Survey on Sentiment Analysis for Twitter

Ankita Gupta
Research Scholar, Department of CSE & IT, The North Cap University
Gurgaon, India
ank21gupta@gmail.com

Jyotika Pruthi
Assistant Professor, Department of CSE & IT, The North Cap University
Gurgaon, India
jyotikapruthi@ncuindia.edu

***Abstract*—Social media has revolutionized the communication among the people. Extracted sentiments are very valuable for decision making. Sentiment analysis is an approach of determining people attitude towards any topic. Main goal is to classify a piece of opinionated text containing expressed opinions into positive, negative or neutral and also determine strength of polarity (strongly positive, mildly negative etc.). This paper presents a review on various tools and techniques that has been used by various researchers in existing literature for sentiment analysis of tweets. Thus aim is to provide illustration of research trend in sentiment analysis.**

Keywords- Sentiment analysis, web 2.0, supervised learning, machine learning, semantic, opinionated.

I. INTRODUCTION

Sentiment analysis has been defined as multifaceted problem by liu[6].Sentiment Analysis is a machine learning technique that is used to classify the people sentiments towards any topic or contextual polarity of any text (containing people opinions) by using natural language processing techniques, computational linguistics and text analysis. There are varieties of data sources for opinionated data but today micro-blogging websites such as Twitter spawned the formation of real time messages about any topic of interest as it is the timeliest among various social media websites. Twitter is ironic source of opinionated data for sentiment analysis thus twitter provide augmented opportunities for researchers to gauge into different and diverse dimensions and applications. Twitter user can be a regular person, celebrity, politician, news reporter or even president, prime minister of a country.. Thus sentiment analysis of twitter data provides an effective way to gain insight into the mood of the vast pool of people by comprehending their opinions and is next footstep to sentiment analysis. Although twitter is an excellent medium for opinion collection but poses a lot of challenges due to its unstructured nature like misspellings, abbreviation, slangs, punctuations, idioms etc. so sentiment analysis of twitter is somewhat different from sentiment analysis of reviews and a lot of progress has been observed in twitter sentiment analysis despite of challenges posed by its unstructured nature.

Surveys, interviews and comment cards from the customers are some of the old fashion techniques for analyzing or obtaining people sentiments towards any topic but presently scenario is opposite as huge amount of opinionated diversified unstructured data is available in digital form in social media websites and it’s too difficult to manually analyze sentiments or opinions from them so here comes the need of automated sentiment analysis techniques for mining sentiments form these opinionated digital data. So sentiment analysis is an important area of research and is in boom now a day’s .Sentiment analysis is a way of automatic analysis of online sentiments expressed by people on any topics. Sentiment analysis is usually done at three levels:-document level, sentence level and aspect level that is classifying polarity of document, sentence or aspect into positive, negative and neutral respectively.

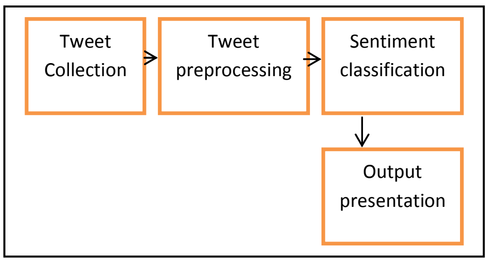


Fig. 1- Showing sentiment analysis process

II. LITERATURE SURVEY

Apple et al.[1] suggested use of hybrid approach is better than simple supervised machine learning algorithms e.g. Naive Bayes(NB) and Maximum Entropy(ME).They assimilated various techniques like sentiment lexicons, fuzzy theory etc in their hybrid approach and have used two different twitter datasets for experimentally proving their results-Twitter A and Twitter B respectively. Twitter B is a classified dataset. They also handled simple negation by incorporating various semantic rules for better estimation of polarity of sentences. They have also used a different movie reviews dataset for experimentally proving their results. They proved it as: On twitter A dataset:

Approach	Accuracy	Precision
Hybrid	0.8802	0.8424
Naive Bayes	0.6785	0.6315
Maximum Entropy	0.6759	0.6293

Likewise hybrid approach was better on other datasets used by Apple et al.

Muhammad et al.[2] found that word's polarity depends on its context both local and global. For local context they handled negation, intensifiers, Capitalization, repeated alphabets etc. For global context they made use of distant supervision learning technique. So they introduced a new system called SmartSA in which general purpose lexicon (SentiwordNet) is extended with domain specific lexicon. They used 3 different datasets Twitter, Digg and MySpace for this purpose. They concluded that SmartSA is better than baseline lexicons and other systems like NB, Support Vector Machine(SVM) etc. with more F1 score.

Saif and He[3] made use of SentiCircles. Meaning of words in different contexts are found by making use of these senticircles. With the help of this the pre-polarity of these words is updated for better sentiment classification.

Prabowo and Thelwall[4] suggested use of multiple classifiers like Rule base, Support Vector Machine, General Inquirer (GIBC),Statistics Based classifier(SBC),Induction Base classifier(IRBC) in hybrid manner for improving effectiveness of sentiment analysis in terms of micro and macro averaged F1.

Kowcika et al.[5] suggested a system for sentiment analysis of twitter data collected form Twitter API and provide rigorous analysis on an efficient scoring system for predicating user age and on Naïve Bayesian classifier for predicting user gender. **Liu[6]** explained sentiment analysis as an multi-faceted problem that is confronted with lot of challenges like feature extraction, opinion orientation etc. Author presented his outlook on past and future of sentiment analysis and proposed that real time applications need fully automated system for analysis. **Agarwal et al.[7]** experimented 3 models-unigram, feature base and tree kernel model on binary and 3-way classification task and found that tree kernel performs better than both by 4.02% and 4.29% respectively. Also after rigorous analysis they found that most important feature are that which combine prior polarity with pos tags and proposed the new 100 features that can improve classifier accuracy.

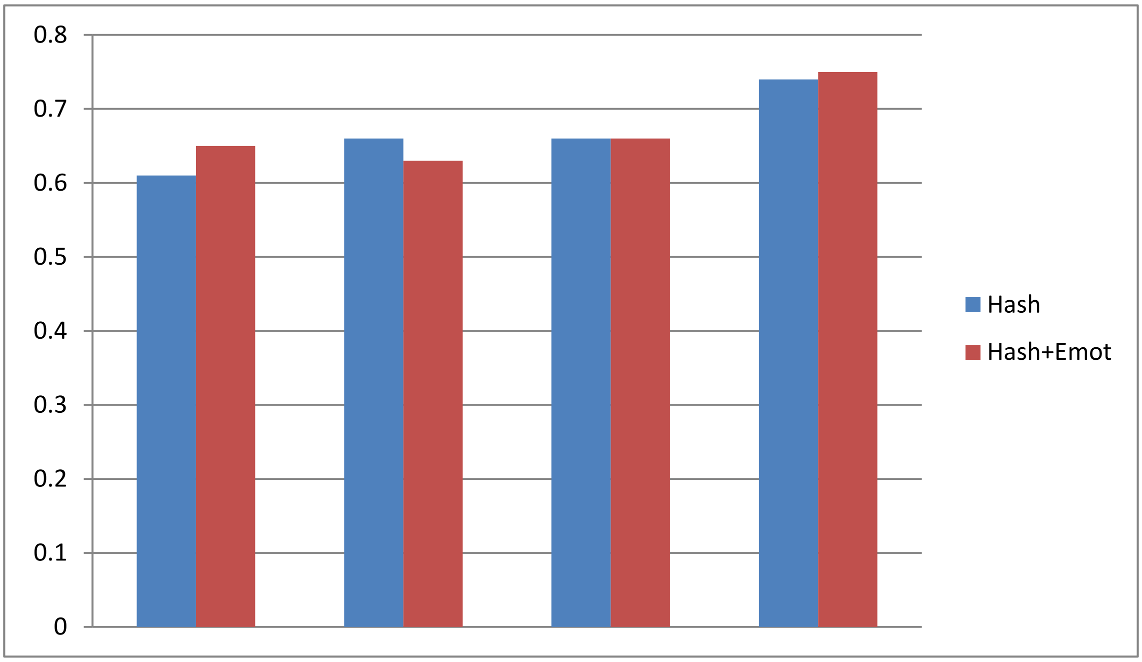
Model	Avg. Acc(%)	Std Dev.(%)
Unigram	71.35	1.95
Senti-Features	71.27	0.65
Kernel	73.93	1.50
Unigram+Senti-Features	75.39	1.29
Kernel+Senti-Features	74.61	1.43

Average and standard deviation for test accuracy for the 2-way classification task using different models: Unigram (baseline), tree kernel, Senti-features, unigram plus Senti-features, and tree kernel plus senti-features.

Pak and Paroubek[8] trained 2 NB classifier–one with n-gram and other with pos feature and experiment showed that bigram model outperforms unigram and pos and attaching of negation word to n-gram improves accuracy but decision is lower. Spancer and Uchyigit[9] suggested sentiment tool that use NB classifier for tweet sentiment analysis. They experimented NB classifier on manually annotated 216 tweets with unigram, unigram+pos ,bigram and bigram +pos and results showed that bigram without pos give highest accuracy 52.31% and 46.76% accuracy for unigram model without pos which was lowest.

Test	Correctly Identified	False Positives
Unigrams	101	46.75%
Unigrams+POS	109	47.2%
Bigrams	113	52.31%
Bigrams+POS	108	50%

Kouloumpis et al.[10] developed three corpus-one is hash tagged dataset, second is emoticons data set and third on is manually annotated Isieve data set used for performance evaluation of classifier and result showed that model trained on hash tagged alone with combination of n-gram +lexicon +micro blogging feature give best performance ,use of pos drop the performance and benefits of emoticon training set decreased if twitter features are included.



Agarwal and Sabharwal[11] suggested cascaded pipeline in which 3 classifiers are built on top of each other to classify tweets into 4 classes-positive, negative, neutral and objective. They experimented 4 way classifier, PNP objective neutral and PNP neutral models by calculating precision, recall and f measure and results showed that f measure of PNP objective neutral are growing at higher rate in contrast to 4 way classifier.

	4-Way			PNP-neutral			PNP-objective-neutral		
Category	*P*	*R*	*F1*	*P*	*R*	*F1*	*P*	*R*	*F1*
Objective	.70	.87	.78	.77	.76	.76	.78	.76	.77
Neutral	.51	.30	.38	.48	.22	.31	.39	.46	.42
Negative	.56	.56	.56	.49	.64	.56	.57	.57	.57
Positive	.59	.56	.57	.51	.67	.58	.61	.53	.57
Average	.59	.57	.57	.56	.57	.55	.59	.58	.58

Narr et al.[12] suggested language independent classifier Naïve Bayesian with n-gram feature trained on twitter data set of 4 different languages English, German, French and Portuguese labeled with positive and negative classes through semi-supervised emoticons heuristics.. Over all unigram NB model give best performance .Mixed language classifier (trained on 300k mix language tweets) obtained 71.5% accuracy on agreed-3 set. **Hemalatha et al.[13]** explained an algorithm for pre-processing of twitter data in order to improve classifier accuracy . They also described use of SentiWordNet dictionary for tweet sentiment analysis where each sentiment word is assigned 3 polarity scores-positivity, negativity and objectivity. **Saif et al.[14]** suggested semantic feature as an additional feature for training Naive Bayesian classifier to improve its accuracy and found interpolation gives best result in terms of average F measure 75.95%.They experimented NB model trained on unigram, unigram +pos, sentiment topic and semantic features and found that semantic NB model increased average F1 measure by 6.47% against unigram and 4.78% against pos +unigram. **Kaushik and Mishra[15]** suggested fast lexicon based approach without compromising classification accuracy for twitter sentiment analysis and implemented an algorithm in Hadoop sandbox version (in HiveQl language which is like SQL for managing large database) for calculating sentiment score of each word of tweet through use of lexicon dictionary. **Kiritchenko et al.[16]** explained SVM supervised text classification techniques for SemiEvaltask 2013 explained and obtained first position in SemiEvaltask 2013 and automatically generated lexicons provide better predictive power than manually generated lexicon. After SemiEvaltask 2013 classifier F1 measure improves to 70.45% for message level and 89.50% for expression level on tweets. They also experimented their system on movie reviews and obtained 85.5% accuracy in classification. **Sahayak et al.[17]** suggested a hybrid approach based on corpus and dictionary methods, using different feature extractors like unigram +bigram, unigram +pos for twitter sentiment analysis. **Wakade et al.[18]** explained Weka data mining tool for creating decision classifier for sentiment analysis of IPhone and Microsoft tweets into positive ,negative and neutral and result showed that decision classifier outperforms Naïve Bayes classifier and also conclude that using emoticons as feature have negative effect on decision classifier performance but slight increase in Naïve Bayes performance. **Carpenter and Way[19]** proposed an algorithm for determining sentiments of tweets over time for a particular topic and designed VSAT tool(Villanova Analytical Sentiment Trackers) for implementing proposed algorithm which will use four types of list of words-Extra wordlist, Main wordlist, negation ,adverb and intensifier list. VSAT tool generates results immediately and experimented results showed that VSAT tool achieve reasonable accuracy even though it slows down speed of algorithm. **Kumar and Sebastian[20]** suggested hybrid prototype model for calculating sentiment polarity of opinion words in tweets by using corpus and dictionary based approach. **Mukherjee and Bhattacharyya[21]** suggested discourse based Bag of word model for tweet classification in which conjunctions, negations, conditional and modals discourse information is incorporated and devised an algorithm for calculating of feature vector having discourse information in it. and experimental results showed that their lexicon base discoursed model achieves 4% improvement in accuracy over baseline lexicon method.

III. SENTIMENT ANALYSIS TECHNIQUES

Existing literature leveraged on two main approaches- Semantic Orientation and Machine Learning

A. Semantic Orientation

It means how far a word is inclined towards positive and negative category by making use of lexical resources. This approach has been further categorized into corpus based and dictionary based approaches.

- Corpus based approach

Finds co-occurrence of pattern of words to determine tweet sentiment. For example PMI(Point Wise Mutual Information) used to measure correlation between two terms and finds out sentiment orientation depending upon proximity of phrase with words like excellent, bad etc.

$$PMI(w1,w2)=log2(p(w1,w2)/p(w1)p(w2))$$

$$SO(w)=PMI(w, excellent)-PMI(w, poor)$$

- Dictionary Based approach

This approach make use of lexicons (opinion dictionary that provides list of sentiment words with their polarity and strength).It is also the traditional way of assigning sentiments by just looking no of positive words and negative words. Shukla[22], Hemalatha[13], used SentiWordNet for determining annotations polarity. Kaushik[15] also used pure lexicon based approach. Carpenter[19] proposed use four types of list of words-Extra wordlist, Main wordlist, negation ,adverb and intensifier list for tweet sentiment analysis. LIWC,GI,BING-LIU,WORDNET ,SENTIWORDNET,Emoticon, are the lexicons that have been used by researchers for Bag of Word model but relying on only lexicons misclassify some tweets as linguistic features like modifiers(very, hardly),negation(not, never), emoticons, punctuations, exclamations ,discourse relations(but ,except that, and) etc are ignored . Hence some researchers have designed opinion rules and algorithm for handling complex sentences grammatical relationship between words(linguistic features) which has the ability to change the sentence polarity. Even though adjectives are the most important sentiment bearing words but noun, adverbs and verbs can also affect sentiment so rules have been formed for verbs, adverbs etc. For sentiment analysis of tweets, rules has been designed for tweet specific features like hashtag, capitalization, exclamation etc. Rule based classifier is unsupervised linguistic approach in which prior sentiment of each word are found independently and then linguistic rules are applied to handle linguistic relations .Polarity of sentence in rule based is determined based on sentence structure and contextual information and do not require labeled training data .

For example:-

(a) I like the restaurant food but service is poor.

In this because of discourse element "but" sentence is conveying negative sentiment.

(b) Movie was not very good

Here sentiment is negative even though good is positive sentiment word because of negation word "not".

Mariana[24] proposed context dependent and independent rules for clausal level analysis of Ukrainian review and achieved average precision of 62% on 200 reviews. Asmi[26] proposed rules for negation like not ,never and also used SentiWordNet, WordNet and other resources for phrase level analysis and used syntactic parser for negation identification and dependency parser for scope identification. Hutto[27] proposed rule based VADER model by developing microblogging specific vader lexicon and then proposed 5 heuristic rules for handling conjunctions etc, and got 0.96 accuracy for tweet classification. Neviarouskaya[28] proposed rule based approach in which rules for verbs are created for phrase level analysis and also created lexicon of modifier words ,modal expression etc. Some researchers used supervised learning in combination with opinion rules so that accuracy could be improved. Swati[29] proposed hybrid approach-rule based and SVM classifier for movie review analysis. They focussed negation handling approach. Zhang[30] proposed augmented lexicon based method for entity level sentiment analysis but due to absence of twitter specific features in lexicon low recall is obtained hence using chi-square test authors extracted opinion indicator and then Binary SVM is trained on result of lexicon. Proposed approach outperformed baseline like only machine learning, lexicon etc.

B. Machine learning approach

Machine learning approach can be supervised and unsupervised but mostly researchers use supervised classifiers . Supervised classifiers need annotated training data (so that they can learn features from text and based upon learning classification is done), test set for evaluating classifier performance. In contrast to that unsupervised approach do not require labelled training data. For example-K-Mean, Hierarchical clustering etc..

Naïve Bayesian, Support Vector machine ,MAX ENT models, decision tree, perceptron, ID3,C5 etc. are various supervised classifiers but most commonly used supervised classifiers in existing literature are-

- *Naive Bayesian*

  Naïve Bayesian classifier is a supervised (analysed labelled training data and then learn a function from training data) generative model as it place or put probabilities over both observed and hidden stuff(mean class) that is P(d,c) .It is based on Naïve Bayes theorem and depend on bag of words representation (it is a collection of words with their counts). So let us first study Naïve Bayes theorem. Naïve Bayes theorem:-

$P(c|d)=P(d|c)\ P(c)/P(d)$

P(c) is prior probability of class c

P(d|c) is the probability of document d given class c

P(d) is the probability of document d

And goal of Naïve Bayes theorem is to predict the probability of class given a document d that is P(c|d) .Now comes the turn of naïve bayes classifier that is goal of classifier is to choose a most likely class that maximize the product of two probabilities that is P(d|c) P(c).So naïve Bayesian classifier is :

CMAP = argmaxcεC P(c|d) where C is set of classes and c represent an individual class from set C and CMAP is called maximum a posteriori that is most likely class that maximize the product of two probabilities that is P(d|c) P(c).

Using Naïve Bayes theorem we get:

$CMAP = \mathrm{argmax}_{c \varepsilon C}\ P(d|c)\ P(c)/P(d)$

Let us represent Document d by feature vector x1, x2,….., xn. So we get:

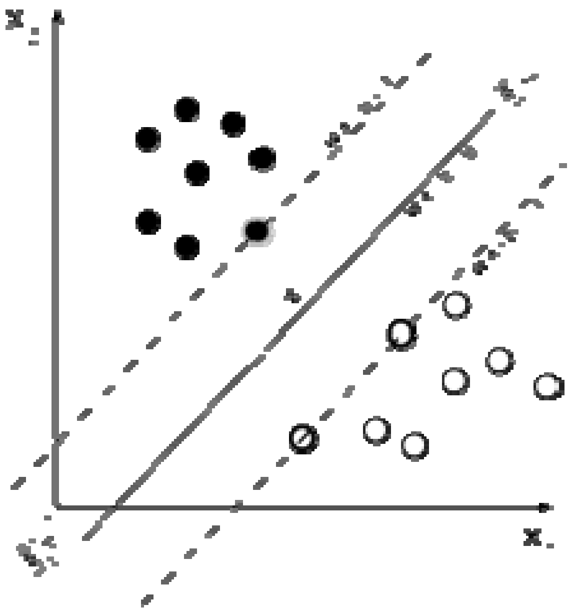
CMAP = argmaxcεC P(x1, x2,….., xn |c) P(c)

Where P(x1, x2,….., xn|c) is joint probability of features given class c.

Naïve Bayesian assumes the independence of probabilities of feature that is P(xi,cj) given class c .It is the simplest algorithm and used for tweet classification where SVM is mostly used for reviews ,posts etc. Kowcika[5] used NB classifier for predicting twitter user gender and then for sentiment analysis. Pak[8],Spencer[9],Go[33],Narr[12],Saif[14] applied their multilingual NB classifier for analysing tweets of Swiss politician for finding out to which party a politician belong to .

- *Support Vector Machine(SVM)*

It is non probabilistic binary linear classifier. It uses supervised learning method for classification and regression analysis and can handle both discrete and continuous variable. SVM can be in linear or nonlinear but in practically classes are nonlinear so a high order function is required for splitting data set form. Main goal of SVM is to find out hyperplane that have maximum margin from nearest element of both the classes because larger the margin lower is the generalization error.



Any hyperplane can be written as-

w.x-b=0

where . denotes the dot product and **W** is the (not necessarily normalized) normal vector to the hyperplane that is w represent orientation of hyperplane. b is a constant representing position of hyperplane The parameter $\frac{b}{\|\mathbf{w}\|}$ determines the offset of the hyperplane from the origin along the normal vector **w**.Hence b and w are parameter that are optimised during svm training and then using the optimised values SVM classifier is used for classifying new unseen examples. Agarwal[7], Kiritchenko[[16], Agarwal[11], Mukherjee and Bhattacharyya[21] used SVM for tweet sentiment analysis. SVM is mostly used for review sentiment analysis.

- *Maximum Entropy Model(MaxEnt)*

It is a feature based discriminative classifier that does not make any assumption over the features independence and put the direct probabilities over hidden structure unlike to NB model that put probabilities over observed data. Training time for maxent model is more that NB but robust results are provided after training. In this model features are weighted so that model expectation match the observed(empirical) expectation and try to maximize entropy subject to feature constraints and choose most uniform distribution. Maxent model is based on principle of maximum entropy which states that-if incomplete information about a probability distribution is available the only unbiased assumption that can be made is a distribution which is as uniform as possible given the available information.

Then from all the models that fits training data select highest entropy model.

Maxent model classify from features sets {f i } to classes {c}. Assign a weight λi to each feature f i . For a pair (c,d), features vote with their weights:

vote(c) = Σλi f i (c,d)

Probabilistic model is formed from above linear classifier-

$$p^*(y|x) = \frac{\exp\left(\sum_i \lambda_i f_i(x,y)\right)}{\sum_y \exp\left(\sum_i \lambda_i f_i(x,y)\right)}$$

Given this model form, parameters λi are choose so to maximise the conditional likelihood of data according to model. Now a document is classified by use of "maximum a posteriori" rule and select the category with the highest probability. Saif[34] evaluated performance of MaxEnt and NB classifier on removal of stop words. MaxEnt performed better than NB when no stop word is removed but NB is found to be more sensitive than MaxEnt with regard to stop word removal. Go[33] compared performance of MaxEnt classifier with SVM and NB.

Some researchers also performed comparative studies of various classifiers and choose the best performing classifier. Pak[8] experimented with NB and SVM both but selected NB because it yielded best result . Go[33] researched performance of NB,SVM and Maxent classifier and selected NB. .Prabowo[4] used one such ensemble techniques by combining rule based, supervised SVM classifier so that if one classifier fails ,document is then passed to another classifier and so on to improve accuracy. They tested their proposed approach on movie, product review and myspace comments. They obtained accuracy between 89-90.38% for different sample of data. Modha[31] proposed to use hybrid approach that is SVM, NB, POS, BOW, sentiment lexicon rules for sentiment analysis of Indian Political news articles. Agarwal[11] designed cascaded pipeline stacking 3 SVM classifiers on top of each other. Kiritchenko[[16] used SVM and various manually created lexicon like NRC emotion, Liu, MPQA lexicon and automatically created tweet specific lexicons from hashtagged and emoticon corpus. Kumar[20] used both corpus and dictionary based approach for tweet sentiment analysis such that adjective score is retrieved through log linear regression model and adverb and verb score through lexicon approach. Sahayak[17] proposed use of supervised classifier and lexicon both for tweet sentiment analysis. Revathy[32] proposed semantic sentiment mining hybrid approach that combined 3 models-one is rule based model, another is SVM trained on sentiment features and last one is NB classifier in which semantic concepts are added as additional feature through interpolation and and all models with combination of features that is unigram, bigram, unigram+Pos, sense features are experimented and compared with baseline like SVM, maxent, NB and results showed that maximum accuracy is obtained through synset features. Filho[23] described hybrid classifier that used 3 different classifier –rule based, lexicon and machine learning approach in sequential order for twitter sentiment analysis and achieved 56.31% f score in SemEval 2013 subtask 2-message level polarity. Chikersal[25] proposed combination of rule based classifier with SVM for tweet sentiment analysis. Rule based approach is based on emoticon related rules and sentiment lexicon related rules. Rule based classifier in their proposed approach refine SVM prediction.

IV. EVALUATION AND DISCUSSION

Table 1 provides the systematic evaluation of various research work done in sentiment analysis. It depicts unique categorization of various techniques of sentiment analysis and experimental results produced so far. Precison,recall,F1-measure and accuracy are evaluation metrics for measuring performance of algorithms. From the table it can be concluded that lot of research work has been done on twitter data set which is a challenging task due to informal language of tweets and it is difficult to tell best performing classification model as performance of models depend on features selection.

S.No.	Authors	Feature Selection	Data source	Models	Accuracy	Precision	Recall	F1
1.	Apple et al. (2016)		Twitter Movie -Reviews	Hybrid(NLP, Sentiment Lexicon &Fuzzy theory)	TwitterA-88.02 TwitterB-86.55 Movie Review-75.85	TwitterA-84.24 TwitterB-84.06 Movie Review-72.78	-	-
2.	Muhammad et al.(2016)		Twitter Digg MySpace	SmartSA -Hybrid Lexical approach	-	-	-	Twitter-77.22 Digg-67.85 MySpace-65.96
3.	Kirtchen ko et al.(2015)	Word ngram ,character ngram, POS,hashtags ,opinion words etc.	Twitter SMS Dataset	SVM	-	-	-	Term level-89.10, 88.34 / Message level-69.02, 68.46
4	Chetan Kaushik and Atul Mishra(2014)	Negation, emoticons, opinion words	Twitter	Lexical Approach	73.5	-	-	-
5	Hutto(2014)	Lexicons	Twitter	VADER Model(micro-blogging specific lexicon)	96	-	-	-
6	Saif et al.(2014)	stopwords	OMD,HCR,STS-GOLD,Semi-Eval,WAB,GASP	Classic	83.09	-	-	78.46
				TF-1	84.50			80.85
				TF-High	82.31			77.58
				IDF	67.85			57.07
				TBRS	84.02			79.60
				MI	85.91			82.23
7	Kowcika et al.(2013)	ngrams, stop words, full screen name	Twitter	NB	84	+ve:-92 -ve:-73 Neutral:-85	-	-
8	Spencer and Uchyigit et al.	Unigram,Bigram POS	Twitter	NB	52.31(bigram without pos)	-	-	-
9	Agarwal and Sabharwal (2012)	Ngrams,pos etc.	Twitter	Hierarchical Cascaded Pipeline	-	PNP Neutral 56	PNP Neutral 57	PNP Neutral 55
						PNP Objective Neutral 59	PNP Objective Neutral 58	PNP Objective Neutral 58
10	Saif et al.(2012)	Semantic Features	STS,OMD,HCR	NB	-	Semantic 77.18	Semantic 75.33	Semantic 75.95
11	Wakade et al.(2012)	Emoticons, pos, neg words list	Twitter	Decision Tree Classifier	97	-	-	97-98
12	Carpenter and way(2012)	Extra word list, Main word list, Negation list, Adv list and Intensify list	Twitter	VSAT tool(Villanova Analytical Sentiment Tracker)	65-85	-	-	-
13	Mukherjee and Bhattacharyya(2012)	Connectives, conditionals ,Modals, Negation ,ngrams, pos	Twitter and Travel Review dataset	Lexical based discourse model and SVM+discourse model	88.13	-	-	-
14	Agarwal et al.(2011)	Ngram, senti features	Twitter	Tree-kernel approach	2 way classification-73.93 3 way classification-60.60	-	-	-
15	Kouloumpis et al.(2011)	Ngram, pos ,lexicon and micro-blogging features	Hashtagged,emoticons and Isieve data set	AdaBoost model	Hashtagged dataset with all features-75	-	-	Hashtagged dataset with all features 65-68
16	Pak and Paroubek(2010)	Unigram, bigram, pos	Twitter	Multinomial NB	70-80	-	-	-
17	Prebowo and Thelwall(2009)	Document frequency	Movie Review and myspace comments	ID3,SVM and Hybrid	89	-	-	-
18	Go et al.(2009)	Unigram. bigram ,pos	Twiiter	NB, Maxent, SVM	NB :- 81	-	-	-

V. CONCLUSION

From the literature survey it is evident that it's a challenging task to handle complicated phenomenon (ungrammatical and out of vocabulary word) but still a lot of progress has been witnessed in area of sentiment analysis of tweets despite of poor semantic and syntactic structure of tweets and also fully automated system has not been introduced yet because of unstructured nature of data. For fine grained analysis it is important to focus on linguistic features like intensification, modality, discourse relation, negation, twitter specific features in addition to supervised classifiers. A lot of research has already been carried out but there is always space of improvement.

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