ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645
Indian Journal of Science and Technology, *Vol 9(41), DOI: 10.17485/ijst/2016/v9i41/97767, November 2016*

Survey and Analysis of Recent Sentiment Analysis Schemes Relating to Social Media

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Abstract

Objectives: Sentiment analysis from the online web and social media contents is an important research and applications field for the organizations, businesses, and political and social life issues; in the business world sentiment analysis provides a clear picture of both quality and user satisfaction about the products, services or an event. **Methods/ Statistical Analysis:** Extraction of the information from the web, classification and prediction of the sentiment polarity is a complex process which performed through various approaches like Part-Of-Speech Tagging (POST), Support Vector Machine (SVM), and so on. In this paper, the efficient sentiment analysis schemes that introduced in the recent years are discussed and analyzed in order to understand the novel ideas behind these methodologies. **Findings**: This paper also highlights the advantages and disadvantages of the analyzed methodologies with the objective of determining the efficiency of the sentiment analysis schemes. Finally the sentiment analysis schemes have been compared in terms of performance evaluation metrics with respect to the social media contents. Thus this paper work provides a detailed analysis of the recent sentiment analysis schemes and throws light on new avenues for future research work in this domain.

Keywords: POS Tagging, Sentiment Analysis, Social Media, Text Mining

1. Introduction

Sentiment analysis is a vital process in evaluation of user opinion about the products, services and any real world events whose sentiment polarity is needed to be determined for enhancing or minimizing the occurrence of such events or manufacturing of the products. For this purpose, sentiment analysis schemes utilize the computational linguistics, text analysis and natural language processing to find out and take out subjective information in source materials. The main aim of sentiment analysis is to determine the attitude of a person who speaks or writes about either overall contextual polarity or certain topic of a full document. The attitude is such that may be the judgment on the topics or self-evaluation of the topics or the emotional view on the communication that would also have an influence on the listeners' or reader's opinions.

Though there are different approaches for analyzing a user sentiment, the feature or aspect based sentiment analysis is considered to be more efficient. These approaches determine the opinions expressed on different features or aspects with automatic identification using syntactic methods or topic modeling. The major advantage of this analysis is its ability to capture nuances about the objects of interest. The accuracy of sentiment analysis is very vital since major business, political, social and other decisions depends on the predicted sentiment polarity.

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In this paper, the recent sentiment analysis schemes proposed by various authors have been studied and analyzed to determine their advantages and disadvantages in the sentiment recognition from the social data. The methodologies are discussed in detail and are compared in terms of efficient performance metrics in order to determine the overall efficiency.

2. Recent Research Methodologies

Many researchers have exploited the sentiment analysis from the social media and other online services to evaluate the demand and satisfaction level of the products and services. Some of the recent sentiment analysis methodologies are discussed in this section.

Cross-domain sentiment classification approach[1] utilizing the sentiment sensitive thesaurus was proposed to align the diverse words stating the same sentiment in diverse sentiments. Thus the feature vectors in a binary classifier were expanded by the automatic creation of thesaurus at training and testing by developing the related lexical elements from the thesaurus. The Li regularized logistic regression was utilized as the classification algorithm. Thus the approach using SentiWordNet to predict the polarity of words and a lexical resource where each WordNet synset is associated with a polarity score. Though the approach was found to be efficient in terms of sentiment classification, the cross domain sentiment classification technique is disbeliever to the properties of the classifier and could be utilized in different binary classifiers for expansion of feature vectors.

Multi-aspect sentiment analysis[2] was developed for the Chinese online social reviews (MSA-COSRs) based on How Net lexicon and topic modeling. MSA-COSRs implemented in social review set for the determination of multi-aspect global topics. In this method there are two components were extracted are the associated sentiment based on a sliding window context and local topics. The local topic of documents was identified by the identification algorithms and the sentiment orientation in the documents was classified based on classification algorithms. MSA-COSR could also help to find out the associated sentiment of these topics and multi aspect topics simultaneously with a better degree of accuracy. The major disadvantage of their approach is the difficulty underlying the selection of appropriate topic number for the purpose of training the LDA model.

SentiView, an interactive visualization system[3] was proposed that investigated famous topics on the internet to find out the public sentiments in it. It modeled the changes of the sentiment by correlating and searching frequently occurred words in text data. The modifications of the relationships and multiple attributes were viewed through SentiView that utilized a time-varying helix and an attribute astrolabe; where the relationship map presents a relationship of interest among the different participants. It compared the time-varying features on both real data and simulated using a new evolution model. SentiView was observed to be adaptable for different social networking platforms and the methods demonstrated the effectiveness of SentiView. However, the time complexity of this system is high.

Static Twitter data analysis problem and trained using the Support Vector Machine (SVM) as sentiment classifier[4] was proposed in which Granger causality test showed that stock-related tweets contains public sentiments in different views were utilized as pointers of stock price movements. By adapting the SVM classifier for the classification of Twitter posts into positive, negative and neutral improved results were achieved. A new stream based active learning approach was proposed with the consideration of continuously changing financial tweet streams with some improvements in the existing approaches. The results proved the modifications in positive sentiment probability and were used as pointers for the modifications in the prices of stock. Once again, their approach was not found to be adaptable with time factor.

A novel Latent Dirichlet Allocation (LDA)[5] based models called as Foreground and Background LDA (FB-LDA) was proposed in order to provide efficient sentiment analysis using the polarity variations on Twitter data. The FB-LDA method distills the longstanding background topics and the foreground topics by analyzing the tweets in significant variation periods. However the removal of interference of the longstanding background topics reduces the readability of the mined reviews. In order to resolve these issues, a efficient and effective model called Reason Candidate and Background LDA (RCB-

LDA) which ranks the topics with the consideration of status within a changes in period of time was proposed and it was found to be efficient in handling more complex mixed topics accurately.

Bilingual approach[6] was proposed for sentiment analysis of Chinese and English social media. The opinion mining from the social media platforms could be performed effectively in the care of single language. Nevertheless, in the care of comments posted in multiple languages, it was difficult to obtain the acceptable level of accuracy and consistency. The proposed bilingual approach conducted the sentiment analysis on both social media of English and Chinese countries in order to retrieve objective opinions from the stream of text that contains both the English and Chinese words. The most advantage of this method is there is no need to process the English and Chinese languages separately. Thus this approach provides sentiment opinions based on multi-language comments. Additionally text-mining models could be implemented to increase the accuracy of sentiment analysis. The major advantage of this approach is that it can be extended to many other languages. The lack of effective visualization tool for the complicated Chinese word segmentation using complicated natural language processing are two major drawbacks of this approach.

Decision support approach[7] was proposed for the online stock forum sentiment analysis. The decision support approach was developed that utilizing Support Vector Machine (SVM), generalized autoregressive conditional heteroskedasticity (GARCH) modeling and sentiment analysis. The financial review data collected from the online websites was found to be helpful in determining the decision of investors and also in predicting the future stock analysis. Training and testing of the financial stock index values is performed with the sentiment data aid in order to achieve the accurate prediction of financial risks using the correlations between online information sentiment and stock price volatility. Though the prediction volatility was found to be improved, the inconclusive performance of larger data and lesser accuracy in judging polarity of stock reviews were found to be the major areas of concern with this approach.

Auto-Encoder based Bagging Prediction Architecture (AEBPA)[8] based on the feature extraction capability and dimensionality reduction of the auto-encoders was developed for effective sentiment analysis. The contribution of this approach includes the combined feature learning along with bagging ensemble method. These methods were processed with various number of bagging sets in the text based datasets. AEBPA was found to effective in combating the problem of the curse of dimensionality which occurs due to text-based data it is has high dimension when it described in raw format and was also effective in minimizing the generalization errors. Though the performance was found to be satisfactory, a better initialization of the weights of the models could not be achieved without better embedding.

The concept of incorporating the appraisal expression patterns into topic modeling[9] was developed for the aspect and sentiment word identification. The Appraisal Expression Patterns (AEPs) were extracted from the reviews using the unsupervised dependency analysis-based approaches. The review data extracted from the social media or other online blogs represented the patterns in which the people expressed their opinions regarding products or services. It can be regarded as a condensed representation of the syntactic relationship between aspect and sentiment words. Topic modeling and the linguistic knowledge were extended to obtain patterns with aspect words accurately and sentiment words were identified with a high level of precision. The problem of domain adaptation of the AEP information was considered to verify the deployment of one source to another in the training. The drawback with this approach is that the inclusion of all AEPs was found to reduce the effectiveness of the AEP information.

PoliTwi method[10] was proposed for early detection of the political topics on twitter which would have an impact on the concept-level sentiment analysis. PoliTwi focuses on a fast detection based on a few tweets even at an early stage of a discussion. The sentiment analysis component was utilized to extend the PoliTwi in order to detect the polarity of topics marked by hashtags. The relation graphs were built between the sentiment hashtags with information like context and polarity. This approach was found to improve the knowledge set based concept-level sentiment analysis methods. Though the level of accuracy is high, the possibility of deriving a context from jointly occurring political topics was found to be minimum.

A new method of ensemble learning[11] was proposed for the reducing the noise sensitivity of the language ambiguity. It also provides a more accurate prediction of polarity. The proposed ensemble method was based on Bayesian Model Averaging. Both the uncertainty and reliability of each single model were taken into consideration. Classifier selection problem was addressed by presenting a greedy approach, in which the contribution of each model with respect to the ensemble was evaluated. The results showed that the proposed approach outperformed both traditional classification and ensemble methods, but at the cost of high computational complexity.

Sentiment analysis that considers tweets in the micro blogging website was studied[12]; they presented an approach to classify the sentiment of tweets automatically with the use of classifier ensembles and lexicons. The Tweets are classified into positive or negative based on a query term. The proposed framework is widely useful for consumers who used sentiment analysis for the search of products. It can also used in companies that monitor the public sentiment of their brands. Experiments performed on a variety of public tweet sentiment datasets proved that the classifier ensembles formed by Random Forest, Logistic Regression , Multinomial Naive Bayes, and SVM improved the level of classification accuracy. However, a tradeoff between classification accuracy and computational savings was a major drawback. Further, the diversity between the data was also not achieved.

A probabilistic approach known as Mixed Graph of Terms (mGT)[13] was proposed that relies on Latent Dirichlet Allocation (LDA) as a Sentiment Grabber, where a set of documents of same knowledge domain, a graph, or terms were automatically extracted using this approach. The sentiment classification was based on a graph that contains a set of weighted word pairs. The proposed method was tested in different contexts as on a standard dataset containing movie reviews or a real-time analysis of social networks posts or a collaborative learning scenario, which showed that the proposed approach was both satisfactory and effective. Though the level of accuracy increased the change was found to very low. However, the main weakness of this approach is that only the historical prices and sentiments derived from social media were considered.

A novel joint segmentation and classification framework[14] was proposed for efficient sentence level classification of the sentiments. As most of the existing methods split the sentences of reviews into word sequence, the inconsistent sentiment polarity between the words and phrase was not observed to be handled effectively. However, in the proposed joint framework, the useful segmentations and prediction of sentence level polarity was performed simultaneously. A candidate generation model is used for generation of segmentation candidates of a sentence, while a segmentation ranking model was employed for scoring each segmentation result of a given sentence. The final prediction of sentiment polarity was performed using a classification model, thus enabling the sentiment analysis to be more accurate.

A topic sentence-based instance transfer method[15] was introduced to solve the minority class information which is being ignored in unbalanced Chinese product review datasets. The concept topic sentence for each product review was identified using an algorithm based on the features of the title, first or last sentence of the review. New feature spaces were introduced based on the feature sets, features of topic sentences and the features of whole review including the syntax features and the frequency of the emotion words and relevant nouns. A feature selection strategy was then presented for transferable instances to choose a set of common features in order to improve of unbalanced data classification. The approach also includes a Smote-based method for processing feature space inconsistency in order to overcome the inconsistency problem while generating a training dataset by immigrating instances depending on the emotion class distribution. However, when the large scale opera are used, the method was found to have adapting issues.

A novel context based sentiment analysis scheme known as ConSent[16] was developed that can be employed in the care of both the regular texts and those texts with a high degree of noise for sentiment analysis. Initially, the information retrieval techniques were utilized to detect the key terms in the text and to analyze the context which contains the terms. The terms detected are then used for the generating the features for supervised learning. The advantages of ConSent are as follows it can use the context of terms in the noisy text and it does not rely on grammatical structures that are not reliable in the noisy text. Further, it is also easier to implement the integration of the information from certain additional resources like meta-data of the analyzed text. Nevertheless, this method was found to have a major drawback which is the occurrence of the multi-class problems in which there will be need for classifying more than two item types simultaneously.

Dual training (DT) and Dual Prediction (DP) algorithm[17] was proposed to use the original and reversed training reviews in pairs for the Dual Sentiment Analysis (DSA). In DT algorithm, the classifier learnt by a maximizing the combination of likelihoods of the original and reversed training set. In DP algorithm, the predictions are obtained by considering both sides of one review. DSA also extended from the polarity classification to the 3-class sentiment classification by also including the neutral reviews as well. Additionally, a corpus-based method was introduced for creating a pseudo-antonym dictionary in order to reduce the dependency of DSA on external antonym dictionary. Then, the accuracy of the dual sentiment analysis could also be improved. However, the complex polarity shifts patterns such as the transitional, subjunctive and sentiment-inconsistent sentences in creating reversed reviews were not supported.

Dynamic non-parametric joint sentiment topic mixture model (d-NJST)[18] was proposed for the detecting and tracking the dynamic sentiment and the topics of social reviews. d-NJST was introduced by adding a sentiment level to the Hierarchical Dirichlet Process (HDP) topic model and the dynamic model adds time decay dependencies of historical epochs to the current epochs. Though the approach was found to improve the sentiment topic extraction, d-NJST still set the time span of each epoch, and to accurately analyzing the sentiment analysis.

A combination of novel weighting schemes and multiple classifiers[19] was introduced for the efficient sentiment analysis. The term frequency inverse document frequency, term frequency inverse class frequency, term weighting based on mutual information, odds ratio, weighted log likelihood ratio and X2 statistic are considered to be the baseline approaches for the sentiment analysis. The proposed weighting schemes exploited the class space density based on the class distribution in the whole document set as well as the class documents set to provide positive discrimination on frequent and infrequent terms. Some drawbacks of this scheme were: a) the automatic sentiment classification was not supported, b) the lack of optimum combination of all term weighting schemes was observed to reduce the success rate.

SACI[20] which is a sentiment analysis method was performed by a collective inspection on the social media content. SACI is a lexicon-based unsupervised method that extracts collective sentiments without being concerned with individual classifications. SACI is based on a directed transition graph among the terms of a post set and on a prior classification of these terms regarding their roles in consolidating opinions. Paths represent subsets of posts on this graph and the collective opinion is defined by traversing all paths. SACI was found to reduce the computational complexity and to increase accuracy. Further, the consolidation of a Web Analytic tool for real-time collective sentiment analysis was found to an added advantage.

A framework for using the sentiment sentence compression model[21] was introduced to improve the aspect-based sentiment analysis. This framework can better solve the over-natural problem of sentiment sentences, which poses a challenge to the syntactic parsers used in the sentiment analysis. This compression framework provides better results similar to the syntactic results. Further, the extraction of rich features helps in obtaining higher level of accuracy. However, feature extraction still needed for improvement through inclusion of more efficient features.

Topic centric model[22] was proposed for predicting the stock price movement using the sentiments from the social media. The sentiments of the specific topics of the company were incorporated into the stock prediction model. The topics and related sentiments were extracted automatically from the texts in a message board. This feature was obtained in two ways, one by using the existing topic model called the Joint Sentiment/Topic Model (JST) and other, buying the proposed method. Topics and sentiments that were extracted in the former method were hidden and the latter was shown. The comparison predicted that the proposed method achieved an accuracy of 9.83% when compared to the historical price method.

Problem of sentiment analysis when sentiment information is crucial in many natural language processing applications were discussed[23]. In order to solve this problem, he integrated distributed semantic features of word sequence into the length of the word sequence. These new features were able to automatically capture both the local and global contexts without comprehensive task-specific feature engineering. The method was measured to improve and it improved the quality of sentiment analysis when compared to several competitive baselines. However, they required excessive task specific engineering.

Problem of topics diversity in Twitter and the difficulty in training a universal classifier to be applied were discussed[24]. Twitter suffers from not having data labeling and a mechanism to rate the labels. Semi-supervised Topic-Adaptive Sentiment Classification (TASC) model with a classifier that depends on the common features and also the mixed labeled data from various topics of the system was proposed. Further, hinge loss was reduced to adapt to the unlabeled data and features. These features were with the topic-related sentiment words, sentiment connections obtained from "@" known as topic-adaptive features and author's sentiments. Co-training has the text and non-text features extracted and then split into two views. The proposed work updated topic-adaptive features which helped in selecting more reliable tweets to improve the performance. Adapting model along a timeline (TASC-t) for dynamic tweets was also proposed. The results demonstrated that TASC outperformed the semi-supervised learning methods without the feature adaption. Also the TASC-t achieved an impressive level of accuracy and F-score. However, it has a problem of classifying a word that has a positive effect on one topic and negative on the other.

A new technique was proposed to improve the performance of domain independent lexicons[25]. The proposed work introduced a new framework called Semi-Supervised Subjective Feature Weighting and Intelligent Model Selection (SWIMS) to obtain the feature weight that relies on the general-purpose sentiment lexicon, SentiWordNet. The aim of SVM was to learn the feature weights and a model selection approach was employed to improve the classification performance. The features were selected based on the effects of their part of speech information and their subjectivity. The performance results proved that the proposed framework outperformed other techniques for sentiment analysis. However, the coverage of features was found to be less, which brings down the model performance.

Unsupervised cross-domain sentiment classification using the sentiment sensitive embeddings[26] was introduced instead of the thesaurus. Unlabeled cross-domain sentiment classification method projects both the words and the documents into the same lower-dimensional embedding, which enforces three requirements that are optimized jointly. Firstly, the set of domain independent features called pivots were selected from the source and the target domains which were mapped accurately in the embedded space. Secondly, the friend closeness and the enemy dispersion of the source domain labeled documents were embedded and preserved. Similarly, the negatively labeled documents are embedded closer to each other and distantly from the positive labeled documents. Thirdly, the local geometry among the documents was preserved by the embedding process, thus the sentiment classification can be more accurate.

Joint Multi-grain Topic Sentiment (JMTS)[27] was proposed to automatically extract the semantic aspects from the online reviews. The sentiment orientation can be detected effectively using the JMTS. JMTS extends the multigrain LDA method by creating additional semantic layer on the presumption that the sentiment-oriented ratable aspects from the regional distributions of topics and sentiment. The JMTS relates sentiment to windows and words, thus enhancing the accuracy of the sentiment prediction. Though the approach was found to be efficient, it was found to lacks the unsupervised aspect summarization and aspect rating prediction which are still considered to be the major drawback of this method.

The classification models that need a set of labeled data were discussed[28]. The labeled data are usually expensive and are also tough to gain. Hence, they employed a type of learning that used both the unlabeled and labeled data in training process which are specifically useful in tweet sentiment analysis especially. This work presented a semi-supervised learning framework where the construction of the unsupervised information that was captured from a similarity matrix created from unlabeled data, using a classifier. Such a similarity matrix can classify unlabeled tweet sets. A well- known Self-training algorithm was introduced for a better tweet sentiment classifier. The results with real-world datasets proved that the proposed framework improved the accuracy of the tweet sentiment analysis However, the similarity matrix was found to restrict certain contribution to the sentiment classification task.

Structured Micro-blog Sentiment Classification (SMSC) framework[29] was introduced which combines social context information with textual content information for improving the classification accuracy. Social contexts such as social connections between micro-blog messages and those by social relations between users were used. Social context information was formulated into a graph structure on sentiments of the messages. The tradeoff between the agreement of content-based sentiment predictions and their consistency with social contexts was the significant function of the proposed work. Further, an efficient optimization algorithm was introduced to solve the system. The results on two Twitter sentiment analysis proved that the proposed method consistently and significantly outperformed other approaches but at the cost of computational complexity.

SentiMI[30] was proposed for the sentiment polarity detection by incorporating the point-wise mutual information in the SentiWordNet. SentiWordNet was used as the label corpus for training algorithm to construct the SentiMI. Each gloss in the SentiWordNet dictionary was treated as a labeled training example and a domain independent training corpus was developed by segregating the subjective examples from the objective ones. SentiMI was built by extracting the sentiment terms with POS information from SentiWordNet and by computing the mutual information for both the positive and negative terms using positive and negative scores. Data acquisition and pre-processing, part of speech tagging and SentiMI based sentiment classification were performed to improve the accuracy of sentiment analysis.

IRCF Text Mining Algorithm[31] with weighted Ranking methodology was proposed to retrieve resumes that are similar from unstructured document without using any manual interference. In IRCF Text Mining Algorithm, document from document warehouse and configuration file were used as an input to the algorithm to retrieve text from the document. By using these inputs, the mining process was successfully completed and unstructured text form is converted into structured table. Based on the importance of each resumes with respect to experience, skill sets, qualification, rank was given to each resumes. The proposed algorithms show better result on execution time.

From the discussions in the previous paragraphs, it's clear that the most of the sentiment analysis methods introduced in the recent years utilize novel and unique approaches in sentiment analysis and computing sentiment polarity of the online social media and review data. However each of the method has its own share of pros and cons in either the implementation or processing stage. This paper provides a comparative analysis of the discussed methodologies in order to determine the efficiency in terms of accurate sentiment analysis.

3. Comparison of Recent Research Sentiment Analysis Methodologies

The sentiment analysis methods and approaches described

Table 1. Comparison of recent sentiment analysis research methodologies

Method Ref.	Approaches used	Merits	Demerits	Results
[1]	Term weighting schemes, SVM, PNN, Gaussian mixture model (GMM), Multiple classifier using voting approach, Borda count approach	Positive discrimination on frequent and infrequent terms can be achieved	Automatic sentiment classification is not supported, lack of optimum combination of all term weighting schemes	Accuracy (using voting scheme)- 91.1%, accuracy (using Borda count)- 91.9%

Table 1 Continued

[2]	Joint multi-grain topic sentiment (JMTS), LDA	Related words and windows, Enhanced classification	Does not include unsupervised aspect summarization and aspect rating prediction	Accuracy- 74%, F1- 82%, MCC- 0.36, NPV- 0.34, PPV- 0.94, Recall- 0.73, Specificity- 0.74
[3]	sentiment sensitive embeddings	Better cross domain sentiment classification	Slightly higher computation complexity	Accuracy-67%
[4]	Cross-domain sentiment classification, Sentiment sensitive thesaurus construction, L1 regularization	Better level of classification accuracy, Feature mismatch problem resolved	Does not support different combinations of cross-domains	Classification accuracy- 0.84
[5]	Sentiment sentence compression model	Higher accuracy in sentiment analysis, Low memory usage	Minimum number of efficient features	Compression result- 72.05%, precision- 78.86%, recall- 61.96%, F-measure- 69.39%
[6]	LDA, Mixed Graph of Terms	Real time analysis, Improved accuracy	Only historical data is considered for sentiment analysis	Accuracy- 88.5%
[7]	natural language processing, integrated distributed semantic features extraction	Obtains both local and global contexts, Improved quality of sentiment analysis	Requires excessive task specific engineering, overly generalized results in poor POS performance	Accuracy-93.18%,
[8]	Semi-supervised learning framework	Improved sentiment analysis, improved feature selection method	similarity matrix restricts certain contribution to improve performance	F-measure- 80%
[9]	Multinomial Naive Bayes, SVM, Random Forest, and Logistic Regression, Bag-of-words, Feature hashing	Efficient public sentiment analysis, Better classification accuracy	Tradeoff between classification accuracy and computational savings, Diversity between data is not achieved	Accuracy- 84.89%, For positive data Precision- 82.9%, recall- 86.3%, F1 score- 84.2% For negative data Precision- 87.5%, recall- 83.6%, F1 score- 85.5%

Table 1 Continued

[10]	Bayesian Model Averaging, Ensemble learning	Efficient solution to classifier selection problem	High computational complexity	Model selection accuracy- 0.7553, Classification accuracy- 0.796
[11]	Dynamic non-parametric joint sentiment topic mixture model (d-NJST), hierarchical Dirichlet process (HDP)	Better detection and extraction of joint sentiment topics, Time decay dependencies improves accurate sentiment analysis	Difficult to set time span of epoch which reduces the overall accuracy	Perplexity- 7, topic strength- 1500 trends
[12]	ConSent	Easy to integrate information, sentiment accuracy improved even in noise data, Utilizes limited number of features	Multi-class problem occurs	Accuracy- 92.8%, F-measure- 60%, Precision- 72%, Recall- 74%
[13]	Semi-Supervised Subjective Feature Weighting and Intelligent Model Selection (SWIMS), SentiWordNet, SVM	Resolves domain dependence & unavailability of labeled corpus, Better accuracy	Coverage of features is less that degrades the performance	Accuracy- 81.5%, F-measure- 82%
[14]	SentiMI, SentiWordNet, part of speech tagging	Faster processing, better accuracy	Computation complexity for computing mutual information	Accuracy- 84%
[15]	topic-adaptive sentiment classification (TASC), adaptive modeling, multi-class SVM	improved accuracy and reliability levels	Difficult to classify the word with positive effect on one topic and negative effect on other	Accuracy- 54%, precision- 56.6%, recall- 52.17%, F-measure- 54.32%
[16]	Topic centric model, joint sentiment/topic model (JST)	Both hidden and revealed topic extraction is possible, better prediction accuracy	Only historical prices and sentiments are considered for prediction	Accuracy- 54.41%

Table 1 Continued

[17]	PoliTwi, Concept-level sentiment analysis	Improved accuracy of knowledge set based Concept-level sentiment analysis,	Difficult to derive a context from jointly occurring political topics	Correlation- 0.68, Probability- 0.346
[18]	Sentiment analysis by collective inspection (SACI), Directed transition graph	Reduced complexity & improved accuracy, Consolidation of Web analytical tool for real time analysis	Detection of social connectivity between users is not possible, Only terms and their relationships are exploited	Accuracy- 79.25%, Macro-F1- 61.3%, Execution time- 5s (for 64000 tweets)
[19]	Auto-encoder-based bagging prediction architecture (AEBPA),	Reduced generalization errors, Resolves curse of dimensionality problem	Initialization of weights require better embedding, Optimization is not performed	Accuracy- 0.788,
[20]	Support Vector Machine (SVM), Granger causality test	Better prediction of stock prices with positive sentiment probability	Not time adaptive	F-measure- 0.5410
[21]	Foreground and Background LDA (FB-LDA), Reason Candidate and Background LDA (RCB-LDA), Gibbs Sampling	More complex mixed topics are detected with higher accuracy	Reduced readability	Recall- 0.74, Association accuracy- 0.84
[22]	Sentence-level sentiment classification, natural language processing, candidate generation model	Accurate sentiment classification, Does not require syntactic or sentiment annotations in segmentation level	Error propagation may occur when joining, The pipelining does not match	Accuracy- 81%, Macro-F1- 85.51%
[23]	Topic-sentence identification method, Homogenization processing of the feature space, instance combination, Smote-based method, SVM	Better performance in N-grams, Improved classification of unbalanced dataset	Large scale corpus are not supported, Over-fitting problem occurs	Precision- 0.89, Recall- 0.88, F measure- 0.88

Table 1 Continued

[24]	SentiView, Attribute astrolabe	Visualizes changes in multiple attributes, Suitable for different social media platforms, high reliability	High time complexity	Render speed- 15-24fps
[25]	Structured micro-blog sentiment classification (SMSC), Optimization algorithm	Better tradeoff between the agreement of content-based sentiment predictions and their consistency	Higher computational complexity	Accuracy- 80%, Run time- 62.42s
[26]	SVM, Generalized autoregressive conditional heteroskedasticity (GARCH), Decision support	Improved prediction volatility, better accuracy	Larger datasets are not supported, Less accuracy in judging polarity of stock reviews	Predictive Accuracy- 64.7%, relative accuracy (positive)- 50%, relative accuracy (negative)- 69%
[27]	Dual training, dual prediction	Low dependency on external antonym dictionary, Maximized likelihood learning for accurate classification	Complex polarity shift patterns are not supported	Accuracy of polarity classification- 90.8%, Three-class Classification accuracy- 73.6%
[28]	MSA-COSRs, LDA model, topic modeling and How Net lexicon	Multi-aspect topic detection with better accuracy, High accuracy in sentiment analysis	Selection of suitable topic number for training LDA is difficult	Topic identification accuracy- 91.23%, Sentiment analysis accuracy- 92.15%
[29]	Appraisal Expression Patterns based LDA (AEP-LDA)	Better precision, Accurate pattern detection	Reduced performance due to unwanted AEP information	Precision- 0.672, Recall- 0.838, F-score- 0.742, Transfer loss- 3.42%

Table 1 Continued

[30]	Bilingual sentiment analysis, dictionary based segmentation, statistics and machine learning based segmentation, Modified Chi-square feature selection, Modified N-Gram method, SVM	High Accuracy & consistency, supports multi-language comments	Word segmentation is complicated due to complicated NLP process, Does not support larger datasets	Precision- 89.98%, Recall- 92.14%, F1- 91.04%, accuracy- 90%
[31]	Augmenting Efficiency of Recruitment Process using IRCF text mining Algorithm	Increases the execution time	computation time of weighted ranking algorithm is high	actual Resume Relevancy ratio -0.71 Resume Relevancy ratio -0.88

in the previous section have been analyzed; in this section a comparative analysis of those methods is introduced. The comparison is shown in Table 1.

4. Performance Evaluations of Efficient Methodologies

This section analysis and compares the performance of the most efficient sentiment analysis methods that were selected from the methodologies analyzed in the previous sections to determine the comparative performance efficiency. The most efficient methods considered for performance comparative analysis in this paper are: JMTS [2], ConSent [12], SWIMS [13], SentiMI [14], Politwi [17], SACI [18], Topic Sentence-based Instance Transfer (TSIT) [23], SentiView [24], AEPs [29], and Bilingual Sentiment Analysis (Bilingual SA) [30].

The comparison was done by the experimental results of the methods in terms of accuracy, precision, recall and F-measure. All the results have been considered for the movie reviews dataset with 64000 tweet comments.

4.1 Performance Metrics

The comparison of the efficient techniques has been carried out in terms of the performance evaluation metrics which are accuracy, precision, and recall and F-measure metrics. The definition and calculation formula for each metric are given bellow

4.1.1 Accuracy

Accuracy is described as the closeness of a measurement to the true value. It is given as follows:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Postive + False\ Negative}$$

4.1.2 Precision

Precision is the closeness of agreement among the set of analysis results obtained, given as follows:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

4.1.3 Recall

Recall is described as the fraction of relevant results from the retrieved set of analysis results, given as follows:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

4.1.4 F-measure

The F-measure is a accuracy testing score considering both the precision and recall, and is calculated as follows:

$$F - measure = 2\frac{Precision \,.\, Recall}{Precision + Recall}$$

4.2 Comparison Results

4.2.1 Accuracy

Figure 1 compares of the selected efficient sentiment analysis methods in terms of accuracy. The graph clearly shows that the ConSent method [12] provides a higher level of accuracy when compared to other methods.

4.2.2 Precision

Figure 2 presents a comparison of the selected efficient sentiment analysis methods in terms of precision. The graph clearly shows that the Bilingual sentiment analysis

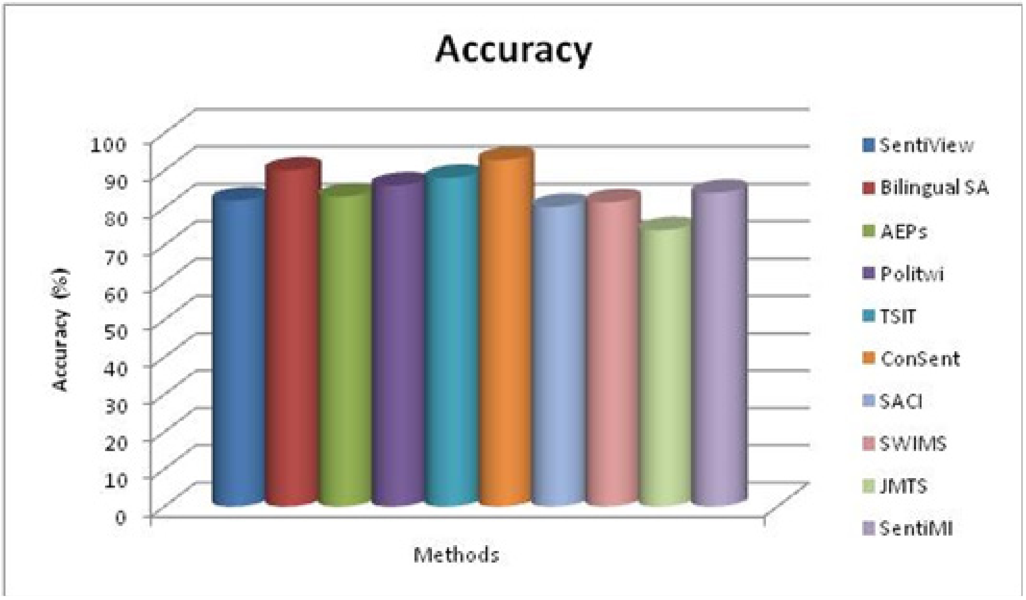

Figure 1. Accuracy comparison

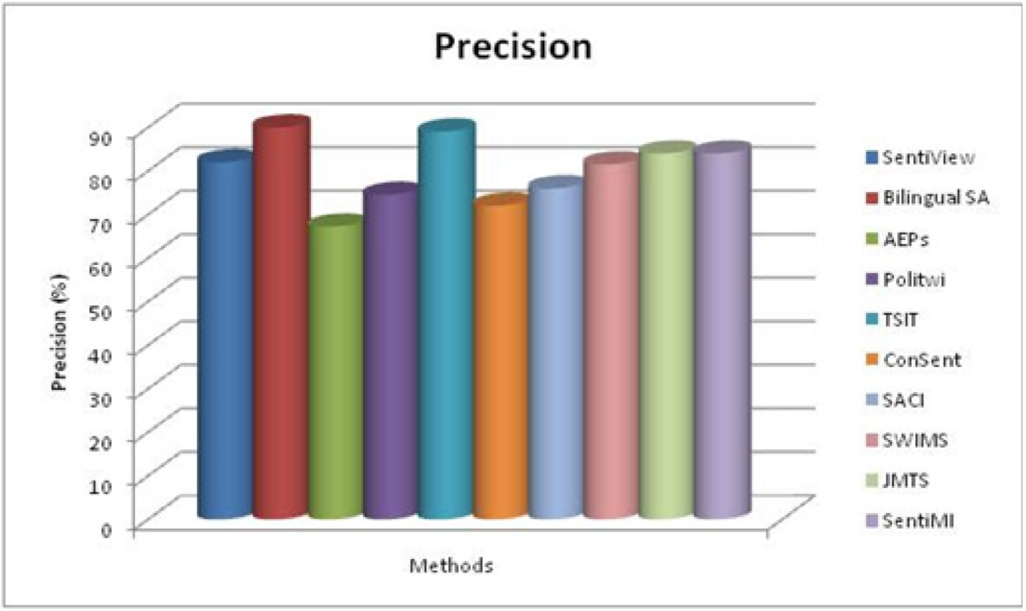

Figure 2. Precision comparison.

method considered in [30] provides higher degree of precision when it compared to other methods.

4.2.3 Recall

Figure 3 compares the selected efficient sentiment analysis methods in terms of recall. The graph clearly shows that the Bilingual sentiment analysis method considered in [30] provides a better degree of recall when it compared to other methods.

4.2.4 F-measure

Figure 4 compare the selected efficient sentiment analysis methods in terms of F-measure. The graph clearly shows that the Bilingual sentiment analysis method considered in [30] offers better F-measure values when it compared to other methods.

From the above results it is clear that in terms of all the parameters, the Bilingual sentiment analysis method

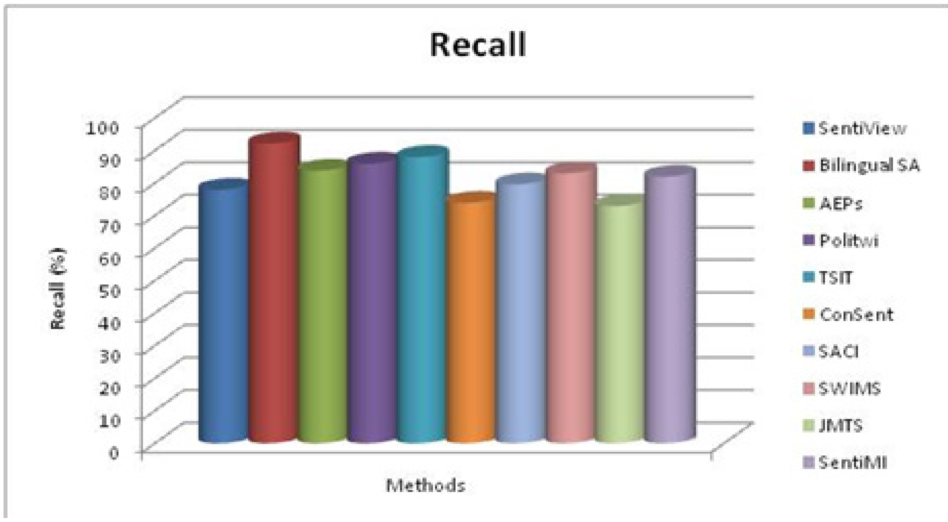

Figure 3. Recall comparison

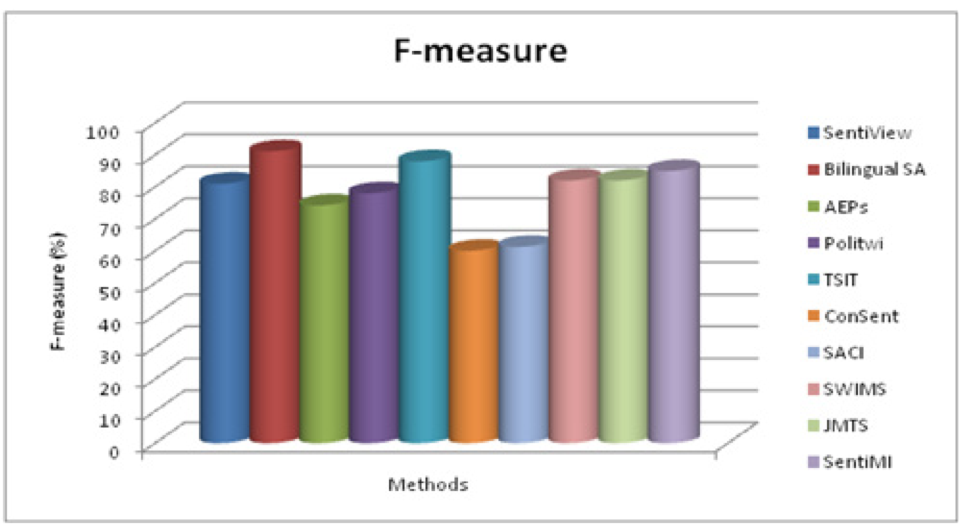

Figure 4. F-Measure comparison.

proposed in [30] performs better than other methods as observed from the results in the literature.

5. Conclusion

Sentiment analysis is a growing field which focuses on achieving maximum accuracy in order to support various applications. In this paper, the recent developments in the sentiment analysis approaches were analyzed by describing the novel ideas incorporated in them. The analysis of the sentiment analysis schemes provides a better understanding of the stages of sentiment analysis thus elevating the hope of efficiency in either modifying or replacing the techniques in order to achieve maximum accurate performance. The comparison of the efficient techniques has been carried out in terms of accuracy, precision, recall and F-measure. This research offers throw light on new research avenues and helps in deriving the motivation for our future research work as well.

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