A Web Content Opinion Mining Based Study of Machine Learning Approaches of Sentiment Analysis

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Abstract— **Sentiment analysis is a growing interest in the research of natural language processing. Correctly identifying the factor into particular category (positive, negative and neutral) is still presenting challenge because of large and vast amount of features in the dataset. In regards to the existing algorithms, support vector machine, Naïve Bayes and maximum entropy algorithms are potentially good for sentiment analysis classification. This paper presents a literature covering the efficient techniques, methods in sentiment analysis, recent state of work and directions in the field of sentiment analysis and opinion mining.**

Index Terms: **machine learning, opining mining, sentiment analysis, sentiment classification**

I. INTRODUCTION

Sentiment analysis is a type of natural language processing for tracking the mood of the public about a particular topic. Sentiment analysis, which is also called opinion mining, involves in building a system to collect and examine opinions about the reviews in blog posts, comments or tweets.

There are several challenges in Sentiment analysis. The first is an opinion word that is considered to be positive in one situation may be considered negative in another situation. A second challenge is that people don't always express opinions in a same way. In sentiment analysis, however, "the movie was great" is very different from "the movie was not great".

However, in the more informal medium like twitter or blogs, the more likely people are to combine different opinions in the same sentence which is easy for a human to understand, but more difficult for a computer to parse. For example, "That movie was as good as its last movie" is entirely dependent on what the person expressing the opinion thought of the previous model.

A. Sentiment analysis:

Computational study of opinions, sentiments, evaluations, attitudes, affects, views, emotions etc. expressed in text.
Text=Reviews, blogs, news, comments, feedback.
Two main types of opinions: *(Liu, 2010)*

a. *Regular opinions:* Sentiment opinion expressions on some target entities.
   i. Direct opinions: The touch screen is really cool.
   ii. Indirect opinions: After taking the drug, my pain has gone.
b. *Comparative opinions:* Comparisons of more than one entity.
   e.g. "iPhone is better than blackberry".

B. Data sources:

Blogs, review sites, web discourse, micro-blog, and news articles are measure source of opinion and user's opinion is a major criterion for the improvement of the quality of services. We consider the data from blogs, review sites and micro-blogging.

a. *Review sites*

A huge amount of user generated review available on the internet for particular product or service. In most case user generated review is in unstructured format, this types of opinion data is used for sentiment classification study are collected from different E-Commerce websites for product review like: www.amazon.com, www.flipcart.com and www.reviewcentre.com has millions of customer reviews for products. Whereas www.yelp.com, www.burrp.com has restaurant reviews, www.gsmarena.com for mobile reviews, www.indiaglitz.com and www.rottentomatoes.com has reviews for movies.

b. *Blogs*

Blog site is also called blogosphere, where people write opinion or about the topics they want share with other on the blog. A blog is a discussion or informational site published on the World Wide Web and consisting of discrete entries ("posts") typically displayed in reverse chronological order (the most recent post appears first). Blogs act as one of the sources of expressing opinion in many of the studies related to sentiment analysis.

c. *Micro-blogging*

Facebook and Tweeter became very popular communication tool among internet user to write comments, opining about particular product or service. Millions of messages appear daily on these types of popular websites. These messages are in unstructured format and short, sometimes these messages express opinion which becomes source data for sentiment classification.

II. LEVELS OF SENTIMENT ANALYSIS

Main research problems of sentiment analysis are based on the level of granularities of the existing research. In general,

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sentiment analysis has been investigated mainly at three levels:

A. Document level sentiment analysis

The main task in document level sentiment classification is to determine whether a whole opinion document expresses a positive or negative sentiment (Pang, Lee and Vaithyanathan, 2002; Turney, 2002). Classifying a document is based on the overall sentiment expressed by opinion holder. It assumes that each document focuses on a single object and contains opinions from a single opinion holder. Thus, it is not applicable to documents which evaluate or compare multiple entities.

The challenge in the document level classification is that the entire sentence in a document may not be relevant in expressing the opinion about an entity. Therefore subjectivity/objectivity classification is very important in this type of classification. The irrelevant sentences must be eliminated from the processing works.

B. Sentence level sentiment analysis

The task at this level goes to the sentences and determines whether each sentence expressed a positive, negative, or neutral opinion. Neutral usually means no opinion. This level of analysis is closely related to subjectivity classification (Wiebe, Bruce and O'Hara, 1999), which distinguishes sentences (called objective sentences) that express factual information from sentences (called subjective sentences) that express subjective views and opinions. However, we should note that subjectivity is not equivalent to sentiment as many objective sentences can imply opinions.

C. Aspect level (Features selection) sentiment analysis

The goal of this level of analysis is to discover sentiments on entities and/or their aspects. For example, the sentence *"The iPhone's call quality is good, but its battery life is short"* evaluates two aspects, call quality and battery life, of iPhone (entity). The sentiment on iPhone's call quality is positive, but the sentiment on its battery life is negative. The call quality and battery life of iPhone are the opinion targets. Both the document level and the sentence level analyses do not discover what exactly people liked and did not like. Aspect level performs finer-grained analysis. Aspect level was earlier called feature level (Hu and Liu, 2004). Instead of looking at language constructs (documents, paragraphs, sentences, clauses or phrases), aspect level directly looks at the opinion itself. It is based on the idea that an opinion consists of a sentiment (positive or negative) and a target (of opinion).

III. Machine Learning Approaches

Naïve Bayesian method is one of the popular techniques for text classification. In (Pang, Lee and Vaithyanathan, 2002) were applied this approach for sentiment classification of movie review into two classes positive and negative using unigram with one of the classifier naïve Bayes or support vector machine and it performed quite well.

A. Naive Bayesian Classification

One approach to text classification is to assign to a given document *d* the class

$$c^* = \arg\max_c P(c \mid d).$$

We derive the *Naive Bayes* (NB) classifier by first observing that by Bayes' rule,

$$P(c|d) = \frac{P(c)P(d|c)}{P(d)}$$

where $P(d)$ plays no role in selecting c^*. To estimate the term $P(d \mid c)$, Naive Bayes decomposes it by assuming the f_i 's are conditionally independent given d's class:

$$P_{NB}(c|d) := \frac{P(c)\left(\prod_{i=1}^{m} P(f_i|c)^{n_i(d)}\right)}{P(d)}$$

our training method consists of relative-frequency estimation of $P(c)$ and $P(f_i \mid c)$, using add-one smoothing.

Despite its simplicity and the fact that its conditional independence assumption clearly does not hold in real-world situations, Naive Bayes-based text categorization still tends to perform surprisingly well (Lewis, 1998); indeed, Domingos and Pazzani (1997) show that Naive Bayes is optimal for certain problem classes with highly dependent features. On the other hand, more sophisticated algorithms might (and often do) yield better results; we examine two such algorithms next.

B. Support Vector Machine

Support vector machines (SVMs) have been shown to be highly effective at traditional text categorization, generally outperforming Naive Bayes (Joachims, 1998). They are *large-margin*, rather than probabilistic, classifiers, in contrast to Naive Bayes and MaxEnt. In the two-category case, the basic idea behind the training procedure is to find a hyperplane, represented by vector $\vec{w}$, that not only separates the document vectors in one class from those in the other, but for which the separation, or *margin*, is as large as possible. This search corresponds to a constrained optimization problem; letting $c_j \in \{1, -1\}$ (corresponding to positive and negative) be the correct class of document d_j, the solution can be written as

$$\vec{w} := \sum_j a_j c_j \vec{d_j},\ a_j \geq 0,$$

where the a_j 's are obtained by solving a dual optimization problem. Those $\vec{d_j}$ such that a_j is greater than zero are called *support vectors*, since they are the only document vectors contributing to $\vec{w}$. Classification of test instances consists simply of determining which side of $\vec{w}$'s hyper plane they fall on. We used Joachim's (1999) SVM^{light} package for training and testing, with all parameters set to their default values, after first length-normalizing the document vectors, as is standard (neglecting to normalize generally hurt performance slightly).

C. Maximum Entropy

Maximum Entropy (ME) classification is yet another technique, which has proven effective in a number of natural language processing applications.

Some-times, it outperforms Naive Bayes at standard text classification. Its estimate of P(c | d) takes the exponential form:

$$P_{ME}(c|d) := \frac{1}{Z(d)} \exp\left(\sum_i \lambda_{i,c} F_{i,c}(d,c)\right)$$

where Z(d) is a normalization function. $F_{i,c}$ is a feature/class function for feature f_i and class c.

$$F_{i,c}(d,\acute{c}) := \{1, n_i(d) > 0 \; and \; \acute{c} = c \\ 0 \; otherwise$$

For instance, a particular feature/class function might fire if and only if the bigram "still hate" appears and the document's sentiment is hypothesized to be negative. Importantly, unlike Naive Bayes, Maximum Entropy makes no assumptions about the relationships between features and so might potentially perform better when conditional independence assumptions are not met.

IV. Literature Review on Sentiment Analysis and Opinion Mining

Sentiment classification is a new field of Natural Language Processing that classifies subjectivity text into positive or negative. Sentiment classification or Polarity classification is the binary classification task of labeling an opinionated document as expressing either an overall positive or an overall negative opinion.

A number of machine learning techniques have been adopted to classify the reviews. Machine learning techniques like Naive Bayes (NB), maximum entropy (ME), and support vector machines (SVM) have achieved great success in text categorization. The other most well-known machine learning methods in the natural language processing area are K-Nearest neighbourhood, ID3, C5, centroid classifier, winnow classifier, and the N-gram model.

Naïve bayes is popular text classifier, in *(Pang, Lee and Vaithyanathan, 2002)* were applied this approach for sentiment classification of movie review into two classes positive and negative using unigram with one of the classifier naïve Bayes or support vector machine and it performed quite well.

Support Vector Machine (SVM) is popular machine learning method for classification, regression, and other learning tasks *(Chang et al., 2011)*. SVM performed better than Naïve Bayes and Maximum Entropy *Pang et al. (2002)* for sentiment classifications. It also performed better in *(Rogati and Yang, 2002)* than kNN used in *(Yang et al., 1997)*. *Pang et al. (2002)* they applied SVM, Naïve Bayesian, and Maximum Entropy for document-level classification on sentiment analysis using movie review data and they used several tokens such as n-grams, POS tags, and adjectives as features to feature spaces. They also found that bigrams did not perform better than unigrams with all three classification methods.

Rogati and Yang (2002) examined major feature selection methods (DF, IG, x and IG2 (the binary version of IG)) with four classification algorithms—Naive Bayesian (NB) approach, Rocchio-style classifier, k-nearest-neighbors (kNN), and Support Vector Machine. They found that feature selection method x statistics has performed well compare to other four feature selection methods.

Forman (2003) study to compare twelve feature selection methods to investigate which feature selection method or combination of methods was most likely to produce the best performance. They found that Information Gain (IG) could get highest precision among the twelve selection methods. Document level classification will classify whether an opinion expression for whole document is positive or negative sentiment *(Pang, Lee and Vaithyanathan, 2002; Turney, 2002)*. Based on given data set system determine whether an opinion review is positive or negative about particular entity, but it is not applicable to which that contain more than one entity.

Dave, Lawrence and Pennock (2003) were used custom technique (i.e., the score function) for sentiment classification instead of standard machine learning technique. *Gamon (2004)*, classification was performed on customer feedback data, which are usually short and noisy compared to reviews. In *(Pang and Lee, 2004)* applied Minimum cut algorithm for sentiment classification. In (*Hu and Liu, 2004)* were proposed a lexicon-based algorithm for aspect level sentiment classification, but the method can determine the sentiment orientation of a sentence as well. *Kennedy and Inkpen (2006)* were applied contextual valence and sentiment shifters for classification.

Snyder and Barzilay (2007) studied the problem of predicting the rating for each aspect, Instead of predicting the rating of each review and proposed two models, aspect model (which works on individual aspects) and agreement model (which models the rating agreement among aspects). *Abbasi, Chen and Salem (2008)* were proposed genetic algorithm for sentiment classification in different languages. *In (Wan, 2008),* the author exploited sentiment resources in English to perform classification of Chinese reviews. *Ikeda et al. (2008)* proposed a polarity-shifting model to capture whether the polarity of a word is changed or not. The model was a kind of binary classification model that determines whether the polarity is shifted by its context. Compared to other features such as Bag-of-Word features, their model obtained higher performance.

Pang et al., (2008) used machine learning techniques for sentiment analysis. The experimental setup consists of movie-review corpus with randomly selected 700 positive sentiment and 700 negative sentiment reviews. Learning methods Naïve Bayes, maximum entropy classification and support vector machines were employed. Experiments demonstrated that the machine learning techniques are better than human produced baseline for sentiment analysis on movie review data.

Tan et al., (2008) has performed sentiment analysis on Chinese documents. They investigated four feature selection methods (MI, IG, CHI and DF) and five learning methods (winnow classifier, K-nearest neighbor, centroid classifier, Naive Bayes and SVM) on a Chinese sentiment corpus. From the results he concludes that, IG performs the best for sentimental terms selection and SVM exhibits the best performance for sentiment classification. *Wu et al. (2009)*, a graph-based method was proposed for Cross-Domain Sentiment Classification. In the graph, each document is a node and each link between two nodes is a weight computed using the cosine similarity of the two documents. Initially, every document in the old domain has a label score of +1 (positive) or -1 (negative) and each document in the new domain is assigned a label score based a normal sentiment classifier, which can be learned from the old domain. *Martineau and Finin (2009)* a new term weighting scheme called Delta TFIDF was proposed and In *(Qiu et al., 2009)*, a lexicon-based and self-supervision approach was used for sentiment classification.

Wan (2009), a co-training method was proposed for cross-language sentiment classification which made use of an annotated English corpus for classification of Chinese reviews in a supervised manner. No Chinese resources were used. In training, the input consisted of a set of labeled English reviews and a set of unlabeled Chinese reviews. The labeled English reviews were translated into labeled Chinese reviews, and the unlabeled Chinese reviews were translated into unlabeled English reviews. Finally in the classification phase, each unlabeled Chinese review for testing was first translated into an English review, and then the learned classifier was applied to classify the review into either positive or negative.

Brooke et al. (2009) also experimented with translation (using only one translator) from the source language (English) to the target language (Spanish) and then used a lexicon-based approach or machine learning for target language document sentiment classification. *Prabowo et al.,(2009)* has combined rule-based classification, machine learning and supervised learning method. For each sample set, they carried out 10-fold cross validation and for every fold, the associated samples were divided into training and a test set. For each test sample, a hybrid classification is carried out. *Long, Zhang and Zhu (2010)* used Baysian network classifier for rating prediction of each aspect instead of predicting of every review for good accuracy. *Paltoglou and Thelwall (2010)* were studied different IR term weighting schemes and compared for sentiment classification.

Qu et al. (2010) introduced a bag-of-opinions representation and each opinion that contain a sentiment word, a modifier and negator. For example, in “not very good”, “good” is the sentiment word, “very” is the modifier and “not” is the negator. For sentiment classification of two classes (positive and negative), the opinion modifier is not crucial but for rating prediction, it is very important and so is the impact of negation. *Wei et al. (2010)* proposed to use a transfer learning method for cross language sentiment classification. In (*Davidov, Tsur and Rappoport, 2010)* sentiment classification of Twitter postings (or tweets) was studied. Each tweet is basically a single sentence. They took a supervised learning approach. *Wang et al. (2011)* proposed a graph-based hash-tag approach to classifying Twitter post sentiments.

Maas et al., 2011), the authors used word vectors which can capture some latent aspects of the words to help classification. *However and Pott (2011)* applied the negation tagging methods proposed by Pang et al.(2002) and improved the classification accuracy from 0.886 to 0.895. In (*Mejova et al. 2011)* tested the effect of different POS tagged features separately and with combination for supervised learning and that selected features contained adjectives, verbs, and nouns. The combination performed better than individuals when treated as features in feature spaces. Adjectives performed the best among the three individual POS tagged features. *Duh et al. (2011)* the authors presented their opinions about the research of cross-language sentiment classification. Based on their analysis, they claimed that domain mismatch was not caused by machine translation (MT) errors, and accuracy degradation would occur even with perfect MT.

Bollegala et al. (2011) proposed a method for cross-domain to automatically create a sentiment sensitive thesaurus using both labeled and unlabeled data from multiple source domains to find the association between words that express similar sentiments in different domains. *Yoshida et al. (2011)* proposed a method for cross-domain to transfer from multiple source domains to multiple target domains by identifying domain dependent and independent word sentiments. *Zhang et al., (2011)* proposed a method which utilizes completely prior knowledge- free supervised machine learning method .They performed sentiment analysis on written Cantonese(restaurant reviews). Their method has proved that the chosen machine learning model could be able to draw its own conclusion from the distribution of lexical elements in a piece of Cantonese review (restaurant reviews).

Saini (2012) used sentiment analysis to determine polarity of Un-solicited Bulk e-mail (UBE) messages in which advertising of stocks and shares was done. He used opinion mining concept for pre-processing steps. It has been found that for almost 50% of cases UBE have positive, almost 30% negatively opined whereas almost 20% cases contained neutral opinion. This is in-line with the general perception and belief that the shares and stocks advertising UBE are sent for its bulk marketing. *Zhou et al., (2012)* investigated movie review mining using machine learning and semantic orientation. Supervised classification and text classification techniques are used in the proposed machine learning approach to classify the movie review. A corpus is formed to represent the data in the documents and all the classifiers are trained using this corpus. Their experimental results showed that the supervised approach is more efficient.

Kaur and Saini (2014a) have presented a survey covering the techniques and methods used in Sentiment Analysis and Opinion Mining. In a similar work, *Kaur and Saini (2014b)* have discussed and analyzed different approaches for Emotion detection and Sentiment Analysis. They considered informal text, in form of chats and micro blogs, written in different languages (Korean, Persian and English) and formal text pieces in form of poetry, proverbs. They have concluded that different machine learning based methods like Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT) are more often used in classification. They have also concluded that Support Vector Machine performs well compared to all other machine learning approaches in case of poetry.

Kaur and Saini (2014c) in another work have analyzed four different Feature Selection techniques. The Feature Selection techniques studied and analyzed by them are Information Gain (IG), Term Frequency-Inverse Document Frequency (TF-IDF), n-gram, Mutual Information (MI) and Modified Mutual Information (MMI). They have advocated that the researchers used these techniques for finding emotional states associated with written text. They have further concluded that IG and TF-IDF are frequently used by researchers in which IG perform well compared to all other Feature Selection techniques. Further, they have also concluded that the performance of IG was independent of its usage and application with respect to writing style, i.e. Formal or Informal as well as the language used.

V. Comparative Analysis of Related Work on Sentiment Analysis

Table 1 Comparison of Features Selection Techniques and Machine Learning Approaches for Sentiment Classification

SR. NO	AUTHOR	YEAR	TECHNINIQUE USED	FEATURE SELECTION	DATA SOURCE	ACCURACY
1	Govindarajan	2014	Proposed Bagged NB Classifier	TF-IDF	Movie-Review Data	92.50%
2		2014	Proposed Bagged SVM Classifier	TF-IDF	Movie-Review Data	93.60%
3		2014	Proposed Bagged GA Classifier	TF-IDF	Movie-Review Data	92.40%
4	Saraswathi and Tamilarasi	2014	Bagging with SVM	Inverse document frequency	Internet Movie Database	88.00%
5		2014	SVM with RBF Kernel	Inverse document frequency	Internet Movie Database	73.33%
6		2014	SVM with Polykernel	Inverse document frequency	Internet Movie Database	87.00%
7	Ortigosa et al.	2013	Machine Learning	LSA	Facebook Messages	83.27%
8	Trilla and Alias	2013	Machine Learning	LSA	Twitter Dataset	72.76%
9	Khang	2012	Naïve Bayes	Unigram, Bigram, Unigram + Bigram	Restaurant search site	81.40%
10	Liu et al.	2012	Decision Tree	Word phrase Extraction,	Hotel Reviews	77.90%
11	Liu et al.	2012	SVM classifier	LSA	Movie Reviews	85.40%
12	Bai	2011	2 stage Markov Blanket classifier	Unigram, Bigram	Movie review, Online review	92.70 %
13	Saleh	2011	SVM	Different N-gram schemes	Blogs and product reviews	91.51 %
14	Khan	2011	Naïve Bayes	Opinion terms/Expressions	Movie Review, Hotel review	86.60%
15	Xu	2011	Multiclass SVM	Linguistic feature	Amazon Reviews	61.00%
16	Zhang et al.	2011	Naïve Bayes	-	Reviews	84.5%
17	Ziqiong	2011	Naïve Bayes	Information gain	Movie review	86.90%
18					restaurant reviews	93.00%
19	Sheng	2011	BPN	Point wise mutual information	Movie review	64.00%
20	Gang li	2010	K-means	TF-IDF	Movie review	78.00%
21	Joshi et al.	2010	Machine Learning	-	Travel Reviews	78.14%
22	Somprasti	2010	Maximum Entropy	Dependency relation	Amazon reviews	F1-75.4% Pre-72.6%
23	Bifet and Frank	2010	Naïve Bayes	-	Micro-blogs	82.00%
24	Davidov et al.	2010	K-nearest neighbor	-	Micro-blogs	66-87%
25	Rudy	2009	SVM, Hybrid	Document Frequency	Movie review, MySpace comments	89.00%
26	Go et al.	2009	Support vector machine	-	Micro-blogs	83.00%
27			Naïve Bayes			82.70%
28			Maximum Entropy			83.00%
29	Melville	2009	Bayesian Classification	n-grams	Blogs	91.21%
30	Tan	2008	**SVM**,Centroid classifier,K-Nearest neighbourhood,Winnow	MI,**IG**,CHI,DI	Chinese blog review	90.00%
31	Godbole et al.	2007	Lexical approach	Graphics distance measurement	Blog posts	82-95%
32	Kennedy and Inkpen	2006	support vector machines	term frequencies	Movie review	86.20%

From the comparison of various machine learning approaches, presented in tabular format in Table 1 and the analysis thereof, it has been found that the most used algorithm is SVM (Support Vector Machine) with average accuracy of 84.37% and it proves to be more efficient when used with TF-IDF technique with 93.60% accuracy which is highest of all other combinations of algorithm and techinques used. We also found that naive baysian classifier is the second efficient method after SVM with accuracy of 86.76%. We found TF-IDF as the most commonly used feature selection technique

CONCLUSION

We have seen the applications of machine learning techniques like Naïve Bayes, Maximum Entropy, Support Vector Machines used for sentiment classification with different features selection, and we found that support vector machine (supervised machine learning) is gives good accuracy compare to other machine learning techniques. Information gain and TF-IDF (attribute selection/feature selection/aspect selection) are best feature selection techniques.

The main challenging aspects exist in use of other languages, dealing with negation expressions; produce a summary of opinions based on product features (attributes) and complexity of sentence. Document level sentiment classification still not finds out the solution for more than one entity in same document. User given opinion is in unstructured format, still is challenging problem for sentiment classification to convert unstructured to structured data. A fully automated and highly efficient system has not been introduced till now.

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