

Affirming Literature on Sentiment Analysis: Contemporary Review

¹Muddada Murali krishna, *Research scholar, Computer Science And Systems Engineering, AUCE (A), Andhra University, Visakhapatnam, Andhra Pradesh, India*

¹E-mail: muralikrishna1926@gmail.com

²Dr.G. Lavanya Devi, *Computer Science and Systems Engineering, AUCE (A), Andhra University, Visakhapatnam, Andhra Pradesh, India*

²E-mail: lavanyadevig@yahoo.co.in

Abstract: Sentiment Analysis can be stated as an effective system of extricating vivid range of emotions and expressions from the users. Gaining insights in to emotions in to vary aspects of personal development is one of the critical elements for holistic development and sentiment analysis can be very resourceful in such process. SA is an integral development in the AI and plays a vital role in the process of polarity detection. It offers a significant opportunity in terms of capturing the sentiments of common public, customers, users etc, pertaining to varied aspects like product choices, stock market factors brand perceptions, political movements and social events etc. In the process of natural language processing, it is one of the contemporary solutions. Emergence of ICT and social media networks turned out to be a better platform enabling rapid exchange of viewpoints, expression etc. There is phenomenal development in the domain of affective computing and sentiment analysis that offers leverage in terms of system-human interaction, multimodal signal processing, and information retrieval in terms of ever-growing amount of varied social data. In this paper, the present state of various techniques of sentiment analysis is discussed. The various techniques used for Sentiment Analysis are analysed in this paper to perform an evaluation study and check the efficacy and resourcefulness of the earlier contributions in the domain. Our work will also help the future researchers to understand present gaps in the literature of sentiment analysis.

Key words: Hybrid approaches, Sentiment analysis, NLP, Machine learning model, Latent Dirichlet Allocation.

1 INTRODUCTION

The rapid growth with regards to user-generated texts over Internet has made automatic extraction of highly beneficial information from several documents to gain wide attraction from several authors in different segments, and particularly the group of language processors (NLP). Sentiment Analysis is one of this. It is the task of computational treatment which generally treats expressions [1].

The opinion mining practices analyse as well as the classification of subjective sentiments, opinions, as well as emotions of individuals towards organizations, products, individuals as well as other kinds of topics as pointed out by [2] that are presented in text, like tweets as [3] points out, forums [4], reviews [5], news [6], as well as blogs [7]. It is also worth pointing out that credible opinion of the end users (target audience) can be predicted by sentiment analysis [8].

Research in this area had been highly popular over the past years, both in the industry and also in academia. The reasons behind the phenomenon may be got in the different sets of applications intended to identify the opinions from different sources [9], [10] such as affective responses of the users of social media to the emerging news stories [11]. Essentially, opinion mining provides both the researchers, as well as the users with the chance of assessing huge chunks of data in a manner that is highly efficient (timely) and also effective (precise). However, simplistic approaches, like comparing occurrences of negative as well as positive terms in the text, are in particular inadequate

due to the contrast in corresponding keywords driven data managers (like the search engines) in which incidence of a word always offers great evidence regarding the topicality of a given document [1]. It is worth pointing out that the same can't be said concerning affective assessment of the documents. This is brought about by the fact that the users of the internet can be creative as they are expressing their opinions, as well as their emotions.

It is also worth pointing out that different kinds of factors are affecting sentiment analysis as pointed out by [12]. These generally entail the typical number of words that is a distinctive constraint of tweets and blog posts, the language, and the domain context.

It is also noteworthy that sentiment analysis is having three tasks, which generally entails feature selection, feature extraction, as well as classification as pointed out by [13]. Feature extraction generally generates diverse representation of the plain text documents referred to as the features. In addition, feature selection then selects besides filtering the features in order to get highly relevant features to the given topic. Finally, a machine learning classifier makes use of the attributes in categorizing the data sources.

Various researchers such as [1], [2] have established that in comparison to other text categorization activities, like topic classification, it is worth pointing out that sentiment categorization is highly challenging. This has been pointed out by [1]. This is brought about by the fact that sentiments are always expressed in more indirect manners, like irony [14]. The other shortcoming includes domain dependence as pointed out by [15], this is brought about by the fact that diverse sentiment expressions are often deployed in different environments. Accordingly, the method learning from only one environment might pose poor performance in other environments due to ambiguity, as well as the uniqueness of the sentiment expressions associated to trained, as well as target domains.

Currently, there are numerous reviews [2], [16] which are linked to information fusion, sentiment analysis, as well as opinion mining. On the contrary, contents on the sentiment analysis are generally not highly comprehensive. Other contemporary reviews like [4] generally looked into the research contributions, which are linked to sentiment classification by sentiment lexicons and machine learning methods.

The main contribution of the manuscript entails reviewing the contemporary contributions of sentiment analysis in recent past literature. At the same time, it also taxonomizes divergent dimensions of learning, as well as lexicon usage strategies in relation to the objectives and context of the current contributions when it comes to sentiment analysis. Additionally, the manuscript generally explores the open problems, as well as the open challenges when it comes to sentiment analysis. The manuscript also introduces techniques for diverse levels as well as settings of opinion mining and other advanced topics. The manuscript also provides some current work, like deep learning for opinion mining.

2 CONTEMPORARY ASSERTION OF RECENT STUDIES

This part of the report provides a highly detailed review of the contemporary literature which is linked to sentiment analysis. This review provides the feature selection techniques and unsupervised, supervised, evolutionary computational, domain specific, as well as feature co-presence training activities which are linked to corpus based, as well as lexicon relying sentiment analysis strategies.

2.1 Feature Extraction strategies

Therefore, effective feature extraction techniques are needed so as to have better accuracy rate in the opinion analysis of the specific group of documents. This paper is mainly aimed at investigating, as well as comparing performances of term characteristics and phrasal characteristics which are utilized in sentiment analysis of the reviews. The result shall be a discussion of the overall performance of different attributes and the components which are contributing to the performance.

The first individuals to develop ML tools based opinion mining were Pang, Li, and Vaithyanathan. They experimented with diverse machine learning methods as well as attribute types. These authors established that unigrams constantly offer the highest accuracy if used with several machine learners. On the contrary, they indicated that bigrams might be highly productive for word sense disambiguation, however, they are useful in their simulation study. On the other hand, research which was carried out by [17] established that the term –association attributes (bigram) posted superior performance in comparison to the word features (unigram). It also established that the use of ensemble classification module is responsible for the superior performance because it indicates the word association data among different terms. Research done by [18] emphasized on ensembles of different types of attributes and classifier. The work focused on the mix of word features, as well as multiple data tags for the generation of the best outcomes. A number of the works which are linked with sentiment-analysis are employed unigrams as features due to the fact that it is very easy yet highly effective. Word associations in phrases are irrefutably significant. Phrasal features like trigram and bigram are preserving some word relation. On the other hand, they need additional calculation load and accordingly, are uncommon handling work involving simple sentiment analysis. This paper generally compares sentiment analysis model performance which applies different kinds of features which are extracted through the use of bigrams, unigrams, as well as trigrams in English language feedbacks.

A research conducted by [19] adopted feedback features through using sector review as an important component of attribute choosing procedure related to share market information. The authors used them with x2 along with (BNS). They presented that a strong attribute choosing strategy ensures boost in classifier accuracy in a better way when it is used together with complex types of feature. Their technique enables the selection of semantically related attributes in addition to lowering the task of over-fitting when deploying an ML learning model.

LSI is the renowned feature transformation methods as pointed out by LSI technique generally converts the text area to a new axial mechanism that is a linear combination of actual term attributes. (PCA) is employed for the achievement of this goal as pointed out by [20]. It generally establishes the axis-system that typically holds the highest stage of data associated with fluctuations in the basic feature values. The primary LSI drawback is that it is generally a highly technique that is unsupervised that is generally blind to the underlying class-distribution.

There are numerous other kinds of statistical models that can be utilized in FS such as HMM & “Latent Dirichlet Allocation (LDA)”. They were employed by [21] for the separation of components in the feedback document from subjective opinions, which detail terms with respect to polarities. It has been the scholar’s proposed novel attribute choosing strategy. LDA are typically generative methods, which allow documents to be detailed clearly by non-monitored and latent issues. It is significant that feature selection methods that were proposed by [21] resulted into highly competitive outcomes for document polarity categorization primarily when implementing the syntactic groups only and lowering overlaps with semantic terms in the final attribute clusters.

Irony detection can be termed as the most difficult task in the extracting features. The main aim of the task includes the identification of irony reviews. The work was proposed by [22]. The researchers were mainly aimed at defining a feature model for representing section of subjective knowledge that is underlying such reviews. It also strives to offer a description of salient irony’s characteristics. They established a method for reflecting verbal irony with respect to six groups of features: POS-grams, n-grams, positive/negative profiling, funny profiling, affective profiling, as well as pleasantness profiling.

Several researchers such as [23] offered proposal of novel attribute lowering methods [24]. Also developed least squares differentiation analysis that depicted that orthogonal analysis is highly important when it comes practical services. Also developed manifold integrating architecture to provide a united opinion for the supervised, unsupervised, as well as semi-supervised attribute lowering techniques [23]. Also proposed an attribute choosing technique on the basis of “linking l_2, l_1 –norms minimization”. It also illustrated its efficiency on the six datasets. Also proposed a novel program for identifying the optimal attribute subset. It indicated that algorithm was highly effective.

Determining sentiment orientation on every aspect within a given sentence is referred to as aspect sentiment classification. Over the past years, it is worth pointing out that there has been a plethora of research in the technique which can be adopted for dimension obtaining [25]. Particularly, in order to deal with this problem, two major techniques which include supervised learning approach, as well as the lexicon based approach have extensively been researched as pointed out by [26]. Though supervised manner have been widely exploited by various researchers, the main problem which is very common when it comes to the use of this method include the fact that it mainly relies on training data. Therefore, it is very hard to extend the approach to different domains.

2.2 Supervised Learning

It should be noted that the supervised approaches are highly popular due to the fact that they are having highly superior classification accuracy [27]. At the same time, in the given modules, attribute engineering is highly significant. Other than the frequently utilized group of- terms attributes on the basis of unigrams and bigrams among others, [28], as [29] points out, syntactic properties, semantic properties as well as impact of negators [30] are also incorporated as the characteristics for activity of sentiment categorization. Due to the face that sentiment opinion can be largely complex to be managed by the conventional characteristics is clear from a study of comparative sentences which was done by [31].

In addition, Pang et al views sentiment classification to be a special context based on the classification concept with negative and positive sentiments [1]. The researchers undertook the simulation with three benchmark programs which generally include Maximum Entropy classification, NB algorithm along with SVM being used over n-gram method. This technique labels sentences within the document as objective or subjective. They have used ML classification module to subjective group that hinders polarity categorization from taking into consideration any data that is misleading. They have also assessed extraction of techniques based on minimum-cut formulation that generally offers a highly effective means of combination of sentence-to-sentence stage data with bags of words.

Additionally, Xia et al took into consideration part-of-speech driven attribute groups, NB algorithm, Maximum Entropy, the term- association based attribute groups for categorization and SVM algorithms aimed at the reason of classification as pointed out by [17]. The weighted combination, fixed combination, meta-classifier combination are assessed for the three ensemble approaches.

Martin-Valdivia et al., have employed MC database for carrying out the sentiment analysis [32]. The researchers produced three primary analysis model i.e., MC-ML that is applying ML training model over MC database provided in Spanish; MCE-ML, which is applying Machine Learning approach over MC database provided in English; MCE-SO, which is using SentiWordNet for the incorporation of lexical data and obtain the polarity categorization as pointed out by [33]. Lastly, voting system, as well as the approach of grouping has been taken into consideration for getting the result.

It is also worth pointing out that Zhang et al., have also put forward a new approach for sentiment grouping that is based on SVMperf as well as word2vec [34]. Word2vec is used for clustering the same features for major purpose of detecting the semantic attributes in the chosen context and Chinese. It is worth pointing out that the authors both trained and classified the feedback words through the use of word2vec, as well as SVMperf. During the process, lexicon-based, as well as POS based attribute choosing techniques are respectively utilized in the generation of the learning file. Tripathy et.al also proposed a technique of sentiment grouping through the use of n-gram ML method as pointed out by [35]. They have employed four diverse machine learning methods like Maximum Entropy, Naïve Bayes, SVM, as well as Stochastic Gradient Descent together with n-gram models like unigram, bigram, trigram, unigram-bigram, bigram-trigram, & “unigram + bigram + trigram”. SVM with unigram + bigram + trigram method offers the optimum outcome in comparison to the other kinds of techniques.

It is significant that Kang & Yoo [36] also suggested developed NB classifier aimed at the provision of solutions to the challenge of the capability for favourable categorization accuracy to present up to around percent higher when compared to the unfavourable categorization accuracy. This results into a problem of reduction of the mean accuracy in scenario of the accuracies of both the groups are being presented as a value which is average.

BN was used by authors in [37] in order to handle practical challenges in which the concept of the researchers is broadly framed through the implementation of three diverse (but interconnected) target parameters. The authors suggested the application of multi-dimensional NB algorithm based classification. The study integrated the diverse test parameters in similar grouping function for the exploitation of the possible relationships that exists between them. At the same time, they generally prolonged the multi-dimensional categorization architecture to semi-supervised context so as to gain from benefits of the large volumes of the un-labelled data that is present in the domain.

ME classifier was also employed Kaufmann [38] for the detection of parallel phrases between any opinion groups with very minimal quantities of learning information. The other methods proposed so as to spontaneously obtain parallel information out of non-parallel datasets utilize language specific techniques or need large volume of learning information.

The authors in [39] utilized 2 multi-phase SVM-driven models: “One-vs-Entire SVM”, & “Single-Machine Multi-class SVM” for the categorization of reviews. They suggested an approach for the assessment of the quality of data in feedbacks presenting it as a categorization challenge. At the same time, they also used the data quality (IQ) architecture in order to access data based attribute group. Further, the researchers functioned on digital cameras, as well as on MP3 reviews.

SVMs have been implemented by researchers in [40] as the sentiment polarity classification model. Different from the problem of binary classification, they were of the argument that opinion subjectivity, as well as expresser credibility also ought to be considered. They suggested an architecture, which presents a compressed number summary of diverse approaches on micro-blogs platforms. The authors detected and obtained the concepts reflected in the syntaxes connected to the user queries, and there after grouped the opinions through the use of SVM.

Moraes and Valiati [41] offered an empirical assessment between SVM, as well as the artificial neural networks ANNs concerning document-level sentiment assessment. The authors did the assessment due to the fact that SVMs were extremely implemented and potentially in SA though the ANNs also gained little attention as a model for opinion learning. The researchers provided a discussion of the requirements, the model which results as well as the contexts in which both the approaches attain better classification accuracy levels. At the same time, the study also implemented a benchmark assessment scenario with the prominent supervised models for attribute choosing and weighing in a conventional BOWs method. The simulation results depicted that ANN produced largely superior outcomes as compared to SVM excluding certain imbalanced information situations.

Hu and Li [42] proposed an approach for mining the content patterns of certain words at sentence-level patterns through the implementation of the MST pattern in order to exploit the links between the topical words, as well as its context words. At the same time, they also invented Topical Term Description Model which can be used for sentiment classification. The defined “topical terms” to be the specific entities or some entity aspects in a given domain. At the same time, the study designed automated mining of the topical words from text on the basis of their environment. Thereafter, they employed the extracted terms in differentiating document topics. It is also worth pointing out that organization acts a part in conveying sentiment information. The model is completely different from normal machine learning tree algorithms. On the contrary, it is in a position for learning the positive, as well as the unfavourable contextual information in a manner that is highly effective.

Yan and Bing [43] offer a graph-based Approach that is generally a propagation technique for incorporating the features of the inside, as well as the outside sentence. Both the phrases are intra-document proofs, along with

inter-document proofs. The study illustrated that the establishment of sentiment course of a feedback sentence needs more than the attributes that are within the given sentence.

Both decision trees, as well as decision standards aim to decide rules on attribute area. On the contrary, the decision tree (DT) generally tends to determine that the goal is achieved through the use of a hierarchical approach. It is also noteworthy that Quinlan [44] researched about the decision tree, as well as the decision rule problems in one framework because as a specified route in the DT might be concerned as rule of classification of text instance. The important variations that present among DTs & rules is the primary cause that these structures are highly stringent hierarchical division of information area, whereas categories based on the rule enable overlaps in decision region.

2.3 Unsupervised Learning

Motivated by success of the word vectors, [45] generally proposes vectors of skip thought, a method of “training sentence encoder” through the prediction of the preceding, as well as the following sentence. The representation which is trained by the purpose generally performs competitively on a wide suite of the assessed tasks. Extremely updated training models like layer-normalization [46] results to further improvement of the results. On the contrary, skip-thought vectors have superior performance over the supervised models that directly obtain the required efficiency parameter on a particular corpus. This is the situation for text classification tasks that measure if a particular concept is encoded well in a representation. This takes place even if the databases are comparatively smaller on the basis of modern standards, which always consists of just some thousand labelled illustrations.

Other than learning generic depiction on 1 big dataset & then evaluating on other datasets, a proposal was made by [47] through the use of similar unsupervised purposes such as sequence auto encoding, as well as language modelling to first pertain a given method on dataset and thereafter fine-tuning it for a particular task. The method posted superior efficiency over training similar model from random initialization. At the same time, the model achieved state of the art on numerous text grouping databases. Combination of modelling of language through the topic-modelling & fitting a minor extractor of supervised feature on top also resulted into the achievement of stronger results on in-domain document stage sentiment analysis as pointed out by [48].

Ko and Seo [49] also proposed a technique which generally divides documents into the sentences, & considered each sentence by using the lists of keyword of every category and with the amount of sentence similarity.

At the same time, Xianghua and Guo [50] invented an unsupervised strategy for learning in order to discover automatically the different aspects which were detailed in Chinese social reviews. They employed LDA model in identifying multi-aspect universal topics of social reviews.

2.4 Sentiment Analysis on the Basis of Lexicons

Wilson et al. [30] also created Opinion mining lexicon where words are classified as negative or positive. The other lexicon is ANEW, which was offered by [51]. This is a lexicon that has affective conditions for English words. At the same time, Nielsen formed a lexicon which was referred to as AFINN and which was taken from the study [52] for the social platforms. It involved terms that are largely popular across these platforms such as “OMG” and “ILY” embedded. Further, in AFINN, the criticizing terms often are weighed over a scale often ranging from -5 to -1 while encouraging terms have scores ranging from +1 to +5. The lexicon is containing 2477 words.

On the same note, the study in [33] also constructed Senti-Word-Net lexicon, which is developed on WordNet. Senti-Strength lexicon was developed by the authors in [53] and it attempts to determine the strength of the term. In [54], two researchers designed NRC lexicon, for capturing the emotions of users, where the terms are associated to a group for computing their emotional values. Further, in [2], Bing Liu’s lexicon is developed, which comprises around 2006 terms that are grouped under positive category and around 4,683 terms grouped under negative category.

The other lexicon, which is referred to as NRC Hash-tag opinion-Lexicon has been obtained through the use of a mix of 775310 tweets that have negative or positive hash-tags; the expressions have been were classified as either discouraging or encouraging by the hash-tag polarities. The opinion value was set up by utilizing point-by-point mutual data. The sentiment score was established through the use of point wise mutual information. The values for each opinion varied within -5 to +5 range. This concept has been modelled by NRC-Canada researchers [55]. At the same time, the same team also presented Sentiment140-Lexicon that makes use of discouraging or encouraging emoticons for grouping the sentiment terms.

Each of the lexicons which have been mentioned above are created for the English language. It is also worth pointing out that the approaches which employ lexicons are facing challenges, like dealing with negations as pointed out by [56]. ALGA's adaptive lexicons can be compared to NRC hashtag, Sentiment140, AFINN, as well as Bing Liu's lexicon have been extensively utilized in the literature.

The dictionary based technique is having a big disadvantage that is the incapability to get opinion words which are having a domain, as well as context specific orientations. Similarly it is important that Qiu & He [57] also utilized the technique based on the dictionary for the identification of sentences of sentiment in the contextual-advertising. The authors proposed a strategy for advertising that is mainly aimed at enhancing the relevance of the ads as well as the general experiences of the users. They employed syntactic parsing, as well as sentiment dictionary. In addition, they suggested a rule based method for embark upon topic word extraction, as well as the identification of the behaviour of the consumers in advertising keyword extraction.

This was also used by Jiaoa and Zhoua [58] for discriminating opinion polarity through several-string structure matching program. The program has been implemented on Chinese internet feedback. The study set up various expressive dictionaries. The authors were working on hotel, car, as well as on computer online reviews. The outcome pointed out that their approach has achieved very high level of performance. In addition, the study [59] utilized bi-layer CRF method with undecided inter-dependencies to obtain comparable associations.

They did this by utilizing the complex inter-dependencies among terms, entities, relations, as well as unfixed interdependencies among the relations. When doing this, their main aim entailed making a graphical model for extracting, as well as for visualizing relative relations between customer reviews, as well as the products. At the same time, they presented the outcomes as comparative association graphs for assistance when it comes to the management of enterprise risk. Additionally, they functioned on various cellular consumer feedbacks from epinions, amazon, SNS, blogs and emails. The results indicated that their method is capable of extracting comparative relations in a manner that is highly accurate in comparison to the other different techniques. Their comparative relation map is probably a highly effective technique which can be used to support enterprise risk management, as well as for the making of decisions.

Cruz and Troyano [60] proposed a taxonomy-oriented technique for the extraction of feature-level opinions. The approach was also used for mapping them into feature taxonomy. The classification is broadly a semantic reflection of opinionated features and parts of a specific object. The researchers' primary aim comprised a domain-specific OM. The study utilized resources which are directly persuaded from the extensive cluster of annotated listings. At the same time, they worked on 3 diverse fields, which includes hotels, headphones, as well as cars reviews) from the website epinions.com. After that, they did a comparison of their approach with the other domain independent methods. The results which they obtained illustrated the significance of domain in constructing precise opinion mining methods since they resulted into various accuracy improvement with regards to sector-independent methods.

2.5 Document, Phrases, and Dimension level Training

The approaches for opinion mining that have been depicted in the current studies with regards to sentence level, document level, as well as aspect level have been summarized in this section.

2.5.1 Document level

Conventional classification models in ML techniques, like SVM, NBs classifier, & maximum-entropy classification model, are utilized for document stage opinion categorization on different types of characteristics that typically comprises bigram, unigram, location data [1], POS tags, Semantic characteristics [61] as well as discourse features as pointed out by has also proposed integrated classification models on the basis of SVM, and NBs classification model.

Motivated by LDA topic method, certain generative methods have generally been suggested for document specific opinion mining, which generally includes combined sentiment topic method as well as dependency-sentiment- LDA method [62] that generally models the changes between term opinions with a Markov-chain.

Certain reweighting mechanisms of sentiment orientations were suggested for the improvement of performances, like intensification, as well as negation indicators as pointed out by [63] as well as discourse structure-oriented reweighting mechanism [64].

For the minimization of dependency on annotated database, certain semi-supervised methods are proposed that generally includes active learning-oriented approaches that manually categorizes sentimentally unclear documents and co-training methods for unbalanced opinion categorization. In the recent past, a joint learning framework that generally mixes semi-supervised model was suggested as pointed out by [65].

2.5.2 Sentence Level

Same to the case of opinion mining in the context of documents, there has been the adoption of supervised classifiers. Naive Bayes classifier, as well as collaboration of NB algorithm classification methods have been utilized for identification of the phrases' subjectivity as pointed out and it is also important that CRFs were used to exploit the dependencies of the sentences as pointed out by In the recent past, there was the proposal of a joint segmentation, as well as classification framework as pointed out by [66].

Because of the unavailability of sentence labels, a series approach, which integrates completely supervised document groups, along with semi-supervised sentence groups are proposed for conducting semi-supervised classification as pointed out by [67].

2.5.3 Aspect Level

Due to minimal annotation, unsupervised techniques are highly beneficial on fine-grained level opinion mining. In order to ensure aspect recognition, association mining algorithm is often employed. At the same time, linguistic knowledge, like part-whole patterns, along with metonymy discriminators have been considered. At the same time, double propagation coding was suggested for hybrid opinion words, as well as for aspects extraction. In addition, rule-based approaches are also largely successful for identifying clear dimensions and entities as pointed out by [68]. Comparative phrases are incorporated in the identification of implied dimensions as pointed and it is also important that clause patterns are also explored for dividing documents into multiple sentences that are beneficial when it comes to aspect detection.

LDA topic model, as well as its deviations are implemented for dimensions identifications and combined aspect along with sentiment recognition as indicated by [69].

An aspect grouping technique that entails extrinsic information was proposed for less supervised dimension recognition as pointed out by [70].

2.6 Ensemble Training Approaches

There are numerous studies which have been conducted on categorization of sentiment in the literature. Nevertheless, the amounts of studies that employ classification model for English language feedback are generally very limited.

Lane and Clarke [71] offered Machine learning model for solving the problem of locating documents that carries negative or positive favourability in media analysis.

The investigation has also been done by Rui and Liu [72] concerning the usage of ML learning model over live information obtained from Twitter. In this research, the scholars strived to investigate whether and the manner in which Twitter (WOM) is affecting the sales of movie through estimating a highly varying panel information model. At the same time, they employed NB, as well as SVM for the purposes of classification. Their major contribution entailed grouping the tweets considering the tweet's unique characteristics. At the same time, they distinguished between pre-consumer opinion as well as post-consumer opinion.

Bai [73] has offered Machine learning technique that is generally a dual-stage estimation program. During the first level, the classification tool is trained regarding inter-dependencies observed between different terms and then these are encoded into Markov-Blanket-Directed-Acyclic chart for obtaining opinion parameter. Having obtained this variable, in the next level, the researchers implemented a meta-heuristic approach to further fine-tune their coding to suit larger cross-verified precisions.

Unsupervised as well as supervised approaches may be pooled jointly. It was carried out by the researchers in [32]. They proposed the utilization of meta-classifiers for building a polarity categorization mechanism. Both the researchers used the Spanish database of movie feedbacks along with a simultaneous database translated to the English language. Initially, the authors created two independent methods on the basis of these datasets and later implemented ML techniques including Support Vector Machine, NBs algorithm, etc. When that was done, the researchers included SentiWordNet opinion dataset into English dataset which resulted into the generation of a novel unsupervised method through incorporation of semantic based method. Further, these researchers also joined the three systems through the use of a meta-classifier. The results generally outperformed the outcomes that are associated with the use of individual corpus. It also indicated that their technique could be deemed to be a highly effective and sufficient strategy for polarity organisation upon the availability of parallel corpora.

ML classifiers are adopted by Walker and Anand [74] for the classification of stance. Stance refers to the comprehensive opinion as perceived by a user with respect to a given idea, object, or a given position. It is worth pointing out that stance is very similar to a perspective or to a point of view. It may be observed to entail the identification of the "side", which a user takes, like for instance agreeing or disagreeing a subsidy policy or an economic move taken by any government.

Work which was carried out by [74] generally classified stance held by group or individual. The work was adopted on political debates.

According to [75], the other highly popular ensemble method is encouraging that is also having numerous variants. Boosting is a process which is highly iterative in which every successive classifier's training subset is selected on the basis of classifier efficiency that was trained formerly. When the previous classifier faced various difficulties in properly classifying a given learning structure, then the given pattern is highly likely to be selected for inclusion in the present classifier's learning dataset. This enables the system to build learners that focus on those hard training patterns. The technique forces every learner to be acting as an expert for categorizing its given data space region.

In the area of ensemble techniques, the major idea generally entails combining various models so as to gain a highly accurate, as well as a highly reliable model when compared to what one model is capable of attaining. The

approaches incorporated for constructing on ensemble method are several and categorization has been offered by [76]. The classification is generally founded on two major dimensions: the manner in which the estimates are integrated along with the way in which the training sequence is executed. In one way, in any protocol structured model, estimates obtained from the base classification tool are considered through a standard rule with the prime agenda of computing their mean estimation accuracy. Some of the main instances of “rule based ensembles” comprise majority voting where output estimation per sample will be the class that is most common; & weighted combination which linearly cumulates the predictions of base classifiers. Meta learning methods generally employ predictions from the classifiers of element as main features aimed at Meta learning method.

As pointed out earlier by [17], the weighted mixtures of attribute groups may be quite effective in the task of opinion grouping due to the fact that the weights of the tool is representing the consequence of diverse feature groups (like POS, n-grams among others.) towards sentiment classification instead of allocating consequence to each feature separately. The rule based ensembles benefits have also been captured by [77] in which numerous voting rules variants have been studied thoroughly in various datasets, with focus on the complexity that which may be brought about by the application of the approaches. In another work, [78] have done a comparison of common voting rule through other methods through the use of three kinds of “subjective-signals”: expressive elongations, emphatic expressions, adjectives, & emoticons. In [17] “Meta classifier ensemble method” is analysed which points out improvements in performance. In addition, both rule based, as well as meta-learning approaches can be strengthened through incorporation of extra knowledge [79]. It is also worth pointing out that the most popular method which processes the sample simultaneously is bagging [76].

2.7 Domain-specific Learning

Because there are several number of domains which are always engaged in online contents which are consumer created, it is in practice, not feasible to obtain sufficient samples for each of them to enable models to learn for domain-specific opinion categorization. This has been pointed out by [80]. As a result, sentiment domain adaptation that generally transmits sentiment understanding from the main source domain with adequate classification information to a domain, which is tested with complete lack of labelled information, was prominently studied in the area of opinion mining as illustrated in [80] and [15]. The main challenge of the sentiment-domain implementation often includes the task of managing the gap of attribute distribution across learning domain and testing domains as presented in [81]. Several opinion domain implementation approaches are suggested for overcoming this limitation in different methods as pointed out by [80] and [15].

So as to effectively manage the domain-reliance issue when it comes to opinion mining, there are numerous methods which are presented. Significant contributions related to opinion mining endeavoured to manage the issue by enabling models to learn domain-specific opinion mining [1], [82]. One of the main challenges which are faced in these techniques include the fact that the classified information in the test-domain might not be adequate and it is highly expensive besides being consuming a lot of time to annotate manually adequate samples. It is worth pointing out that without adequate labelled data, it is very hard to train a robust and an accurate sentiment classifier.

At the same time, [82] also proposed a very interesting method for obtaining both aspects, as well as sentiment expressions in the tourism industry, which are specific to target domain summarization, as well as for visualization. Other researchers suggested to deal with domain-dependence problem via adoption of a general sentiment lexicon to the domain which is targeted [83] or to construct domain-specific sentiment lexicon as pointed out by [84]. The methods always depend on general sentiment lexicons, as well as on the non-categorized information of the testing domain. But, mostly important opinion data in different domains is generally not taken into consideration in these techniques.

The work [85] also proposed a negativity-meter scheme which considers the drug side effect. They pointed out that sentiment words, as well as the subjective phrase may not be highly efficient in medical reviews because there

exists a big number of objective sentences that imply sentiment. Different studies were carried out by [86] which researched about the link or the connection between bio-entities. The research also defined newer attributes for SVM machine classifier and thereafter combined them with the other methods that are using sentiment lexicons and elevated the strength of relationship through the use of SVR. A different challenge linked to drug reviews has also been mentioned by [87]. They suggested taking into consideration the time when expressed undesirable or desirable fact takes place. These types of sentence only imply opinion if they take place after the drug has been taken and not before they are taken.

In addition, obtaining quantitative pharmaceutical keywords such as LDL, as well as HDL are highly important in the biomedical opinion mining [88] extracted numeric fields using regular expressions.

In addition, Dickinson and Hu [89] also predicted a sentiment value for tweets related to stock on Twitter. He illustrates the influence of the opinion on stock trading.

The contribution portrayed in [90] uses emoticons and human effort to label the opinion as positive or negative, which further used to train the ensemble classifier model [91].

The contemporary contributions [55], [92] are using sentiment lexicons and the other factors such as emoticons, which were networked to employ emotional stretch for opinion categorization. In the work which was done by features which are extracted on the basis of semantic fundamentals and are included in the learning set. In the work which was done by [93], a different approach which employs divergent aspects of the terms are being used to identify the sentiment polarity of the given opinion. The study in [93] depicted a new concept of additional-lexicon that computes weights for objective terms and non-vocabulary terms. The author incorporated a scoring mechanism for attributes. The study in also suggested an adaptation process for opinion lexicons for interpreting the true sense of terms under divergent twitter trends [94] o identify the sentiment polarity of twitter messages. Lu [95] employed microblog-microblog relations, which incorporates social relations, as well as text similarities to build a partially supervised classification model. Further, the author in [96] incorporated a new method to obtain the structure of terms and assess it on tweet-level in addition to entity-level opinion understanding. The researcher integrated hidden semantic associations to improve the level of accuracy of the classification. Baccchi et al. [97] employed a multi-dimensional method for feature learning to categorize the tweets which might be containing pictures. In addition, the study in [98] also included emotional symbols in a non-Supervised Learning scenario in Tweets. The authors in [99] employed a method that assigns certain score to the tweets, which is based on the scope of positive and negative sentiment lexicons. In addition, the study in [100] engaged a lexicon-driven approach, in which the authors computed sentiment-orientation along with its robustness in tweets. Finally the authors in [101] embedded social networking links among twitter messages of similar researcher and social associations among different consumers for the enhancement of the precision rates.

2.8 Sentiment Analysis of the Basis of Correlation between Entities

Pre-trained word vectors are a highly significant component of a number of the modern NLP systems [102]. The representations, which are learnt through modelling word co-occurrences, play a key role in increasing data efficiency, as well as generalization capability of the NLP systems as pointed out by [103]. It is also worth pointing out that topic modelling is also capable of discovering factors in a dataset of text, which synchronizes to manually understandable sectors such education or art [104].

Getting co-occurrence patterns, as well as seed semantic terms might be carried out via the application of various kinds of statistical models. This might be carried out by extracting subsequent polarities through co-existence of adjectives in the dataset. This was presented in the study in [105]. It is often feasible to incorporate the complete group of indexed files over the online as the dataset for constructing the dictionary. This plays a major role in

overcoming the challenge of non-availability of certain terms in case the adapted database is smaller in size as indicated in [1].

Latent Semantic Analysis (LSA) refers to a statistical method that is employed for the analysis of the relationships between various documents as well as the terms which are mentioned in the documents so as to generate a group of useful structures associated with files and words in them. The study in [106] also engaged LSA for detection of the semantic features from the feedback texts in order to evaluate the impact of various attributes. The primary aim of the research was to gain knowledge on the reason for some specific feedbacks gain large number of usefulness ticks while certain feedback get limited or no ticks. Accordingly, instead of estimating a useful level for feedbacks containing no ticks, the researchers identified multiple types of aspects that can impact the count of usefulness ticks that a particular feedback gains. Both 'yes' and 'no' ticks are also considered. The authors developed on software algorithm consumers' review from download.cnet.com. The researchers depicted that the semantic features are largely effective as compared to other features in determining the count of usefulness ticks obtained by the specific feedback message.

Semantic-orientation of any term corresponds to a statistical method that is utilized in conjunction with the PMI approach. Further, incorporation of semantic area, also mentioned as HAL has been presented by the researchers in the study in [107]. Semantic space refers to the space where the terms are reflected by points. The position of all points together with every axis is in a way connected to the meaning of the words [108] also developed a technique that is founded on HAL and which is referred to as S-HAL. In this approach, Semantic-orientation data of terms is typically differentiated through a particular vector-space. This is followed by the learning of the classification tool to guarantee that they identify the term's semantic orientation (phrases or words). The accuracy of the presumption was made through the method of semantic orientation interpretation from PMI. The technique that they employed generated a group of weighted attributes on the basis of nearby terms. Further, they researched on newspapers besides adopting a Chinese corpus. The outcome which they got pointed out that they outperformed SO-PMI. At the same time, it also indicated the benefits which are brought about by modelling semantic-orientation features when compared to initial HAL approach.

The method defined in [109] obtained both discouraging and encouraging appraisals, and further assisted customers when they are making their decisions. Their technique can be used in helping firms to be in a better position to understand service or product appraisals, and based on this, they can translate the beliefs into artificial-intelligence to be implemented as the basis for enhancements of services, as well as for products. Additionally, that they functioned on Taiwan Fast-food feedback. The outcomes depicted that the suggested model is largely effective in providing e-WOM feedbacks that are associated with products and services.

Semantic approaches and statistics can be used, which was put forward in [110] who adopted the two techniques to establish the various weaknesses of the products from the internet feedbacks. The limitations identifier often obtained the characteristics along with group external through the use of morpheme-based techniques for the identification of feature words based on the reviews. They adopted how net-based similarity measure for establishing the frequent together with the infrequent explicit characteristics that are describing similar aspect. In addition, they noted the implied characteristics with statistics-driven choosing technique PMI. The study was successful in determining different limitations of the goods as it was perhaps the highest unsatisfied dimension within the reviews of the customers. It was also the aspect that is more unsatisfied in comparison to the product reviews of the competitors. The results pointed out the weakness finder's good performance.

2.9 Deep Learning

Driven by strong pace of in-depth training of ML models, different research works aimed to construct small-dimensional, dense, along with vector of real-valued in the form of word characteristics for sentiment analysis deprived of any kind of characteristic engineering. And the task of the sentiment expression obtaining is typically

presented as token-stage series classification issue. So as to effectively address a challenge like that, numerous works utilize CRF or partial-CRF with different characteristics which are manually designed like phrase features, word features, as well as syntactic features as pointed out by [111]. It is also worth pointing out that RNNs are typically prominent approaches, which presented reliability in different NLP problems.

The concept is typically an advancement of the traditional feed-forward NN that contains the capability of managing varying space input structures. Accordingly, RNNs can be practically implemented for language modelling and for different kinds of associated problems. The research in [112] implemented Deep-RNNs for opinion mining from the phrases. It depicted that these Deep RNNs had superior performance over CRFs. And the model is improved often through “stacking Elman-type RNNs” one over the other. Each segment of Deep-RNN considers the memory schedule from the earlier structure as feeding sentence. Simultaneously, it calculates its own memory reflection.

In region of NLP, the syntactic parsing is regarded as the main problem due to its prominence in functioning with both terms and their underlying meanings. The studies [113] also included the concept of CVG vector that often integrates PCFGs with syntactically combined RNN, which often trains syntactic-semantic, compositional-vector reflections. In addition, the study in [114] also proposed a new model which is termed as Recursive-NTN. The study presents a sentence through the utilization of word-vectors along with a parsing-tree. Following this, the study calculates the vectors aimed at greater nodes in tree through the identical composition formula based on the tensor. Similarly, the study in [115] worked on the prominence of a similar tree structured RNN for fine-tuned opinion mining.

In the recent past, multiple studies are presented refined kinds of RNNs for functioning with various shortcomings of vanilla RNN model. It is worth pointing out that “Bidirectional-RNNs” are improved often on indication that outcome at a given point-of-time t can be based on both the past components in the sequence & also on further elements. For instance, in esteem to estimate a word that is missing in specified sequence, the person would check both the right and left context. The Bidirectional RNNs are generally not complicated. They are dual RNNs, which are placed one over the other. After that, the result is calculated on the basis of RNNs latent circumstances. “Deep bidirectional-RNNs” function on same lines as that of bidirectional-RNNs, although there are now several layers for each sequence. In real life, it results into greater learning capacity. Mikolov et al. [116] offered numerous modifications of the first RNN language approach.

Sequential models such as LSTMs and RNNs are also verified to be highly powerful techniques for semantic composition as pointed out by [117]. Liu et al. [118] also suggested a typical group of different approaches on the basis of RNNs and terms integrations, which can be engaged in fine-tuned semantic analysis without including and problem-specific attribute selection task.

The other highly dominant NN for semantic combination is CNNs. [119] described a convolutional framework which is referred to as Dynamic-CNNs, which is used in semantically modelling phrases. The system engages variable k -max pooling, which is generally a universal pooling task over linear series. The system is managing feed phrases with lengths that changes and it also incorporates an attribute chart over phrases. In addition, it is noteworthy that the feature graph is able to explicitly capture short, as well as long-range relations.

Enhancements in term reflections that utilizes NNs have prominently added to the advances in sentiment analysis through the use of deep learning techniques. Mikolov et al. [120] also introduced the CBOW as well as the skip-gram language approaches. They presented the prominent word2vec10 toolkit. CBOW technique generally estimates the current term based on incorporation of contextual terms. The skip-gram approach generally predicts the adjacent words based on inserting the current word. Additionally, [103] suggested GloVe. It represents a non-Supervised Learning program that is incorporated for extracting vector representations of terms. Learning is carried out on the cumulative universal word-to-word co-existence data from the dataset.

In the NLP realm a large volume of research in in-depth training was shifted towards methods which entail training term vector reflections via the utilization of neural language methods as pointed out by [121]. Un-interrupted reflections of terms like vectors has usually proven as highly effective method in the amount of NLP tasks comprising sentiment analysis as pointed out by [122]. In this regard, word2vec is generally one of the most prominent approaches that ensures modelling terms as vector representations as pointed out by [120]. Word2vec is founded on Skip-gram, as well as CBOW models for performing the computation of distributed representations. Whereas CBOW is mainly aimed at predict a word because of the context, Skip-gram generally estimates the context in which a term is provided. The Word2vec generally computes uninterrupted vector reflections of terms form a very big dataset. The word vectors which have been computed recollect a huge quantity of syntactic and semantic regularities present in particular language existed as relationship offsets in resultant space of vector. The method is on the basis of word2vec will be doc2vec [123] which generally models the whole documents or the entire sentences as vectors. Another technique in depiction learning will be auto-encoder which is type of synthetic neural network utilized in the unsupervised -learning. The “Auto-encoders” is employed aimed at training new reflections on the extensive range of the ML tasks like reflections of training from the distorted data pointed out by [124].

In the deep-learning aimed at SA, the most interesting method requires augmenting knowledge comprised in embedding vectors through the other sources of information. The added information may be sentiment specific word embedding as pointed out by [122]. The work which was presented by [125] pointed out that the attribute group obtained from term integration is typically enriched with hidden context characteristics, which combines them in ensemble scheme. At the same time, they experimentally illustrate that the enriched reflections are highly effective in enhancing polarity classification performance. The other approach which incorporates novel data to embedding’s has been described by [61], where in-depth learning is engaged so as to obtain sentiment features together with the semantic features. In addition, [126] offered a description of an approach in which distant supervised information is employed in refining the metrics of NN from unsupervised NLP method. On the same note, a coordinated filtering program may be employed as pointed out by [127] in which the researchers include sentiment data out of a small portion of data.

While including sentiment data, [128] points out the manner in which sentiment “Recursive Neural Network (RNN)” might be engaged along with other NN framework. Usually, there will be tendency which tries to include more data to term integration is formed by the in-depth training networks. A highly interesting work has been described by [129], in which both sentiment-driven, as well as the standard integrations are employed together with several pooling functions for the extraction of target-based sentiment of the Twitter comments. It is also worth mentioning that enriching the information which is included in term embedding’s is not the sole trend when it comes to deep learning for SA. Research into the compositionality in “sentiment classification task” has usually proven as highly relevant, as pointed out by [114]. The work generally proposes “Recursive Neural Tensor Network (RNTN)” model & it also points out that RNTN is better in performance in comparison to the past models on binary, as well as in sentiment analysis which is grained finely. The RNTN technique generally depicts a phrase utilizing word vectors & parse tree, vectors of computing for superior nodes in tree via the utilization of tensor-based composition formula. With regards to the ensemble schemes illustrated in Section 3.4, certain authors [130] have employed a “geometric mean rule” aimed at merging 2 sentiment methods: continuous representations of sentences, the language model approach, as well as weighted BOW. Ensemble is exhibiting a very high performance on sentiment prediction of movie reviews, as well as improved efficiency as compared to element classifiers.

2.10 Emerging Computational Methods

This chapter primarily researches the adaptation of emerging programs in opinion mining. The study in utilized a hybrid GA for attribute choosing in opinion categorization in different online platforms. The study in [131] utilizes a combination of SVMs along with particle-swarm optimization for opinion mining of the film feedbacks. [111] considers a huge set of semantic, syntactic, as well as discourse level features. It also uses GA for choosing attributes

that improve the precision. The study in [132] engages an artificial-immune scheme for sentiment categorization. Individual structure that they suggested is in binary structure, in which each bit depicts the existence of a term. In the context of [133], PSO/ACO2, Particle-Swarm concept along with ant-colony concept are employed in order to find if a post is containing specific arguments. In addition, Govindarajan [134] employs a combination of NBs algorithm along with GA for categorization of film feedbacks. Simultaneously, the study in [135] also presented a GA to choose theoretical terms from a broad range of terms for opinion mining of twitter messages.

Genetic-Programming refers to the evolutionary algorithm which has gained much attention because of its success in providing solutions to real-world problems which are very hard. It is also worth pointing out that GP has extensively been known for achieving human-competitive outcomes. In actual sense, GP has out-performed the solutions which have been found by humans in the numerous problems which they are facing. For example, since the year 2004, there have been competitions referred to as Humpies which is conducted at “Genetic & Evolutionary Computation Conference (GECCO)” where GP methods possesses always awarded gold medals as 7 and 2 silver & 1 bronze from the year 2004 to the year 2014. It is only in the year 2011 that GP failed to get any kind of award. Nevertheless, a modified of the “GP Cartesian GP” got the silver medal. And even with productiveness which has been proven, to the best of our ability, GP has almost not been employed in tackling sentiment analysis problem as pointed out by [136]. The utilization of GP towards the completion of word- processing is much rare as pointed out by [137]. In the past work GP, was employed so as to enhance the weighting mechanisms of vector space method for the classification of text. Additionally, the work which was one by [138] suggested GP for emerging characteristics with the main aim of minimizing data dimensionality.

Sentiment analysis generally poses so many challenges in which GP may be an option which is feasible. Some of the problems are coming from the high-dimensional representation, as well as the remarkable learning set volume. To provide an understanding of prominent course of dimensionality, a general practical database for word-mining is depicted via the utilization of few tens to few thousands of coordinates, as well as few thousands examples. A number of vector elements are nevertheless 0. And the GP system which is the most prominent [139] are not using sparse representation and this generally makes them to be unfeasible for tackling problems with the characteristics because of memory restrictions.

A number of the papers in GP literature have been highly dedicated to providing solutions to issues through high-dimensional depiction, and size of training which is considerable. The work [140] employs a GP ensemble produced on the issue with about 300,000 exemplars on 41 dimensions. In the work which was done by [141], a simple regression task is handled in which there are about 1,000,000 points having 20 dimensions. In the work which was done by [142], it was suggested to train a multiplexor of about 135bits which is representing a learning size of about 2135. Nevertheless, the tens concept only utilizes mere 1,000,000 learning cases. Unlike, looking at issues that have great-dimensional representation in the work done by [143], new symbolic regression model will be suggested on a challenge having 340 dimensions and 600 learning instances. Various reviews indicates that GP implementation on tasks comprising large-dimensional representation and substantial size of training are very rare. It might be probable that a single limitation include the time which is needed to get a solution which is acceptable on the GP. And the confine has been pointed out formerly by [144].

It is significant that semantic GP which makes use of new semantic operators appear to be the feasible alternative for tackling the problems of text mining. This is brought about by their quick convergence ratios, as well as the traditional incorporations; being capable of evaluating a novel independent in $O(n)$, where n represents the volume of learning dataset. In the diverse semantic operators, the ones which appear to possess the highest rate of convergence have been suggested by [145]. And the 2 methods were motivated through geometric semantic that was suggested by Moraglio et al. [146] with the combination of Vanneschi et al. as pointed out by [147]. The main idea for the new techniques entails the creation of the best spring that can be obtained through a linear composition of parents.

3 OBSERVATIONS

3.1 Lexical Challenges

It is worth pointing out that sentiment analysers are facing the following three major limitations at lexical stage: The first one is data sparsely which generally entails handling of the presence of phrases or words which are unseen (like the movie is messy, incomprehensible, uncouth, and vicious as well as absurd). The second one is lexical ambiguity, for example, getting relevant interpretations of a term on the basis of the situation (for instance, Her face fell during the time she was opted out from the group vs The girl fell from the stairs, in which the term “fell” has to be understood in different contexts). The third concept is domain reliance that often entails handling terms that modify polarity from one environment to other. (Similar to the term unpredictable being encouraging in the context of a film while in the context of driving in automobile sector is discouraging) Several approaches are put forward so as to efficiently handle various lexical stage hurdles through: the use of WorldNet sunsets, as well as word cluster data for tackling lexical ambiguity, as well as data sparsely. This has been pointed out by [148], and the second one is mining the words which are dependent on domain.

3.2 Syntactic Challenges

Challenges at syntax level commences if the considered words follow a largely complicated pattern and the phrase related terms are required to be handled before executing SA [62].

3.3 Semantic and Pragmatic Problems

This sub-chapter is related to challenges that occur in larger layers of NLP including pragmatic and semantic ones. Problems observed in these layers typically are in handling: (i) Opinions presented implicitly (such as Boy gets her, he loses her, and viewers fall numb.) (ii) Existence of the sarcasm and some type of mockery (for instance, you attend this film because the hall contains air-conditioning) & (iii) Upset/thwarted opinions (like acting is acceptable.

Problems such as the ones mentioned above are highly complex to manage through traditional NLP approaches as they are both language oriented and also consist of pragmatic information. A number of attempts towards dealing with thwarting [149], sarcasm as well as irony [150], depend on long-distance supervision-based methods (like leveraging hashtags) as well as stylistic or pragmatic features. Addressing the challenges for language wise well-established texts, amidst non-presence of external hints (like emoticons), often is observed to be challenging through either textual or stylistic characteristics only.

- Thwarted expectations [1] that takes place when final sentences of a document modifies its entire sentimental appraisal:
- Irony, which takes place when expressions or words having a characteristic positive sentimental content are symbolically employed in order to express negative opinions.
- Assorted emotions when more over 1 diametrically opposed expressions are communicated in short segment of text:
- Context, if it is not explicit text information of a interaction which is containing private state expression, instead of context which is incorporated. For instance the statement:

While denoting to movie, it clearly points out a very robust negative bias to it, though the textual content will not explicitly comprise any sentimental information.

The type of effective understanding that can be executed and the outcome of the opinion mining programs also differ significantly and this is always on the basis of sentimental analysis. And some of instances comprise:

- A ternary estimation on whether text which has been assessed is containing negative positive affective content or is objective or neutral. Some of the instances usually comprise the reviews on online which praises or which criticises products as pointed out by [1] or opinions against or in support proposed legislation.

- A categorical mining of useful information where the output might be one of numerous probable states like anxiety, nervousness, fatigue, fear, as well as tension [151].
- Numeric prediction in a given affective dimensions, like arousal or valence [152] which points out the level or positivity, as well as mobilization respectively.

4 CONCLUSION

This manuscript contributed a systematic review of sentiment analysis. The complexity of data presentation and dimensionality, diversified usage requirements, the sentiment analysis or opinion mining emerged as critical research objective since a decade. This review explored the contemporary review of the machine learning based sentiment analysis models found in recent literature, meticulous comparison of the techniques used and possible and potential research objectives for future research. This review evinces that entire tasks of sentiment analysis are challenging, understanding & knowledge of issue and its result are still confined. The significant cause is that it will be a “natural language processing task”, which is a complex due to lack of prototype to represent semantics. However, the review stated significant contributions in contemporary literature, it is obvious to conclude that the sentiment analysis is having potential scope for future research and one of that is exposing the scope of evolutionary computational or soft computing techniques and the hybridizing these techniques towards feature extraction, selection to classify the sentiment.

5 REFERENCES

- [1] Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan. "Thumbs up?: sentiment classification using machine learning techniques." Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10. Association for Computational Linguistics, 2002.
- [2] Liu, Bing. "Sentiment analysis and opinion mining." Synthesis lectures on human language technologies 5.1 (2012): 1-167.
- [3] Ritter, Alan, Sam Clark, and Oren Etzioni. "Named entity recognition in tweets: An experimental study." In EMNLP 2011. 2011.
- [4] Ravi, Kumar, and Vadlamani Ravi. "A survey on opinion mining and sentiment analysis: Tasks, approaches and applications." Knowledge-Based Systems 89 (2015): 14-46.
- [5] Turney, Peter D. "Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews." (2002).
- [6] Balahur, Alexandra, et al. "Sentiment analysis in the news." arXiv preprint arXiv:1309.6202 (2013).
- [7] He, Ben, et al. "An Effective Statistical Approach to Blog Post Opinion Retrieval." (2008).
- [8] Khan, Farhan Hassan, Usman Qamar, and Saba Bashir. "SWIMS: Semi-supervised subjective feature weighting and intelligent model selection for sentiment analysis." Knowledge-Based Systems 100 (2016): 97-111.
- [9] Asur, Sitaram, and Bernardo A. Huberman. "Predicting the Future With Social Media." (2010).
- [10] Kramer, Adam DI. "An unobtrusive behavioral model of gross national happiness." Proceedings of the SIGCHI conference on human factors in computing systems. ACM, 2010.
- [11] Thelwall, Mike, Kevan Buckley, and Georgios Paltoglou. "Sentiment in Twitter events." Journal of the Association for Information Science and Technology 62.2 (2011): 406-418.
- [12] Paltoglou, Georgios. "Sentiment analysis in social media." Online Collective Action. Springer Vienna, 2014. 3-17.
- [13] Hung, Lai Po, et al. "A review on the ensemble framework for sentiment analysis." Advanced Science Letters 21.10 (2015): 2957-2962.
- [14] Reyes, Antonio, and Paolo Rosso. "On the difficulty of automatically detecting irony: beyond a simple case of negation." Knowledge and Information Systems 40.3 (2014): 595-614.

- [15] Glorot, Xavier, Antoine Bordes, and Yoshua Bengio. "Domain adaptation for large-scale sentiment classification: A deep learning approach." Proceedings of the 28th international conference on machine learning (ICML-11). 2011.
- [16] Balazs, Jorge A., and Juan D. Velásquez. "Opinion mining and information fusion: a survey." Information Fusion 27 (2016): 95-110.
- [17] Xia, Rui, Chengqing Zong, and Shoushan Li. "Ensemble of feature sets and classification algorithms for sentiment classification." Information Sciences 181.6 (2011): 1138-1152.
- [18] Hassan, Ammar, Ahmed Abbasi, and Daniel Zeng. "Twitter sentiment analysis: A bootstrap ensemble framework." Social Computing (SocialCom), 2013 International Conference on. IEEE, 2013.
- [19] Hagenau, Michael, Michael Liebmann, and Dirk Neumann. "Automated news reading: Stock price prediction based on financial news using context-capturing features." Decision Support Systems 55.3 (2013): 685-697.
- [20] Abdi, Hervé, and Lynne J. Williams. "Principal component analysis." Wiley interdisciplinary reviews: computational statistics 2.4 (2010): 433-459.
- [21] Duric, Adnan, and Fei Song. "Feature selection for sentiment analysis based on content and syntax models." Decision Support Systems 53.4 (2012): 704-711.
- [22] Reyes, Antonio, and Paolo Rosso. "Making objective decisions from subjective data: Detecting irony in customer reviews." Decision Support Systems 53.4 (2012): 754-760.
- [23] Nie, Feiping, et al. "Efficient and robust feature selection via joint ℓ_2 , 1-norms minimization." Advances in neural information processing systems. 2010.
- [24] Nie, Feiping, et al. "Orthogonal vs. uncorrelated least squares discriminant analysis for feature extraction." Pattern Recognition Letters 33.5 (2012): 485-491.
- [25] Liu, Zhiyuan Chen Arjun Mukherjee Bing. "Aspect extraction with automated prior knowledge learning." Proceedings of the 52nd annual meeting of the Association for Computational Linguistics. 2014.
- [26] Rana, Toqir A., and Yu-N. Cheah. "Aspect extraction in sentiment analysis: comparative analysis and survey." Artificial Intelligence Review 46.4 (2016): 459-483.
- [27] Pang, Bo, and Lillian Lee. "Opinion mining and sentiment analysis." Foundations and Trends® in Information Retrieval 2.1-2 (2008): 1-135.
- [28] Dave, Kushal, Steve Lawrence, and David M. Pennock. "Mining the peanut gallery: Opinion extraction and semantic classification of product reviews." Proceedings of the 12th international conference on World Wide Web. ACM, 2003.
- [29] Nakagawa, Tetsuji, Kentaro Inui, and Sadao Kurohashi. "Dependency tree-based sentiment classification using CRFs with hidden variables." Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 2010.
- [30] Wilson, Theresa, Janyce Wiebe, and Paul Hoffmann. "Recognizing contextual polarity in phrase-level sentiment analysis." Proceedings of the conference on human language technology and empirical methods in natural language processing. Association for Computational Linguistics, 2005.
- [31] Ganapathibhotla, Murthy, and Bing Liu. "Mining opinions in comparative sentences." Proceedings of the 22nd International Conference on Computational Linguistics-Volume 1. Association for Computational Linguistics, 2008.
- [32] Martín-Valdivia, María-Teresa, et al. "Sentiment polarity detection in Spanish reviews combining supervised and unsupervised approaches." Expert Systems with Applications 40.10 (2013): 3934-3942.
- [33] Esuli, Andrea, and Fabrizio Sebastiani. "SentiWordNet: a high-coverage lexical resource for opinion mining." Evaluation (2007): 1-26.
- [34] Zhang, Dongwen, et al. "Chinese comments sentiment classification based on word2vec and SVMperf." Expert Systems With Applications 4.42 (2015): 1857-1863.

- [35] Tripathy, Abinash, Ankit Agrawal, and Santanu Kumar Rath. "Classification of sentiment reviews using n-gram machine learning approach." *Expert Systems with Applications: An International Journal* 57.C (2016): 117-126.
- [36] Kang, Hanhoon, Seong Joon Yoo, and Dongil Han. "Senti-lexicon and improved Naïve Bayes algorithms for sentiment analysis of restaurant reviews." *Expert Systems with Applications* 39.5 (2012): 6000-6010.
- [37] Ortigosa-Hernández, Jonathan, et al. "Approaching Sentiment Analysis by using semi-supervised learning of multi-dimensional classifiers." *Neurocomputing* 92 (2012): 98-115.
- [38] Kaufmann, Max. "JMaxAlign: A Maximum Entropy Parallel Sentence Alignment Tool." *COLING (Demos)*. 2012.
- [39] Chen, Chien Chin, and You-De Tseng. "Quality evaluation of product reviews using an information quality framework." *Decision Support Systems* 50.4 (2011): 755-768.
- [40] Li, Yung-Ming, and Tsung-Ying Li. "Deriving market intelligence from microblogs." *Decision Support Systems* 55.1 (2013): 206-217.
- [41] Moraes, Rodrigo, João Francisco Valiati, and Wilson P. Gavião Neto. "Document-level sentiment classification: An empirical comparison between SVM and ANN." *Expert Systems with Applications* 40.2 (2013): 621-633.
- [42] Hu, Yi, and Wenjie Li. "Document sentiment classification by exploring description model of topical terms." *Computer Speech & Language* 25.2 (2011): 386-403.
- [43] Yan-Yan, Zhao, Qin Bing, and Liu Ting. "Integrating intra-and inter-document evidences for improving sentence sentiment classification." *Acta Automatica Sinica* 36.10 (2010): 1417-1425.
- [44] Gautam, Geetika, and Divakar Yadav. "Sentiment analysis of twitter data using machine learning approaches and semantic analysis." *Contemporary computing (IC3)*, 2014 seventh international conference on. IEEE, 2014.
- [45] Kiros, Ryan, et al. "Skip-Thought Vectors." *arXiv preprint arXiv:1506.06726* (2015).
- [46] Ba, Jimmy Lei, Jamie Ryan Kiros, and Geoffrey E. Hinton. "Layer Normalization." *stat* 1050 (2016): 21.
- [47] Dai, Andrew M., and Quoc V. Le. "Semi-supervised Sequence Learning." *arXiv preprint arXiv:1511.01432* (2015).
- [48] Dieng, Adji B., et al. "TopicRNN: A Recurrent Neural Network with Long-Range Semantic Dependency." (2016).
- [49] Ko, Youngjoong, and Jungyun Seo. "Automatic text categorization by unsupervised learning." *Proceedings of the 18th conference on Computational linguistics-Volume 1*. Association for Computational Linguistics, 2000.
- [50] Xianghua, Fu, et al. "Multi-aspect sentiment analysis for Chinese online social reviews based on topic modeling and HowNet lexicon." *Knowledge-Based Systems* 37 (2013): 186-195.
- [51] Bradley, Margaret M., and Peter J. Lang. "Affective Norms for English Words (ANEW): Instruction manual and affective ratings." (1999).
- [52] Nielsen, Finn Årup. "A new ANEW: Evaluation of a word list for sentiment analysis in microblogs." *arXiv preprint arXiv:1103.2903* (2011).
- [53] Thelwall, Mike, Kevan Buckley, and Georgios Paltoglou. "Sentiment strength detection for the social web." *Journal of the Association for Information Science and Technology* 63.1 (2012): 163-173.
- [54] Mohammad, Saif M., and Peter D. Turney. "Crowdsourcing a Word-Emotion Association Lexicon." *arXiv preprint arXiv:1308.6297* (2013).
- [55] Mohammad, Saif M., Svetlana Kiritchenko, and Xiaodan Zhu. "NRC-Canada: Building the State-of-the-Art in Sentiment Analysis of Tweets." *arXiv preprint arXiv:1308.6242* (2013).
- [56] Cambria, Erik, et al. "New avenues in opinion mining and sentiment analysis." *IEEE Intelligent Systems* 28.2 (2013): 15-21.
- [57] Qiu, Guang, et al. "DASA: dissatisfaction-oriented advertising based on sentiment analysis." *Expert Systems with Applications* 37.9 (2010): 6182-6191.
- [58] Jiao, Jian, and Yanquan Zhou. "Sentiment Polarity Analysis based multi-dictionary." *Physics Procedia* 22 (2011): 590-596.

- [59] Xu, Kaiquan, et al. "Mining comparative opinions from customer reviews for Competitive Intelligence." *Decision Support Systems* 50.4 (2011): 743-754.
- [60] Cruz, Fermín L., et al. "'Long autonomy or long delay?'The importance of domain in opinion mining." *Expert Systems with Applications* 40.8 (2013): 3174-3184.
- [61] Su, Zengcai, et al. "Chinese sentiment classification using a neural network tool—Word2vec." *Multisensor Fusion and Information Integration for Intelligent Systems (MFI)*, 2014 International Conference on. IEEE, 2014.
- [62] Li, Fangtao, Minlie Huang, and Xiaoyan Zhu. "Sentiment Analysis with Global Topics and Local Dependency." *AAAI*. Vol. 10. 2010.
- [63] Taboada, Maite, et al. "Lexicon-based methods for sentiment analysis." *Computational linguistics* 37.2 (2011): 267-307.
- [64] Bhatia, Parminder, Yangfeng Ji, and Jacob Eisenstein. "Better document-level sentiment analysis from rst discourse parsing." *arXiv preprint arXiv:1509.01599* (2015).
- [65] Li, Shoushan, et al. "Semi-Stacking for Semi-supervised Sentiment Classification." *ACL* (2). 2015.
- [66] Tang, Duyu, et al. "A joint segmentation and classification framework for sentence level sentiment classification." *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 23.11 (2015): 1750-1761.
- [67] Täckström, Oscar, and Ryan McDonald. "Semi-supervised latent variable models for sentence-level sentiment analysis." *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: short papers-Volume 2*. Association for Computational Linguistics, 2011.
- [68] Gindl, Stefan, Albert Weichselbraun, and Arno Scharl. "Rule-based opinion target and aspect extraction to acquire affective knowledge." *Proceedings of the 22nd International Conference on World Wide Web*. ACM, 2013.
- [69] Wang, Linlin, et al. "Sentiment-Aspect Extraction based on Restricted Boltzmann Machines." *ACL* (1). 2015.
- [70] Zhai, Zhongwu, et al. "Clustering product features for opinion mining." *Proceedings of the fourth ACM international conference on Web search and data mining*. ACM, 2011.
- [71] Lane, Peter CR, Daoud Clarke, and Paul Hender. "On developing robust models for favourability analysis: Model choice, feature sets and imbalanced data." *Decision Support Systems* 53.4 (2012): 712-718.
- [72] Rui, Huaxia, Yizao Liu, and Andrew Whinston. "Whose and what chatter matters? The effect of tweets on movie sales." *Decision Support Systems* 55.4 (2013): 863-870.
- [73] Bai, Xue. "Predicting consumer sentiments from online text." *Decision Support Systems* 50.4 (2011): 732-742.
- [74] Walker, Marilyn A., et al. "That is your evidence?: Classifying stance in online political debate." *Decision Support Systems* 53.4 (2012): 719-729.
- [75] Schapire, R. E. "The Boosting Approach to Machine Learning An Overview In *MSRI Workshop on Nonlinear Estimation and Classification*." (2002): 149-1.
- [76] Rokach, Lior. "Ensemble methods for classifiers." *Data mining and knowledge discovery handbook*. Springer US, 2005. 957-980.
- [77] Fersini, Elisabetta, Enza Messina, and Federico Alberto Pozzi. "Sentiment analysis: Bayesian ensemble learning." *Decision support systems* 68 (2014): 26-38.
- [78] Fersini, Elisabetta, Enza Messina, and Federico Alberto Pozzi. "Expressive signals in social media languages to improve polarity detection." *Information Processing & Management* 52.1 (2016): 20-35.
- [79] Xia, Rui, and Chengqing Zong. "A POS-based Ensemble Model for Cross-domain Sentiment Classification." *IJCNLP*. 2011.
- [80] Pan, Sinno Jialin, et al. "Cross-domain sentiment classification via spectral feature alignment." *Proceedings of the 19th international conference on World wide web*. ACM, 2010.
- [81] Sun, Shiliang, Honglei Shi, and Yuanbin Wu. "A survey of multi-source domain adaptation." *Information Fusion* 24 (2015): 84-92.

- [82] Marrese-Taylor, Edison, Juan D. Velásquez, and Felipe Bravo-Marquez. "A novel deterministic approach for aspect-based opinion mining in tourism products reviews." *Expert Systems with Applications* 41.17 (2014): 7764-7775.
- [83] Choi, Yejin, and Claire Cardie. "Adapting a polarity lexicon using integer linear programming for domain-specific sentiment classification." *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 2-Volume 2*. Association for Computational Linguistics, 2009.
- [84] Huang, Sheng, Zhendong Niu, and Chongyang Shi. "Automatic construction of domain-specific sentiment lexicon based on constrained label propagation." *Knowledge-Based Systems* 56 (2014): 191-200.
- [85] Yalamanchi, Deepak. Sideeffective-system to mine patient reviews: sentiment analysis. Diss. Rutgers University-Graduate School-New Brunswick, 2011.
- [86] Swaminathan, Rajesh, Abhishek Sharma, and Hui Yang. "Opinion mining for biomedical text data: Feature space design and feature selection." *The Nineth International Workshop on Data Mining in Bioinformatics, BIODDD*. 2010.
- [87] Liu, Bing, and Lei Zhang. "A survey of opinion mining and sentiment analysis." *Mining text data*. Springer US, 2012. 415-463.
- [88] Bhatia, Ramanjot S., et al. "Extracting information for generating a diabetes report card from free text in physicians notes." *Proceedings of the NAACL HLT 2010 Second Louhi Workshop on Text and Data Mining of Health Documents*. Association for Computational Linguistics, 2010.
- [89] Dickinson, Brian, and Wei Hu. "Sentiment analysis of investor opinions on twitter." *Social Networking* 4.03 (2015): 62.
- [90] Liu, Kun-Lin, Wu-Jun Li, and Minyi Guo. "Emoticon smoothed language models for twitter sentiment analysis." *Aaai*. 2012.
- [91] Da Silva, Nadia FF, Eduardo R. Hruschka, and Estevam R. Hruschka. "Tweet sentiment analysis with classifier ensembles." *Decision Support Systems* 66 (2014): 170-179.
- [92] Hu, Xia, et al. "Exploiting social relations for sentiment analysis in microblogging." *Proceedings of the sixth ACM international conference on Web search and data mining*. ACM, 2013.
- [93] Bravo-Marquez, Felipe, Marcelo Mendoza, and Barbara Poblete. "Combining strengths, emotions and polarities for boosting Twitter sentiment analysis." *Proceedings of the Second International Workshop on Issues of Sentiment Discovery and Opinion Mining*. ACM, 2013.
- [94] Coletta, Luiz Fernando Sommaggio, et al. "Combining classification and clustering for tweet sentiment analysis." *Brazilian Conference on Intelligent Systems, 3th*. Universidade de São Paulo-USP, 2014.
- [95] Lu, Tao-Jian. "Semi-supervised microblog sentiment analysis using social relation and text similarity." *Big Data and Smart Computing (BigComp), 2015 International Conference on*. IEEE, 2015.
- [96] Saif, Hassan, et al. "Semantic patterns for sentiment analysis of Twitter." *International Semantic Web Conference*. Springer, Cham, 2014.
- [97] Baecchi, Claudio, et al. "A multimodal feature learning approach for sentiment analysis of social network multimedia." *Multimedia Tools and Applications* 75.5 (2016): 2507-2525.
- [98] Hu, Xia, et al. "Unsupervised sentiment analysis with emotional signals." *Proceedings of the 22nd international conference on World Wide Web*. ACM, 2013.
- [99] Bakliwal, Akshat, et al. "Mining Sentiments from Tweets." *WASSA@ ACL*. 2012.
- [100] Saif, Hassan, et al. "Senticircles for contextual and conceptual semantic sentiment analysis of twitter." *European Semantic Web Conference*. Springer, Cham, 2014.
- [101] Wu, Fangzhao, Yongfeng Huang, and Yangqiu Song. "Structured microblog sentiment classification via social context regularization." *Neurocomputing* 175 (2016): 599-609.
- [102] Collobert, Ronan, et al. "Natural language processing (almost) from scratch." *Journal of Machine Learning Research* 12.Aug (2011): 2493-2537.

- [103] Pennington, Jeffrey, Richard Socher, and Christopher D. Manning. "Glove: Global vectors for word representation." In EMNLP. 2014.
- [104] Blei, David M., Andrew Y. Ng, and Michael I. Jordan. "Latent dirichlet allocation." *Journal of machine Learning research* 3.Jan (2003): 993-1022.
- [105] Fahrni, Angela, and Manfred Klenner. "Old wine or warm beer: Target-specific sentiment analysis of adjectives." *Proc. of the Symposium on Affective Language in Human and Machine, AISB*. 2008.
- [106] Cao, Qing, Wenjing Duan, and Qiwei Gan. "Exploring determinants of voting for the "helpfulness" of online user reviews: A text mining approach." *Decision Support Systems* 50.2 (2011): 511-521.
- [107] Lund, Kevin, and Curt Burgess. "Producing high-dimensional semantic spaces from lexical co-occurrence." *Behavior Research Methods, Instruments, & Computers* 28.2 (1996): 203-208.
- [108] Xu, Tao, Qinke Peng, and Yinzhao Cheng. "Identifying the semantic orientation of terms using S-HAL for sentiment analysis." *Knowledge-Based Systems* 35 (2012): 279-289.
- [109] Pai, Mao-Yuan, et al. "Electronic word of mouth analysis for service experience." *Expert Systems with Applications* 40.6 (2013): 1993-2006.
- [110] Zhang, Wenhao, Hua Xu, and Wei Wan. "Weakness Finder: Find product weakness from Chinese reviews by using aspects based sentiment analysis." *Expert Systems with Applications* 39.11 (2012): 10283-10291.
- [111] Das, Amitava, and Sivaji Bandyopadhyay. "Subjectivity detection using genetic algorithm." *Computational Approaches to Subjectivity and Sentiment Analysis* (2008): 14.
- [112] Irsoy, Ozan, and Claire Cardie. "Opinion Mining with Deep Recurrent Neural Networks." EMNLP. 2014.
- [113] Socher, Richard, John Bauer, and Christopher D. Manning. "Parsing with compositional vector grammars." *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Vol. 1. 2013.
- [114] Socher, Richard, et al. "Recursive deep models for semantic compositionality over a sentiment treebank." *Proceedings of the 2013 conference on empirical methods in natural language processing*. 2013.
- [115] Paulus, Romain, Richard Socher, and Christopher D. Manning. "Global belief recursive neural networks." *Advances in Neural Information Processing Systems*. 2014.
- [116] Mikolov, Tomáš, et al. "Extensions of recurrent neural network language model." *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on*. IEEE, 2011.
- [117] Tai, Kai Sheng, Richard Socher, and Christopher D. Manning. "Improved semantic representations from tree-structured long short-term memory networks." *arXiv preprint arXiv:1503.00075* (2015).
- [118] Liu, Pengfei, Shafiq R. Joty, and Helen M. Meng. "Fine-grained Opinion Mining with Recurrent Neural Networks and Word Embeddings." EMNLP. 2015.
- [119] Kalchbrenner, Nal, Edward Grefenstette, and Phil Blunsom. "A convolutional neural network for modelling sentences." *arXiv preprint arXiv:1404.2188* (2014).
- [120] Mikolov, Tomas, et al. "Efficient estimation of word representations in vector space." *arXiv preprint arXiv:1301.3781* (2013).
- [121] Kim, Yoon. "Convolutional neural networks for sentence classification." *arXiv preprint arXiv:1408.5882* (2014).
- [122] Tang, Duyu, et al. "Learning Sentiment-Specific Word Embedding for Twitter Sentiment Classification." *ACL* (1). 2014.
- [123] Le, Quoc, and Tomas Mikolov. "Distributed representations of sentences and documents." *Proceedings of the 31st International Conference on Machine Learning (ICML-14)*. 2014.
- [124] Chen, Minmin, et al. "Marginalized denoising auto-encoders for nonlinear representations." *International Conference on Machine Learning*. 2014.
- [125] Zhang, Pu, and Zhongshi He. "Using data-driven feature enrichment of text representation and ensemble technique for sentence-level polarity classification." *Journal of Information Science* 41.4 (2015): 531-549.

- [126] Severyn, Aliaksei, and Alessandro Moschitti. "Twitter sentiment analysis with deep convolutional neural networks." Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, 2015.
- [127] Kim, Jihie, et al. "Sentiment Prediction Using Collaborative Filtering." ICWSM. 2013.
- [128] Li, Changliang, et al. "Parallel recursive deep model for sentiment analysis." Pacific-Asia Conference on Knowledge Discovery and Data Mining. Springer, Cham, 2015.
- [129] Vo, Duy-Tin, and Yue Zhang. "Target-Dependent Twitter Sentiment Classification with Rich Automatic Features." IJCAI. 2015.
- [130] Mesnil, Grégoire, et al. "Ensemble of generative and discriminative techniques for sentiment analysis of movie reviews." arXiv preprint arXiv:1412.5335 (2014).
- [131] Basari, Abd Samad Hasan, et al. "Opinion mining of movie review using hybrid method of support vector machine and particle swarm optimization." Procedia Engineering 53 (2013): 453-462.
- [132] Baldominos Gómez, Alejandro, Nerea Luis Minguenza, and María Cristina García del Pozo. "OpinAIS: an artificial immune system-based framework for opinion mining." (2015).
- [133] Stylios, George, Christos D. Katsis, and Dimitris Christodoulakis. "Using Bio-inspired intelligence for Web opinion Mining." International Journal of Computer Applications 87.5 (2014).
- [134] Govindarajan, M. "Sentiment analysis of movie reviews using hybrid method of naive bayes and genetic algorithm." International Journal of Advanced Computer Research 3.4 (2013): 139.
- [135] Carvalho, Jonnathan, Adriana Prado, and Alexandre Plastino. "A statistical and evolutionary approach to sentiment analysis." Proceedings of the 2014 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)-Volume 02. IEEE Computer Society, 2014.
- [136] Arora, Shilpa, et al. "Sentiment classification using automatically extracted subgraph features." Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text. Association for Computational Linguistics, 2010.
- [137] Escalante, Hugo Jair, et al. "Term-weighting learning via genetic programming for text classification." Knowledge-Based Systems 83 (2015): 176-189.
- [138] Mayfield, Elijah, and Carolyn Penstein-Rosé. "Using feature construction to avoid large feature spaces in text classification." Proceedings of the 12th annual conference on Genetic and evolutionary computation. ACM, 2010.
- [139] White, David R. "Software review: the ECJ toolkit." Genetic Programming and Evolvable Machines 13.1 (2012): 65-67.
- [140] Zhang, Yifeng, and Siddhartha Bhattacharyya. "Genetic programming in classifying large-scale data: an ensemble method." Information Sciences 163.1 (2004): 85-101.
- [141] Korn, Michael F., and Loryfel Nunez. "Profiling Symbolic Regression-Classification." Genetic Programming Theory and Practice VI. Springer US, 2009. 1-14.
- [142] Iqbal, Muhammad, Will N. Browne, and Mengjie Zhang. "Reusing building blocks of extracted knowledge to solve complex, large-scale boolean problems." IEEE Transactions on Evolutionary Computation 18.4 (2014): 465-480.
- [143] McConaghy, Trent. "Latent variable symbolic regression for high-dimensional inputs." Genetic Programming Theory and Practice VII (2010): 103-118.
- [144] Espejo, P. G., S. Ventura, and F. Herrera. "A Survey on the Application of Genetic Programming to Classification." IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 2.40 (2010): 121-144.
- [145] Graff, Mario, et al. "Semantic Genetic Programming Operators Based on Projections in the Phenotype Space." Research in Computing Science 94 (2015): 73-85.

- [146] Moraglio, Alberto, Krzysztof Krawiec, and Colin G. Johnson. "Geometric semantic genetic programming." Proceedings of the 12th international conference on Parallel Problem Solving from Nature-Volume Part I. Springer-Verlag, 2012.
- [147] Castelli, Mauro, Sara Silva, and Leonardo Vanneschi. "A C++ framework for geometric semantic genetic programming." Genetic Programming and Evolvable Machines 1.16 (2015): 73-81.
- [148] Maas, Andrew L., et al. "Learning word vectors for sentiment analysis." Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1. Association for Computational Linguistics, 2011.
- [149] Ramteke, Ankit, et al. "Detecting Turnarounds in Sentiment Analysis: Thwarting." ACL (2). 2013.
- [150] Joshi, Aditya, Vinita Sharma, and Pushpak Bhattacharyya. "Harnessing Context Incongruity for Sarcasm Detection." ACL (2). 2015.
- [151] Strapparava, Carlo, and Rada Mihalcea. "Learning to identify emotions in text." Proceedings of the 2008 ACM symposium on Applied computing. ACM, 2008.
- [152] González-Bailón, Sandra, Rafael E. Banchs, and Andreas Kaltenbrunner. "Emotions, Public Opinion, and US Presidential Approval Rates: A 5-Year Analysis of Online Political Discussions." Human Communication Research 38.2 (2012): 121-143.