	Natural Language processing	Practical sentiment extraction	Low size of trained data, the inclusion of computational complexity
	Jena [19]	Analyzing sentiment for electric car	Deep learning (CNN, RNN, document to vector)	Improvise decision making for the designer, manufacturer, consumer	Dynamic change of sentiment not analyzed concerning time.
	Pai et al. [20]	Forecasting sales of vehicles from tweets	The least-squares support vector regression, multivariate regression	Improve accuracy of forecast	The forecast depends on extracted keywords of tweets.
Product / Service Review	Ali et al. [21]	Extracting customer opinion for Uber services	Extraction of a prominent aspect of sentiments, unsupervised learning, hybrid approach	Service enhancement	It entirely depends upon the dictionary.
	Basiri et al. [22]	Revies of drug	Deep learning	Higher accuracy	Inclusion of maximum training time
	Kastrati et al. [23]	Educational review	CNN, LSTM	Higher accuracy	Lacks inclusion of context during analysis
Travel / Tourism	Kirilenko et al. [24]	Automated analysis of tourism sentiment	Artificial neural network, Rapid Miner	Cost-effective approach, good accuracy	Uses only Homogenous data
	Chen et al. [25]	Online travel classification	Microsoft Knowledge graph, semantics, classification	Simpler method	Uncertainty inapplicability of methods
	Yu et al. [26]	Analyzing over-tourism	Lexicon-based approach	Simpler approach	Area-specific analysis
Health	Oyebode et al. [30]	Analysis of mental health	Supervised learning	Supervised, binary classification	Lacks granularity in analysis
	Polisena et al. [31]	Analyzing health technologies	Lexical/machine learning	Good theoretical study	-N/A-
	Wang et al. [32]	COVID-19 data analysis	BERT Model	Simplified Model	Uses only Homogenous data
Financial Service	Bos [33]	Constructing financial sentiment	Bayes's Theorem, Pointwise Mutual Info	Better performance	Accuracy Score not sufficient
	Mishev et al. [34]	Assessing financial sentiment	Statistical method, deep learning	Not dependent on a large dataset	Lacks benchmarking
	Wan et al. [35]	Correlation between news and finance	Natural Language Processing	Can assess the volatility of finance	Lacks extensive analysis

sentiment analysis over travel and tourism data. Apart from this, various other similar categories of implementation are [27-29]

- *Healthcare-based Services*: Every month, there is a massive generation of medical data in various formats. The text-based healthcare data can analyze various clinical information to arrive at a particular conclusion for diagnosis or treatment specifications. The studies carried out by Oyebode et al. [30], Polisena et al. [31], Wang et al. [32] emphasized analyzing healthcare data.
- *Financial Services*: Financial data are pretty challenging and have multi-facet complex information within them. For more than a decade, sentiment analysis has been a contribution to finance. Such work is carried out by Bos [33], Mishev et al. [34], and Wan et al. [35] associated with financial data analysis. The summarization of the above-discussed sentiment analysis approaches is tabulated in Table 1 to provide quick insight to the readers.

Apart from the applications mentioned above, there are various other areas where sentiment analysis can be used. Various evolving areas of applications are associated with books [36], electronics [37], entertainment [38], fashion [39], Malls and stores [40], online services [41], etc. Fig. 2 highlights the taxonomies of the new arena of applications with highlights of various attributes associated with the application, which offers various insights of the features used for performing extraction of essential sentiments. The various application can also be designed by integrating multiple forms of application areas. Hence, a new arena of applications with mining techniques and big data approach offers more insights to feature extraction and sentiment analysis.

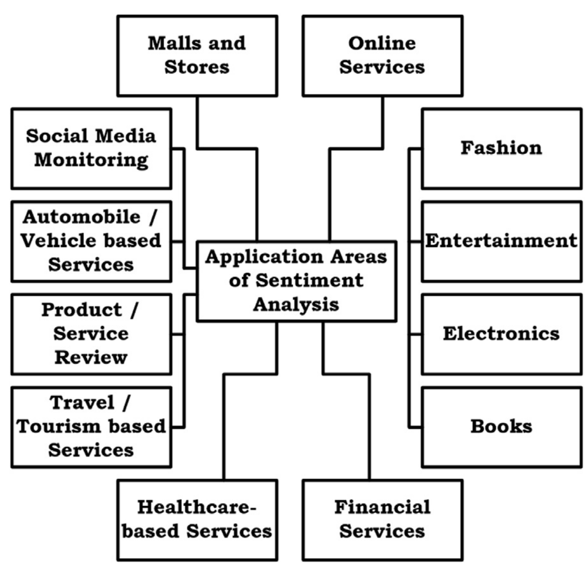

Fig. 2. Existing Applications of Sentiment Analysis.

3. Taxonomy of research

Since the evolution of sentiment analysis, researchers have been deliberatively addressing domain independence, overheads of natural language processing, huge lexicons, bipolar words, extraction of keywords and features, etc. Moreover, in sentiment analysis, various studies are carried out by solving different forms of research problems. This section briefs about principal research methodology evolved by researchers in current time.

- *Lexicon-based Approach:* This is the conventional mechanism of performing sentiment analysis which mainly makes use of dictionary-based methods (Xu et al. [42]) and corpus-based methods (Sanagar and Gupta [43]). This approach is unsupervised and is independent of any apriori trained data. However, it usually involves preprocessing, selecting features, calculating sentiment score, classification of sentiment. The corpus-based method is further classified into statistical (Ilanezet al. [44]) and semantic methods (Fang et al. [45]).
- *Hybrid Approach:* The hybrid-based method mainly integrates machine learning (supervised) with a lexicon-based approach (Zhang et al. [46]). The prime intention of this algorithm is to offer a better form of classification of sentiments.
- *Machine-Learning Approach:* There are three generic approaches of machine learning used in sentiment analysis viz. unsupervised-approach (Wang et al. [47]), supervised approach (Aziz & Starkey, [48]), and semi-supervised approach (Li et al. [49]) of learning. Out of all this, the most frequently used are supervised learning approach, e.g., k-nearest neighborhood (Agarwal and Poornalatha [50]), neural network (Aydin & Gungor [51]), support vector machine (Ren et al. [52]), and Naïve Bayes (Wongkar and Angdresey [53]).
- *Deep Learning Approach:* This is one of the most preferred approaches in existing times towards sentiment analysis,i.e., deep belief network (Chen and Hendry, [54]), hybrid neural network (Ling et al. [55]), recurrent neural network (Sadr et al. [56]), deep neural network (Sadr et al. [56]), recursive neural network (Sadr et al. [56]), and convolution neural network (Jianqiang et al. [57]).
- *Task-Oriented Approach:* This approach is associated with various specified tasks. Some of the frequency, as well as upcoming task, are classification of polarity (Dragut et al. [58]), valence level (Wang et al. [59]), beyond polarity (Calefato et al. [60]), identification of subjectivity/objectivity (Cabezudo et al. [61]), sentiment analysis based on aspect/feature (Gao et al. [62]).
- *Granularity Approach:* These approaches mainly focus on obtaining a higher degree of precision considering a significant corpus level in it. It is further classified into word-level (Azzeddine et al. [63]), sentence-level (Azzeddine et al. [63), and document-level analysis (Azzeddine et al. [63]).

Fig. 3 highlights the standard taxonomy of the upcoming trend on research methods associated with the sentiment analysis.

4. Schematic analysis

This section discusses the essential findings associated with different methodologies involved in sentiment analysis. In addition, the discussion is carried out concerning the identification of research trends.

An interesting finding has been found while assessing the different techniques associated with sentiment analysis. It has been seen that there are theoretical as well as technical aspects of the methodologies. The theoretical aspects make use of lexical, Part-of-Speech, Maximum Entropy, Semantic technique, an n-gram. In contrast, the technical aspect of methodology uses n-gram, Bag-of-Words, Part-of-Speech, maximum entropy, and others. Hence, there is a more theoretical approach compared to the technically implementable approach. After reviewing the last 5 years' research approach, it is found that multiple attributes emphasized by researchers are dataset, domain-oriented, lexicon type, and accuracy. The studies have also used different variants of lexicons, e.g., WordNet [64], How Net [65-67], and SentiNet [68-70]. Usually, the utilized lexicon consists of polarity and sentiment word information. Such forms of classification in sentiment analysis are categorized

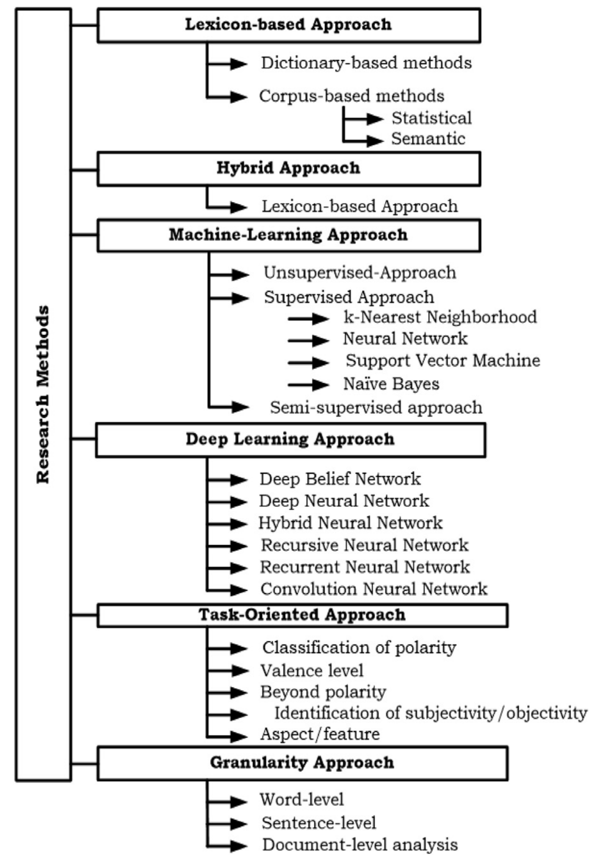

Fig. 3. Standard Taxonomy of Research Methods in Sentiment Analysis.

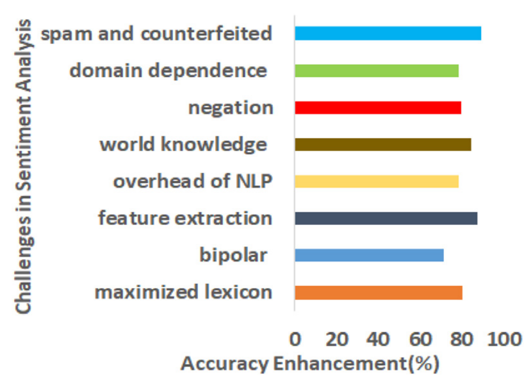

Fig. 4. Outcome of Accuracy assessment in Sentiment Analysis.

the three forms viz. i) negative polarity and positive polarity, ii) positive, negative, neutral, mixed, and iii) positive polarity, positive, neutral, negative, and very negative polarity [71-73].

From the viewpoint of accuracy parameters, Figure 4 highlights the improvement that has been introduced by various researchers by addressing various set of problems viz. maximized lexicon (*acc*=80.05%), bipolar (*acc*=71.2%), feature extraction (*acc*=87.12%), overhead of NLP (*acc*=78.45%), world knowledge (*acc*=84.25%), negation (*acc*=79.41%), domain dependence (*acc*=78.62%), and spam and counterfeited (*acc*=89.01%). The outcome shows that spam and counterfeited issues and feature extraction are being addressed by the maximum number of research work and the highest accuracy range as a success factor. It should be noted that the accuracy mentioned above is averaged concerning the appropriate proportion of text-based datasets.

From the above numerical findings in Table 2, it can be seen that more studies have been carried out towards the neural network-based

Table 2
Publication on Existing Methodologies (2015-2021).

Methodology	Journal
Lexicon-Based Approach	
-dictionary	49
-corpus	39
Hybrid-based Approach	29
Machine learning	
-naïve Bayes	16
-SVM	55
-Neural Network	157
-KNN	1
Deep Learning Approach	
-CNN	38
-RNN	19
-DNN	87
Granularity Approach	
document	131
sentence	35
word level	49
Task-oriented Approach	
polarity classification	66
subjectivity identification	4
objectivity identification	11

approach (=157) while implementation using Deep Neural Network (DNN) is just a starting (=87). It is also seen that the granularity-based approach is also witnessed with a more significant number of works on the document-based approach (=131). The next level of research work is emphasized on the polarity-based approach (=66) towards sentiment analysis. Other methodologies have been used in very scattered ways with no dominant usage of any specific method. The next section discusses the research gap.

5. Discussion

This section discusses the findings of the proposed study and highlights the significant research gap.

The identified research gap is as follows:

- Existing studies have not focused much on the complexities of data, which is real-time generated data. Moreover, most of the approaches are associated with categorization of sentiment polarity, domain dependence, negation, low recall performance, huge lexicon, bi-polar words, etc.
- Almost all the analysis and implementation of sentiment analysis to date is about a specific subset of data under one domain. However, the inclusion of many subsets of data in one domain will increase complexities. Moreover, the inclusion of many different domains will further degrade the performance of existing frameworks. Hence, data heterogeneity is not dominantly found to be addressed in existing models.
- The framework structure in existing studies has been designed to take the data input for one time and then subject to processing leading to the analytical outcome. There is no provision for the inclusion of data for processing while the system carries out sentiment analysis. It will eventually mean that the existing system is not built for addressing a stream of data for performing sentiment analysis. With the rise of mobile computing and mobile networks, data could be generated in multiple forms and formats, and it is necessary to process such a massive data size. Unfortunately, this is not feasible in existing approaches, and still, it is under the roof of research and development.
- The adoption of machine learning and artificial intelligence is one of the frequently adopted techniques for sentiment analysis. However, although this technique contributes significantly towards achieving accuracy, it is highly resource-dependent and consumes time. Hence, it cannot be suitable for performing analysis which is a time-bound application.
- None of the existing approaches towards sentiment analysis can discuss computational efficiency apart from achieving accuracy. Therefore, to ensure the developed algorithm to be executed cost-effectively, it is necessary to incorporate lower processing time and lower memory utilization to showcase a computationally cost-efficient analysis process.

6. Conclusion

This paper has mainly discussed the essentials of sentiment analysis. The research concept aged more than a decade, but there were some recent developments in this area. This leads to the evolution of new methodologies for sentiment analysis. This paper contributes towards i) discussing the compact insights about sentiment analysis associated with research implementation, ii) discuss popularly adopted dataset in it, iii) discuss proper taxonomies of the methodologies concerning all prominent approaches and techniques, iv) highlight the research trends associated with the pattern of recent methodologies being evolved, and v) discuss research gap. The future work will be carried out towards developing a framework to address the open-end research problems discussed in the prior section.

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