

# Tools and Techniques for Lexicon Driven Sentiment Analysis: A Review

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**Abstract**— The growth of user’s generated content increased in microblogging platforms like Facebook, Twitter and Blogger in form of client reviews, comments and opinion. Using this bulk of helpful data is difficult to analyze and also a time consuming task. So it is needed to have such an intelligent text mining system that automatically analyze such vast data and categorize them into positive or negative class. Due to the noisiness in data, it is difficult to design such text mining systems because they suffer from mistakes of spelling, grammatical and improper punctuation. Opinion mining is a useful tool to monitor consumer’s feedback and public mood about certain product in terms of negativity or positivity. For example the management of customer relations can use these feedbacks and improve the products by keeping in view the complaints. Lexical tools are one of the famous and useful techniques for sentiment classification. Many extensions and modifications of these tools are available now days. The purpose of this research is to study the available lexical tools and techniques to raise an interest for this research area.

**Keywords**— Lexicon Driven, Sentiment Analysis, Techniques, Tools and Text Mining

## I. INTRODUCTION

Opinion mining and sentiment analysis is a trending research area, a lot of work is being done in this area in recent years as it have multiple applications in different aspects. The motive of this research area is to classify the polarity of a given text at the deepest level and identify if the given text has positive or negative. Different Classifiers and classification approaches are used for opinion mining & sentiment analysis such as lexicon based approach, graph propagation and machine learning approach as described by [1]. Lexicon-driven methods are based on vocabulary, dictionary and other specific pre-tagged patterns in parts of speech. There are several lexicon based algorithms and methods available that used for polarity detection as either positive or negative for a given data set, these methods can also give points to the data sets and detect sentiments in 5 categories as Extremely Positive, Positive, Neutral, Negative and Extremely Negative. Almost all lexicon based methods are based on the assumption that the sum of sentiment orientation of each word in a given text is its collective sentiment orientation. [2] originally used semantic orientation

to detect sentiments from reviews. There are two types of lexicons that are manually created i.e. Common lexicons that have same semantic orientation across different scopes and the Category specific lexicons that contains indexes about a specified category as discussed by [3]. Common Lexicons are further divided into following categories:

**Default Sentiment Words:** these are the words having same sentiment across all scopes, for example the word “bad” is marked as negative sentiment. Both polarities have respective score of +1 or -1

**Negation Words:** these are the words that reverse the polarity of the sentiment for a given word, for example “Not Bad” reverse the polarity of “Bad” from negative sentiment to positive sentiment.

**Blind Negation Words:** these words exist at sentence level and reflects to the presence or absence of something that over all affects a product or a feature, for example, “I need a better internet” here need can be referred as blind negation word.

**Split Words:** these words divide sentences into clauses and may be referred for multi-mood sentences for example, “Internet’s download speed is good but the upload speed is poor”

## II. RELATED WORK

An extensive work has already been done in the area of Sentiment analysis or opinion mining using lexicon based methods, Opinion mining is the process of categorizing the unstructured data and text into positive, negative and neutral. In the recent years microblogging platforms like Facebook and Twitter attracted millions of users around the globe to give them open platform to share their thoughts as described by [4]. Traditionally sentiments are considered to be binary classification as either positive or negative. There are different lexicon based methods those can be used for sentiment analysis.

[5] proposed a lexicon based method for sentiment classification called “sentistrength” assigning polarity values between 1 and 5 to the provided text. The later version included the idiomatic phrases as explained by [6]. [7] presented another lexicon-based approach to detect sentiments from the given datasets, proposed algorithm is called Semantic Orientation Calculator (SO-CAL), and it uses semantically

oriented words dictionaries having polarity and strength scores. [8] introduced LIWC (Linguistic Inquiry and word count) which is a text analysis tool used for the calculation of Emotional, intellectual and architectural components of a given text. [9] associated three different scores against a given text for sentiment classification with the Sentiwordnet.

[10] proposed senticnet that can be referred as the linear descendant of the [11] delivering a lots of semantics for text classification with varying marks of positive and negative classifications. [12] developed the Affective Norms for English Words (ANEW) it provided a collection of normative emotional ratings for a huge amount of words and phrases in English language. [13] proposed a web based application to allow users to calculate sentiments from any form of text including un-structured social media data. [14] introduced the AFINN Lexicon that was inspired from the ANEW and is capable of using blog and twitter language including the slangs. A polarity based lexical resource was introduced by [15] called the OPF or opinion finder lexicon.

### III. LEXICON DRIVEN TOOLS

#### A. *SentiStrength*

A lexicon-driven method called “SentiStrength” was proposed by [5] that was designed to detect polarity of a given data set as either positive or negative and their respective strength values for both polarities ranging from 1 to 5. This proposed algorithm also uses emoticons, negations and boosting words during polarity detection and performed better than machine learning classifiers with respect to detection of negation in a given set, while for the positive sentiments it was below the line. SentiStrength is developed on two platforms i.e. Java platform and the windows platform. The Windows version is offered free to use and is made available on their site <http://sentistrength.wlv.ac.uk/> and the Java platform version that is commercial and is available for purchase from developer and can be requested for download for researchers and educational users. SentiStrength online site provides an interface to try it out and it includes English version and several other languages. [6] upgraded the same algorithm by adding idiomatic phrases list and strength boosting by emphatic lengthening and the results were enhanced significantly and the sentiment strength wordlist was increased up to three times of the original. This algorithm was tested on different data sets from different sources including twitter data and resulted better results from the previously proposed version of the algorithm. SentiStrength’s commercial users include London 2012 Olympic Games and Yahoo, during Olympic Games it was used to power display continually monitoring the Olympic-related tweets. SentiStrength’s Java version is designed in such a way that it can process up to 16,000 tweets in each second on a normal PC and can be configured to process more tweets every second. SentiStrength must point to a file for its resources like sentiment lexicon and emoticon list. Text can be processed by

it in multiple ways like command line, single or multiple batches of text. Further it can support ip/port listening and reading using stdin.

The core of SentiStrength is 2310 lexicon sentiment words and terms from Linguistic Inquiry and Word Count (LIWC) program, the general inquirer list of terms and ad-hoc addition during testing. Stemming used in it is very simple and indicated in the lexicon like football\* which will match all the words starting from football such as footballer. The scores between 1 to 5 discussed above were initially assigned by the humans upon a development of a corpus having 2,600 comments from MySpace and later updated through additional testing. Many terms occurs in the text rarely and this is the primary reason of relying upon human input. SentiStrength splits the text into words and then separate out the emoticons and punctuations, after splitting of the words it is checked against lexicon matching for any sentiment term. The score is retained if any match is found against sentiment term. For example, the text “Nauman is attractive and lovely but you are nasty” would be classified as follows, “Approximate classification rationale: Nauman is attractive [2] and lovely [2] but you are nasty [-3] [sentence: 2, -3] [result: max + and - of any sentence] [overall result = -1 as positive < negative] obtain Sentiment), the above text has positive strength 2 and negative strength -3.

SentiStrength does not use grammatical parsing to disambiguate between different words senses e.g. it won’t use the grammatical parsing for the part of speech tagging. The reason behind not using grammatical parsing is that there many informal text and phrases available on the social web, it does not depends upon the standard linguistic grammar for ideal performance. SentiStrength do use some of the grammatical information, however idiomatic phrases table can be utilized for a brute force based approach. It is also available in the following languages Finnish, German, Arabic, Polish, Persian, Dutch, Spanish, Russian, Portuguese, French, Swedish, Greek, Welsh, Italian and Turkish. A simple comparison can be made between humans and SentiStrength scores but for the best results at least three humans must be used as coders to code manually because the coding process is subjective and a single coder can give unusual results then the average of three or more.

#### B. *Emoticons*

It is one of the most effective methods of expressing sentiment. The term “emoticon derived from combination of “Emotion Icon”. Emoticons are commonly used by the users to express emotions with face like icon in comments, posts and tweets which can be positive, negative or neutral. Emoticons are the simplest way to detect polarity in a given message having different emoticons in it, if a message contains more positive emoticons it can be tagged as positive and if it is comprised of more negative labeled emoticons it can be tagged as negative.

Since text message does not reflect expression of sender,

emoticon provides the way of communicating facial/non facial expressions and intensity of subject. Same text message can be interpreted differently by inserting smiling face or sad face. Use of emoticons is rapidly growing on social media and micro blogging websites, emoticons are primarily face based that represents multiple emotions, for example :-)) and :) represents “ ? ” (a happy face) while :-( and :( represents “ ? ” a sad face. There are different emoticons for different emotions, where as there are multiple non-facial emoticons too such as </3 represents a broken heart. Polarity from emoticons can be extracted using a predefined list of labeled emoticons as either positive negative or neutral as describe by [16]. Text having multiple emoticons can be treated by detecting the polarity first appearing emoticon or by applying total scorings. A list of emoticon with their semantic orientation and relative symbols is provided in the mentioned Table I.

TABLE I: Emoticons, polarity and their symbols

Emoticon	Polarity	Symbols
☺	Positive	:) :] :} :o] :o] :o]:-[:-[: :-] =) =] =:] =^] =^] =^] :B :-D :-B :^D :^B =B =^B =^D :') :'] :'} =') ='] <3 ^.^ ^.^ ^.^ ^^ :* =* :-* ;) ;] :-p :-P :-b :^p :^P :^b =P =p \o/ /o/ :P :p :b =b =^p =^P =^b \o/
☹	Negative	D: D= D-: D^: D^= :( :[: :o{ :o{ :^ ( :^ [ :^ { =^ ( =^ { >= ( >= [ >= { >= ( >:- [ >:- ( >=^ [ >:- ( :- [ :- ( = [ = { =^ [ >:- ( >= [ >=^ ( :' ( :' :{ '= { '= [ = \ : \ = / : / =\$ o.O O_o Oo:\$:-{ >:-{ >=^ { :o{
☺	Neutral	:  =  :-  >.< >> >_< :o :0 =0 :@ =@ :^o :^@ -.-.-' -_- -_-' :x =X :# =# :-x :-@ :-# :^x :^#

**C. LIWC (Linguistic Inquiry and Word Count)**

Emotional, cognitive and structural components of a provided text is calculated using this text analysis tool. This calculation is done using a classified dictionary having different categorized words in it as described by [17]. LIWC also provide additional sets of sentiment categories instead of detecting positive and negative affects only, for example the word “agree” represents “assent, affective, positive feeling and cognitive process” categories. It is available commercially and also provides optimization options by allowing user to add their own customized dictionary instead of restricting them to use the default one for polarity detection. There have been different versions of LIWC, second version was presented in 2001 by [18], third was presented in 2007 by [19] with an expanded dictionary and a modern software design. The latest is LIWC 2015 by [8], dictionary and software has been upgraded significantly, rather than a basic update of

previous versions LIWCS 2015 has its software and dictionary updated entirely.

**D. SentiWordNet**

It is based on English lexical dictionary WordNet that was originally proposed by [20]. Adjectives, nouns, verbs and other grammatical norms are grouped into synonym sets called synsets in this dictionary, three scores are associated by SentiWordNet with synsets to identify the sentiment from the given text as either positive, negative or neutral as described by [9]. Four different versions of SENTIWORDNET have been discussed in publications:

- I. SENTIWORDNET 1.0, presented in [9] and made available publicly for research purposes.
- II. SENTIWORDNET 1.1, only discussed in a technical report;
- III. SENTIWORDNET 2.0, it is only discussed in detail in PhD thesis of the second author[21];
- IV. SENTIWORDNET 3.0, which is being presented here for the first time.

The version 1.1 and 2.0 haven’t been discussed rationally in any formal publications, the differences between different versions are given as under:

I. SENTIWORDNET Version 1.0 was comprised of an annotation of the old version of WORDNET 2.0, while the version 3.0 is an annotation of the newer version of WORDNET 3.0.

II. Automatic annotation was performed via a weak supervision, semi-supervised learning technique for SENTIWORDNET 1.0 and 1.1. On the other hand, for SENTIWORDNET 2.0 and 3.0 this semi- supervised learning algorithm resulted only as an intermediate step of the annotation process, as it was supplied to an iterative random walk process that is ran for convergence.

III. Glosses of WORDNET synsets were used by the SENTIWORDNET Version 1.0 and 1.1 as the semantic representations of the synsets themselves having a semi-supervised text classifier and a process is appealed that classifies the glosses of the synsets into categories as either Positive, Negative or Objective. This is referred as the first step of the process in SENTIWORDNET version 1.0 and for the second step the random-walk process mentioned above is used but these are automatically sense disambiguated versions from EXTENDED WORDNET as explained by Harabagiu et al., (1999). The SENTIWORDNET 3.0 used both the first and the second steps (semi-supervised learning process and the random-walk process respectively) instead of manually disambiguated glosses from the Princeton WordNet Gloss Corpus2.

**E. SenticNet**

People around the globe use social media networks to express their opinions about many topics, like a football match, elections or some any other activities. Sectors such as e-commerce, it is very useful to extract that kind of

information present on the social web, but it is a very difficult task. SenticNet is best alternative to obtain this sort of info. An effective approach to the concept level sentiment analysis is SenticNet. This is affective and publicly available semantic resource. It practices dimensionality reduction to achieve the schism of common sense concepts and a public resource is therefore provided for opinion mining from ordinary language text at a semantic level, rather than merely providing it on the syntactic level. SenticNet can be regarded as a lineal descendant of the work of [11]. Author worked on three precepts. Commencing with the finding of common intellect, knowledge from the Open Mind Common Sense (OMCS) corpus and the integral component of the procedure being used to produce the SenticNet is the demand that the knowledge must cater for the affective dimensions similarly for identifying the understood sentiment through induction process. SenticNet is the combination of WorldNet-Affect and ConceptNet. Methodology according to which SenticNet has been produced can be categorized into two sections. Compilation of the concept deposited therein is the foremost piece and the band of values with polarity is allied with each concept in the latter part specifies. As the first part of the algorithm, the single and multiword are obtained and separated from the ConceptNET and combined with the effective and multiple information sources from the given WorldNet-Affect. A two steps procedure is adopted for attaining the merge operating of the graph ConceptNet and the lexicon WorldNet-Affect. In the first step every given resource must be transferred into a special matrix. This step of the matrix representation is referred as the Analogy Space. While both matrices are combined in the second step. As a result of the procedure the newly formed matrix is affective semantic network named affectionately. AffectNet rows and listings are concepts only such as Rabbit or baked cake etc., having columns as wither sense and affective features such as “Is A-pet” or “has Emotion-joy” and whose categorization represents the exact values of the given statements. Thus, in AffectNet every given concept is mapped with a vector in the space of possible feature having values as positive for features that may produce an proclamation of positive values such as An Ostrich is a bird, having a negative feature that exhales an assertion of negative perspective such as “An Ostrich cannot fly” and reflects zero when none of the outputs are experienced about the proclamation. AffectNet is very effective in mapping of the common sense knowledge. As information based, SenticNet provides a lot of semantics, linguistic orientations, and polarity related to 50,000 natural language notions. In particular, the semantics are the concepts that are most Semantically-resembled to the input concept, scientists has crafted the emotion classification values replicated in terms of four specifically affective dimensions i.e. “The Pleasantness”, “The Attention”, “The Sensitivity”, and “The Aptitude” and for these four dimensions the polarity is floating value between -1 and +1 representing -1 as extremely negative and +1 as extremely positive. This

knowledge base is available to be downloaded for free in a standalone XML file and the latest version (that is issued every couple of years) can also be accessed as an integrated API.

[10] proposed That SenticNet is sentiment analysis and opinion mining technique that explores AI and semantic web techniques. The polarity of a given text is discovered using common sense concepts of natural language processing at a semantic level as either positive or negative instead of exploring the target content according to the syntax algorithm. NLP (Natural Language Processing) is utilized by this tool to set a set of about 14000 concepts with their polarities. For example, in the message “Yahoo, its weekend”, the algorithm will first identify the concept and afterwards assign polarity scores as either positive or negative accordingly. By combining linguistic, commonsense computing and machine learning algorithms the accuracy of polarity detection can be enhanced and it can outperform state-of-the-art statistical methods as described by [22]. Old versions of SenticNet were focused to collect polarity of thought analysis using common sense, but due to their inability to infer they were not performing up to the target. SenticNet 4 by [23] was developed to overcome these limitations by enhancing conceptual primitives automatically generated by the means of hierarchical clustering and dimensionality reduction.

#### ***F. Happiness Index & ANEW (Affective Norms for English Words)***

Happiness index depends on three different indexes, a health-related index, an economic index and an index related to personal feelings, values. Most common happiness indexes like how much happy you are? How happy you were day before? How much happiness you felt today? Economic Indexes likewise how much you are satisfied with your material possessions? Comparing of your income with others income? Compared with those around you, how much you compare material possessions? How much you are comfortable with your salary? And health related index like how do you relate your personal health? When you visited the doctor last time? How this is important for you to care about yourself? Same as indexes related to a personal value are important just like are you fare with your feelings and emotions as explained by [24]. The Affective Norms for English Words (ANEW) was designed and crafted by [12] the major purposed of this algorithm was to provide a collection of normative emotional ratings for a huge amount of English language words, originally ANEW is a collection of 1034 words having their respective affective dimension of valence, arousal and dominance. A newer tool that used ANEW-Affective Norms for English Words was introduced by [25], it generates a score for a given text between 1 and 9 depicting the quantity of happiness available in the provided text.

Emotions produce impressive impact on human feelings. Tons of research has been done on examining the emotions to haunting the Stimuli (sounds, movie clips, icons, lyric). How

much these stimuli are different from the natural stimuli at the behavioral level with the brain level. An evaluation was performed with the help of 958 graduate and undergraduate students (female =633 & males=325; SD=5.41 and M =22.82 years). These students were from different disciplines (technologies, Science, Economics and Humanities). Also, these students were selected from different universities, some from private sectors and some of Government Universities. All the selected sources were native EP speakers and they were selected from districts of all Portugal, which includes the Madeira and Azores islands. Filtering further the majority of the speakers were right-handed comprising about 92.1% of the total and had normal about 54.6% or corrected to normal visual perception of 45.4%. The author concluded that ANEW words were perceived in a comparative way by EP, Spanish and American sources, having same sex and cross cultural differences were experimented with this research. They found that EP adoption of the ANEW is a useful tool and it is valid for the researchers to handle and tackle the effective properties of stimuli.

### G. AFINN Lexicon

The AFINN lexicon technique is basically based on ANEW (affective Norms of English Words) lexicon that offers emotional ratings for a huge amount of English Words Dictionary. But as this method was crafted long before the advent of social media and slang words commonly used doesn't exist in this bucket. Inspired from ANEW, [26] crafted AFINN lexicon, it looks around for the language used in microblogs and social networks including the categorization of the slang words too. This algorithm also caters slangs and obscene words used in the social media and lists them as acronyms and the web terminology. The positive words from the list are marked from 1 to 5 and the negative words are marked from -1 to -5 for polarity categorization for the feed.

### H. OpinionFinder Lexicon

The OpinionFinder Lexicon generally referred as OPF, is a polarity based lexical algorithm which was developed by [15] it includes phrases and subjective sentences and is also an extension of MPQA (Multi-Perspective Questioning-Answering) dataset. Multiple humans tags each sentence with the polarity as either positive, negative or neutral, then the tags having low agreements are removed via the pruning phase resulting a detailed list of sentences and unigrams that are latter used for classification.

### I. The NRC Lexicon

The NRC lexicon is the lexicon that involves a huge set of pre-tagged and categorized words with the emotional tags. [27] crafted a word lexicon containing 14,000 unique English language words annotated according to the Plutchik's wheel of emotions by committing an activity of tagging in the crowdsourcing of AMT or the Amazon Mechanical Trunk platform. This list of words were arranged for multiple

categories, eight emotional and semantic categories were detected and selected during the formation of this lexicon as following coupled sentiments as "Joy-Trust", "Sadness-Anger", "Surprise-Fear" and "Anticipation-Disgust" composing of four opposite pairs. Eight features under NRC lexicon are available as NRC Joy (NJO), NRC Trust (NSU), NRC Fear (NFE), NRC Anticipation (NANT) and NRC Disgust (NDIS).

### J. SentiBench

There exist several methods for sentiment classification and the opinion mining but the authenticity and superiority of any one particular cannot be decided randomly, there are many famous methods for polarity detection and sentiment analysis but it is not clear which of them yields the best results, there is a strong need of comparison between these methodologies and techniques as the data is originated across different domains and different data sources. SentiBench as explained by [28] is a standard comparison of 24 famous sentiment analysis technique, while the benchmark of eighteen labeled datasets were evaluated containing social network posts, movies and products reviews and the opinions or comments in the news articles of different platform, the results shows how the performance of different sentiment analysis and polarity detection methods varies across different datasets.

### K. Bias-Aware Thresholding (BAT)

Lexicon methods for sentiment analysis and polarity detection yields more efficiency using its manually developed effective words list but the predictions of these methods can be sometimes biased towards positive or negative sentiments resulting in poor overall analysis. [29] proposed BAT (Bias-aware Thresholding) and offered to combine it with any lexicon based method to make it bias-aware.

The Bias-Aware Thresholding (BAT) is designed for sentiment detection and to reduce PBR towards zero while keeping in view and to maintain high prediction accuracy and making low error rate. BAT is based on cost-sensitive classification model reducing specific error while implementing a prediction threshold and maintaining the low error rate. In simple words it can be evaluated that when the prediction threshold is modified, this change is associated with one type of errors over the others making it uniform across the standard classification. This algorithm used for sentiment classification can be combined with any lexicon-based model, using the following decision rule:

$$C_{BAT}(d) = \begin{cases} + & \text{when } (S_A^+(d) - S_A^-(d)) > t \\ - & \text{otherwise} \end{cases}$$

A small set of labelled data can be used to effectively and accurately find the value of threshold  $t$ .  $t$  is looked for in this given simple root finding problem where the PBR is zero. This formulation can be sorted by using any line search

algorithm such as the bisection method. Even a small set of labelled data that yields low values of  $t$  even below the PBR on the test as per the evaluations made by the researchers of this algorithm.

#### L. Sentimeter-Br:

Sentimeter-Br is a Brazilian sentiment analysis technique based on Portuguese dictionary targeted on a specified area of study having the grammatical tenses and negation words treated different words accordingly to calculate the polarity of the short texts extracted from twitter as either positive or negative as explained by [30]. The Portuguese dictionary's performance was further evaluated by comparing its result with the famous sentistrength. The topic "Hair Care" was selected for the sentiment analysis and before developing any architecture the researchers did a preliminary screening for the target topic with most commonly used google searches and trends spanning to a period of four months. AFINN was used to develop a words based on the target topic having dictionary concentration of the hair care specialized products and items included in it. Two specialists valued the words and phrases from +5 to -5 depending on their semantic orientation and then these list of words were arranged within the dictionary and the final scores were calculated on the basis of suggestions made by the specialists and the existing AFINN words list. The Specialists mostly mentioned the adjectives, verbs and the negative words in their selection.

Sentimeter-Br dictionary is comprised of 2596 words having about 700 words as grammatical tenses, collectively 1600 positive and negative adjectives, 130 slang and absurd words, 116 words having emotions in them and 50 negation words. After formulating the dictionary 500 texts from twitter were analyzed and studied most of them were slangs and some were negative words. Sentimeter-Br is based on a script written in python language for sentiment strength calculation, a script for text extraction is used to collect tweets using twitter search API and the data is gathered and collected in the JSON format.

#### M. iFeel

[13] presented a new tool for sentiment analysis, iFeel is a web application that lets users to calculate sentiments from any form of text including un-structured social media data. It provides the users with access to seven different sentiment analysis methods embedded in a single platform including SentiWordNet, Emoticons, PANAS-t, SASA, Happiness Index, SenticNet and SentiStregh. Users can manipulate and test results with different combinations of sentiment analysis methods with an interactive, flexible and user friendly interfaces. An asynchronous thread for the given seven sentiment analysis tools as listed above, process the given text concurrently. Every process in the iFeel algorithm has its own rules for data handling and natural language processing of sentiment detection. iFeel can be evaluated in two ways, one in the form of efficacy that deals with the profitability by

combining and comparing different methods and second in the form of scalability that evaluates how much time and other resources are required.

## IV. DISCUSSION

In our study different lexicon based sentiment classification methods were studied and evaluated. Following mentioned table briefly represents the average accuracy of all the evaluated lexicon based sentiment classification tools. Three datasets were used for the evaluation of these tool i.e., Twitter Dataset, DIGG Comments dataset and the BBC Comments dataset. A list of lexical tools with their features and accuracy is provided in the below mentioned Table II.

TABLE 2: Tools, Features and their accuracy on different datasets

S#	Author Name	Publication Year	Tool Name	Features	Twitter Data	DIGG Comments	BBC Comments
1	Cambria	2016	SenticNet 4	Polarity: positive, negative, Subjectivity, Aspect	70.49	69.4	66.07
2	Pennebaker	2015	LIWC2015	emotional, cognitive, and structural components of a given text	89.22	70.67	63.21
3	Thelwall	2013	SentiStrength	negative, neutral, positive, method score for the positive category	95.33	92.09	93.93
4	Baccianella	2010	SentiWordNet 3.0	sum of the scores for the positive words that matches the lexicon and sum of the scores for the negative words that matches the lexicon	72.99	62.17	57.49
5	Nielsen	2011	AFINN Lexicon	sum of the scores for the positive words that matches the lexicon and sum of the scores for the negative words that matches the lexicon	84.42	70.94	66.56
6	Wilson	2005	OpinionFinder Lexicon	number of positive words that matches OpinionFinder number of negative words that matches OpinionFinder	80.77	71.14	74.43
7	Mohammad	2012	NRC Lexicon	number of words that matches the joy word list ... matches the trust word list ... matches the sadness word list ... matches the anger word list ... matches the surprise word list ... matches the fear word list ... matches the anticipation word list ... matches the disgust word list	71.3	74.69	84.45
8	P. S. Dodds	2009	Happiness Index				
9	Iqbal	2015	BAT	Bias-Aware Thresholding (BAT)	74	80	87
10	Rosa	2013	Sentimeter-Br	uses SentiStrength and AFFIN Lexicon	89	-	-
11	Ribeiro	2015	SentiBench	A Bench mark comparison			
12	Aranjo	2014	iFeel	Comparative study			

## V. CONCLUSION

There are a lot of studies and researches available on lexicon based sentiment classification tools and techniques but comprehensive and compact information on this particular topic was required. Our study will serve all the beginners and newbies to have a detailed understanding of the lexicon or dictionary based tools and techniques for sentiment classification. A comprehensive comparison on different dataset is also available in the research that can be used for ready reference in future research works.

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