Abstract  Sentiment is natural to human beings. Sentiments are expressed in different forms ranging from written, spoken to exhibiting. Our ancient scriptures record classifications of sentiments and propose Rasa Theory as the earliest study on human mind and its expressions. At the advent of digital era, sentiments are being poured into social media. The study on computational linguistics has become encouraging in developing computational models for automatic detection of sentiments in a given text be it a document or a social media posting though both the varieties project different class of problems for finding sentiments with them. This article discusses on some linguistic approaches known in the paradigm of natural language processing and their uses in sentiment detection. The approaches discussed are lexical analysis, corpora based, aspect based, social semantics and the trends of research in this field. It also discusses on exploring sentiments in a text of multiple domains.

1 Introduction

The Theory of Rasa as proposed by Bharat Muni is the ancient treatise that lists the sentiments usually invoked by actors while enacting a play. In Natya Sastra as the saint says, a play is only complete when it has naab rasha i.e. the nine types of sentiments viz. Hashya (laugh), Raudra (fury), Veera (fighting),Srngar (love), Shantam (peace), bibhatsa (disgust), Karunya (kindness), Bhaya (frightening) and abdhutam (wow, amazing). The work of the saint is dated somewhere in 500 BCE to 500 CE. Indian classical dance forms are based upon this theory of Bharat Muni. Further, the works of the great poet Kalidasa pens poetic treatises like Meghaduta, Kumarasambhab and Raghubansha in Sanskrit narrating the sentiments of the characters in his works.
Modern times linguists extend the classic idea of *rasa* in dance to languages and view those words that express cognitive states of speakers as emotive or sentiments words. Linguists label a word indicating the sentiment(s) the word conveys. Psychologists go further in studying emotions to define its affective sentiments. But, the sociologists claim that sentiments are not only affective due to cognitive state of a person but also depends on its socio-cultural ambience. While identifying sentiment characteristics, the representation of emotions are researched to visualise the semantic continuity of emotions of a person. Psychologists no more view emotions as discreet events. While emotion is viewed as a point in a dimensional space that models human cognitive space, then there can be plausible paths in the defined space so that dynamic change of emotions can be explained. The first such dimensional approach is presented in [6]. It labels one hundred plus emotions in a space with dimensions showing arousal and valence. Another such two dimensional space to represent emotions is reported in [7]. Latest, it is shown that emotion can be effectively expressed in four dimensional space viz. valence, potency, arousal and unpredictability [8]. Thus research on emotions has been from different domains including psychologists, sociologists and linguists. In recent times, computational linguists and computing scientists have taken up the lead to understand the sentiments and emotions expressed in digital contents like text, image and video etc.

On receiving a message, one reacts either as an active or a passive responder. A passive responder i.e. ignoring a message to react, conveys its unacceptability to the message. Whereas an active responder may react to the message by conveying its understanding of the message. This understanding includes recognising the issues in a communication. Other than this, there is a cognitive expression of an active responder. An active responder, conveys an emotion like happy, jubilant, unhappy, perturbed, confused and etc. aroused due to the message. Thus, a communication makes an affect at its receiver. While the research in Natural Language Processing has been engaged in understanding a text by syntactic and semantic analysis; the recent trend is to understand the emotions conveyed in a message. Because, emotions are the effects, messages make at the receivers. Now, in the renewed quest for artificial intelligence, there is also an interest in study on emotion as one can’t deny its role in making of intelligence. Because, emotions resulting to sentiments in a person, play decisive role in decision makings. This is giving rise to a new discipline of study called *Affective Computing* [1]. As sentiment analysis is foundational base of this new computing paradigm and it has many useful applications in different domains ranging from governance to business, the study on sentiment analysis has assumed immense interest among researchers.

Sentiment analysis, at early stages of research, has been with text understanding and summarisation resulting to categorisation of a text as either positive or negative in its sense. Thus the sentiment here is bipolar. Further, based on some measures like the numbers of positive and negative words present in a text, order of a bipolar sentiment can be ascertained. But, some more researchers, use multiple labels to express sentiments; that is the extension of bipolar sentiment label scheme to multi-polar one. So, there are many emoticons for communication on cyber spaces. The research interest is in auto classification of texts to the sentiment labels. This has
been one of the research interests for the researchers engaged in sentiment analysis. Further for growing importance in social media mining, the sentiment analysis of the posts in Twitter, facebook, blogs and other online platforms is a recent research trend. The techniques used for sentiment analysis can be categorised to statistical approach [2], knowledge-based approach [4] and hybridised approach [5] that combines both statistical and knowledge based approaches. Statistical techniques in analysing texts for sentiments are void of consideration of text semantics. This gives a blunt view on emotions, at times out of context. Again, these techniques are sensitive to the quality as well as bulk of data collected. Some researchers report the use of soft computing techniques for labelling a text. This classification also depends on quality of samples collected for supervised classification. An unsupervised technique for the purpose also depends on quality and amount of data collected. On the other hand, knowledge based approach considers semantic of the text in classifying and labelling a text. Being associated with semantics, sentiments assigned by these techniques remain contextual. But the difficulty with these techniques is with the coverage as well as quality of the knowledge collected for solving a problem. This chapter wishes to explore the roles of natural language processing techniques in sentiment analysis. It doesn’t claim an experimental analysis of the techniques mentioned but plans to trace some of the landmark points in the course of the research in this field. In the next section, a general concept on natural language processing in sentiment analysis has been explained. The research works on three dimensions viz. lexical, corpora and aspect are introduced in the following three sections in sequence. Each section presents some of the important works carried out following a research dimension. The chapter ends with a brief concluding remark.

2 Natural Language and Sentiments

Semantics indeed flow from language. Computational linguistics have shown interest in developing techniques to understand sentiments of a text. Basically, they study the polarity of a text in its sense either positive or negative. The positive polarity of a text is computed from the count of positive words the text has. For example let’s take the sentences:

*The lockdown announced by the government was appreciated.*

*The lockdown brought devastating effect on the national economy.*

The first sentence is positive for having the word *appreciated* that gives a positive connotation to the sentence. For the second sentence, the word *devastating* presents a negative mark. A text is positive when its count of positive words outnumbers that of negative words. In order to characterise the sentiment of a word, conventional natural language processing techniques follow the ideas of linguistics. Some of the techniques include corpus based technique, lexical analysis, statistical measures of word associations and semantic analysis. All these methods of course use a prior
defined polarity of a word. Lexical analysis technique is used to identify the words of interest (adjectives and adverbs) in a text. For sentiment detection, usually adjectives in a text are traced. And the Corpus based techniques use constraints on co-occurrence of words with the similar or dissimilar polarity. Statistical measures on co-occurrence of words with prior priority are computed to ascertain the distribution of such words and their formulations based on which the sentiment of a text is derived.

The above methods assume, words are assigned with prior priority. Some researchers ascertain prior priority of a word by referring to glosses available with WordNet. Computational linguists look for strategies to label a word with a sentiment choosing it from a given set of sentiments. One of such work is reported in [3]. The work reports a novel technique for sentiment recognition and polarity detection of a given text. First the author lists twenty four types of emotions under four categories viz. pleasantness, aptitude, attention and sensitivity. And each category has six types of emotions. The observations from fMRI experiments show that different parts of a brain gets activated at different types of emotions. The transitions of intensities of brain activations is modelled as an invertible bell function that shows positive and negative emotions along the range of values the function assumes i.e. \((-1, 1)\). The spatial arrangements of twenty four emotions is seen as an hour glass so the method is named as Hour Glass of Emotions. The paper while identifying twenty four types of emotions presents a scale for assigning priority to each. This idea can be translated to assign polarity to the words of emotions. A scale can be designed to map sentiments to polarity numbers from the range \((-1, 1)\). Then determining polarity of a text is a problem of summarisation. However, identifying a sentiment of a word with context reference is a linguistic problem because identifying sentiment of a word along with its neighbouring words becomes illusive. For example:

*He was not a great runner for the day.*
*Anita ruthlessly smashed all the records.*

In the first case the sentiment of the sentence is negative, though the word *great* is positive. But, the second sentence has positive priority though it has the word *ruthless* of negative connotation. Thus, understanding sentiment has to take context into account as the work [2] proposes. In order to find contextual polarity of a word, first the words are annotated as positive or negative polarity and in the second step disambiguity resolution is carried out. A disambiguity in word polarity occurs when the word is situated in the midst of conflicting polarities. Annotation of words with respect to its context is carried out by using a corpus that is developed by multi-perspective question answering scheme applied on a given set of demonstrative sentences. Then the second step is executed to disambiguate conflicting contextual priorities in a sentence. For the purpose machine learning techniques are applied. Features like positive, negative and neutral words, sentences and documents are considered by learning algorithms in designing of classifiers that learn from training data. The four types of learning algorithms viz. boosting, memory-based learning, rule learning, and support vector learning, are used for the recognition of contextual polarity. Finding sentiments of a document uses a lexicon-based model or a corpus-based model. A
lexicon based model is primarily an unsupervised one. It uses an available dictionary with sentiment words. But, the technique is limited by the size of the dictionary. It is found at times comparatively inefficient than statistical methods for processing large number of words. But, corpus-based approach follows a supervised technique to train SVM like classifiers. Thus, again, its performance is dependent on training data sizes. Considering the drawbacks as well as strength of both the methods, [9] proposes a hybrid technique that uses both the models in designing of sentiment classifiers. In a given text, some words are tagged with their sentiments using a dictionary with annotated sentiments discovered manually. At the first stage, lexicon analysis of a text is performed. It divides a sentence into different zones based on structural analysis of a statement. Then for each zone, sentiment words are recognised and their impacts on zones are computed; this computation returns sentiment of a sentence by aggregating impacts of words in zones. The process carried on for different texts so the dictionary grows. From a given text, there is a set with sentiment classified words and there is another set with unclassified words. Now the second step of the proposed method starts taking the two sets of words obtained from the first stage as inputs. The features of the classified words are found. Similarly features of the words in unclassified set are found. Now classifiers like SVM are used for learning so unclassified words are subjected to classification. The authors by experiment have found that hybrid technique performs better because both the techniques individually are biased. While lexicon based is positive priority biased, corpus based model is better to identify negative priority. With experimentation results the authors vouch for a hybrid of both the techniques for classifications of sentiments in text documents.

Another work uses NLP techniques for sentiment findings in microblogs. The authors in [10] reports an algorithm that performs two functionalities viz. realtime sentiment detection and microblog user sentiment profiling. The techniques applied for sentiment detection on microblogs, are classified into two categories viz. subject dependent and subject independent. For the prior case, hashtags indicate the domain of discussion so the related words are searched to identify priority of words. Whereas the later is domain independent. Sentiment of a microblog is determined by processing reactions of people to a microblog. While the previous case analyses the contents the later analyses the reactions to a content. Analysing sentiments in reactions to a microblog provides a sentiment profile on an issue. Similarly sentiment profile of a user can be carried out. The paper follows a general approach in computing priority of a microblog sentence. The technique it follows for sentence priority calculation has three steps. First, it finds segments i.e. sub sentences; and then words in a segment are annotated with the part of speech. In second step, the polarity of a segment is computed. For it, key words of the segment is matched with a dictionary and patterns of words are matched with repository of mined patterns. On matching, polarity of a segment is computed based on the polarity assigned to patterns. Then the third and the final step computes the sentence polarity as an aggregation of polarity of its segments.
\[ \lambda(s_i) = \frac{1}{\min(1, N - i + 1)}, \quad 1 \leq i \leq N \]  

(1)

\[ P(S) = \sum_{i}^{N} [\lambda(s_i) \times p(s_i)] \]  

(2)

An idea of sentence segments and their contributions towards polarity of sentence is modelled in the formula above. Linguistics have observed that position of a segment in a sentence has its impacts in computation of a sentence sentiment. Usually, segments at the begin and towards end have more importance than the middle ones. Let’s define variables used in the formula as: \( s_i \) is the \( i \)th segment and its polarity is \( p(s_i) \) and \( \lambda(s_i) \) is its positional value, \( N \) the number of segments and \( S \) is the sentence. The summation of products of segments’ positional and polarity values results to \( P(S) \) the polarity of a sentence \( S \). For fastness of computation the authors used binary search and parallelize computation so the demand of online sentiment assessments of microblogs is met.

The works multilingual sentiment analysis is reviewed in [11]. The use of multilingual sentiment analysis is obvious as social media population is gradually turning to a heterogeneous society with people of diversified culture and languages. Multilingual sentiment analysis though largely follows three approaches viz. lexicon based, corpora based and hybrid models for sentiment analysis still needs special attention to deal with a challenge that is language specific. One approach is to translate statements from other languages to English and then use the readily available tools for the purpose. But, the approach is vulnerable to the loss of information caused by the translation. The process of translation including tokenisation and segment detection is tricky and so also is semantic interpretation. Then the second approach is to deal with each language separately. But, it requires a semantic mapping for words of one language to the other. The mapping at times could be ill defined. However, a good number of researchers engaged in multilingual sentiment analysis is developing multi-language corpora that help in summarisation of sentiments expressed in multiple languages. The paper gives a comparison of works in this area. The interested readers may refer to the paper. The variety of approaches the authors follow include lexicon based, seed word selection, SentiWordNet, supervised machine learning and some heuristics. For semantic inadequacy in lexicon based strategies and knowledge incompleteness in corpora, researchers have seen efficacies in hybrid techniques in both monolingual and multilingual sentiment analysis. Having a good research progress in the field, users of various domains have shown interests in sentiment driven applications like marketing, pedagogy, counselling, community development and governance. Each kind of users wishes to analyse comments and reviews on a particular aspects of its interests. This has given rise to research on aspect based sentiment analysis.

Aspects are the dimensions on which people view in its world of communication. For example, on a product, customers view on its cost, functionality, maintenance support, durability and issues like these in interest of users. So, a review can be
one of these aspects. In order to assess sentiments of a product, user sentiment on each aspect of a product is required to be assessed and then an aggregation of these sentiments is to be done to compute the product sentiment as a sum total of its aspect sentiments. The process of aspect based sentiment analysis is divided into aspect identification, classification and aggregation. In analysis of a review, the first work is to identify the words conveying aspects. This is called sentiment-target pairing. Next, the classification of sentiment-target pairs is done based on the polarity of a pair i.e. either positive or negative pair. However, for some target pairs there may be already defined priority based on the paired sentiment words. Finally, the sentiment values of each aspect is aggregated to provide a comprehensive view. The paper [13] gives a review of works carried out in this area. It provides a taxonomy in categorising techniques applied for aspect based sentiment analysis. Reported works are put into three divisions viz. aspect identification, sentiment detection and the third category includes the both. The algorithms used for aspect detection are further divided into frequency based, syntax based, supervised machine learning, unsupervised machine learning and hybrid approaches. While the sentiment analysis follows techniques those are dictionary referencing, supervised machine learning or unsupervised machine learning types. The third type is jointly finding aspects and sentiments following one of the techniques among syntax-based and supervised, unsupervised learning and hybrid machine learning.

On having an over all idea on natural language based sentiment analysis we will look into each approach to understand basic nuance of it.

### 3 Lexical Based

Lexical based approach deals with vocabulary used in a text for sentiment analysis. Ideally we would like to understand the subjects and the sentiments a given text has. In that sense, it’s natural to look for the nouns and their adjectives. A noun, associated verb, adverb and associated words may also throw some light on sentiment(s) a sentence has. For example lets take sentences as:

- He was happy at the news.
- She sang not so sweet.

While the first sentence gives a positive polarity having the word ‘happy’, the second sentence have negative polarity for the phrase ‘not so sweet’. In the later case though there exists a positive word ’sweet’ still accompanying words ’not so’ brings in just opposite. This shows, the first step is to identify words conveying sentiments in a text. Then the polarity due to these words are identified. Polarity of a text, is due to the aggregation of sentiments of opinion words found in a text. The aggregation indicates the number of positive and negative sentiments the text has. But, in case of microblogs, the sentiment analysis is done at sentence level. Usually, first microblog sentences like Tweets are put into a cleaning process that removes noises like unusual abbreviations. Then the part-of-speech (pos)of the words in the
sentences are found. A sentence with pos information is put into sentiment analysis study. A sentiment analyser consults dictionary and SentiNet like repository to identify describing words and their sentiments. Though, in aggregation sentiment is bipolar i.e. positive and negative, but in reality there could be subdivisions to positive emotions viz. happy, praising, cheerful, smart and etc. In such case, a graded emotion quantification scheme can be worked out. For polarity aggregation, an average score of polarity of sentiment words is usually carried out.

The paper [14] presents a detail work on lexicon-based sentiment analysis emphasizing the need for semantic based approach for having some applications that need analysis at sentence level for not having corpora as such available. As the most of the corpora based system needs a large size of corpora, availability of such large amount of data becomes a limitation. The paper makes a distinction between semantic orientation and semantic analysis. Semantic orientation is about judging polarity of words in a sentence or a text. Whereas semantic analysis is about general methods to find subjectivity and its polarity in a text. The paper discusses semantic orientation that’s appropriate for computing sentiment of a microblog. The calculation goes with metrics to quantify the impacts of features viz. i. adjectives ii. noun, verb and adverb iii. intensification iv. negation v. irrealis moods and vi. text level repetitions present in a sentence. For a given word and its semantic orientation feature, a measure of the sentiment the word may invoke at the reader is determined. For each feature, a scale has been defined considering two extreme emotions e.g. love and hate with scale (+5, -5) while in between eight more associated emotions can be placed. The authors have suggested for auto generation of dictionary by association of words to a given set of seed words. For the purpose a set of six features named text is self explanatory except few; those we will put here. The words like slightly, somewhat, pretty, really, beautiful and excellent are the intensifiers for they express a degree of a emotion on goodness. One can define a range of values associated to these words in a range (1, 6) where the intensifier ‘slightly’ assumes score (1) and (6) for ‘excellent’. Similarly, negation in a sentence affects polarity of a statement. A negation to a positive feature may be assigned a negative of its positive value e.g. ‘not excellent’ may be assigned sentiment score as -6. However, such convention is open to criticism as ‘not excellent’ is open to interpretation. In a language there are some negators like never, noway, none, nobody and nothing can be considered negative sentiments. Verbs and prepositions like lack and without also convey negative semantics e.g. lacks an order, it was without discipline.

While considering lexicons contributing to sentiments, there are some lexicons which should be ignored as argued by the authors as these in reality are not contributing types. They have identified them of two types viz. irrealis and repetitions. In linguistic domain the former refers to the features those are irrelevant in the sense of their reliability e.g. But for middle aged people, a visit to the place could have been enjoyable. The sentiment expressed in this sentence is obfuscated. Similarly, a sentence with repeating emotions may not add to the sentiments e.g. The place has nice roads and nice gardens. This repetition of the word nice doesn’t add to sentiment score.
Devising strategy for sentiment detection as seen in the paper [14], is language specific, and needs expertise of linguists. Having done with the identification of language specific sentiment orientation then sentiment score is calculated. The authors propose to compute semantic orientation scoring for a word. It refers to SentiNet dictionary for getting positive and negative score of a word with respect to a sense. It may be noted here that a word may have use in different senses and an order is defined over these senses. Semantic score computation may choose the positive and negative scores in the best sense which usually is the first in order. However, another approach could be the average of the scores due to all the senses. A score value assumes a value within $(0, 1)$. The computation of semantic orientation is carried out as:

$$\text{SO}(w) = (\text{Pos}(w_f) - \text{Neg}(w_f))$$

i.e. $\text{SO}(w)$ semantic orientation of a word $w$ is the difference between its the first sense positive and negative scores ($w_f$ is the first sense semantic orientation of the word $w$). With respect to all the senses the semantic orientation for the word $w$ is computed as:

$$\text{SO}(w) = \frac{1}{|\text{senses}|} \sum_{x \in \text{senses}} (\text{Pos}(w_x) - \text{Neg}(w_x))$$

where $\text{Pos}(w_x)$ and $\text{Neg}(w_x)$ are respectively positive and negative scores of the word $w$ with respect to a sense $x$ where senses is a set indicating the different aspects of sentiments a word may invoke. This way the paper proposes a novel approach of semantic orientation for sentiment computation that uses sentiment associated with a word as well as of words in its neighbourhood. That way the semantic expressed with a word is considered for sentiment computation. In case of microblogs, because of limitation on text length as it is for Twitter, though the scope to compute semantics and sentiments is limited still some researchers vouch for NLP techniques for sentiment computation. Extending the role of language in assessing sentiments, some researchers have considered corpora that stores a genre of writings giving much scope for semantics in sentiment computation. The next section discusses on the corpora based sentiment computation.

4 Corpora Based

A corpora is a database of linguistic information of a genre that shows distinguishable features identifying a genre uniquely. A corpora can be used for understanding a text by matching words of the text to its genre and scooping out the meanings in the context of the text. Words exhibiting a unique aspect of a genre are identified and classified to different aspects. These words are weighted based on their degrees of participations in distinguishing a genre. Then, a group of words useful to describe an
aspect is associated to a function as its parameters. These functions are considered as discriminating function used for classifications. This general concept of corpora based NLP is also used for sentiment analysis. With a given sentiment corpora, a text can be classified to a sentiment in applying corpora defined discriminating functions. Understanding the subjectivity of a text by using corpora is reported in [15]. Subjectivity of a text refers to aspects of a language used to express opinions. The factual information a text presents, give objectivity of the text. A language mainly has features to express positive, negative and speculative subjectivity. The words like beautiful and terrible reflect positive and negative subjectivity whereas a word like possible is speculative one. In order to identify such polarity in expression, corpora is used. Further, there could be an associated degree to a polarity e.g. ’pretty, attractive, beautiful’ like words exhibit degrees of positive polarity in describing something beautiful. Corpora may generate a grading of such words associating each with a weight according to its grade. This process of grading can be automated by bootstrapping with a given seeding positive word; at times the process could be manual tagging too. An experiment on corpora generation for sentiment analysis is reported in [16]. In two steps corpora has been created. First, a text is taken from customer opinions on different web services. Then opinion polarity is identified and annotated manually by a set of annotators. The project built corpora for detecting irony and sarcasms. Further [17] reports another experiment to find the words that express sentiments. They use two methods primarily based on LSA: Latent Semantic Analysis technique that’s a statistical method for extracting a semantic space from a large corpora. This work tells, the corpora performs better when it remains domain specific. The two methods viz. SO-LSA (Semantic Orientation Latent Semantic Analysis) and DI-LSA (Dictionary based Latent Semantic Analysis). In SO method, affective aspect i.e. sentiment due to a word is estimated from its frequency of occurrences with other surrounding words. These words with a given seed word form a vector. This word vector is matched against given set of aspect vectors for similarity detection. For the purpose a cosine similarity of an aspect vector with word vectors having known aspects is computed. The degree of similarity provides the degree polarity to a known aspect. But, the technique may not be useful for aspect words not having patterns of frequent co-occurrences. In that case, lexicon based LSA method is used. The technique instead of looking for frequent word patterns, it finds the occurrence of similar lexicons in a dictionary. A dictionary is initiated with known seed words and its range of words from negative to positive polarities. Based on word matching in dictionary, polarity value of a word is ascertained. The paper in view that for specific domain with limited corpora size, the performance in sentiment analysis is appreciable. The observation though sounds trivial still the method proposed in the paper is useful for many business applications looking for automation of sentiment detection in customer comments.

Translation of a text from one language to another has enormous applications. Among the difficulties in language translation, maintaining emotion in one language to another adds to its complexity. The problem is addressed in [18] suggesting creation of parallel corpora that for a word projects word(s) in other languages, conveying the same sentiment so that consistency of an emotion in a text is maintained in the
translated text. Translating to parallel languages need each language specific tools. The researchers have proposed a simple mechanism that only uses language specific NER: Named Entity Recognition software and emotion dictionary. The strategy for translation, does not follow method of summarisation because in that local sentiment may get lost. In translation one has to look for sentence level translation to maintain consistency of emotion in translation. For the purpose, the paper follows a window approach. In a sentence, emotion is viewed around a subject. Around a subject word a word-window of six words width, is created to find two levels of positive and negative words. It’s found that this simple heuristic works well for text translations in seven European languages. Then emotion dictionary of the text language is referred to find the polarity of words in the window. Then, the sum total polarity of words in a window is computed. Further, the emotion intensifiers may add or reduce polarity based on their positive or negative connotations. This simple approach is appreciable for it is not computation heavy. Next we present a work following the trend.

The simultaneous usage of multi language corpora for sentiment analysis is particularly tried for sentiment analysis in tweets. In [19], researchers process tweets in multiple languages using multi-lingual Twitter corpora. These investigations are classified into two categories; one when tweet language is known and the other unknown. For unknown case, they follow multilingual and monolingual approaches to identify sentiment. In former case, they use a multilingual trained corpora to identify sentiment expressed in one among the trained languages. In later case, the processing is in two stages i.e. first language identification and then sentiment finding. The case is ofcourse easy when the language of the tweets is apriori known. The experiment the paper reports uses tweets in English and Spanish. Following a multilingual approach, they trained the system with English and Spanish sentiment words and mixed two training sets for uses in sentiment analysis without recognising the language of a given tweet. They introduced a concept called code-switching corpus with sentiment labels and have exhibited the robustness of the multilingual sentiment analysis. The process for multilingual method has tow phases viz. one does feature extraction and another on context detection. For, multilingual tweets processing [19], after tokenisation of a tweet, tokens are matched with multilingual corpora. A tweet can be of a language among the many a corpora has. Once a token is matched with a word in multilingual corpora then its language is known. After that parsing and other steps are carried with respect to the known language. This process, is called code-switching. The features it extracts are words, lemmas, parts of speech tags and psychometric properties. Words of interests are selected on the basis of their number of occurrences. Root words are identified in lemmatisation so the processing of different forms of the same word is avoided. Then the words with psychometric properties are identified. These words basically indicate the sentiments of a tweet. The part-of-speech tags for words are identified with respect to the grammar and the corpora of the language. Now for Indian languages there are many parsers, syntax analysers and corpora available. Using these available software the above steps can be carried out. Now from a tweet we get a set of words and with each word tagged with part-of-speech and psychometric properties i.e. $T = (t_1, t_2, ..., t_n)$. Then the associations among words are explored. We may get $((t_j)^p_{j=1}, r, (t_k^q_{k=1}))$ where $r$
is the relation that binds tweet words \((t_j \ldots t_k)\) telling about the sentiments the tweet expresses. Computational linguistics use \(n\)-gram technique to extract meaning of a sentence. The same technique can be followed to find sentiments in a sentence. An algorithmic description of the said method is given below.

**Algorithm 1 Multilingual_Tweet_Sentiment\( (t_w:\) tweet, \(K:\) Corpora)\)

\(t_w\): a tweet;
\(T = PickFreqWord(t_w)\)
\(T_{post} = PartOfSpeechT(T)\)
\(T_o = GetOriginWord(T_{post})\)
\(T^*_o = ChkPsychoProp(T_o)\)
\(T_{ngf} = FindNgramFeature(T^*_o)\)

The function \(PickFreqWord\) with a tweet \(t_w\) as input finds the words those are not frequent and tweet slang. On finding the set of words \(T\) of the tweet \(t_w\), it recognises the language of the words on using a given multilingual corpora \(K\). It is to be noted that, for processing a tweet must be in one of the language of the corpora \(K\). Then in sequence the part of speech tagging of the words, lemmatisation and psychological aspects of the words are carried out respectively by the functions \(PartOfSpeechT(T)\), \(GetOriginWord(T_{post})\); the function \(FindNgramFeature\) finds the dominant features that reflect some relationships of entities with words and their psychological features. The found dominating ones or identified with many \(n\)-gram feature(s) reflect sentiments and accompanying other less dominant sentiments present in a tweet. These can be corroborated on further analysis of the tweets emerging from the same tweet-handler. A person in consequence to an event, may exhibit several types of emotions that we call aspects of emotions. For example, the dominating features can be seen as different emotional aspects. In the next section we will discuss on some work on aspects of sentiments.

5 Aspect Based

An event can be viewed in more than one ways and so may induce different types of emotions. For each type there is a context associated. This is termed as aspect based emotion. For example, a pandemic like Covid-19 may induce several emotions like fear, concern, disgust and helplessness. Now while detecting sentiments the aspects of emotions are identified. A work [20] reports different emotions people at large express on suffering migraine. They have collected tweets (in English) for a time period and processed to find out different aspects of emotions people have expressed using their tweeter handlers. At the beginning cleaning of tweets is carried out by transforming tweet-centric words to formal English words. Tweet-centric words, we mean the words in distorted forms used in tweets. Then lemmatisation of words is carried out and the root words are identified. Aspect based sentiment detection
follows qualitative approach while quantitative approach resorts to statistical methods in finding frequencies of occurrences of polarised words. The former approach being qualitative finds out different signatures of emotions by finding n-gram features in words of tweets. In a collection of tweets on migraine, the n-gram features (combination of tweet words) are recognised and then a feature is assigned to a sentiment category following Latent Dirichlet Allocation method for topic modelling. The researchers have found that their method is able to find out relations between different aspects like treatment and cure, suffering and profanity etc. While finding aspects of sentiments in general with the disease, they have also profiled sentiments of frequent tweeterites on determining their activeness on social media and performing tweeter level sentiment analysis.

Aspect based segment detection not only goes beyond the recognition of bipolarity sentiments i.e. positive and negative but also identifies sentiments people may have on different contexts associated with an entity. The problem of context identification turns difficult for many reasons like detection of isolated features and overlapping features. Overlapping features may mean the same or similar contexts. The approach to meet the challenge is by understanding word semantics instead of resorting only to statistical approach. Having words embedded with meanings, it is possible to get semantic associations the sentiment words make. Aspect category detection problem is a part of aspect based semantic detection. The problem is studied in [21]. The authors report a hybrid model that blends association rules with semantic rules where the prior is statistics based and the later follows semantic association. The usual approach is to identify aspect words and corresponding opinion words and then association mining is carried out following statistical approach. These established associations find rules among aspect words and views. This association rules further augmented by word embedded meanings. Thus a new set of class based semantic rules is generated and these rules are used to detect aspect categories. According to the researchers, the work is the first attempt to find semantic rules for aspect category detection.

While syntactic analysis is an established method for aspect based sentiment detection, it has limitation to analyse natural impulse based sentiments as such expression often doesn’t follow a grammar in strict sense so there exists chances of missing some words of sentiments and aspects. A work reported in [22] proposes a new framework that’s novel sentiment detection and claims as better than a syntax based approach for the purpose. The authors have analysed Chinese language for aspect based sentiment detection. Even though the proposed approach has some language specific processing still the approach is generic. The first step is to compress a sentence. This compression is meant to reduce a sentence simpler form for syntactic analysis. This transformation is done in two ways viz. extractive and abstractive. In case of the former, the words of aspects and verbs are extracted. Whereas in case of abstraction, an abstraction of a given sentence is carried out by generalisation of word semantics. These approaches work well when a given sentence is grammatically correct. But, for natural expression like *My God atleast camera works good.* is put for sentence compression to generate a simple sentence preserving its sentiment as *Camera works good.* Again a simple transformation based on aspect-sentiment words may not be
enough as seen in this case: *Great atleast camera works good*. This case just picking up aspect-sentiment word associations as *Camera works good* is not enough as it misses sentiment polarity words like *great* and *atleast*. In order to get over the challenge the researchers have propose Conditional Random Fields (CRF) model to label words and their associations with probability based on which the words are selected to form a compressed sentence for sentiment analysis. The work proposes a framework that has three steps viz. (1) Sentence Compression (2) Aspect based Sentiment Analysis (3) Aspect and Polarity word collocation extraction and then recognition of Aspect Polarity. The first step i.e. sentence compression, is important for not allowing the loss of sentiment as well as filtering out the words not required for the purpose. The compression process has two main steps viz. the first to pick up basic features that common sentence compression technique achieves. The features include words, Part of Speech (PoS) tags and semantic features of the words. The second step is the recognition of sentiment features in a sentence. Sentiment features include perception features e.g. *red* and polarity feature *deep* in the phrase *deep red*. And the third step is to collect potential semantic features. These are the prefix or suffix to a polarity words. The idea here is to capture some semantic features that are language specific. In some language, words prefix or suffix to a feature word bear some hidden sentiments. Further, it considers brown clustering of words that collects words that look different but have the same semantic. Similarly, it also considers soft clustering of words that collects words with the similar meanings to one class. This kind of classification helps to compress words without loss of meaning. In addition another two techniques viz. word embeddings and dependency search can be taken up in finding features. Word embeddings is another technique [23] to find similarity in words when each word is judged from different dimensions i.e. mapped to a multidimensional space. The closed colocating words in multidimensional space represent similarly among the words. Exploring dependency among features requires knowledge on syntactic relation that forbids deletion of a word as the words related to it may loose meanings without the word. Such dependencies are to be recognised by experience as studied in [24]. Having these feature words identified, then a structure, like parse tree is generated showing the dependency structure exists among the feature words. A generated structure is labelled by conditional probability using CRF Modelling. And then a bi-directional traversal of the labelled tree is performed to pick up aspect words and corresponding priority words. A sentiment word is taken as a root and then at both the sides aspect and priority words are picked up. These colocated words give an aspect-sentiment pair. Usually aspect based semantic search considers aspect semantic pairs of words. This work is special for considering priority of semantic so it is capable of identifying major and minor aspects of a sentiment. The to-and-fro traversal continues till the parse tree is traversed completely.

Aspect based sentiment detection looks at granular level exploring all the possible dimensions responsible for evoking sentiments in an observation. This technique is useful in studying market reaction of a product. Customers’ comments can be analysed to find the aspects of a product they like and the aspect they don’t. Having a good deal of business potential, there has been growing interest in sentiment study. It’s true the sentiment is an imprint of mental status of a speaker. In the next section we
will discuss a seminal work that explores the relation between the study of psychology and that of language in expressing sentiments. The next section first referring to early works with psychology perspective then charts the trends of research in this field.

6 Trends

A Communication carries cognitive status of a speaker and so reversely from communication it should be possible to identify speakers’ cognitive status. Language is a medium of a communication. Language features present cognitive status of a speaker. The researchers of computational linguistics supported by computing technology are in search of algorithms so they can churn the messages and identify sentiments present in. In this context we find it’s fitting to discuss an early seminal work reported in [25]. This paper provides a glimpse of several text analysis techniques and presents a method called Linguistic Inquiry and Word Count (LIWC) that detects cognitive meanings to words in experimental settings. Historically, psychologists, first have tried to understand human cognition from its communication. This follows the general understanding that the mind hidden is visible behind the words spoken. Probably, that’s why news analysts on television panel discussions try to read aloud many things in the words spoken by spokespersons. Initially, the methods psychologists follow for mind study are indirect in nature. For example a technique is stimulus-based. A subject is put to an experiment setting e.g. answering to a set of questions on looking at a picture. It is not transparent to the person under observation for cognitive mapping. Again, the interpretation of an answer and mapping it to a cognitive state is a business of a psychologists. Later, the researchers got interest in content analysis which is a direct means not stimulus based. At the advent of the computing technology and computational linguistic study, the possibility of algorithm based generic text analysis became a reality [26]. The program General Inquirer the authors developed, was a complex one with algorithms to detect several psychological disorders through the analysis of word usages. However, the algorithms used the expertises of psychologists while manipulating word weights and deriving possibility of mental disorders based on word associations and their weights. Thus the analysis is hidden to the people whose text is being analysed. In a sense, the first generic transparent method for cognitive study through text analysis is reported in [27]. The researcher opines that the words used in day to day life are powerful enough to paint cognitive states of people. With this premise a computer software was developed and used for many applications. However, LIWC is a transparent and popular computational method that has looked into the same problem. This being a foundational work on language processing and sentiment recognition, the next para presents a brief on the method.

LIWC, the first computer based method for sentiment recognition has two components, one is the software that reads text word by word and the second is a dictionary. A read word is matched with the dictionary. On matching a word, it’s required to measure the psychological impact the word makes. Psychometrics of words depend
upon the usage of words. The paper identifies those usages and counts the number of such usages to provide an aggregate sentiments a text projects. Some of the aspects include: (1) the use of pronouns (2) the types of words associated with those pronouns. e.g. ‘he is excellent’ (3) association of verb with a pronoun e.g. ‘I did this’—an assertive expression. (4) Social relationship e.g. ‘under me’—a social hierarchy for dominating attitude (vertical relationship), ‘you and me’—A cordial relationship (horizontal relationship) (5) deceptive identification e.g. ‘heard from some one’—referring to an unidentified speaker to assert on an issue. In order to understand sentiment of a text LIWC proposes to keep count of such linguistic occurrences and assign their weights statistically according to the occurrence distribution. This early work is simple and seminal. On the advent of microblogging the focus of sentiment study has shifted to sensing sentiments in short texts like tweets, facebook postings, images and videos. Analysing short texts like tweets is challenging for its peculiar writing styles. Various attempts including NLP techniques are being applied for the purpose of sentiment detection. Till now we have discussed on lexical, corpora, aspect based techniques. In order to chart the trend of research, we present two issues in the following subsections.

6.1 Social Semantic

Not only the grammar of a language plays a role in analysing sentiments in a text but also the context of a communication and its participants have roles to play. For example, in the context of a common interest a person may have a certain view and his tweets reflect the view. As the birds of the same feather flock together, a person’s social contacts may have the same view as the person has. These aspects in communication may add in devising strategy for sentiment analysis, particularly in case of tweets. Tweets are noisy and limited in size. These make tweet processing challenging. A work reported in [28] proposes a strategy that uses social as well as contextual relationships of postings in sentiment analysis. The factors considered include: topic context, user context and friend context. Topic context is a matrix that shows the topics a message has. Let $M \in R^{N \times N_T}$ be message-topic matrix where $N$ and $N_T$ are the number of messages and topics respectively and $M_{i,j} = 1$ means the $i$th message has $j$th topic otherwise $M_{i,j} = 0$. Connection matrix $T$ provides relations among microblog messages as $T = M \times M^T \in R^{N \times N}$ such that $T_{i,j} > 0$ the value indicates the number of topics the messages $i$ and $j$ share between. Next message-user matrix $P \in R^{N \times N_U}$ where $N$ and $N_U$ are the number of messages and users respectively. Now $P_{i,j} = 1$ means the message $i$ has been posted by the user $j$ otherwise 0. Then the message-user-topic relation is given by $U = (P \times P^T) \circ T \in R^{N \times N}$ where $\circ$ is Hadamard product as $(A \circ B)_{i,j} = A_{i,j} \times B_{i,j}$; $(P \times P^T)$ matrix indicates two messages are posted by the same user. $U_{i,j} > 0$ means the message $i$ and the message $j$ are posted by the same user on the same topic, otherwise $U_{i,j} = 0$. Retweets and shares of microblog posts show a homophily tendency of people i.e. a kind of herd behaviour that usually seen in social media. Such similar postings not
only shows topic-user context but also shows Friend context that gives an idea on polarity of a message. A connection matrix defined by friends, the authors define as \( F = (P \times S \times P^T) \circ T \in \mathbb{R}^{N \times N} \) where \( S \in \mathbb{R}^{N \times N} \), the matrix \((P \times S \times P^T)\) indicates whether two messages posted by two users have social relationship. \( F_{i,j} > 0 \) indicates the messages \( i \) and \( j \) are posted by two users with social relationships and the messages are of the same topics. Now for sentiment computation these two factors like talking on the same topics and talking by many on the same topic, contribute to content based sentiments.

\[
sm_i = Cs(m_i) + \alpha \sum_{i \neq j, j=1}^{N} U_{ij} \times (|Cs(m_j) - Cs(m_j)|)
\]

\[
+ \beta \sum_{i \neq j, j=1}^{N} F_{ij} \times (|Cs(m_i) - Cs(m_j)|)
\]

where for the message \( m_i \), \( Cs(m_i) \) is the content based sentiment computed on the basis of language features like lexicons and aspects or by any other technique that considers message context but not the social context for sentiment computation. The above formula for sentiment computation has two additives viz. user and friend contexts. The values of the multiplicative factors \( \alpha \) and \( \beta \) can be assigned considering the domain specific requirements. For example in some cases sentiments on social contexts may be treated negative e.g. panic sentiments during pandemic, so \( \alpha \) and \( \beta \) may assume a value from a range of values \((-1, 1)\). However, the paper [28], instead of computing sentiment directly as it is shown above, has considered the problem as an optimisation problem so that contributions of social contexts towards sentiment computation could be minimal and normalised so these factors don’t overwhelm the sentiment computation. For details the readers may refer to the paper [28].

### 6.2 Multi Domain

Another challenging area is the multi-domain sentiment assessment that is necessary when one needs to analyse opinions on objects of different domains also when opinions are expressed in more than one language. In such cases, a simple method may use labelled corpora of each domain and annotated mappings to corpora of other domains. But, this is an expensive approach for creating corpora of different domains. In general sentiment computation problem is considered as a binary classification problem. A classifier trained for a domain may not work well for other domains for their corpora mismatches. Thus the problem is challenging, at the same time attracts researchers for its practical implications. A work reported in [29] presents a method for multi-domain sentiment assessment. First, it creates a thesaurus considering texts
of different domains. Each text has a topic vector. Then a distribution of topic vectors is generated. The topic vectors of the texts having known sentiments are labelled accordingly. This gives a sentiment sensitised thesaurus having word distributional similarity. This thesaurus is used as the base for further expansion during sentiment classification of new texts.

In plain speaking, the premise of the concept lies with co-occurrence of the words in a text, expressing the same and similar sentiments. Based on this premise a method is proposed that first builds a sentiment-sensitive thesaurus giving distribution of sentiment words in a text. Then, for a given lexical element or sentiment element \( u \) in a text, let there be a co-occurring lexical or sentiment element \( w \) that adds to the feature vector of the element \( u \). \( f(u, w) \) returns a value for the feature \( w \) in vector \( u \). The vector \( u \) can be seen as a compact representation of the distribution of \( u \) over a range of words those co-occur with \( u \) in a given text. The distribution hypothesis says the words that have similar distributions have the similar sentiment. A quantification of \( f(u, w) \) following the principle of point wise mutual information between a lexical element \( u \) and feature \( w \) is made by

\[
f(u, w) = \log \left( \frac{c(u, w)}{\frac{\sum_{i=1}^{n} c(i, w)}{N} \times \frac{\sum_{j=1}^{m} c(u, j)}{N}} \right)
\]

where \( c(u, w) \) is the number of sentences in which element \( u \) and \( w \) cooccur. \( N = \sum_{i=1}^{n} \sum_{j=1}^{m} c(i, j) \), \( n \) is the total number of lexical elements and \( m \) is the total number of features exist in the given sentences.

Basically \( f(u, w) \) is a measure of cooccurrence of \( u \) and \( w \) with respect to cooccurrence of \( w \) with all other elements multiplied by the number of cooccurrence of \( u \) with each feature elements. All the cooccurrences are seen in proportion to total number of lexical elements and features. Then, The relatedness between two lexical or sentiment elements say \( u \) and \( v \) is computed as

\[
\gamma(v, u) = \frac{\sum_{w \in \{x \mid f(v, x) > 0\}} f(u, w)}{\sum_{w \in \{x \mid f(u, x) > 0\}} f(u, w)}
\]

The above gives a measure of proportion of pointwise mutual information features of \( u \) is shared with element \( v \). It’s to be noted that, relatedness of two elements is not symmetric i.e. \( \gamma(u, v) \neq \gamma(v, u) \). This metric helps to define similarity among elements in a thesaurus. It’s to be noted that the authors emphasise on the uniqueness of their thesaurus for its sentiment-sensitivity i.e. associating sentiment to a semantic.

\[
\text{Score}(u_i, d) = \frac{\sum_{j=1}^{N} d_j \gamma(w_j, u_i)}{\sum_{j=1}^{N} d_j}
\]

For a text \( d \) there is a vector \( d \) having features \( w_1, \ldots w_i, \ldots w_N \) where \( N \) is the total number of feature elements. Let \( u_i \) be a base entry of the text \( d \). \( d_j \) is the number
of uni-grams or bi-grams the \( w_j \) has in \( d \). Score of an entry word \( u_i \) in a text \( d \) is a normalised value of summarisation of relatedness of \( u_i \) with all the other features of \( d \). The metrics relatedness and score are used to expand multi-domain thesaurus. Expansion of it is required as it enables to store a hitherto unknown basic feature. A lexical or a sentiment element of a domain may not have a direct mapping element in other domain. In that case for an unknown basic element \( b \) in a domain, there is a need of finding an equivalent lexical or sentiment word in other domain. Now, the relatedness of \( b \) with each feature in thesaurus is to be computed and then score value for each is also computed. A feature having high score with \( b \) is considered as its equivalent and the sentiment score of the matched feature is also ascribed to \( b \) and included as a new entry to the thesaurus; thus the thesaurus is expanded. For details of the proposed scheme the readers may refer to [29]. The problem of multi-language and multi-domain sentiment translation is further complex by one more level for finding a lexical or sentiment term in a language to its equivalent term in another language. The problem is challenging but important for having many applications e.g. analysis of the reviews of a product(s) expressed in different languages.

7 Conclusion

Emotions are not always expressed but it sits in words in between. Psychologists see the real personality that is hidden, distorted and occluded, in the words the person speaks. A higher degree of sentiment study lies with a higher degree understanding of natural language. Again understanding emotion also depends on the similarity of the realms both speaker and listener reside in. It’s not only content of a communication but the style of communication matters in conveying sentiments. In the context of social media conversation, it is important to note the style of communication and lexical used in communication. The socio-psychological basis has a definite role in expressing self through languages. If both the communicators are in different language frames then the mapping in sentiment metrics of word usages is a tricky issue.

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