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Comparative Study of Machine Learning Approaches for Amazon Reviews

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ABSTRACT

Sentiment analysis is a broadly employed method for finding and extracting the appropriate polarity of text sources using Natural language Processing (NLP) methods. This paper focuses on examining the efficiency of three machine learning techniques (Support Vector Machines (SVM), Naive Bayes (NB) and Maximum Entropy (ME)) for classification of online reviews using a web model using supervised learning methods. The reviews are divided as positive, neutral and negative. This is not only helpful for consumers those want to search the reviews of products prior to purchase but also for companies those want to observe the public's reaction to their products. We have extracted Amazon Reviews using Amazon API. We have also used unigrams and weighted unigrams to train machine learning classifiers. The results have shown that machine learning algorithms work well on weighted unigrams and SVM has resulted maximum accuracy.

Keywords: Amazon Reviews; sentiment classification; opinion mining; sentiment analysis; machine learning

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1. Introduction

With the advancement in field of computers and internet, online marketing has also emerged as advanced field. While buying any product online, rating and reviews of existing users puts a high impact. It also affects the reputation of companies who use online market for their product promotion (1) . The extraction of user reviews is very time consuming and hectic process as the nature of reviews in unstructured; therefore techniques of sentiment analysis are used. Sentiment analysis analyzes people's attitudes and opinions towards entities such as products, events,

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topics, etc (2) (3). Key task includes aspect and sentiment extraction. Taking as example, the sentence "The Samsung's J7 display is good, but its camera quality is bad" evaluates two aspects, display and camera quality, of Samsung (entity). The sentiment about display is positive but the sentiment on camera quality is negative.

Sentiment analysis detects the relative polarity of the text (4) (5) (6). It finds whether given text is positive, negative or neutral. Since it finds out the opinion or attitude of the speaker, it is also identified as opinion mining. The social networking and shopping sites act as a medium where the users can post reviews about products, which can be used for classification (7) (8) (9) . Lots of research work is being done in this field due to its impact on marketing level competition and varying needs of people. It requires training set for accurate evaluation of reviews (10) (11).

Sentiment Analysis is a classification procedure as shown in Fig. 1 (12). It can be classified into three levels:

a) Document-level Sentiment Analysis (DSA): It classifies the opinion document based on expressing positive or negative opinion/sentiment. The entire document is considered as one unit which is talking about only one topic either negative or positive (2) (12).
b) Sentence-level Sentiment Analysis (SSA): It considers the sentiment expressed in each sentence. Firstly we need to identify that weather a sentence is subjective or objective. When the sentence comes out to be subjective than SSA will decide whether the sentence talks about positive opinions or negative opinions (2) (13). However researchers shown that there is no primary variation between sentence level and document level classifications as we can say that sentences are just small documents (2).
c) Aspect-level Sentiment Analysis (ASA): In this sentiments are classified based on the definite aspects of entities. To begin we need to identify entities and their properties. Reviewer can provide dissimilar opinions for diverse aspects of single entity for example ''the colour of this dress is not good, but the fabric is awesome'' (2) (14) .

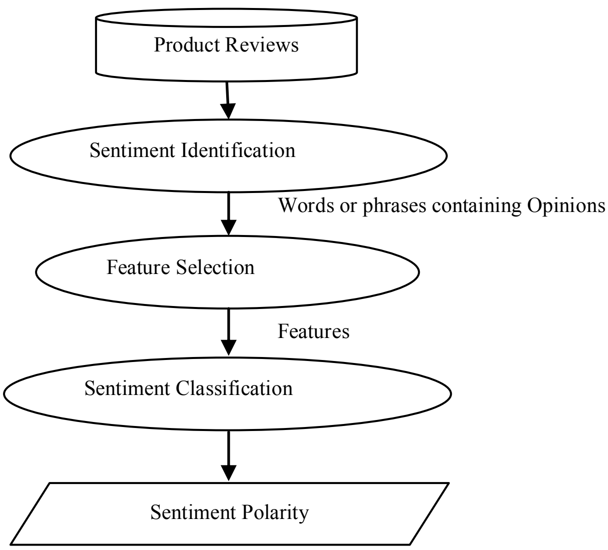

Fig. 1. Sentimental Analysis Process (4)

2. Methodology

In this paper our methodology is to compare aspect extractors and different machine learning classifiers to find out which is best for classifying the reviews of amazon.com. We have considered three machine learning techniques: Support Vector Machines (SVM), Naive Bayes (NB) and Maximum Entropy (ME). We have use unigrams and weighted unigrams containing positive and negative keywords for feature extraction (7) (15). A framework was build to treat classifiers and feature extractors as two different mechanisms. In this framework we have tried different set of combinations of feature extractors and classifiers.

2.1. Query Term

The consequences of query terms are normalized. The sentiment analysis regarding a product is performed by the user. If query term will contain positive or negative sentiment it can bias the results. Taking example: suppose query term is `ABC', we have normalized the sentiment carried by 'ABC'. The query term 'ABC' is barely interesting and we have classified it as negative. If the word 'ABC' by has a positive sentiment, it can alter the results. Each query term is presented as a QUERY TERM equivalence class.

2.2. Emoticons

Emoticons play an important role in classification emoticons are used as raucous labels in training process. Emoticons are stripped by us from training data. Leaving the emoticons can put the reverse impact on the accuracies/results of the Maximum Entropy classifiers and SVM classifiers, but less effect on Naive Bayes classifiers, this is due to the dissimilarity in arithmetical models and aspect weight selection of ME and SVM (3). Classifier learns from the other aspects like unigrams and bigrams in reviews **(5) (16)**. These non-emoticon features are used by classifier to determine the sentiment. As we have neglected emoticons so even if our test data has an emoticon, it will not affect the result of classifier as emoticon is not component of training data (6).

2.3. Feature Reduction

Amazon.com reviews contains several parts, we focus on following properties to decrease the feature space:

a) reviewerID and reviewerName : Reviewer ID is the unique id of the person writing a review, and reviewer name is the username. AT_USER equivalence class removes all words that start with @ and spaces in username.
b) reviewText : it is the actual text that is of our use. We need to do feature reduction to get actual text of our use. Lots of filler words or stop words such as "an", "a", "the", "is" used in a review does not specify any sentiment so they are filtered out (3). Review can contain repeated letters, for example, if you search "poor" in a review it can have random number of o"s in the middle (for e.g. poooor, pooooooor), which is irreverent. We have preprocessed any letter repeating more than 2 times in a word, is replaced with 2 occurrences, in given example these given words will be changed into the token "poor". The above reduction shrinks feature to 8.88% of its original size (4).

2.4. Aspect Vector

Once preprocessing is done the training set consist of data as 9500 positive reviews, 9500 negative reviews and 2500 neutral reviews; feature vectors are computed as given:

a) Unigrams: After preprocessing we get almost 21508 features as unigrams and each feature has equal weights.

b) Weighted Unigrams: we have weighted the positive/good and negative/bad keywords more than the other aspects/characters in the aspect vector, as a substitute of weighing each of the unigrams equally. We have used our list to weight the positive/good and negative/bad keywords more as compared to remaining/other aspects (6).

3. Machine Learning (ML) Approaches

Machine learning approaches depend on the famous Machine Learning (ML) algorithms to resolve the Sentimental Analysis as a normal text categorization problem that uses syntactic and linguistic features (17) (18) (19) (20) (21) (22) (23) (24) (25) (26) (27) (28). We have tested different classifiers known as Keyword-Based (KB), Naïve Bayes (NB), Maximum Entropy (ME) and Support Vector Machines (SVM) for Amazon reviews extracted using Amazon API.

3.1. Keyword-Based

In this method we have used the positive/good and negative/bad keyword list and for each review we have counted the number of positive, negative and neutral reviews. The polarity of the highest count is returned by classifier.

3.2. Naive Bayes (NB) Classifier

It is the simplest and mainly used classifier (1). On the basis of allocation of the words in document, this categorization model calculates/computes the subsequent probability of a class. This model works with the BOWs feature extraction ignoring the position of words in the document (2) (29) (30) . Bayes Theorem is used to calculate the probability that specified feature set is part of particular tag (1). This is shown by Equation 1.

$$\mathbf{P(tag|features)} = \frac{\mathbf{P(tag)*P(features|tag)}}{\mathbf{P(features)}} \quad (1)$$

where

P(tag) : It is preceding probability of tag or the possibility that arbitrary feature sets tag.
P(features) : It is preceding probability that specified feature set has occurred.
P(features|tag) : It is preceding probability that specified feature set is characterized as tag.
.

If we consider Naive assumption which says that all the features are independent, the equation can be written as shown (1):

$$\mathbf{P(tag|features)} = \frac{\mathbf{P(tag)*P(f1|tag)*....P(fn|tag)}}{\mathbf{P(features)}} \quad (2)$$

Improved NB classifier was firstly introduced by Kang and Yoo (31) which solves the problem of trend of positive classification accuracy to be 10% more than negative classification accuracy. Therefore when the accuracies of two classes are shown as an average value, the problem of reducing the average accuracy is formed. Naive Bayes is an easy model working well on text categorization problems (32) (33). Multinomial Naive Bayes model is used by us. In which Class $c*$ is assigned to review r (20), where value of $c*$ is as shown in Equation 3.

$$c^* = argmac_c P_{NB}\ (c|r) \quad (3)$$

$$\boldsymbol{P_{NB}}(\mathbf{c|r}) := \frac{\mathbf{P(c)} \sum_{\mathbf{i=1}}^{\mathbf{m}} \mathbf{P(f|c)^{n_i(r)}}}{\mathbf{P(r)}} \quad (4)$$

In Equation 4, feature is f and the count of feature fi found in review r is ni(r). m is total number of features.
P(c) and P(f|c) are parameters obtained by maximum likelihood estimates, and for unseen feature add -1 smoothing is utilized.
To classify and train using the Naïve Bayes (NB) method we have used Python NLTK (34) library.

3.3. Maximum Entropy (ME) Classifiers

This classifier is also known as a conditional exponential classifier, using encoding it translates labeled feature sets to vectors (35) (36) (37) (38). This encoded vector after that is utilized to estimate weights of each feature that are united to choose the most liable label of the feature set

(25). This classifier has parameters as a set of W{weights}, which combines joint features generated from feature-set by E{encoding}. The encoding maps each C{(featureset, label)} pair to a vector (24). To compute probability of every label we have used equation 5 as given below:

$$P(fs|label) = \frac{\text{dotprod(weights,encode(fs,label))}}{sum(dotprod\ (weights,encode(fs,l))forlinlabels)} \tag{5}$$

By using small amounts of training data Kaufmann (39) used it for detecting parallel sentences between any language pairs. Machine Entropy (ME) classifiers can generate constructive results for almost all language pairs. So that parallel corpora for numerous new languages can be created.

Maximum Entropy model is used with idea that we must choose the most uniform models that suit the given restraint (40) (41). They are feature-based models. Like Naives Bayes, ME formulate no autonomous assumptions for its features. To represent model we have used equation 6 as given below:

$$P_{ME}(\mathbf{c}|\mathbf{r},\boldsymbol{\lambda}) = \frac{\exp\left[\sum_i \lambda_i f_i(c,r)\right]}{\sum_{c'} \exp\left[\sum_i \lambda_i f_i(c,r)\right]} \tag{6}$$

In this formula, class is c, review is r, and weight vector is λ which decides the importance of a feature in classification. If feature has high weight it means that it strongly indicates a class. By numerical optimization of the λi's , the weight vector can be found to maximize the restrictive probability.

Maximum Entropy can handle enhanced feature overlap therefore it performs better than Naive Bayes theoretically. But, in practice, Naive Bayes (NB) classifier performs good on a range of problems (40).

To train and classify using the Maximum Entropy (ME) method we have used Python NLTK (22) library. We have used conjugate gradient ascent for training the weights.

3.4. Support Vector Machines (SVM) Classifiers

It is among the trendy classification techniques (42). SVM lies on the principle of determining linear separators in the search space that can finest divide the diverse classes (30). For SVM classification test data is well suited due to bare nature of text, in which some aspects can be unrelated, but are correlated with each other and are arranged into linearly divisible categories (43) (44) (45) (46).

One of the important applications of SVM is to classify reviews according to their quality. Two multiclass SVM-based approaches were used by Chen and Tseng (47). Considering product reviews as a categorization problem, they have projected method for calculating quality/value of information in product reviews. To find information oriented feature set, on Iphone reviews, they have adopted an information quality (IQ) framework. They can accurately categorize reviews in provision of their quality (32).

Li and Li (48) used SVM as sentiment polarity classifier they said that opinion subjectivity and user credibility must be taken into concern. They proposed framework to provide compact numeric summarization of opinions on micro-blogs platforms (33). They have classified the opinions using SVM after recognizing and extracting the topics in opinions related with queries of the users. Twitter posts were used for their experiments. They proved that for aggregating micro-blog opinions the consideration of opinion subjectivity and user credibility is necessary.

The libsvm (49) library is used by us with linear kernel for our experiment. Two sets of vectors are included in input data each of size X. Every entry in vector correlates to occurrence of a feature. When feature is present: value 1 is assigned but when it is not present value 0 is assigned. To speed up overall processing **(50)** we have used feature presence inspite of count, therefore we do not need to range input data.

4. Evaluation

4.1. Experimental Setup

We have taken reviews from publicly available data sets of Amazon (51) in the given format:

Table 1.Amazon Reviews Format

PRODUCT	Productid: Title: Price:	B00009HAXW nice television for the price unknown
REVIEW	Userid: Profilename: Helpfulness: Score: Summary: Text:	R3LDJA7HU2Q0FS John Koto 10 4.0 Service and product quality very good Delivery was very prompt. The picture of this TV was great! Very clear images so don't need to change my eye glass prescription after all.

Table 2 explains the particulars of training and test data as shown below. We have randomly chosen 3000 reviews for the test dataset, which were not utilized to train the classifiers.

Table 2. Example Reviews

DATASET	POSITIVE (helpful)	NEGATIVE (harmful)	NEUTRAL (unbiased)	TOTAL
Training	9500	9500	2500	21500
Test	Randomly chosen Reviews			3000

We have retrieved Amazon reviews using Amazon API in English (en). Since the training data is English so this classification will work only on review in English. Web interface has been used to search the Amazon API for a given keyword. The filtered reviews are feeded into trained classifiers. After that the output is revealed in the form of graphs in the web interface.

5. Results

The results show that user reviews are very important for the decision making of customers. But the more surprising and interesting part is to bifurcate reviews into positive, negative and neutral. After comparing three machine learning approaches using unigrams features and weighted unigram features in Amazon reviews the accuracy of classifiers is as shown in Table 3.

Table 3. Accuracy of Classifiers

FEATURES	SUPPORT VECTOR MACHINES (SVM)	MAX ENTROPY (ME)	NAÏVE BAYES (NB)
Unigrams	62.86	60.21	66.84
Weighted Unigrams	81.20	70.35	77.42

Unigrams: This is the easiest way to fetch features from a review. We can see from Table 3 that machine learning classifiers had average performance with our feature vector; the reason can be smaller training dataset of 20000+ reviews. If the classifier is trained for millions of reviews than accuracy can improve significantly.

Weighted Unigrams: In this we have given weight to the positive/good keywords and negative/bad keywords more than other words when trying to categorize sentiment of review and resulted in economical accuracy as Table 3 shows that. SVM performed finest with 81.20% accuracy and unexpectedly Naive Bayes (NB) classifier performed better that Max Entropy (ME) i.e. 77.42% to 70.35%. Pang and Lee (20) also showed nearly the same.

Figures 2-5 shows the Amazon review analysis of topic 'IPHONE 7' from reviews between 6th to 11th February.

Fig. 2. Keyword- based

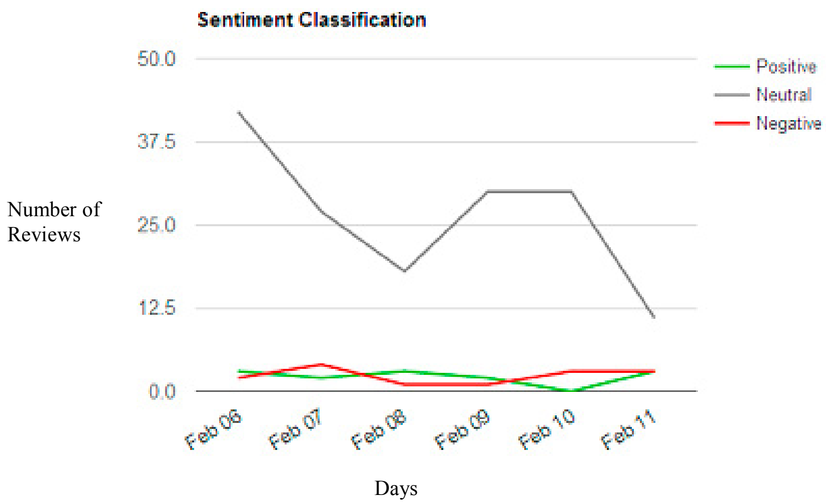

Fig. 3. Naive Bayes

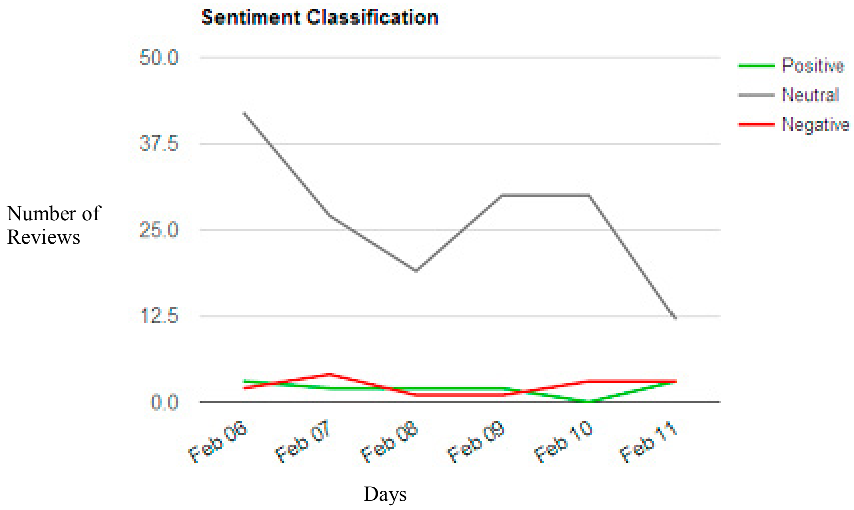

Fig. 4. Maximum Entropy

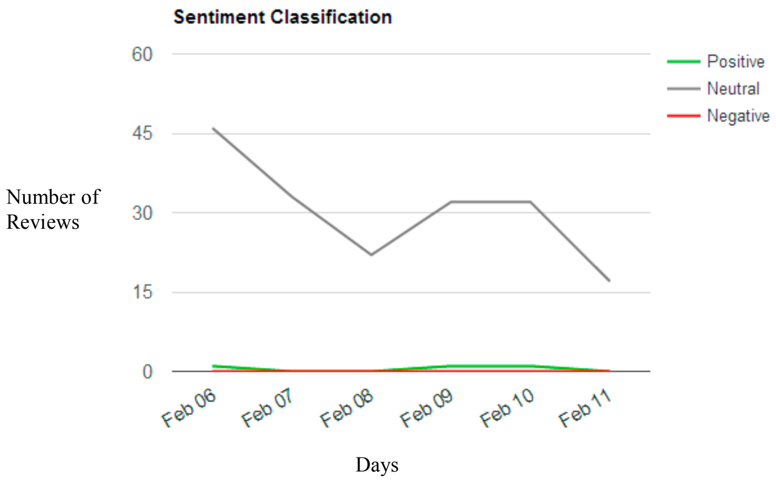

Fig. 5. Support Vector Machine

6. Conclusion

Amazon product reviews are not only important for individual person buying the product but also for company selling the product. The conducted study in this paper showed that product reviews are not only important source of information for customers to maintain their buying decision but also for companies selling their products. Textual product reviews are in much unstructured form so there is firstly the need to classify them as positive, negative and neutral. Efficiency of user reviews needs to be increase for correct prediction.

Our research has shown that machine learning method, SVM can be regarded as the baseline learning method for Amazon reviews as it has highest accuracy. Applying weight to the reviews has increased the accuracy, so we can say that "more precise the data more exact results can be obtained".

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