PRODUCT REVIEW SENTIMENT ANALYSIS – A SURVEY

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Abstract

Now a day's more and more people are buying products online. In order to enhance customer shopping experience, it has become a common practice for online merchants to enable their customers to write reviews on products that they have purchased. As a result, the number of reviews that a product receives grows rapidly. Manual analysis of customer opinions is very time consuming due to the multitude of contributions. So the sentiment analysis is use to extract, aggregate and analysed the opinions on product from discussion forums. Sentiment analysis has gained much attention in recent years. Sentiment analysis is a kind of text classification that classifies texts based on the sentimental orientation (SO) of opinions they contain. Sentiment analysis of product reviews has recently become very popular in text mining and computational linguistics research. In the field of sentiment analysis there are many algorithms exist to tackle Natural Language Processing problems. Each algorithm is used by several applications. In this paper i have revised the various sentiment analysis based neural network methods. Data used in this study are online product reviews collected from Amazon.com. Experiments for neural network methods which are performed with promising outcomes.

Keywords – Sentiment Analysis, NLP, Opinion mining , Classification , Support Vector Machine and Navie Bayes.

1 . INTRODUCTION

World Wide Web has become the most popular communication platforms to the public reviews, opinions, comments and sentiments. These sentiments refer to opinions about products, places, books or research papers become daily text reviews. The number of active user bases and the size of their reviews created daily on online websites are massive. There are 2.4 billion active online users, who write and read online around the world. According to 2013 Study 79% of customer's confidence is based on online personal recommendation reviews. As the result, a large number of studies and research have monitored the trending increase of online research resources year by year.

Recently, several websites encourage researchers to express and exchange their views, suggestions and opinions related to scientific papers. Sentiment analysis aims at determining the attitude of a writer with respect to some topics or the overall sentiment polarity of a text, such as positive or negative. Sentiment analysis depends on two issues sentiment polarity and sentiment score. Sentiment polarity is a binary value either positive or negative. On the other hand, sentiment score relies on one of three models. Those models are Bag-of-words model (BOW), part of speech (POS), and semantic relationships. BOW model is the most popular for researchers and based on the representation of terms. The term refers to words in Bag-of-Words model. It neglects language grammar and words ordering. POS tagging is a grammatically tagging model especially verbs, adjectives and adverbs. **For example**; (The book is not good.) declaring in (The/DT book/NN is/VBZ not/RB good/JJ. /.). In the example DT refers to "Determiner", NN refers to "Noun", singular or mass, VBZ refers to "Verb", RB refers to "Adverb", and JJ refers to "Adjective". But it neglects logical meaning. The last model called a semantic relationship that is the most complex method. It is based on the relationship between concepts or meanings **for example**; antonym, synonym, homonym etc.

Sentiment analysis (also known as opinion mining) refers to the use of natural language processing, text analysis, and computational linguistics to identify and extract subjective information in source materials. Sentiment analysis is widely applied to reviews and social media for a variety of applications, ranging from marketing to customer service. The objective of Sentiment Analysis is evaluating the sentiments and opinions of a writer respectively, one topic domain or multi-topic domain. It calculates the aggregate sentiment polarity of online real reviews for one topic based on sentiment classification levels, such as positive or negative. Existing analysis approaches to sentiment reviews can be grouped into four main categories: word level, sentence level, document level, and aspect/ entity level.

2 . SENTIMENT ANALYSIS WORKFLOW

There is an approach to use sentiment analysis is with constructing a lexicon with information about which **words and phrases** are positive and which are negative. **For example**, SentiWordNet is an overtly obtainable lexical resource in which each WordNet. Synset is ascribed three numerical scores describing how objective, positive, and negative the terms in the synset. This lexicon can either compile manually or be acquired automatically. The annotation of lexical or corpora is usually done by hand, and classifiers are then trained with large sets of features to classify a new batch of words or phrases. There are other approaches to analyze sentiments focus on the mining of **sentences or entire documents,** rather than to depend on the parity of words. This approach usually works with corpora of text documents. The essential problem with document classification (polarity classification) which is that it has to determine the overall sentiment characteristics of an entire document, while the expressedsentiment can be included in just one sentence or word. In other cases, the sentiment can be expressed implicitly, which makes it even more difficult to detect and classify. However, the context surrounding these 'hidden' sentiments can provide very beneficial information for classifying it. Based on this division of the field of sentiment analysis, we often speak of **word-level**, **sentence-level** and **document-level** sentiment classification.

On other hand, we find another approach in the mining of sentiment is **on the web**. Web opinion mining aims at extracting summarize, and track various aspects of subjective information on the Web. This can prove helpful for advertising companies or trend watchers. By a synopsis of **Sentiment analysis** defection (also called as opinion mining) that refers to the use of natural language processing (NLP), text analysis (TA) and computational linguistics (CL) to identify and extract subjective information in source materials. Sentiment analysis is widely utilized for online reviews and social media for a variety of applications, ranging from marketing to customer service.

Importance of sentiment analysis

There are millions online users, who write and read online and Internet usage around the world. Online daily sentiments become the most significant issue in making a decision. According to a new survey conducted by Dimensional Research, the survey discusses the percentage of trust online customer reviews as much as personal recommendations. According to 2011 Study 74% of customer's confidence is based on online personal recommendation reviews, 60% in 2012 study, and 57% in 2013 Study. But this percentage increases with respect to 2014 Study: 94% of customer's trust on online sentiment reviews.

3. SENTIMENT ANALYSIS TECHNIQUES

Sentiment analysis has been done on a range of topics. For example, there are sentiment analysis studies for movie reviews, product reviews, and news and blogs. Below some general sentiment analysis concepts are discussed.

3.1 Unsupervised Techniques

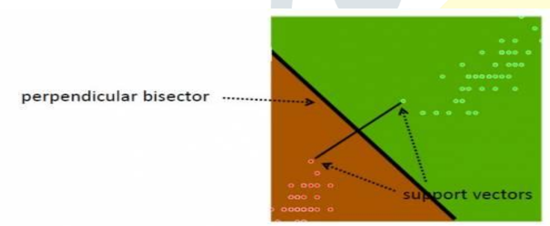
In unsupervised technique, classification is done by a function which compares the features of a given text against discriminatory-word lexicons whose polarity are determined prior to their use. For example, starting with positive and negative word lexicons, one can look for them in the text whose sentiment is being sought and register their count. Then if the document has more positive lexicons, it is positive, otherwise it is negative. A slightly different approach is done by Turney (2002) who used a simple unsupervised technique to classify reviews as recommended (thumbs up) or not recommended (thumbs down) based on semantic information of phrases containing an adjective or adverb. He computes the semantic orientation of a phrase by mutual information of the phrase with the word 'excellent' minus the mutual information of the same phrase with the word 'poor'. Out of the individual semantic orientation of phrases, an average semantic orientation of a review is computed. A review is recommended if the average semantic orientation is positive, not recommended otherwise.

3.2 Supervised Techniques

The main task here is to build a classifier. The classifier needs training examples which can be labeled manually or obtained from a user-generated user labeled online source. Most used supervised algorithms are Support Vector Machines (SVM), Naive Bayes classifier, Decision Tree and Multi Layer Perceptron. It has been shown that Supervised Techniques outperform unsupervised techniques in performance (Pang et al, 2002). Supervised techniques can use one or a combination of approaches we saw above. For example, a supervised technique can use relationship-based approach, or language model approach or a combination of them. For supervised techniques, the text to be analyzed must be represented as a feature vector. The features used in the feature vector are one or a combination of the features in below section

3.2.1 SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is primarily a classier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. The black line that separate the two cloud of class is right down the middle of a channel.The separation is In 2d, a line, in 3D, a plane, in four or more dimensions an a hyperplane. Mathematically, the separation can be found by taking the two critical members, one for each class. This points are called support vectors. These are the critical points (members) that define the channel.The separation is then the perpendicular bisector of the line joining these two support vectors. That's the idea of support vector machine.



$$\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i$$

subject to the constraints:

$$y_i\left(w^T\phi(x_i)+b\right)\geq 1-\xi_i \; and \; \xi_i \geq 0, i = 1,....,N$$

where C is the capacity constant, w is the vector of coefficients, b is a constant, and ξ_i represents parameters for handling nonseparable data (inputs). The index i labels the N training cases. Note that $y \in \pm 1$ represents the class labels and xi represents the independent variables. The kernel ϕ is used to transform data from the input (independent) to the feature space. It should be noted that the larger the C, the more the error is penalized. Thus, C should be chosen with care to avoid over fitting.

3.2.2 NAVIE BAYES

The Naive Bayes algorithm is based on conditional probabilities. It uses Bayes' Theorem, a formula that calculates a probability by counting the frequency of values and combinations of values in the historical data. Bayes' Theorem finds the probability of an event occurring given the probability of another event that has already occurred. Bayes' theorem: Probability of **event** A given **evidence** B

Prob(A given B)=Prob(A and B)Prob(A)Prob(A given B)=Prob(A and B)Prob(A)

where:

- A (Class) represents the dependent event: A target attribute
- and B(Instance) represents the prior event: A predictors attribute

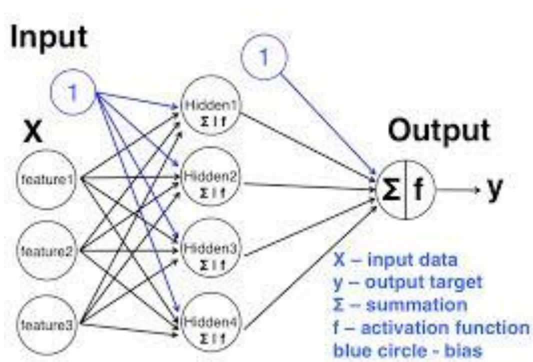
$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- P(A) is a priori probability of A (The prior probability) Probability of event before evidence is seen. The evidence is an attribute value of an unknown instance.
- P(A|B) is a posteriori probability of B. Probability of event after evidence is seen.

Posteriori = afterwards, after the evidence .

3.2.3 MULTILAYER PERCEPTRON

A multi-layer perceptron (**MLP**) has the same structure of a single layer perceptron with one or more hidden layers. The backpropagation algorithm consists of two phases: the forward phase where the activations are propagated from the input to the output layer, and the backward phase, where the error between the observed actual and the requested nominal value in the output layer is propagated backwards in order to modify the weights and bias values.



3.3 FEATURE ENGINEERING

Since most of sentiment analysis approaches use or depend on machine learning techniques, the salient features of text or documents are represented as feature vector. The following are the features used in sentiment analysis.

3.3.1 Term presence or term frequency :

In standard Information retrieval and text classification, term frequency is preferred over term presence. However, Pang et al. (2002), in sentiment analysis for movie reviews, show that this is not the case in sentiment analysis. Pang et al. claim that this is one indicator that sentiment analysis is different from standard text classification where term frequency is taken to be a good indicator of a topic. Ironically, another study by Yang et al. (2006) shows that words that appear only once in a given corpus are good indicators of high-precision subjectivity.

3.3.2 POS (Part of speech) Tags :

POS is used to disambiguate sense which in turn is used to guide feature selection (Pang and Lee, 2008). For example, with POS tags, we can identify adjectives and adverbs which are usually used as sentiment indicators (Turney, 2002). But, Turney himself found that adjectives performed worse than the same number of uni-grams selected on the basis of frequency.

3.3.3 Syntax and negation:

Collocations and other syntactic features can be employed to enhance performance. In some some short text (sentence-level) classification tasks, algorithms using syntactic features and algorithms using n-gram features were found to give same performance (Pang and Lee, 2008). Negation is also an important feature to take into account since it has the potential of reversing a sentiment (Pang and Lee, 2008).There are attempts to model negation for better performance (Das and Chen, 2001, Na et al., 2004). Na et al. (2004) report 3% accuracy improvement for electronics product reviews by handling negation. Note also that negation can be expressed in more subtle ways such as sarcasm, irony and other polarity reversers.

4. EXPERIMENTATION RESULT

This section presents the results of the study. The accuracy value shows the percentage of testing data set which was classified correctly by the model. The accuracy of three different machine learning algorithms are shown in below table

	Naive Bayes	**SVM**	**MLP**
Product Reviews	74.3 %	94.02 %	98.6 %

Table 1: The accuracy of the machine learning methods on the whole data set

Two algorithms have achieved accuracies over 90% for this product review, although MLP got better results.

5. CONCLUSION

Sentiment analysis becomes the most important source in decision making. Almost people depend on it to achieve the efficient product. Although, there are hundreds of thousands of researcher, who write and read online papers daily, the research in this field finds not enough till now. The main goal of this study was to determine which machine learning algorithm of MLP, SVM and Naive Bayes methods performs better in the task of text classification. This was accomplished by using the Amazon beauty products as data set. The classifiers were evaluated by comparing their accuracies in different cases of experiments. In terms of accuracies, MLP tends to do better than SVM, although the differences aren't very large, and the algorithms can reach more than 90% of classification correctly.

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