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SENTIMENT ANALYSIS: COTEMPORARY RESEARCH AFFIRMATION OF RECENT LITERATURE

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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 manuscript, the present state of various techniques of sentiment analysis for opinion mining like machine learning and lexicon-based approaches are 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 thegroup of language processors (NLP).Sentiment Analysis is one of this. It is the task of computational treatment which generally treats expressions of the private states in written text as pointed out by [1]. This includeshuman states which are generally not open to objective verification or observation. It is worth pointing out that Sentiment Analysis, which is also referred to as opinion mining as pointed out by [2] and [3] was initially proposed during the early 20^{th} century. It has gradually been a highly active area of research.

Opinion mining or Sentiment analysis refers to a discipline dealing with the analysis 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 [3]that are presented in text, like tweets as [4] points out, forums [5], reviews [6], news [7], as well as blogs [8].It is also worth pointing out that sentiment analysis generally makes it highly possible to identify the trends of individuals as pointed out by [9].

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 which it has been used: from forecasting the box office movie revenues as pointed out by [10] to estimating the gross happiness indexes of the countries [11]as well as following affective responses of the users of social media to the emerging news stories [12]. Essentially, opinion mining provides both the researchers, as well as the userswith the chance of assessing huge chunks of data in a manner that is highly efficient (timely) and also effective (precise). This makes them to be in a position to extract affective content. Analysis like that is non-trivial and always highly challenging given that various studies have indicated that even the humans generally tend to disagree on online communication's affective contents pointed out by[13]. Simplistic approaches, like comparing occurrences of negative as well as positive terms in the text, are in particular inadequate as pointed out by [1]. The major reason for this is because in contrast to the keyword drivendatamanagers (like the search engines) in which incidence of a word always offers great evidence regarding the topicality of a given document, 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 [14]. These generally entails 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 [15]. Feature extraction generally generates diverse representation of the plain text documents referred to as the features. In addition, feature selection then selects besides filtering thefeatures in order to get highly relevant features to the given topic. Finally, a machine learning classifier makes use of the attributesin categorizing the datasources.

The major goal of sentiment analysis entails automatically predicting the polarity of the sentiment (like negative, neutral and positive) of a piece of the text. Various researchers such as [3], [2], [1] have established that in comparison to other text categorization activities, like topic classification, it is worth pointing out that sentiment categorization ishighly 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 [16]. The other shortcoming includesdomain dependenceas pointed out by [17], [18] and 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 environmentsdue to ambiguity, as well asthe uniqueness of the sentiment expressions associated to trained, as well as target domains.

Currently, there are numerous reviews [3], [19]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 [5] and[20]generally looked into the research contributions which are linked to sentiment classification through the use of machine learning, as well as lexicons.

The main contribution of the manuscript entails reviewing the present state of the art linked to sentiment analysis. At the same time, it also taxonomizesdivergent 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 exploresthe 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 andunsupervised, supervised, evolutionary computational, domain specific, as well as feature co-presencetraining 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 ascomparingperformances of term characteristics and phrasal characteristics which are utilized in sentiment analysis of thereviews. 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 developML tools-basedopinion mining were Pang, Li, and Vaithyanathan. They experimented with diverse machine learning methods as well as attribute types. These authors established that unigrams constantlyoffer the highest accuracyif 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 [21]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 [22]emphasized on ensembles of different types of attributes and classifier. The work focused on the mix of word features, as well as multipledata tagsfor the generation of the best outcomes. A number of the works which are linked withsentiment-analysis are employed unigrams as features due to the fact that it is very easy yet highly effective. Word associations in phrases areirrefutablysignificant. 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 [23]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 alongwith (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 attributesin addition to lowering the task of over-fitting when deploying an ML learning model.

LSI is one of the well-known feature transformation techniques as pointed out by [24]. LSI technique generally converts the text area to a new axial mechanism that is a linear combination of actual term attributes. (PCA) isemployed for the achievement of this goal as pointed out by [25]. 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 isgenerally a highly technique that isunsupervised that is generally blind to the underlying class-distribution [26].

There are numerous other kinds of statistical models that can be utilized in FS such as HMM as well as the Latent Dirichlet Allocation (LDA). They were employed by [27]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 worth pointing out that the feature selection schemes that were proposed by [27]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 mostdifficult task in the extracting features. The main aim of the task includes the identification of irony reviews. The work was proposed by [28]. The researchers were mainly aimed at defininga feature model for representingsection of subjective knowledgethat 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.

Various researchers like [29], [30], [31]offered the suggestionof novel attribute lowering methods. [32]Also developed least squares differentiation analysis that depicted that orthogonal analysis is highly important when it comes practical services. [29]Also developed manifold integrating architecture to provide a unitedopinion for the supervised, unsupervised, as well as semi-supervised attributelowering techniques. [30]Alsoproposed anattributechoosing technique based on joining l2, 1 –norms minimization. It also illustrated its efficiency onthe six datasets. [31]Alsoproposeda novelprogram 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 [33]. 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 [34]. 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[2]. At the same time, in the given modules, attribute engineeringis highly significant. Other than the frequently utilizedgroup of- termsattributeson the basis of unigrams and bigramsamong others, [35], as [36] points out, syntactic properties, semantic properties [37]as well as impact of negators[38]are also incorporatedas 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 [39].

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, MaximumEntropy, the term- association based attribute groups for categorization andSupport Vector Machine algorithms for the purpose ofclassification as pointed out by [21]. The weighted combination, fixed combination, meta-classifier combination areassessed for the three ensemble approaches.

Martin-Valdivia et al., have employed MC database forcarrying out the sentiment analysis[40]. The researchers produced three primary analysis modeli.e., MC-ML that is applying ML training model over MC databaseprovided in Spanish; MCE-ML, which is applyingMachine Learning approach over MC databaseprovided in English; MCE-SO,which is using SentiWordNet for the incorporation oflexical data and obtain the polarity categorization as pointed out by [41]. Lastly, voting system, as well as the approach of grouping has beentaken into consideration for getting the result.

It is also worth pointing out that Zhang et al., have also put forward a new approachfor sentiment grouping that is based on SVMperfas well as word2vec [42]. Word2vec is used for clustering the same features for major purpose of detecting the semantic attributes inthe chosen context and Chinese. It is worth pointing out that the authorsboth 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 [43]. They have employed four diverse machine learning methods like Maximum Entropy, Naïve Bayes, SVM, as well as Stochastic Gradient Descenttogether with n-gram methods such as bigram, unigram, unigram bigram, trigram, bigram trigram, as well as unigram+bigram+trigram. SVM with unigram+bigram+trigrammethod offers the optimum outcome incomparison to the other kinds of techniques.

It is also worth pointing out that Kang and Yoo [44] also proposed an improved NB classifier for the provision of solutions to the challenge of the capability for favourablecategorization 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 valuewhich is average.

BN was usedby authors in [45] 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 [46]for the detection of parallel phrases between any opinion groups withvery minimal quantities of learning information. The other methods proposed so as to spontaneouslyobtain parallel information out of non-parallel datasets utilize language specific techniques or need large volume of learning information.

The authors in [47]utilized two multi-class SVM-driven methods: One-vs-Entire SVM, and Single-Machine Multi-class SVM for the categorization ofreviews. 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 [48] as the sentiment polarity classification model.Different from the problem ofbinary classification, theywere of the argument that opinion subjectivity, as well as expresser credibility also ought to be considered. They suggested an architecture, which presents acompressednumber 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 thereaftergrouped the opinionsthrough the use of SVM.

Moraes and Valiati [49] offered an empirical assessment between SVM, as well as the artificial neural networks ANNs concerning document-level sentiment assessment. The authors did the assessmentdue 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 resultsas 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 modelsfor attributechoosing and weighing in a conventional BOWs method. Thesimulation results depicted that ANN produced largely superior outcomes as compared to SVM excluding certain imbalanced information situations.

Hu and Li[50]proposed an approach for mining the content patterns of certain wordsat 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 Modelwhich 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 automatedmining 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 the structure plays a role in conveying sentiment information. Themodel 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 [51]offers 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 ofsentiment course of a feedback sentence needs more than the attributes that are within the given sentence.

Both decision trees, as well as decision standardsaim to decide rules on attribute area. On the contrary, the decision treegenerally tends to determine that the goal is achievedthrough the use of a hierarchical approach. It is also noteworthy that Quinlan[52]researched about the decision tree, as well as the decision rule problems in one framework because as a specified route in the decision tree might be regarded as a classification rule of the text case. The main differences which exists between decision trees and rules is the primary cause that these structures are highly stringent hierarchical division of information area, while rule-based categories allow overlaps in the decision area.

2.3 Unsupervised Learning

Motivated by success of the word vectors, [53]generally proposes skip thought vectors, a technique of training sentence encoder through the prediction of the preceding, as well as the following sentence. The representation which is trained by thepurpose generally performs competitively on a wide suite of the evaluated tasks. Highly advanced training methods like layer-normalization[54]results into further improvement of the results. On the contrary, skip-thought vectors have superior performance over the supervised models that directly obtain the requiredefficiencyparameter on a particular corpus. This is the situation for text classification tasks thatmeasure if a particular concept is encoded well in a representation. This takes place even if the databases arecomparatively smaller on the basis of modern standards, which always consists of just some thousand labelled illustrations.

Other than learning a generic representation on one big dataset and then assessing on other tasks or on other datasets, a proposal was made by [55]through the use of similar unsupervised purposessuch as sequence auto encoding, as well as language modelling to first pertain a given model on a dataset and thereafter fine-tuning it for a particular task. Themethod posted superior efficiency over trainingsimilar model from random initialization. At the same time, the model achieved state of the art on numerous text grouping databases.Combination of language modelling with the topic modelling and fitting a small supervised feature extractor on top has also resulted into the achievement of stronger results on in-domain document stage sentiment analysisas pointed out by [56].

Ko and Seo[57]also proposed a technique which generally divides documents into sentences and categorized every sentence through the use of keyword lists of eachcategory andby the measure of sentence similarity.

At the same time, Xianghua and Guo [58]invented an unsupervised strategy for learning in order to discover automatically the different aspects which were detailedin 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.[38] also created Opinion mining lexiconwhere words are classified as negative or positive. The other lexicon is ANEW, which was offered by [59]. 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 [60] 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 [41]also constructed Senti-Word-Net lexicon, which is developed on WordNet. Senti-Strength lexicon was developed by the authors in [61] and it attempts to determine the strength of the term. In [62], 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 [3], 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 obtainedthrough the use of a mix of 775310 tweets that have negative or positive hash-tags; the expressions have been were classified as either discouragingor 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[63]. At the same time, the same team also presented Sentiment140-Lexicon that makes use of discouraging or encouraging emoticons for groupingthe 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 [64]. ALGA's adaptive lexicons can be compared to NRC hashtag, Sentiment140, AFINN, as well as Bing Liu's lexicon that have been widely used in literature.

The dictionary-basedtechnique is having a big disadvantage that is the incapability to get opinion words which are having a domain, as well as context specific orientations.At the same time, it is worth pointing out that Qiu and He [65]also used the dictionary-based technique for the identification of sentiment sentences in 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-basedmethodforembark upontopic 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[66]for discriminatingopinion polarity throughseveral-string structure matching program. Theprogram has been implementedon Chinese internet feedback. The studyset upvariousexpressive 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 [67]utilizedbi-layer CRF methodwith undecided inter-dependencies to obtain comparable associations.

They did this by utilizingthe complexinter-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 visualizingrelative relations between customer reviews, as well as the products. At the same time, they presented the outcomesas comparative association graphs for assistance when it comes to the management of enterprise risk. Additionally, they functioned on variouscellular consumerfeedbacks 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 [68] 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 featuresand parts of a specific object. The researchers' primary aim comprised a domain-specific OM.At the same time, the authors defined a wide range of domain-oriented resources that are holding most useful information related to how users are presenting opinions on a given sector. The studyused resources that were persuadeddirectly from a broad set of annotated listings.At the same time, they worked on three different domains, 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 domainindependent methods. The results which they obtained illustrated the importance of the domain in constructing precise opinion mining systems 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 miningthat have been depicted in the current studies withregards to sentence level, document level, as well as aspect level have been summarized in thissection.

2.5.1 Document level

Conventional classification models in ML techniques, likeNBs classifier, SVM, and maximum-entropy classification model, are utilizedfor document stageopinion categorization on different types of characteristics thattypically comprisesbigram, unigram, location data [1], POS tags, Semantic characteristics [69]as well as discourse features as pointed out by[70]. [71] has also proposed integrated classification modelson the basis of SVM, and NBs classification model.

Motivated by LDA topic method, certain generative methods have generally been suggested for document specificopinion mining,which generally includes combined sentiment topicmethod [72]as well as dependency-sentiment- LDA method[73] 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 [74]as well as discourse structure-oriented reweighting mechanism [75].

For the minimization of dependencyon annotated database, certain semi-supervised methodsare proposed that generally includes active learning-oriented approaches [76] thatmanually categorizes sentimentally unclear documents and co-training methods[77] for unbalanced opinion categorization.In the recent past, a joint learning framework that generally mixes semi-supervised model was suggested as pointed out by [78].

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 by [79]. At the same time, it is worth pointing out that CRFs were used to exploit the dependencies of the sentences as pointed out by [80]. In the recent past, there was the proposal of a joint segmentation, as well as classification framework as pointed out by [81].

Because of the unavailability of sentence labels, a series approach, which integrates completely supervised document groups, along with semi-supervised sentence groupsare proposedforconducting semi-supervised classification as pointed out by [82].

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 oftenemployed. At the same time, linguistic knowledge, like part-whole patterns [83], along with metonymy discriminators [84] have been considered. At the same time, double propagation codingwas suggested for hybrid opinion words, as well as for aspects extraction [85]. In addition, rule-based approachesare also largely successful for identifyingcleardimensionsand entities as pointed out by [86]. Comparative phrases are incorporated in the identification of implied dimensions as pointed out by [87]. At the same time, it is worth pointing out that clause patterns are also exploredfor dividing documents into multiple sentencesthat arebeneficial when it comes to aspect detection [88].

LDA topic model, as well as its deviations are implementedfor dimensionsidentifications [89] and combined aspect along with sentimentrecognitionas indicated by [90].

An aspect grouping technique that entails extrinsicinformationwasproposedfor less supervised dimension recognition as pointed out by [91].

2.6 Ensemble TrainingApproaches

There are numerous studies which have been carried out on sentiment categorization in literature. However, the number of the studies that employclassification model for English language feedback are generally very limited.

Lane and Clarke [92]offered Machine learning modelfor solving the problem of locating documents that carries negative or positive favourabilityin media analysis.

The investigation has also been done by Rui and Liu [93] concerning the usageof ML learning model over liveinformation obtained from Twitter. In this research, the scholars strived to investigate whether and the manner in which Twitter (WOM) is affectingthe 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 tweetsconsidering the tweet's unique characteristics. At the same time, they distinguished between pre-consumer opinion as well as post-consumer opinion.

Bai[94] 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 [40]. 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 researchersincludedSentiWordNetopinion dataset into English dataset which resulted into the generation ofa novel unsupervised method through incorporation of semantic based method. Further, these researchers alsojoined 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[95]for the classification of stance. Stancerefers to the comprehensive opinion as perceived by a user with respect to a given idea, object, or a given position[96]. It is worth pointing out that stance is very similar to a perspectiveor 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[95]generally classified stance held by an individual or a group. The work was adopted on political debates.

According to [97], 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 based on the efficiency of the classifier who was previously trained. When the previous classifier faced various difficulties in properly classifying a given learning structure, thenthe 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 categorizingitsgiven 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 buildingon an ensemble technique are numerous and a categorization has been offered by [98]. 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 rile with the prime agenda of computing their mean estimation accuracy. Some of the main examples of rule-based ensembles include majority voting, in which the output prediction per sample is the class which is the most common; and weighted combination, that linearly aggregates the base classifiers predictions. Meta learning methods generally employ predictions from element classifiers asthe main features for Metalearning model.

As pointed out earlier by [21], theweighted mixtures of attribute groups may be quite effective in the task of opinion grouping due to the fact that the weights of the tool arerepresenting the relevance of the diverse feature sets (like POS, n-grams among others.) to sentiment classification, rather than assigning relevance to every feature individually. The rule-based ensembles benefits have also been captured by [99] in whichnumerous variants of voting rules have been studied exhaustively in several datasets, with focus on the complexity that which may be brought about by the application of the approaches. In another work, [100]have done a comparison of majority voting rule with other approaches through the use of three kinds of subjective signals: emoticons, adjectives, emphatic expressions, as well as expressive elongations. In [21]a Metaclassifier ensemble model isanalysed 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, as pointed out by [101]. The researchers have suggested the application of several rule-based ensemble models, which includes a sum rule, as well as two weighted combination approaches trained with other loss functions. Base classifiers are trained with n-grams, as well as POS features. The models gain huge outcomes for cross-domain opinion categorization process.

For the second dimension, it is worth pointing out that the concurrent models generally divide the original dataset into numerous subsets from whereseveral classifiers learn in a parallel fashion, something which creates a classifier composite. It is also worth pointing out that the most popular method which processes the sample simultaneously is bagging as pointed out by [98]. Bagging generally intends to enhance the classification through mixing predictions of classifiers which are built on random subsets of original data. Sequential approaches generally do not divide the dataset, however, there is a collaboration between the steps of learning, taking advantage from past iterations of the process of learning for the improvement of the quality of global classifier. A highly interesting sequential technique is boosting, that consists in iteratively enabling poor-performing models to learn on diverse training data. It is worth pointing out that the classifiers which are trained in this way are thereafter combined into one classification model thatcanattain better performance in comparison to the element classifiers.

2.7 Domain-specific Learning

Because there are several numbers of domains which are always engaged in onlinecontents which are consumercreated, 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 [102]. 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 [102] and [17]. 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 [103]. Several opinion domain implementation approaches are suggested for overcoming this limitation in different methods as pointed out by [102] and[17].

So as to effectively manage the domain-relianceissue when it comes to opinion mining, there are numerous methods which are presented. A number of researchers have attempted to manage the issue by enabling models to learn domain-specific opinion mining [1], [104]. One of the main challenges which are faced in these techniques include the fact that the classified information in the test-domainmight 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, [104]also proposed a very interesting method for obtaining both aspects, as well as sentiment expressions in the tourism industry. In addition, they suggested a novel approach for domain-specific sentiment 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[105] or to construct domain-specific sentiment lexicon as pointed out by [106]. 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 isgenerally not taken into consideration in thesetechniques.

[107]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 [108]which researched about the link or the connection between bio-entities. The research also defined newerattributes for

SVMmachine classifier and thereafter combined them with the lexicon-based approach for predicting polarity. At the same time, the research also identified the strength of relationship through the use of SVR. A different challenge linked to drug reviews has also been mentioned by [109]. 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 inthe biomedical opinion mining. [110] extracted numeric fields using regular expressions.

In addition, Dickinson and Hu [111] also predicted a sentiment value for tweets related to stock on Twitter. He illustrates that there is a correlation between the opinion and motion of the stock price of a firm within a real-time liveenvironment thatdepicted that consumer facing firms are always affected differently in comparison to the other firms.

In addition, Liu et al. in [112] also formed a dataset and thereafter labelled the tweets through the use of both emoticons, as well as manual labelling. In addition, Da Silva et al. [113]also proposed the use of classifier ensembles for Twitter sentiment classification.

Certain techniques generally combine the use of lexicons, as well as learning-basedmethods for opinion grouping like [114]and [63]. At the same time, it is worth pointing out that Hu et al. in [115] incorporated the data that was networked to employ emotional stretch for opinion categorization. Inthe work which was done by [116], features which are extracted on the basis of semantic fundamentals and are included in the learning set. In the work which was done by [117], a different approach which employs meta-level attributes for Twitter opinion mining is engaged. In this method, different aspects of terms are analyzedsubjectivity along with polarity categorization. The study in [117] 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 [118] also suggested an adaptation process for opinion lexicons for interpreting the true sense of terms in different contexts in Twitter. The methods which are put forward in this report majorly attempts to generate an adaptive sentiment lexicon. It is also worth pointing out that Coletta et al. in [119]employed an SVM classifier with a cluster ensemble for the categorization of twitter messages. Lu [120]employed microblog-microblog relations, which incorporates social relations, as well as text similarities to build a partially supervised classification model. Further, the author in [121] 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.Baecchi et al. [122]employed a multi-dimensional method for feature learning to categorize the tweets which might be containing pictures. In addition, the study in [123]also included emotional symbols in anon-Supervised Learning scenario in Tweets. The authors in [124] employed a sentiment scoring function to classify tweets. In addition, the study in [125] engaged a lexicon-driven approach, in which the authors computed sentiment-orientation along with its robustness in tweets. Finally, the authors in [126] embedded social networking links among twitter messages of similar researcher and social associations among different consumers for theenhancement 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 [127]. The representations, which are learntthrough 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 [128]. 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 [129].

Getting co-occurrence patterns, as well asseed 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 [130]. 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 in smaller in size as indicated in [1].

Latent Semantic Analysis (LSA) refers to a statistical methodthat is employed for the analysisof 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 [24]. The study in [131] 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 gets 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 gain. 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 [132]. Semantic space refers to the space where the terms are reflected by points.The position of all pointstogether with every axis is in a wayconnected to the meaning of the words. [133]also developed a technique that is founded on HALand 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. Theoutcome whichthey got pointed out that they outperformed SO-PMI. At the same time, it also indicated the benefits which are brought about by modelling semantic-orientationfeatures when compared to initial HAL approach.

It is also worth pointing out that semantics of e-WOM content is employed in examiningeWOM content analysis in a manner that was Pai and Chu[134] proposed. They obtained both discouraging and encouragingappraisals, and further assisted customers when they are making their decisions. Their technique can be used in helping firms to be in a better position tounderstandservice or product appraisals, and based on this, they can translate thebeliefs 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. Theoutcomes depicted that the suggested model is largely effective in providing e-WOM feedbacks that are associated with products and services.

Semantic approaches can be used together with the statistical techniques to carry out SA task as the research, which was put forward in [135] who adopted the two techniques to establish the various weaknesses of the products from the internet feedbacks. Thelimitations 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. At the same time, they assembled products feature words into matching aspects through the application of semantic techniques. They have used sentence-based SA approaches for the determination of the polarity of every aspect within the sentences considering the effects of adverbs of degree. The study was successful in determining different limitations of the goods as it was perhaps the highest unsatisfied dimensionwithin 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 of the.

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 real-valued vector as word characteristics for sentiment analysis without any type of characteristic engineering. The task of the sentiment expression obtaining is typically presented as token-stage series classification issue. So as to effectively address achallenge 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 [136]. 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 [137] implemented Deep-RNNs for opinion mining from the phrases. It depicted that these Deep RNNs had superior performance over CRFs. The method is often developed by stacking Elman-kind 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 the NLParea, syntactic parsing is regarded as the main problem due to its prominence in functioning with both terms and their underlying meanings. The studies [138]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 [139]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 for larger nodes in the tree via the similar tensor-based composition formula. Similarly, the study in [140] worked on the prominence of a similar tree structured RNN for fine-tunedopinion mining.

In the recent past, multiple studies are presented refined kinds of RNNsfor functioning withvarious shortcomings of vanilla RNN model. It is worth pointing out that Bidirectional-RNNs are often developed on the idea that the outcome at a given point-of-time t can be based on both the past components in the sequence andalso on the future elements. For instance, in order to predict a word which is missing in a given sequence, a 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 based on the latent conditions of the RNNs. Deep bidirectional-RNNs function on same lines as that of bidirectional-RNNs,although there are now several layers foreach sequence. In real life, it results into greater learning capacity. Mikolov et al. [141]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 [142]. Liu el al. [143]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 dominantNN for semantic combination is CNNs. [144]described a convolutional framework which is referred to as Dynamic-CNNs, which is used in semantically modelling phrases. The system engagesvariable 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. [145], [146]also introduced the CBOWas 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-gramapproach generally predicts the adjacent words based on inserting the current word. Additionally, [128]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-existencedata from the dataset.

In the NLP realm a large volume of research in in-depth training was shifted towards methods which entails training term vector reflections via the utilization of neural language methods as pointed out by [147]. Un-interrupted reflections of terms like vectors has generally proven to be a highly effective technique in a number of the NLP tasks, including sentiment analysis as pointed out by [148]. In this regard, word2vec is generally one of the most prominent approaches that ensures modellingterms as vector representations as pointed out by [145]. 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 forma very big dataset. The word vectors which have been computed retain a big amount of syntactic, as well as semantic regularities existing in the specific language [149], presented as association offsets in the corresponding vector space. An approach based on word2vec is doc2vec[150]which generally models the whole documents or the entire sentences as vectors. Another technique in representation learning is auto-encoder that is a kind of artificial neural network used in unsupervised learning. Auto-encoders have been employed for training novel reflections on a wide range of ML tasks, such as training reflections from distorted data, as pointed out by [151].

In deep learning for SA, a highly interesting approach entails augmenting the knowledge contained in the embedding vectors with the other information sources. The added information may be sentiment specific word embedding as pointed out by[148], [152]. The work which was presented by [153]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 theenriched reflections arehighly effective in enhancing polarity classification performance. The other approach which incorporates noveldata toembedding'shas been described by [69], where in-depth learning is engaged so as to obtain sentiment features together with the semantic features. In addition, [154]offered a description of an approach in which distant supervised information isemployed in refiningthe metrics of NN from unsupervised NLP method.On the same note, a coordinated filtering program may be employed as pointed out by[155] in which the researchers include sentiment data out of a smallportion of data.

While including sentiment data, [156]points out the manner in which sentiment Recursive Neural Network (RNN) may be employed in parallel to otherneural network framework. Generally, there is atendency that attempts to incorporate more information to the term integration is formed by the in-depthtraining networks. A highly interesting work has been described by [157], in which both sentiment-driven, as well as the standard integrations areemployed together with several pooling functions for the extraction oftarget-based sentiment ofthe Twitter comments. It is also worth mentioning that enriching the information which is included in term embedding's is not thesole trend when it comes to deep learning for SA. Research into the compositionality in sentiment classification task has generally proven to be highly relevant, as pointed out by [139]. The work generally proposes Recursive Neural Tensor Network (RNTN) method and it also points out that RNTN is better in performance in comparison to the past models on binary, as well as in fine-grained sentiment analysis. RNTN technique generally represents a phrase using word vectors, as well as a parse tree, computing vectors for bigger nodes in the tree via the utilization of tensor-based composition formula.With regards to the ensemble schemes illustrated in Section 3.4, certain authors [158]have employed a geometric mean rule for combining three sentiment models: 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 researchestheadaptation ofemerging programs in opinion mining.The study in [159] utilized a hybrid GA for attribute choosing in opinion categorization in different online platforms. The study in [160] utilizes a combination of SVMs along with particle-swarm optimization for opinion mining of the film feedbacks. [136] 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 [161] 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 [162], 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 [163]employs a combination of NBsalgorithm along with GA for categorization of film feedbacks. Simultaneously, the study in [164]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 [165]. It is also worth pointing out that GP has widely been known to obtain human-competitive results. 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 a competition referred to as Humpies which is conducted at the Genetic and Evolutionary Computation Conference (GECCO) in which GP systems have always been awarded 7 gold medals, 2 silversas well as 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 variant of GP Cartesian GP got silver medal. Even with theeffectiveness which has been proven, to the best of our ability, GP has almost not been employed in tackling sentiment analysis problemas pointed out by [166].The utilization of GP towards the completion of word- processing is much rare as pointed out by [167]. In the past work GP, was employed so as to enhance the weighting mechanisms of vector space method forthe classification of text. Additionally, the work which was one by [168] suggested GP for emerging characteristics with themain aim of minimizing data dimensionality [169].

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 fewthousand examples. A number of the elements of the vectors are however zero. The GP system which is the most prominent [170]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 problems with high-dimensional representation, as well as considerable training size. [171]employs an ensemble of GP created on a problem with about 300,000 exemplars on 41 dimensions. In the work which was done by [172], a simple regression task is handled in which there are about 1,000,000points having 20 dimensions. In the work which was done by [173], it was suggested to train a multiplexor ofabout 135bits which is representinga learning size ofabout 2135. Nevertheless, the tens concept only utilizesmere 1,000,000 learning instances. On the contrary, looking at problems which have high-dimensional representation in the work done by [174], new symbolic regression method is suggested on a challenge having 340 dimensions, as well as 600 learning instances. Various reviews indicate that the application of GP on tasks comprising large-dimensional representation, as well as considerable training size are very scarce.It may be possible that a single limitation includesthe time which is needed to get a solution which is acceptable on GP. The restriction has been previously pointed out by [175].

It is worth pointing out that the semantic GPwhich makes use of new semantic operatorsappear to be the feasible alternative for tacklingthe problems of text mining. This is brought about by their quick convergence ratios, as well as the traditional incorporations; beingcapable of evaluatinga novel independent in O (n), where n represents the volume of learning dataset.In the diverse semantic operators, the ones which appear to have the greatest convergence rate have been proposed by [176] and[177]. The two techniques were motivated by the geometric semantic crossoverwhich was proposed by Moraglio et al. [178]through the incorporation of Vanneschi et al. as pointed out by [179]. 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 thatoften 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 datafor tackling lexical ambiguity, as well as data sparsely. This has been pointed out by [180], [37], [181], [182], [183]and the second one is mining the words which are dependent on domain [184].

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 [185], [73].

3.2.1 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: (a) Opinions presented implicitly (such as Boy gets her, he loses her, and viewers fall asleep.) (b) Existence of sarcasm and some type of mockery (for instance, you attend this film because the hall contains air-conditioning.) and (c) Upset/thwarted opinions (such asthe acting is acceptable. Climaxepisodes are top-notch. However, I believe it to be a less than average film.

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 [186], sarcasm as well as irony [187], [188], depend on long-distancesupervision-basedmethods (like leveraging hashtags) as well as stylistic or pragmatic features (emoticons, or laughter expressions like “lol” etc.). Addressing the challengesfor language wise well-established texts, amidst non-presence of external hints (likeemoticons), often is observed to be challenging through either textual or stylistic characteristics only.

- Thwarted expectations [1]that takes place when the last sentences of a document modifyits overall affective appraisal:
- Irony, which takes place when expressions or words having a typical positive affective content are figuratively employed in order to express negative opinions.
- Mixed emotions, if more over one diametrically opposedexpressions are communicated in a short text segment:
- Context, if it is not the explicit text information of a communication which is containing an expression of a private state, rather the context that it is integrated. For example, the statement:

While referring to a movie, clearly points out a very strong negative bias towards it, though the textual content is not explicitly containing any affective information.

The type of effective understanding that can be executed and the outcome of the opinion mining programs alsodiffer significantly and this is always based on environment of the analysis. Some of the examples include:

- A ternary prediction on whether the text which has been assessed is containing negative positive affective content or is objective or neutral (does not contain expressions of private states). Some of the examples generally include online reviews which praises or which criticises products as pointed out by [1] or opinions against or in support proposed legislation.
- A categorical extraction of useful information where the result may be one of numerous possible states like anxiety, nervousness, fatigue, fear, as well as tension[189].
- Numeric prediction in a given affective dimensions,like arousal or valence [190]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 taxonomy of the sentiment analysis process, 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 all the sentiment analysis tasks are very challenging, understanding and knowledge of the problem and its solution are still limited. The main reason is that it is a natural language processing task, which is complexes 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.

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