Hybrid Tools and Techniques for Sentiment Analysis: A Review

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***Abstract*— Sentiment analysis and opinion mining is closely coupled with each other. An extensive research work is being carried out in these areas by using different methodologies. Sentiments in a given text are identified by these methodologies as either positive, negative or neutral. Tweets, facebook posts, user comments about certain topics and reviews regarding product, software and movies can be the good source of information. Sentiment Analysis techniques can be used on such data by businesses executives for future planning and forecasting. As the data is obtained from multiple sources and it depends directly on the user which can be from any part of the world so the noisiness in data is a common issue such as mistake in spellings, grammatical errors and improper punctuation. Different approaches are available for sentiment analysis which can automatically sort and categorize the data. These approaches are mainly categorized as Machine Learning based, Lexicon based and Hybrid. A hybrid approach is the combination of machine learning and lexicon based approach for the optimum results, this approach generally yields better results. In this research work different hybrid techniques and tools have been discussed and analyzed from different aspects.**

***Keywords*— Hybrid Technique for Sentiment Analysis, Opinion Mining, Polarity Detection and Social Media**

I. INTRODUCTION

The combination of the lexicon based approach and machine learning approach have improved the classification performance compared to machine learning and lexicon approach alone. Due to rapid increase and globalization of internet, millions of users come online daily and the amount of user-generated information and data is increasing with the same pace. The internet has become the need for several services and businesses in our daily lives. A lot of textual data is generated by people using social websites such as facebook and twitter in the form of posts and tweets. Some of the websites and blogs today contain the section of user's comments or feedback so valuable information can also be taken from these sites to get the sentiments of the users about any particular topic or the feedback about new product or software etc. Extraction of sentiments from such data can yield valuable information about any particular topic, movie and product services etc [1]. Several tools and techniques are available now days to extract and classify the sentiments from the provided data as either positive, negative or neutral. Tools and techniques from Lexicon based approach uses domain specific dictionary and lexicons as the major source of lookup for sentiment classification[2]. These lexicons have predefined semantic orientations that are later compared with the input data set for classification as explained by [1]–[7]. Machine learning based approach on the other hand follow the supervised learning algorithms such as Naive Bayes and Support Vector Machine to create the training data set [8]–[10]. Then on the basis of this trained dataset the inputs are compared and classified as either positive, negative or any other sentiment [11], [12]. The Hybrid approach which uses the combination of both lexicon based approach and machine learning approach. The basic goal of this combination is to yield the best and optimum results using the effective feature set of both lexicon and machine learning based techniques, and to overcome the deficiencies and limitations of both approaches. Many researchers have combined different lexicon and machine learning based techniques to generate better and effective hybrid tools [13]–[17]. In this research, we will study, analyze and compare different hybrid tools and techniques for sentiment classification and will discuss different feature sets and accuracies of the studied approaches.

II. HYBRID TOOLS AND TECHNIQUES

A. pSenti

pSenti is a concept-level sentiment analysis tool that was presented by [18], it combines lexicon and learning based sentiment classification methods. As compared to the pure lexicon based methods pSenti achieved greater accuracy in sentiment strength detection and polarity classification. On the other hand, when the tool was compared against pure machine learning based methods it yielded slightly lower accuracy. Extensive experiments on two different datasets i.e., CNet Software Reviews Dataset and IMDB Movie Reviews Dataset for the evaluation of the proposed approach were performed. Learning based approach used in the proposed method is not only responsible for tiny tasks like adjustment of sentiment values or sentiment words detection but it is also responsible for evaluation of all aspects of sentiment system.

The main component of the system measures the given opinionated text and gives the output in terms of collective sentiment, such as customer feedback. The final results are shown with a real valued score between -1 and +1 that can be transformed as either positive/negative or into a score between 1-5 stars in a latter stage. Advantages of the proposed approach are that the system can be extended by adding new linguistic rules or sentiment lexicon can be expanded at any instance/level. The proposed system is not sensitive to the changes in the topic. It works better than SentiStrength [5] and lexicon only as well but its accuracy is slightly lower than learning only.

B. Combining Lexicon Based and Learning Based methods for Twitter Sentiment Analysis

For entity level sentiment analysis, [19] used an augmented lexicon based method. First, they obtained additional opinionated indicator, i.e. words and symbols, by applying Chi-square test on results gathered from the lexicon-based method. Additional opinionated tweets were identified with the help of new opinionated indicators. For entities in the newly identified tweets, a sentiment classification algorithm is employed to assign sentiment polarity scores. The result of the lexicon method is basically the training data for the classifier and the whole process has no manual labeling except test set. This research used five datasets based on the query entities Obama, Harry Potter, Tangled, iPad and Packer. Proposed method achieved 85.4% accuracy on the five datasets used in this research. In the proposed technique (LMS) a relative improvement over the lexicon-based method was observed. However, it performed worse in comparison to the pure learning-based technique but having advantage that it does not require pre-labeled data. Therefore, the proposed approach is easy in implementation but cost some performance.

C. SAIL

Another hybrid methodology was developed by [15]. This study proposed a system for twitter and SMS sentiment analysis based on hierarchical model, affective lexicon and a language modeling approach. It is observed that language model was not good alone but an improved performance was noticed when using with lexicon-based model. The hierarchical model proved very successful even using the n-grams, affective ratings and part-of-speech. The proposed tool uses an affective lexicon that was spontaneously generated from massive corpora of raw web data. Words and bigrams are used for affective ratings calculations and statistics. As far as the unconstrained data is concerned the lexicon models were combined with a learning classifier that is based on the Max-Ent language models that are primarily taught on a huge external dataset. These two classification methods for sentiment analysis are then combined to formulate the final results. The combination of the two proved to be affective and yielded better results.

D. NILC_USP

The researchers in [14] describes NILC_USP system in SemEval-2013 and proposed a trio classification process that combines three classification approaches i.e. the rule-based approach, the lexicon-based approach and the machine learning based approach. The proposed algorithm has five steps.

Normalization: The first step is normalization of the given input dataset, it can also be referred as pre-processing, it basically cleans and normalizes the input text, and following operations are performed by this step.

- Hashtags, URLs and mentions are formulated in consistent set of codes
- Emoticons are categorized as per their physical appearance as either happy, sad, laugh, etc. and assigned with particular codes
- Exaltation signals are detected and marked such as multiple signs of exclamation
- Misspelled words are corrected
- Part-of-speech tagging is performed

Rule Based Classifier: In this step the pre-processed text is handed over to the rule based classifier, the only rule applied by this classifier uses emoticons which are present in the given text. Empirically it was noticed that the presence of the positive emoticons in the sentences and tweets are the indicator of an overall positivity in the text. Likewise, the presence of negative and bad emoticons refers to negative aspects in the given text. This step returns a number of appearances of positive and negative emoticons in the result.

Lexicon-based Classifier: In the proposed system the lexicon provided by SentiStrength [5] was used. This lexicon provides a vocabulary of emotions, an emoticons list, negation and boosting words list. The semantic orientation of every single word in the given text is calculated in the proposed algorithm. The polarity of the word is decreased if the words are negated, likewise the polarity is increased when the words are intensified, the classifier labels the text as positive, negative or neutral.

Machine Learning Classifier: Labeled examples are used by the Machine learning classifiers to learn and classify the given text, SVM algorithm provided by CLiPS pattern was used. In the proposed model, bag of words, part of speech sets and the existence of negation in the sentences were used as the feature set by the classifier.

The results of this study showed that the hybrid classifier approach can improve results based on the advantage of multiple sentiment analysis techniques over rule-based, lexicon-based and machine learning methods.

E. Combining Lexicon based and Learning based approaches for improved performance and convenience in sentiment classification

[16] proposed a hybrid approach to improve the performance of sentiment analysis process. The programing language chosen for the implementation of this algorithm was Python. The proposed algorithm is composed of three steps after pre-processing, the first part refers to the lexicon-based model and it deals with finding the optimum parameters for the classifier. While the second part refers to the learning-

based model and deals with the analysis of the model that performs better. Lastly, the third part refers to the hybrid model that analyze and decides the optimal MID ratio.

The Lexicon-Based Model: A training set is not required by the lexicon-based model. Only a lexicon is required from which the classifier fetches the sentiment classification and negation words, and the aforementioned test set that the classifier runs on for further processing. The lexicon based model used in the proposed research work was AFINN as described by [20].

The Learning Based Model: At this stage, it utilizes the aforementioned SciKit Learn framework, that provides a pipeline structure and allows several transformations to be applied to the data and formulate it as needed, creating a final model that classifies the data. By replacing the modeling part of the pipeline structure it can be tested with different classifiers to evaluate and calculate which classifier yields the best and optimal results. Following three classifiers were tested by the researchers Multinomial Naive Bayes, Bernoulli naive Bayes and SVM.

F. A Hybrid approach for sentiment classification of Egyptian Dialect Tweets

A hybrid approach was proposed by [21] that was crafted to improve the performance measures of sentiment analysis for the Arabic Language. This study focused on tweets sentiment classification for Egyptian dialect. Arabic is one of the widely used languages on the web [22]. Many researchers have worked on Arabic language sentiment analysis on different data sets with different tools and algorithms [23].

Following steps were carried out by the researcher for the implementation of the hybrid technique:

- Step 1: The features to be used by the machine learning approach are identified and separated.
- Step 2: The annotated corpus to be used for training and validation of the best classifier at different corpus sizes is built by the system.
- Step 3: Sentiment lexicon of different sizes is built using the annotated corpus
- Step 4: Theses different approaches are combined and tested for better and optimized results
- Step 5: Straight forward and simple method is crafted to detect negations in the hybrid approach

The results obtained by this study using hybrid approach showed better performance than other sentence-level classification systems,

G. Sentiment Analysis: A Review and Comparative Analysis of Web Services

The authors in [24] conducted the comparison of 15 sentiment analysis techniques/tools , many of these tools were based on hybrid approach (combining the Machine Learning based algorithm and Lexicon based algorithms). According to researcher tools like Alchemy and Semantria can be used for any kind of text classification even if the texts are large in size. These tools can be the good option if the text is ironic. Moreover, other tools such as Wingify and Viralheat may not be the good options due to the less effective results however further testing of these tools on different data sets is needed.
They have pointed out that there are many interlinked and closely coupled tasks which are observed during the sentiment analysis; it is difficult to separate them clearly as most of them are quite close to each other and share common aspects. Some of the important tasks are as under:

- Sentiment Classification: Each text, sentence or document represents some sentiments which may be positive, negative or neutral. Searching for these sentiments are sometimes referred as sentiment orientation or sentiment polarity detection as described by [25].

- Subjectivity Classification: An objective sentence may contain factual information while the subjective sentence may contain opinion, emotion and belief etc. Subjectivity detection is a crucial task in sentiment analysis. This process is deemed to be even more complex than normal sentiment classification (positive, negative or neutral) as explained by [26]–[29].

- Opinion Summarization: It is an important task to summarize the opinion within a text and detects the major features of an object shared within one or multiple documents as explained by [30].

Other than these three, there are other tasks such as Opinion retrieval [31], Sarcasm and Irony detection [32] and others [33].

H. Alchemy API

Alchemy API [34] is offered as a service and used for enriching the text content using automated tagging, semantic analysis and semantic mining. It is a hybrid tool based on NLP and machine learning algorithms. It offers features like named entity extraction, concept tagging, keyword extraction, sentiment analysis, relation extraction, automatic language identification, structured data extraction and many other features[35]. IBM acquired Alchemy API in 2015 and this technology in now a core component of cognitive APIs offered on IBM's Watson developer cloud. All the services are accessed via HTTP REST interface and different SDKs are available for Java, C# or Perl. The researcher explained the usage of Alchemy API for enterprise grade text analysis in [36]. It classifies the sentiment from text being analyzed into three categories: Positive, Negative and Neutral. The degree of sentiment is measured in the range of [-1,1] and it supports English and German languages. The API is capable of performing sentiment analysis on document, entity or keywords level and it is able to detect directional sentiment for subject-action-object relations.

I. Building Large-Scale Twitter-Specific Sentiment Lexicon: A Regression Learning Approach

The study [37] proposed TS-Lex, that is a large scale twitter specific lexicon and it is based on a representation learning approach. The proposed methodology was comprised of two parts. In the first part a representation learning algorithm was used for effective learning of phrases embedding, which were later used as features for classification. In the second part a seed expansion algorithm was used. This algorithm expands a small list of sentiment seeds to obtain the training data from them which will be further used for building the phrase-level classifier. Precisely the tailored neural architecture was introduced that integrated the sentiment information of tweets with its hybrid loss function and then it was used for learning sentiment-specific phrase embedding (SSPE). SSPE was obtained by looking for positive and negative emoticons in the tweets, no manual annotation was made on it. To further collect the training data, alike phrases from Urban Dictionary were used to expand a trivial list of sentiment seeds that were later used to build phrase level classifier. TS-Lex experimental results showed that sentiment lexicons that were previously introduced were out performed by this algorithm and further it adds improvements to the top-performing system in SemEval 2013 by combining features.

J. Sentiment Analysis on Twitter

A hybrid approach was proposed by [38], both the corpus based and the dictionary based approaches were used in it to detect semantic orientation of the opinion words from twitter dataset. To obtain the sentiment polarity, opinion words were taken from the dataset (Combination of adjectives, verbs and adverbs). Adjectives score was calculated using log linear classifier whereas verbs and adverbs score was calculated using word seed list. If the verbs and adverbs are not recognized by the WordNet then they are rejected because they may not be the legitimate words. Afterwards the corpus based approach was used to find the linguistic orientation of the adjectives while the dictionary based method was used to find semantic orientation of verbs and adverbs. If the orientation was not calculated, these would be de-listed from the opinion word list. An emotion intensifier was applied through a linear equation and overall sentiment of the tweet was calculated. A case study of a tweet was presented for illustration purposes to verify the effectiveness of the suggested method. The experimental results proved that the proposed system has the features of recognizing the semantic orientation and served as a partial view of the occurrence. Study recommends more research using larger samples to validate or invalidate these findings.

K. Sentiment Analysis using Sentiment Features

The study [39] proposed a hybrid approach for twitter sentiment analysis. Sentiment lexicons were used to generate a new feature set and this lexicon was used to train a linear SVM classifier. The results showed that the suggested hybrid method outperformed the state of the art unigram baseline. It was evaluated in perspective of sentiment analysis that moving towards sentiment features is optimal than conventional text processing features. All the features can be computed in a very short time and it performs better than unigram feature set. The proposed system has a low memory and time complexity because of very small feature set size. The baseline SVM unigram model with emoticons and stop words was selected because it performed better than all other combinations. The SVM achieved an overall accuracy of 86.7% as our baseline and it performed better than Naïve Bayes and likewise Naïve Bayes performed better than MaxEnt. The proposed method showed the accuracy of 89.13% with significant margin with the baseline.

L. Sentiment Analysis using Support Vector Machines with diverse information sources

Tony Mullen and Nigel Collier worked on the sentiment analysis with the help of support vector machine. In this study [40] they used diverse information sources. For the classification of text, author introduced negative and positive approach using SVM. SVM is powerful and well known tool that allows to classify the vectors of real valued feature. The proposed method was applied on Movie reviews data set from Epinions.com and the results showed that the hybrid SVM which combines unigram styled feature based on SVMs showed better result as compared to the SVMs that are based on real-valued favorability measures. Current techniques emphasize on the use of variety of random information sources and SVM helps as an ideal tool to bring the sources together. Researchers used different techniques of assigning semantic importance to words & phrases available in the text. In this approach the researchers concluded that words within the text worked in an efficient way as compared to the old approach (bag-of-word). The model is further combined with unigram models that have shown effective results in the past as explained by [41].

M. Improving Twitter Sentiment Analysis with Topic-Based Mixture Modeling and Semi-Supervised Training

Multiple approaches to improve Twitter sentiment analysis were studied by Bing Xiang & Liang Zhou [42]. They proposed improvement of twitter sentiment Analysis with the help of topic based mixture modeling approach along with semi supervised training. The aim of this study was the presentation of different approaches for advanced Twitter sentiment analysis. In this study initially they built a state of the art baseline for rich feature set then a topic-based sentiment mixture model was built having the topic specified data arranged in a semi supervised training structure. The information regarding topic is generated with the help of topic modeling which is based on an application of LDA (Latent Dirichlet Allocation).The proposed approach performed better than the top system in the task SemEval-2013 in terms of averaged F-Scores. Several experiments were carried out on data from the task B of Sentiment Analysis in Twitter in SemEval-2013. They used data distributed in positive, negative and neutral to tune parameters and features of classification. Experiments showed that weighting adds 2% of improvement and the universal sentiment mode achieved 69.7 average F-Score with all features combined.

N. MSA-COSRs

Multi-aspect sentiment analysis was analyzed by Xianghua et. al [43] for the Chinese online social reviews that was based on topic modeling and the HowNet lexicon. In this research authors proposed an efficient way to spontaneously find the aspects that are under discussion in Chinese social reviews. They called this approach as a Multi-aspect Sentiment Analysis for Chinese Online Social Reviews (MSA-COSRs). In this study first they applied the Latent Dirichlet Allocation (LDA) model to find out the multi aspect global topics of social reviews, after that they extracted the local topics and sentiment associated with it. Multi aspect analysis is composed of two subtasks: first is pulling out the aspects and the second subtask is orientation of sentiment calculation of aspect. The LDA trained model identified the aspects of local topics and polarity of sentiment related with text is classified by HowLexicon. Results of this approach help in improving the sentiment analysis. Multi fine grained topics and linked sentiments are identified by it. This is very helpful to tackle the sentiment analysis and it helps to study the sentiment orientation with deep accuracy. With the success of this method it is difficult to train the LDA model for a suitable topic. Experimental results showed that the proposed model not only gain optimal topic partitioning results, but it also helps in the improvement of sentiment analysis accuracy.

III. DISCUSSION

Sentiment Analysis and classification is partially dependent on the sentimental separation of the text, reviews, comments or any input datasets. The lexicon based approach works better when there is a clear boundary between the positive and negative sentiments within the input dataset. When there are no clear boundaries between the specific sentiments on the target dataset the machine learning based approach works better. One of the main reasons behind the poor sentiment separation in the text obtained from different sources on the web like Facebook posts, tweets, product and movie reviews is that these are user entered data and may contain wrong punctuations, grammatical mistakes, fuzzy and noisy texts. We've discussed different hybrid techniques in this paper which performed better than the lexicon based approach and the learning based techniques. The ease of implementation which makes the hybrid approach a substantial and affective option for sentiment analysis. Comparison of the feature list and the results obtained on different data sets have been arranged and presented in this research for a better understanding of the hybrid approach and for future reference.

IV. CONCLUSION

There are a lot of studies available on the hybrid methods for sentiment classification but comprehensive and compact information on this particular topic was required. In our research we have discussed different hybrid techniques and tools. Significant outcomes and results have been obtained while comparing these hybrid techniques and tools. Our study will serve the researchers to have a better view of the hybrid approach for sentiment classification. A comparative analysis of the techniques by using different dataset is also available in the research that can be further extended.

Table 1: Tools / Techniques, Features and their accuracy

SR#	Author Name	Year	Reference	Features	Accuracy
1	Mudinas	2012	[18]	- Concept Level Sentiment Analysis System - integrates lexicon and learning based methods - Achives significantly higher accuracy in Sentiment Polarity Classification - Offers more structured and readable results with aspect-oriented explanation and justification	89.64%
2	Zhang	2011	[19]	- Hybrid Approach, combines lexicon and learning based sentiment analysis classifiers - Unsupervised method except for the initial lexicon - More desireable and practical method - Adaptive to new fashion in language, neologisms and trends	85.40%
3	Malandrakis	2013	[15]	- Based on the Affective Lexicon and Part of speech tag information - Combination of constrained model with Maximum Entropy model trained on external data	85.80%
4	Balage	2013	[14]	- Hybrid Approach, combines lexicon and learning based classifiers - Expression Level and Message Level Classification - Positive, Negative & Neutral Classification	65.39%
5	Sommar	2015	[16]	- Perfroms better than lexicon based classifier - Effortless Setup - Prospective Performance - Appealing approach for binary classification	79.67%
6	A. Shoukry	2015	[21]	- Hybrid Approach - used specifically for arabic language and egyptian dialect tweets - Combines Lexicon and learning based approaches for classification	80.90%
7	Serrano-Guerrero	2015	[24]	- 15 Different sentiment analysis test - Comparison of different web services	-
8	Joseph	2013	[34]	- Document level, sentence level, Entity level - Language, Datanews and vision part of IBM watson cloud	73.60%
9	Tang	2014	[37]	- Large Scale twitter specific lexicon - uses seed expansion algorithm for expansion of small list of seeds - uses urban dictionary	85.65%
10	Akshi	2012	[38]	- Hybrid Approach, uses corpus and dictionary based approaches - uses combination of adjectives along with verbs and adverbs	
11	Syed-Ali	2013	[39]	- Hybrid approach, uses sentiment lexicon and linear SVM - effective than the unigram baseline models	89.13%
12	Mullen	2004	[40]	- uses SVM as base - favorability measures for phrases and adjectives	86.00%
13	Xiang	2014	[42]	- based on topic based sentiment mixture model	69.7 F-score
14	Xianghua	2013	[43]	- un-supervised approach - used for automatic discovery of aspects being discussed in chinese social reviews	91.23%

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