# Review of Twitter sentiment analysis

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**Abstract.** Twitter data has recently been considered to perform a large variety of advanced analysis. Analysis of Twitter data imposes new challenges because the data distribution is intrinsically sparse, due to a large number of messages post every day by using a wide vocabulary. Sentiment Analysis task is divided in two steps: Feature selection methods and Sentiment classification methods. Feature selection methods aims at selecting appropriate words from the text used for sentiment analysis. Sentiment classification methods are classified as machine learning methods, lexicon based methods and hybrid methods. Each method is having its own limitations. The paper mainly focuses on the twitter sentiment datasets and tools which are freely available for research purposes.

**Keywords:** twitter, sentiment, machine learning, feature selection, datasets, tools

## 1. Introduction

In recent years, social networks and online communities such as Twitter and Face book have become a powerful source of knowledge. Such sites are accessed by millions of people every day. Building a Social Media Monitoring tool requires at least 2 modules: one that evaluates how many people are influenced by the campaign and one that finds out what people think about the brand.

Evaluating the generated buzz is usually performed by considering the number of followers/friends, the number of likes/shares/RTs per post and more complex ones such as the engagement rate, the response rate and other composite metrics. On the other hand, being able to evaluate the opinion of the users is not a trivial matter. Evaluating their opinions requires performing Sentiment Analysis, which is the task of identifying automatically the polarity, the subjectivity and the emotional states of particular document or sentence. It requires using Machine Learning and Natural Language Processing techniques and this is where most of the developers hit the wall when they try to build their own tools.

Twitter is a social networking and micro blogging service that lets its users post real time messages, called tweets. Tweets have many unique characteristics, which implicates new challenges and shape up the means of carrying sentiment analysis on it as compared to other domains.

Twitter, with nearly 600 million users and over 250 million messages per day, has quickly become a gold mine for organizations to monitor their reputation and brands by extracting and analyzing the sentiment of the Tweets posted by the public about them, their markets, and competitors.

Performing Sentiment Analysis on Twitter is trickier than doing it for large reviews. This is because the tweets are very short (only about 140 characters) and usually contain slangs, emoticons, hash tags and other twitter specific jargon.

In the following section, we present some of the most relevant work that has been recently conducted in sentiment analysis of twitter and describe the research trends in this field.

## 2. Sentiment Analysis of Twitter

Twitter sentiment analysis task can be broadly divided in two steps as

Feature selection Methods: The first step in the SC problem is to extract and select text features. Some of the current features selection techniques are

1. Terms presence and frequency:
2. Parts of speech (POS): finding adjectives, as they are important indicators of opinions.
3. Opinion words and phrases: these are words commonly used to express opinions including good or bad, like or hate.
4. Negations: the appearance of negative words may change the opinion orientation like not good is equivalent to bad.

Sentiment Classification techniques

Sentiment Classification techniques can be roughly divided into machine learning approach, lexicon based approach and hybrid approach. The Machine Learning Approach (ML) applies the famous ML algorithms and uses linguistic features. The Lexicon-based Approach relies on a sentiment lexicon, a collection of known and precompiled sentiment terms. It is divided into dictionary-based approach and corpus-based approach which use statistical or semantic methods to find sentiment polarity. The hybrid Approach combines both approaches and is very common with sentiment lexicons playing a key role in the majority of methods

## 2.1 Feature Selection Methods

Feature Selection methods can be divided into lexicon-based methods that need human annotation, and statistical methods which are automatic methods that are more frequently used. In the following sections we will review some of the commonly used statistical methods in feature selection

### 2.1.1 Point-wise Mutual Information (PMI)
Pointwise mutual information (PMI),or point mutual information, is a measure of association used in information theory and statistics. In the PMI method, associations between an unknown word and positive/negative seed terms such as "excellent" and "poor" are used to recognize the sentiment of that word.

- Authors in [1] proposed a verb oriented sentiment classification approach for social domains.The proposed approach focuses on the verb as the core element of an opinion.
- Authors in [2] use the Point-wise Mutual Information (PMI) between the keywords to identify similar words. They compute the PMI between the noun phrases in each domain. Given that there are pairs of words who appear only once, only the noun phrases present more than twice are considered. After computing the PMI score, only the pairs of keywords with PMI scores more than a threshold are linked by skip edges

**Problems with PMI:**

1. Bad with sparse data

— Suppose some words only occur once, but appear together
— Get very high score PMI score
— Consider our word clouds. High PMI score might not necessarily indicate importance of bigram
2. Bad with word dependence
— Suppose two words are perfectly dependent on each other
— the rarer the word is, the higher the PMI is
— High PMI score doesn't mean high word dependence (could just mean rarer words)
— Threshold on word frequencies

### 2.1.2. Chi-square ($X^2$)

Chi-square is a statistical test commonly used to compare observed data with data we would expect to obtain according to a specific hypothesis. The chi-square test is always testing what scientists call the null hypothesis, which states that there is no significant difference between the expected and observed result.

- To compare sentiment analysis score with its corresponding star rating authors in [3] conducted cross tabulation and chi square analyses for all the datasets. The chi-square test is used to determine whether there is a significant difference between the expected frequencies and the observed frequencies in one or more categories.
- Authors in [4] compared the approach (denoted as *STD*) with the Chi-square test based approach (*CHI-Square*). Chi-square test uses the distinction between word real distribution and expected distribution in sentiment category to measure word significance. Authors proved that the *STD* approach is significantly better than *CHI-Square* approach in both precision and recall.

**Problems with Chi-Square**

1. The chi-square test does not give us much information about the strength of the relationship or its substantive significance in the population.

2. The chi-square test is sensitive to sample size. The size of the calculated chi-square is directly proportional to the size of the sample, independent of the strength of the relationship between the variables

3. The chi-square test is also sensitive to small expected frequencies in one or more of the cells in the table.

### 2.1.3. Latent Semantic Indexing (LSI)

LSA assumes that words that are close in meaning will occur in similar pieces of text. A matrix containing word counts per paragraph (rows represent unique words and columns represent each paragraph) is constructed from a large piece of text and a mathematical technique called singular value decomposition (SVD) is used to reduce the number of rows while preserving the similarity structure among columns. Words are then compared by taking the cosine of the angle between the two vectors formed by any two rows. Values close to 1 represent very similar words while values close to 0 represent very dissimilar words.

- Authors in [5] present a novel approach to predicting the sentiment of documents in multiple languages, without translation. The only prerequisite is a multilingual parallel corpus wherein a training sample of the documents, in a single language only, has been tagged with their overall sentiment. Latent Semantic Indexing (LSI) converts that multilingual corpus into a multilingual "concept space".
- Sentimental analyses of the public have been attracting increasing attentions from researchers. Authors [6] paper focuses on the research problem of social sentiment detection, which aims to identify the sentiments of the public evoked by online micro blogs using LSI. The general social sentiment model combining society and psychology knowledge are employed to measure social sentiment state.

### Problems with LSI

1. The resulting dimensions might be difficult to interpret.

2. LSA cannot capture polysemy (i.e., multiple meanings of a word).

3. The probabilistic model of LSA does not match observed data: LSA assumes that words and documents form a joint Gaussian model (ergodic hypothesis), while a Poisson distribution has been observed. Thus, a newer alternative is probabilistic latent semantic analysis, based on a multinomial model, which is reported to give better results than standard LSA.

### 2.2 Sentiment Classification techniques

Sentiment Classification techniques can be roughly divided into machine learning approach, lexicon based approach and hybrid approach.

### 2.2.1 Machine Learning approach

Machine learning tasks can be of several forms.

In supervised learning, the computer is presented with example inputs and their desired outputs, given by a "teacher", and the goal is to learn a general rule that maps inputs to outputs.

In unsupervised learning, no labels are given to the learning algorithm, leaving it on its own to groups of similar inputs (clustering), density estimates or projections of high-dimensional data that can be visualized effectively.

In reinforcement learning, a computer program interacts with a dynamic environment in which it must perform a certain goal, without a teacher explicitly telling it whether it has come close to its goal or not.

- In [7] authors have discussed possibility to improve accuracy of stock market indicators predictions by using data about psychological states of Twitter users. For analysis of psychological states authors used lexicon-based approach, which allow us to evaluate presence of eight basic emotions in more than 755 million tweets. The application of Support Vectors Machine and Neural Networks algorithms to predict DJIA and S&P500 indicators are discussed.
- The new model proposed in [8] is based on Bayesian algorithm and machine learning that is one of the most popular methods for sentiment classification.
- Authors in [9] have described a machine learning approach for detecting positive/negative sentiment in multilingual documents.
- In [10] authors present work on Chinese opinion mining, with emphasis on mining opinions on online reviews. Authors have developed based on machine learning methods.
- Standard supervised approach to sentiment classification requires a large amount of manually labeled data which is costly and time-consuming to obtain. To tackle this problem, authors [11] propose a novel semi-supervised learning method based on multi-view learning.

### Problems with Machine learning algorithms:

1. Most of the machine-learning algorithms require a special training phase whenever information is extracted

2. Learning in dynamic environments is cumbersome (if possible at all) for most machine-learning methods.

3. Another common problem is that, in general, machine-learning techniques are data oriented: they model the relationships contained in the training data set. In turn, if the employed training data set is not a representative selection from the problem domain, the resulting model may differ from actual problem domain.

**4.** Finally, machine-learning algorithms have difficulties in handling noise. Though many of them have some special provisions to prevent noise fitting, these may have a side effect of ignoring seldom occurring but possibly important features of the problem domain.

## 2.**2.2 Lexicon Based Approach**

Lexicon-Based approaches to Sentiment Analysis (SA) differ from the more common machine-learning based approaches in that the former rely solely on previously generated lexical resources that store polarity information for lexical items, which are then identified in the texts, assigned a polarity tag, and finally weighed, to come up with an overall score for the text. Such SA systems have been proved to perform on par with supervised, statistical systems, with the added benefit of not requiring a training set.

- In [12] authors present a sentiment lexicon building method called dependency expansion method (DEM), which exploits the relations described in dependency trees between sentiment words and degree adverbs. By taking advantage of the observation that degree adverbs modify sentiment words, two extraction rules are made, through which sentiment words and degree adverbs can be effectively expanded.
- In [13] authors present a completely unsupervised approach for creating a sentiment lexicon. The approach has been realized by designing a pipeline which implements an unsupervised system that covers different aspects: the automatic extraction of user reviews, the pre-processing of text, the use of a scoring measure which combines: entropy, term frequency, inverse document frequency, and finally a cross lingual intersection.
- Most of the sentiment analysis work based on Lexicon based approach is depicted in [14],[15],[16],[17] and [18].

**Problems with Lexicon Based Approach:**

When using the lexical approach there is no need for labeled data and the procedure of learning, and the decisions taken by the classifier can be easily explained. However, this usually requires powerful linguistic resources (e.g., emotional dictionary), which is not always available, in addition it is difficult to take the context into account.

## 2.**2.3 Hybrid Approach**

The hybrid Approach combines both approaches and is very common with sentiment lexicons playing a key role in the majority of methods. In most of such systems, a SL is used to generate features for training an ML classifier. We refer to such features as sentiment features.

- Authors in [19] propose a hybrid human machine system based on an expert weighting algorithm that combines the responses of both humans and machine learning algorithms. The general topic of the paper is the use of the crowd to interpret text, and the power of that interpretation to predict future events.
- Authors in [20] present a hybrid sentiment analysis approach for product-based sentiment summarization of multi-documents with the purpose of informing users about pros and cons of various products.
- The hybrid method proposed in [21] utilizes a Sentiment Lexicon to generate a new set of features to train a linear Support Vector Machine (SVM) classifier.
- In [22], a kinds of hybrid methods, based on category distinguishing ability of words and information gain, is adopted to feature selection.
- Authors in [23] propose a novel hybrid Hierarchical Dirichlet Process-Latent Dirichlet Allocation (HDP-LDA) model. This model can automatically determine the number of aspects, distinguish factual words from opinioned words, and further effectively extracts the aspect specific sentiment words.

# 3.   Twitter Sentiment Analysis Evaluation Datasets

In this section we present 6 different datasets widely used in the Twitter sentiment analysis literature [24]. All the datasets are publically available for research purposes. The datasets are also manually annotated. Tweets in these datasets have been annotated with different sentiment labels including: Negative, Neutral, Positive, Mixed, Other and Irrelevant.

### 3.1 Stanford Twitter Sentiment Test Set (STS-Test) [24]

The Stanford Twitter sentiment corpus (http://help.sentiment140.com/), introduced by Go et al. [24] consists of two different sets, training and test. The training set contains 1.6 million tweets automatically labelled as positive or negative based on emotions. The

test set (STS-Test), on the other hand, is manually annotated and contains 177 negative, 182 positive and 139 neutrals tweets. These tweets were collected by searching Twitter API with specific queries including names of products, companies and people.

## 3.2 Health Care Reform (HCR)

The Health Care Reform (HCR) dataset was built by crawling tweets containing the hashtag \#hcr" (health care reform) in March 2010 [25]. A subset of this corpus was manually annotated by the authors with 5 labels (positive, negative, neutral, irrelevant, unsure(other)) and split into training (839 tweets), development (838 tweets) and test (839 tweets) sets.

## 3.3 Obama-McCain Debate (OMD)

The Obama-McCain Debate (OMD) dataset was constructed from 3,238 tweets crawled during the first U.S. presidential TV debate in September 2008 [26]. Sentiment labels were acquired for these tweets using Amazon Mechanical Turk, where each tweet was rated by at least three annotators as positive, negative, mixed, or other.

## 3.4 Sentiment Strength Twitter Dataset (SS-Tweet)

This dataset consists of 4,242 tweets manually labeled with their positive and negative sentiment strengths. i.e., a negative strength is a number between -1 (not negative) and -5 (extremely negative). Similarly, a positive strength is a number between 1 (not positive) and 5 (extremely positive). The dataset was constructed by [27] to evaluate Senti Strength, a lexicon-based method for sentiment strength detection.  The original dataset is publicly available at http://sentistrength.wlv. ac.uk/documentation/ along with other 5 datasets from different social media platforms including MySpace, Digg, BBC forum, Runners World forum, and YouTube.

## 3.5 Sanders Twitter Dataset

The Sanders dataset consists of 5,512 tweets on four different topics (Apple, Google, Microsoft, ter)( http://www.sananalytics.com/lab/twitter-sentiment/). Each tweet was manually labeled by one annotator as positive, negative, neutral, or irrelevant with respect to the topic. The annotation process resulted in 654 negative, 2,503 neutral, 570 positive and 1,786 irrelevant tweets The Sanders dataset is available at http://www.sananalytics.com/lab

## 3.6 SemEval-2013 Dataset (SemEval)

This dataset was constructed for the Twitter sentiment analysis task (Task 2) [28] in the Semantic Evaluation of Systems challenge (SemEval-2013).6 The original SemEval dataset consists of 20K tweets split into training, development and test sets. All the tweets were manually annotated by 5 Amazon Mechanical Turk workers with negative, positive and neutral labels. The turkers were also asked to annotate expressions within the tweets as subjective or objective. The dataset of SemEval 207 is also available for sentiment classification task used by the authors in [29].

# 4. Great tools for Twit Intelligence

## 4.1 TWITALYZER

TWITALYZER (www.**twitalyzer**.com/) provides activities analysis of any Twitter user, based on social media success yardsticks. Its Time-based Analysis of Twitter Usage produces graphical representation of progression on various measures. Using Twitalyzer is a easy; just enter your Twitter ID and that's it! It doesn't require any password to use its service. Speed of analysis is depending on the size of your Followed and Followers lists.

## 4.2 MICROPLAZA

MICROPLAZA (https://twitter.com/**microplaza)** offers an interesting way to make sense of your Twitter streams. Called itself "your personal micro-news agency," it aggregates and organizes links shared by those you follow on Twitter and display them as newstream. Status updates that contain similar web links are aggregated into 'tiles.' Within a tile, you can see updates from those you follow and also those you don't. Another interesting feature is 'Being Someone', which you can peek into someone's world and see their 'tiles'; designed to facilitate information discovery.

### 4.3 TWIST

TWIST (www.**twist**.com.tr/) offers trends of keywords or product name, based what Twitter users are tweeting about. You can see frequency of a keyword or product name being mentioned over a period a week or a month and display them on a graph. Select an area on the graph to zoom into trend for specific time range. Click on any point on the graph to see all tweets posted during a specific time. One can also see the latest tweets on the topic. Twist also allows you do a trend comparison of two (or more) keywords.

### 4.4 TWITTURLY

TWITTURLY (**twitturly**.com/) tracks popular URLs tracker on Twitter. With Digg-style interface, it displays 100 most popular URLs shared on Twitter over the last 24 hours. On Digg, people vote for a particular web content, whereas on Twitterurly, each time a user share a link, it is counted as 1 vote. This is a good tool to see what people are 'talking' about in Twitterville and see total tweets that carry the links. Its URL stats provides information on number of tweets in last 24 hrs, last 1 week and last 1 month. It also calculates total estimated reach of the tweets. Another interesting site is Tweetmeme, which can filter popular URLs into blogs, images, videos and audios.

### 4.5 TWEETSTATS

TWEETSTATS (www.**tweetstats**.com/ )is useful to reveal tweeting behavior of any Twitter users. It consolidates and collates Twitter activity data and present them in colorful graphs. Its Tweet Timeline is probably the most interesting, as it shows month-by-month total tweets since your joined Twitter (TweetStats showed Evan Williams, co-founder of Twitter, started tweeting since March 2006; 80 tweets during that month). Twitterholic can also show when a person joined Twitter but not in graphical format.

### 4.6 TWITTERFRIENDS

TWITTERFRIENDS (https://twitter.com/hashtag/**twitterfriends** ) focuses on conversation and information aspects of Twitter users' behaviors. Two key metrics are Conversational Quotient (CQ) and Links Quotient (LQ). CQ measures how many tweets were replied whereas LQ measures how many tweets contained links. Its TwitGraph displays six metrics - Twitter rank, CQ, LQ, Retweet Quotient, Follow cost, Fans and @replies. Its interactive graph (using Google Visualization API) can displays relationships between two variables. In addition, you can search for conversations between two Twitter users. This app seems to slice-and-dice data in more ways compared to other applications listed here.

### 4.7 THUMMIT QUICKRATE

THUMMIT QUICKRATE (https://twitter.com/**thummit)** offers sentiments analysis, based on conversations on Twitter. This web application identifies latest buzzwords, actors, movies, brands, products, etc. (called 'topics') and combines them with conversations from Twitter. It does sentiment analysis to determine whether each Twitter update is Thumms up (positive), neutral or Thumms down (negative). Click on any topic to display opinions on the topic found on Twitter. In addition, it allows people to vote on topics via its website or mobile phones. The idea behind this app is good but still has some kinks to work out.

### 4.8 TWEETEFFECT

TWEETEFFECT (www.**tweeteffect**.com/) matches your tweets timeline with your gain/lose followers timeline to determine which tweet makes you lost or gain followers. It analyze the latest 200 tweets and highlights tweets that coincides with you losing or gaining two (or more) followers in less than 5 minutes. This application simplistically assumed that your tweet is the sole factor affecting your gain/lose followers pattern. But, in reality, there are many other factors involved. Nevertheless, TweetEffect is still a fun tool to use; just don't take the results too seriously.

## 4    Twitter Sentiment Analysis : Challenges

Even though Twitter is flooded by simple and short messages, that usually do not contain sophisticated syntax structures or complicated meanings, they often contain slang terms, internet writing style, acronyms or even internet jokes and commonly-used web phrases. That of course may lead us to wrong syntax analysis of texts (while NLP parser is being trained by normal English writings), which may become a reason for the hybrid classifier to miss a subjective pattern or even proceed to a wrong classification of a tweet.

The following are some challenges faced in sentiment analysis of Twitter feeds [30].

- Named Entity Recognition (NER) — NER is the method of extracting entities such as people, organisation and locations from twitter corpus.
- Anaphora Resolution—The process of resolving the problem of what a pronoun or noun phrase refers to. "We had a lavish dinner and went for a walk, it was awful". What does "It" refer to?
- Parsing — the process of identifying the subject and object of the sentence. The verb and adjective are referring to what?
- Sarcasm — what does a verb actually stand for? Does 'bad' mean bad or good?
- Sparsity—Insufficient data or very few useful labels in the training set.
- Twitter abbreviations, poor spellings, poor punctuation, poor grammar, incomplete sentences.
- The accuracy of tweets classification as compared to human judgments.

## 5    Conclusion and Future Scope

**Conclusion: Twitter sentiment analysis plays a driving role for most of the decision making situations where public opinion is needed to be considered.  This paper attempts to be the first paper for providing the research oriented review and analysis of various twitter sentiment analysis tasks. It outlines the various methods for the feature selection as well as sentiment classification task. The various twitter sentiment analysis datasets which are freely available for research purpose are listed along with the available twitter analysis tools available online.  Though a lot a work has already been done in this area, many issues are still to be investigated.**

## 6    References

1.  Mostafa Karamibekr, Ali A. Ghorbani, "Verb Oriented Sentiment Classification", 2012 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology
2.  Minjie Zheng, Zhicheng Lei, LIU Yue, Xiangwen Liao, Guolong Chen, "Identify Sentiment-Objects from Chinese Sentences Based on Skip Chain Conditional Random Fields model", 2012 Sixth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing
3.  Parisa Lak, Ozgur Turetken,'' Star Ratings versus Sentiment Analysis - A Comparison of Explicit and Implicit Measures of Opinions", 2014 47th Hawaii International Conference on System Science.
4.  Keke Cai, Scott Spangler, Ying Chen, Li Zhang, "  Leveraging Sentiment Analysis for Topic Detection", 2008 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology.
5.  Brett W. Bader, W. Philip Kegelmeyer, and Peter A. Chew,  "Multilingual Sentiment Analysis Using Latent Semantic Indexing and Machine Learning", 2011 11th IEEE International Conference on Data Mining Workshops.
6.  Xinzhi Wang, Xiangfeng Luo, Jinjun Chen, "Social sentiment detection of event via microblog", 2013 IEEE 16th International Conference on Computational Science and Engineering.
7.  Alexander Porshnev, Ilya Redkin, Alexey Shevchenko," Machine learning in prediction of stock market indicators based on historical data and data from Twitter sentiment analysis, 2013 IEEE 13th International Conference on Data Mining Workshops.
8.  Zhen Niu, Zelong Yin, Xiangyu Kong, "Sentiment Classification for Microblog by Machine Learning", 2012 Fourth International Conference on Computational and Information Sciences.
9.  Brett W. Bader, W. Philip Kegelmeyer, Peter A. Chew, "Multilingual Sentiment Analysis Using Latent Semantic Indexing and Machine Learning", 2011 11th IEEE International Conference on Data Mining Workshops.
10. Changli Zhang, Wanli Zuo, Tao Peng,Fengling He, " Sentiment Classification for Chinese Reviews Using Machine Learning Methods Based on String Kernel", Third 2008 International Conference on Convergence and Hybrid Information Technology.
11.  Yan Su, Shoushan Li, Shengfeng Ju, Guodong Zhou, Xiaojun Li, "Multi-view Learning for Semi-supervised Sentiment Classification", 2012 International Conference on Asian Language Processing.
12.  Jiguang Liang, Jianlong Tan, Xiaofei Zhou, Ping Liu, Li Guo, Shuo Bai, " Dependency Expansion Model for Sentiment Lexicon Extraction", 2013 IEEE/WIC/ACM International Conferences on Web Intelligence (WI) and Intelligent Agent Technology (IAT).
13.  Pierluca Sangiorgi, Agnese Augello, Giovanni Pilato," An unsupervised data-driven cross-lingual method for building high precision sentiment lexicons", 2013 IEEE Seventh International Conference on Semantic Computing.
14.  Marina Boia, Boi Faltings, Claudiu-Cristian Musat, Pearl Pu, "A :) Is Worth a Thousand Words: How People Attach Sentiment to Emoticons and Words in Tweets", SocialCom/PASSAT/BigData/EconCom/BioMedCom 2013.
15. Nir Ofek, Cornelia Caragea, Lior Rokach, Prakhar Biyani, Prasenjit Mitra, John Yen, Kenneth Portier, Greta Greer, "Improving Sentiment Analysis in an Online Cancer Survivor Community Using Dynamic Sentiment Lexicon", 2013 International Conference on Social Intelligence and Technology.
16. *Albert Weichselbraun, "Extracting and Grounding Contextualized Sentiment Lex-cons", 1541-1672/13/$31.00 © 2013 IEEE 39 published by the IEEE Computer Society.*
17. Rahim Dehkharghani, Berrin Yanikoglu, Dilek Tapucu,Yucel Saygin, " Adaptation and Use of Subjectivity Lexicons for Domain Dependent Sentiment Classification", 2012 IEEE 12th International Conference on Data Mining Workshops.

18.  Haiping Zhang, Zhenzhi Yu, Ming Xu, Yueling Shi, "An Improved Method to Building a Score Lexicon for Chinese Sentiment Analysis", 2012 Eighth International Conference on Semantics, Knowledge and Grids.

19.  Germ´an G. Creamer, Yong Ren, Yasuaki Sakamoto, Jeffrey V. Nickerson ,"News and Sentiment Analysis of the European Market with a Hybrid Expert Weighting Algorithm", SocialCom/PASSAT/BigData/EconCom/BioMedCom 2013

20.  Seyed-Ali Bahrainian, Andreas Dengel, "Sentiment Analysis and Summarization of Twitter Data", 2013 IEEE 16th International Conference on Computational Science and Engineering

21.  Seyed-Ali Bahrainian, Andreas Dengel, "Sentiment Analysis using Sentiment Features", 2013 IEEE/WIC/ACM International Conferences on Web Intelligence (WI) and Intelligent Agent Technology (IAT)

22.  Suge Wang, Yingjie Wei, Deyu Li, Wu Zhang, Wei Li, "A Hybrid Method of Feature Selection for Chinese Text Sentiment Classification", Fourth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD  IEEE2007)

23.  *Wanying Ding, Xiaoli Song, Lifan Guo, Zunyan Xiong, Xiaohua Hu, "A Novel Hybrid HDP-LDA Model for Sentiment Analysis",* 2013 IEEE/WIC/ACM International Conferences on Web Intelligence (WI) and Intelligent Agent Technology (IAT) 978-1-4799-2902-3/13 $31.00 © 2013 IEEE

24.  Hassan Saif, Miriam Fernande, Yulan He and Harith Alani, "Evaluation Datasets for Twitter Sentiment Analysis", Knowledge Media Institute, The Open University, United Kingdom

25.  Speriosu, M., Sudan, N., Upadhyay, S., Baldridge, J.: Twitter polarity classification with label propagation over lexical links and the follower graph. In: Proceedings of the EMNLP First workshop on Unsupervised Learning in NLP. Edinburgh, Scotland (2011)

26.  Shamma, D., Kennedy, L., Churchill, E.: Tweet the debates: understanding community annotation of uncollected sources. In: Proceedings of the first SIGMM workshop on Social media. pp. 310. ACM (2009)

27. Thelwall, M., Buckley, K., Paltoglou, G.: Sentiment strength detection for the social web. Journal of the American Society for Information Science and Technology 63(1), 163{173 (2012)

28.  Nakov, P., Rosenthal, S., Kozareva, Z., Stoyanov, V., Ritter, A., Wilson, T.: Semeval- 2013 task 2: Sentiment analysis in twitter. In: In Proceedings of the 7th International Workshop on Semantic Evaluation. Association for Computational Linguistics. (2013)

29.  Kirange D. K, Deshmukh R. R, "EMOTION CLASSIFICATION OF NEWS HEADLINES USING SVM", Asian Journal Of Computer Science And Information Technology 2: 5 (2012) 104 – 106.

30.  Farhan Hassan Khan, Saba Bashir, Usman Qamar, "TOM: Twitter opinion mining framework using hybrid classification scheme", Decision Support Systems 57 (2014) 245–257, © 2013 Elsevier