A Survey of Twitter Sentiment Analysis Approaches

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***Abstract*—** Sentiment analysis has turned out to be one of the fastest emerging research areas in the last decade. A compendious survey of the research area of sentiment analysis like what is sentiment analysis, applications, challenges, etc. has been presented in the paper. Further, it also has surveyed about various sentiments analysis techniques applied for Twitter sentiment analysis in recent years. Finally, the paper is concluded with the future directions for helping in recognizing the emerging areas of the sentiment analysis.

Keywords— Sentiment analysis(SA), Opinion Mining, SA techniques, Hybrid SA approach, Machine-learning SA Approach, and Lexicon SA Approach

I. INTRODUCTION

Our society is based on the very subtle idea of "what will people say" or "what will people think." With the advent of web, the tendency of quenching the curiosity of finding out the opinions and reviews of others has led us to involve a large number of people all over the globe to influence our decision making abilities whether it is about buying a product, watching a movie or even giving a vote to a party. The availability of the online surveys, review sites, tweets trending about a topic and blogs about a particular subject has led to developing a new research field opinion mining, the term was first used in the paper [2] and interpreted more broadly in [3]. Sentiment analysis which can also be synonymized with opinion mining can be expounded as methods, techniques and tools for detection and extraction of subjective information, determination of the stance of a user concerning opinions and attitudes of a product or a service or a trend whose reviews are made public on the internet, for ratings opinion polarity (neutral, positive or negative) and for finding the overall contextual polarity or emotional reaction by the use of natural NLP, text analysis & computational linguistics [1]. The concept of modern sentiment analysis aggrandized only in the mid-2000 as the results of the development of machine learning methods and availability of datasets, online surveys and review aggregation sites, the applications of the field in commercial and intelligence areas. The field of sentiment analysis provides practical and potential applications which can be of great use in areas like in business and government intelligence and also it can be augmented with other technologies like recommendation system etc. as a sub-component technology. Sentiment classification is performed at different granularity levels like document level, sentence level, feature/aspect level concept-level, tweet-level, word level, etc. by making using of various approaches like machine learning , lexicon and hybrid approaches.

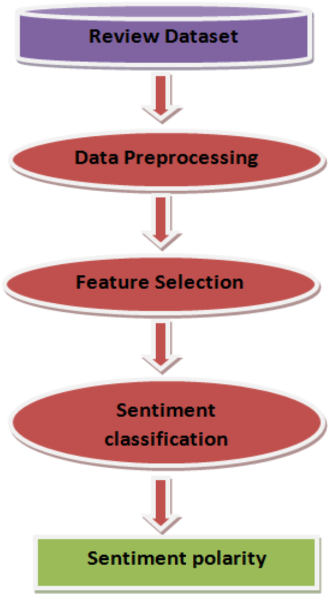

Fig.1 Flow diagram of the sentiment analysis process

II. VARIOUS APPROACHES FOR SENTIMENT ANALYSIS

The existing sentiment classification techniques use the following three approaches:

A. Machine learning based approach: In this approach, the sentiment analysis is treated as basic text classification problems that make use of linguistic features and are solved by using the famous machine learning algorithms:

1. *Supervised learning methods:* This method is used to infer functions from the labeled training dataset which contains the training examples. The function deduced using labeled training set is used for mapping new examples. A brief explanation of various types of classifiers used in sentiment analysis is:

a. Probabilistic classifier: These classifiers are also known as generative classifiers, which uses the mixture models for classification. They give a probability distribution over the set of classes rather than providing the most likely classes as output from the sample set. Three main types of such classifiers are Naïve Bayes (NB), Bayesian Network (BN) and Maximum Entropy (ME).

b. Linear *Classifier:* In a two-dimensional model, a linear classifier can be considered as a line which separates the objects into different classes they belong to by the decision based on the linear combinations of their characteristics or a vector of the feature values. They work well in solving a problem with many variables (features) and especially in document classification. Two of the most famous types are Support Vector Machines (SVM) and Artificial Neural Networks (ANN).

c. Decision Tree classifiers: It imposes a series of questions and conditions on the attribute for decomposing the training dataset into a tree hierarchy. The roots and nodes of the DT contain the attribute conditions which classifies the data that have different feature values in separate groups. The terminal nodes are labeled as Yes or No in DT. The condition or predicate used in the division can be of various types: (a) Single Attribute spilt , it performs the division on the basis of whether particular words or phrases are present or absent at a particular node in the tree, (b) Similarity-based multi-attribute split, computes similarity between the documents and document or frequent words cluster in order to perform the division and (c) Discriminate-based multi-attribute spilt, make use of the discriminates, e.g., Fisher discriminate for the splitting the training set.

d. Rule-based classifier: An algorithm with some rules is encoded for modeling the data space. It is different from DT classifiers in the way that DT follows a strict hierarchy approach, but the rule-based classifier allows the overlapping in decision space.

2. *Unsupervised learning methods*: The approach of using unlabelled data for the classification is called unsupervised learning, e.g. the creation of a sentiment lexicon, bootstrapping, in which the output of an available classifier is used, etc.

3. Semi-supervised learning methods: SSL makes use of both labeled data and unlabeled data for learning. This approach is somewhat novel to opinion mining. Though unlabeled data do not have information about classes, it can give an idea about the classification features. The limitation of limited labeled data required for supervised learning approach can be improved using SSL. Also, by incorporating prior knowledge to unsupervised models, SSL can overcome the drawback of the unsupervised learning methods. Graph-based methods, self training, multi-view learning, and generative models are some of SSL algorithms.

B. Lexicon- Based Approaches: Many sentiment classification tasks make use of the opinion, polar or sentiment words. Opinion words are of two types (a) Base types: The positive opinion words represent the desired state, e.g., amazing, good and beautiful and the undesired state has expressed by the negative opinion words, e.g., bad, horrible and unexpected. Apart from opinion words, opinion lexicons which have idioms or phrases like sick as a dog are also available. They are used to give a direct opinion about an object. (b) Comparative types: They are used to express the comparative and superlative forms like better, worse and best. Unlike base types, they are used for the comparison of one or more kind of objects. For compiling the opinion, three approaches are defined:

a. Manual Approach: This is a quite a time-consuming method and generally does not used alone, It is done basically as a final check for avoiding any error or mistakes that can be a result from the automated methods.

b. Dictionary-based Approach: The method involves the manual collection of a small set of words with known sentiment orientations, called the seed list. Then this seed list is grown by the addition of new words found by searching the antonyms and synonyms in well-known corpora or online dictionary like WordNet. The process is repeated until the new words are found. After the iteration stops, the manual checking is carried out to check for any possible error or mistake. The main shortcoming of this approach is that it does not focus on the domain and context specific orientation of the opinion words. For instance, the speaker is loud, is positive but in the sentence the car is loud, is a negative expression. To overcome this drawback, a corpus-based method is used.

c. Corpus-based Approach: This approach finds the opinion words with their context-specific orientations. The method of finding such words depends on the syntactic or co-occurrence patterns along with seed words list. This method when performed alone is not as efficient as the dictionary-based approach because it is a difficult task to create a big corpus to cover all the words. But, the main advantage is that it provides us the way to list the domain and context specific opinion words with their orientation, which is not possible in the dictionary-based method. It can be implemented using the semantic and statistical approaches.

C. Hybrid Approach: The strengths of both the above-mentioned existing SA approaches are considered to overcome their weaknesses to build a sentiment classification system that achieves the improved performance for the process of sentiment classification.

III. ISSUES, CHALLENGES AND FUTURE DIRECTIONS

The following is a list of i*ssues that can be considered by* researchers to work upon in the time ahead for upgrading the field of sentiment analysis:

i. The sentiment analysis techniques for detecting implicit opinions are still very finite and less. The new techniques must be developed to handle this problem.

ii. The pre-processing steps (handling spelling corrections, abbreviations emerging slangs, etc.) is the most time-consuming step and also can lead to less

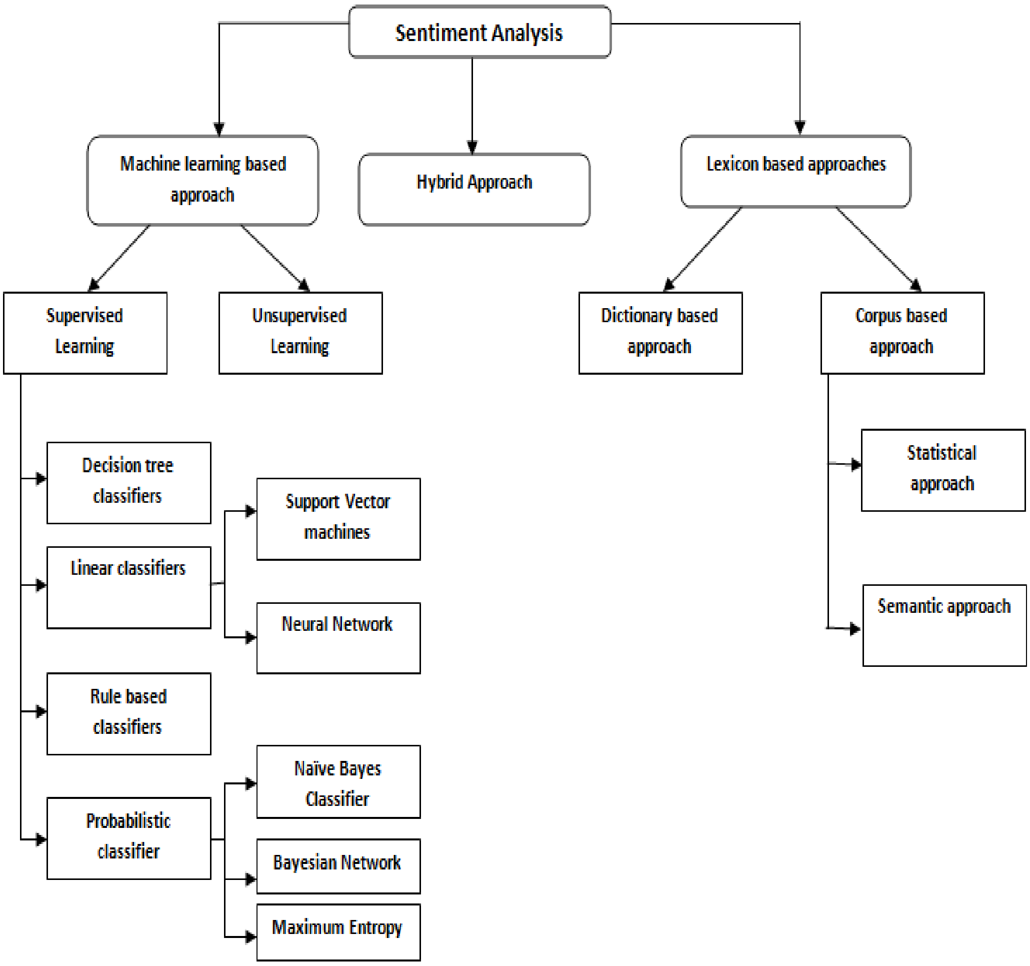

Fig. 2 Various sentiment classification techniques

accurate results. New approaches must be needed to handle with new better approaches

iii. More computational approaches are needed to be created for the handling of posts or statements having ironical & sarcasm words that may vary from language to language.

iv. A lot of efforts should be made in the area of aspect-based sentiment analysis for achieving improved comparison results by comparing their set of features/set.

v. The approaches of combining both machine learning and ontology-based techniques are still a difficult job. The combination can be used to build an automatic system with high accuracy and with no issues of scalability and vagueness.

vi. The use of optimization techniques for better feature set selection may be explored for improving sentiment analysis results.

vii. Cross-domain and cross-lingual sentiment analysis are areas where still a lot of things are needed to be done for achieving better performance.

viii. The lack of availability of proper review spam should be resolved for tackling the problem of opinion spam detection.

ix. The new and efficient algorithm may be proposed for analyzing non- English languages for achieving better and improved performance.

x. Suggestion mining: The problem has been recently explored and lots of work like problem definition, datasets and methods can be performed.

xi. Opinion leader detection: The birth of a generation of internet users helped a company to maintain its online reputation. Opinion leaders or influencers are those who are popular, experienced or able to provoke the emotions of other users are needed to be identified as they can be proved beneficial. New and better approaches should be built for identifying them.

xii. Sentiment Visualization: The sentiments and opinions extracted from datasets or texts can be represented in a visual form by using a basic pie chart, bar chart, and extensive visual analytics systems. This field has become a prominent topic over the last few years which can be opted for further research by researchers.

IV. SOME APPROACHES FOR TWITTER SENTIMENT ANALYSIS

1. *Fuzzy-Based Hybrid Hierarchical Clustering Sentiment Analysis Approach*

Suresh and Raj (2017) proposed a method that used hierarchical clustering which is an unsupervised technique for the process of sentiment analysis [4]. The approach used a fuzzy-based hierarchical clustering model to overcome the limitations of both the bottom-up and top-down hierarchical clustering methods. It first estimated the mutual clusters with the divisive approach and to stay the cluster intact applied the agglomerative approach. It then applied another top-down clustering approach to separate each mutual cluster for the computation of correlation between trees.

Conclusion: The proposed method surpassed both the agglomerative and divisive approach with an overall accuracy of 79.8%.

2. *Meta-Heuristic Method Using Cuckoo Search and K-Means for SA*

Pandey et al. (2017*)* presented a novel meta-heuristic method (CSK) for clustering the sentimental contents of the Twitter by using cuckoo search and k-means [5]. The proposed method performed in three steps: - (a) the twitter contents were preprocessed to get only the words that contained sentiments. (b) The next step involved the conversion of tweets into feature vectors. (c) The normalized feature vector was given as input to the proposed method.

Conclusion: The proposed approach was compared with the existing systems, and regarding accuracy it outperformed them.

3. *Ensemble-Based Technique for Sentiment Analysis using Sentiment Lexicons*

Silva et al. (2014) presented an approach that showed that the use of ensemble learning method with classifiers combined with scores obtained from sentiment lexicons could automatically classify the sentiments of tweets [6]. It also compared the BoW and feature hashing- based representations of the tweets to be classified. The main methodology included the preprocessing of data and then extracting features using BoW or feature hashing-based. The feature vector was assigned as input to the learning classifiers (Random Forest, NB, SVM linear and LR) and the output of each classifier was combined by an ensemble method.

Conclusion: The tweet sentiment analysis results got better using the classifier ensemble. Also, the proposed classifier ensemble methods achieved better accuracy than all the existing methods on all four datasets. Feature hashing reduces the computational cost while the use of Bag-of-Words achieves the improved accuracy.

4. *Sentiment Analysis Model using Feature Selection and Ensemble-Based Approach*

Fouad et al. (2018) presented a machine learning based system for sentiment analysis of Twitter [7]. The paper proposed an approach which represented the input labeled tweets using different techniques and also used information gain for the feature selection. The combination of SVM, NB, and LR is implemented using MVE classifier.

Conclusion: The proposed approach worked well for the twitter sentiment analysis. The Information Gain feature selection boosted the accuracy and ensemble of the classifiers also performed well as compared to the performance of the individual classifiers.

5. *Building Adaptive Sentiment Lexicon Using Genetic Algorithm for SA*

Keshavarz and Abadeh (2017) combined corpora-based and lexicon-based approaches for finding an optimum and adaptive sentiment lexicon to analyze the twitter data [8]. The method involved the process of developing an adaptive sentiment lexicon based on ALGA features. ALGA features were computed as the average sum of sentiment scores of each word in a tweet if the final score is positive, then tweet was predicted as positive else negative. Along with the ALGA features, other two features were also considered: - (1) meta-level features extracted from Bing Liu’s lexicon and (2) term frequencies of n-gram. The sentiment lexicon was optimized by using a genetic algorithm that helped in the determination of the best lexicon for a given dataset to maximize the sentiment accuracy.

Conclusion: The proposed method yielded better results than state-of-the-art methods. When tested on six datasets produced better accuracy in two of them and good F-score in the other four datasets. It has also proven that stop words can also contribute to improving the sentiment analysis performance in the social media texts, hence must not be removed while preprocessing the dataset.

6. *Building A Dynamic Opinion Lexicon from Existing Sentiment Lexicons and Automatically Annotated Tweets*

Marquez et al. (2016) gave an approach for the expansion of sentiment lexicon by making use of the automatically annotated tweets and the existing sentiment lexicons [9]. For the lexicon expansion, tweets were collected from the target domain, and the expansion time period was fixed. Two approaches were used for labeling the target collection: - (a) Emoticon-based approach, when the tweets collected from target domain contained a sufficient number of +ve and -ve emoticons and (b) The model transfer approach, when tweets having positive and negative emotions were collected from a general domain. The POS tagger tagged all the words of the target collection. The associations were modeled according to the PMI-SO and SGD-SO to determine associations between words and sentiments. Based on this information word-level features were calculated. Then a classifier was trained to label the remaining unlabelled words.

Conclusion: The method has outperformed word-level sentiment analysis obtained by PMI-SO alone which is a using state-of-the-art measure for word-level. The ensemble of lexicons (Seed lexicons (fusion of 4 manually created lexicons: - MPQA subjectivity lexicon, Bing Liu, AFINN, NRC emotion Lexicon) and 4 expanded lexicons (STS, ED.EM, ED.SL, and ED.T07)) has also yielded better results as compared to the SentiWordNet and outperformed the SentiStrength.

7. Contextual Semantics for Sentiment Classification of twitter

Saif et al. (2015) introduced SentiCircles, a novel lexicon-based method for analyzing tweets for sentiment classification and also built and released STS-Gold dataset [10]. SentiCircles considered the co-occurrence patterns of the words in different contexts to know about their latent semantics and built a dynamic representation of words that updated the assigned sentiment orientations in the existing sentiment lexicons accordingly. SentiCircles employed the following methods: (a) for entity-level, the polarity was determined based on the location of the geometric median (g) of all the sentiment words. If g lied in positive quadrants then the polarity was positive, negative quadrants meant negative and neutral region represented neutral polarity. (b) For tweet-level, three different approaches were implemented: - (a) median method, (b) pivot method and (c) the pivot hybrid method.

Conclusion: For entity-level SentiCircles has outperformed the baseline methods in terms of accuracy & F-measure for detecting subjectivity and polarity. At tweet-level, its performance was significantly better than state-of-the-art SentiStrength for two datasets but slightly poor in the third dataset.

8. Sentiment Analysis Model Using Sentiment Indexing and Sentiment Lexicons

Huang et al. (2017) proposed two things: (a) NDSI (Normalized Different Sentiment Index) for the identification of frequently occurring words capable of predicting the positive or negative sentiments on the subsets of tweets with emojis/emoticons. (b) A new hybrid model, e-senti, which performs sentiment analysis by combining 3 attributes (AFINN lexicon, tweet features and new Normalized Different Sentiment Index based word rank list) into the classifier [11]. The lexicon was selected by comparing the AUC and the accuracy of 4 sentiment lexicons on the subsets of tweets with emojis/emoticons, out of which AFINN yields the highest accuracy also, it, includes online slang which suits the social media context.

Conclusion: The new model combining AFINN sentiment lexicon, features extracted from tweets, and the proposed Normalized Different Sentiment Index based word rank list performed better than most of the existing approaches on the large volume of the social data.

9. Hybrid Ontology-Based SA Model Combining Concept-Based and Machine Learning Methods

Kumar and Joshi (2017) proposed a sentiment analysis tool for mining into the views of people on social web about the government policies of India [12]. The ontology, IndiaGov-O was built for the Ministries of Government of India and then a hybrid model was proposed which combined the concept based and ML techniques to perform sentiment analysis of the views posted on the social web by the people towards government policies.

In the proposed work, first of all, ontology was created which contain features, their attributes, and components of the domain mostly discussed on the social web. Then a Naïve Bayesian classifier is trained using the features extracted from the IndiaGov-o ontology for performing the task of sentiment analysis.

The proposed model achieved an accuracy of 77% and extracted opinion of the people on policies and performance of the government of India.

10. Enhanced Sentiment Lexicons Including Hash-tags Information for Effective Sentiment Analysis

Rezapour et al. (2017) built a sentiment model that included the hash tags into a sentiment lexicon for improving the performance [13]. With the help of this approach, it was tested to what extent the ranks of the candidates correlated with the outcome of the New York primary elections. The approach was compared with the LIWC, LBA without negations, LBA with the negations, LBA with POS, and LBA without POS.

Conclusions: The addition of informative hashtags manually to a sentiment lexicon in combination with negation detection technique and disregarding POS increased the prediction accuracy of sentiment analysis by 7%, and it performed better than all the compared approaches.

V. CONCLUSION

The paper presents a comprehensive study of sentiment analysis research. Some of the recent papers on sentiment analysis based on different techniques have been compared according to their needs, pros, cons, levels, etc. Further, future directions and research issues are also discussed to help researchers for exploring and addressing the new challenges of the respective field.

Table 1 Comparison of some approaches for Twitter analysis

SA approach and its authors	Dataset, Baseline approach and level of analysis	Need and pros and cons of the SA approach
Sentiment Analysis Model using Feature Selection and Ensemble-Based Approach [7]	*Datasets*: HCR, Sanders, Stanford twitter dataset *Baseline Approach*: Machine learning based methods: MVE (SVM, NB, LR) + information gain for feature selection. *Level of Analysis:* tweet	*Need:* The system classify tweets into positive polarity and negative polarity *Cons:* The system did not consider the neutral tweets for the sentiment analysis purpose of the tweets.
Fuzzy-Based Hybrid Hierarchical Clustering Sentiment Analysis Approach [4]	*Datasets:* Twitter samples collected by using twitter API *Baseline Approach:* Machine learning based method: Fuzzy-based hybrid hierarchical clustering *Level of analysis*: Aspect	*Need:* The proposed method is needed to analyze that how unsupervised learning approach (clustering techniques) can be employed for the prediction of the social behavior. *Pros:* The proposed method is apt for managing large datasets. The major issues of the clustering approach like the vagueness of termination criteria, inability to make corrections once merging or splitting is done can also be handled well by this approach.
Meta-Heuristic Method Using Cuckoo Search and K-Means for SA [5]	*Datasets:* Testdata.manual 2009, Sanders apple2, Sanders apple3, Twitter dataset *Baseline Approach:* Machine learning based methods: K-means + Cuckoo search *Level of analysis:* tweet	*Need:* The proposed approach is required for finding the optimum cluster heads for initializing the cuckoo search for efficient sentiment analysis of twitter content. *Pros:* The random initialization of cuckoo search is modified by using k-means for improved sentiment classification. *Cons:* The proposed approach is computationally better in comparison to existing systems except for DE (Differential evolution) method.

Table 1 Continued…

SA approach and its authors	Dataset, Baseline approach and level of analysis	Need and pros and cons of the SA approach
Building Adaptive Sentiment Lexicon Using Genetic Algorithm for SA [8]	*Dataset:* Sanders twitter corpus, OMD (Obama-McCain debate), SOMD (Strict OMD), SemEval Stanford twitter and HCR (HealthCare Reforms) *Baseline Approach:* Lexicon-based methods: ALGA + Bing Liu lexicon + uni, bi, trigrams *Level of analysis:* word	*Need:* The proposed approach is required to find optimum sentiment lexicons for classifying the text of the twitter into positive, negative or neutral. *Pros:* The proposed adaptive lexicon can capture and update the changing trends in the habits of Twitter users easily. The training phase need not be very big for achieving better performance. *Cons:* The proposed approach does not perform well for datasets having records of ambiguous polarity. The lexicon creation phase of the proposed approach is a time-consuming task, especially for large datasets. ALGA cannot generate a comprehensive lexicon that can be used for different domains.
Enhanced Sentiment Lexicons Including Hash-tags Information for Effective Sentiment Analysis [13]	*Datasets:* Gold standard dataset of tweets; Sentiment lexicons: subjectivity sentiment lexicon created by Wiebe & colleagues. *Baseline Approach:* Hybrid Approach: Hash-tags informed LBA with negation and without POS *Level of analysis:* tweet	*Need:* The proposed approach is required for testing the effectiveness of including corpus based hashtags to a lexicon with negation to check the performance of sentiment classification. *Pros:* The proposed model showed that hashtags contain information about the sentiments present in a tweet. It gave results that sentiment analysis accuracy bettered by not including PoS features. *Cons:* The proposed approach does not specifically account for sarcasm and metaphorical language.

Table 1 Continued…

SA approach and its authors	Dataset, Baseline approach and level of analysis	Need and pros and cons of the SA approach
Hybrid Ontology-Based SA Model Combining Concept-Based and Machine Learning Methods [12]	*Datasets:* Twitter posts of Ministries departments of Government of India. *Baseline Approach:* Hybrid Approach: Ontology of Ministries of Government of India (IndiaGov-O) with Naïve Bayes classifier. *Level of analysis:* Concept	*Need:* The proposed model is required for mining and extracting sentiment polarity of the citizens towards Indian government policies and rules. *Pros:* The proposed model is the first sentiment analysis system for analyzing twitter posts for Ministries of Government of India their schemes, policies, etc.
Sentiment Analysis Model Using Sentiment Indexing and Sentiment Lexicons [11]	*Datasets:* Sentiment140, tweets collected from LA County, California (USA); Sentiment lexicons: AFINN *Baseline Approach:* Hybrid Approach: AFINN with tweet features, NDSI unigrams, and Random Forest classifier *Level of analysis:* tweet	*Need:* The proposed approach is required for predicting sentiment polarities from a large volume of tweets by identifying the positive and negative sentiment words that occur frequently and by proposing a normalized difference sentiment index. *Pros:* The proposed approach explicitly used emoticons or emojis as for training data. The implementation of the approach can be done easily and efficiently.
Building a Dynamic Opinion Lexicon from Existing Sentiment Lexicons and Automatically Annotated Tweets [9]	*Dataset:* 6HumanCoded, Sanders, and SemEval *Baseline Approach:* Lexicon-based methods: Seed Lexicon (fusion of 4 sentiment lexicons: - MPQA subjectivity lexicon, Bing Liu, AFINN, NRC Emotion lexicon) with four expanded lexicons *Level of analysis:* Sentence	*Need:* The proposed approach is required for automatically building an opinion lexicon for Twitter sentiment analysis that can combine information from automatically annotated tweets and existing handmade sentiment lexicons in a supervised fashion. *Pros:* The proposed approach enables the inference of word from unlabeled tweets. It also presented a new way to compute word-level features from soft labels. As compared to existing systems it is not much time-consuming. Several SA methods using SWN can be easily adapted applied on by using the proposed expanded lexicon.

Table 1 Continued…

SA approach and its authors	Dataset, Baseline approach and level of analysis	Need and pros and cons of the SA approach
Contextual Semantics for Sentiment Analysis of twitter [10]	*Datasets:* For tweet level: (OMD) Obama-McCain Debate and (HCR) HealthCare Reforms; for entity-level: STS-Gold *Baseline Approach:* Lexicon-based methods: For tweet level: SentiCircle with median + MPQA/SWN/Thelwall lexicon; SentiCircle with Pivot + MPQA/SWN/Thelwall; SentiCircle with Pivot-Hybrid + MPQA/SWN/Thelwall lexicon: For entity level: Senti Median with SWN/MPQA/ Thelwall lexicon *Level of analysis:* Both tweet and entity	*Need:* The proposed approach is needed to able the existing sentiment lexicons adapt them according to the changing vocabulary and sentiment over time. It helps in bridging the semantic gap between the polarities captures in the lexicon and the polarities of the terms in a specific context. *Pros:* The proposed approach can be used for many languages. It takes into account both the local and global context. The combination of distant supervised data from multiple social media platforms can help in case if there is not sufficient data from the target platform. *Cons:* It also does not provide any knowledge about which genres are compatible with each other for combination in case if there is no sufficient data from the target platform.
Ensemble-Based Technique for SA Using Sentiment Lexicons [6]	*Datasets:* Sanders Twitter sentiment corpus, Stanford Twitter sentiment corpus, OMD (Obama-McCain debate) and HealthCare Reforms (HCR) *Baseline Approach:* Machine learning based methods: Ensemble of (LR, Random Forest, and Multinomial NB) + BoW + Lexicons *Level of analysis:* tweet	*Need:* The approach is beneficial to consumers for searching better products, for the firms that aim at monitoring the public sentiments of their brands and for many other applications by the use of classifier ensembles and lexicons. *Pros:* The proposed approach performed a study on classifier ensembles obtained from the combinations of lexicons, Bag-of-Words, emoticons, and feature hashing. *Cons:* The use of classifier ensembles lead to additional computational cost.

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