REAL TIME SENTIMENT ANALYSIS OF E-COMMERCE WEBSITES USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

With the advent of social media, sentiment analysis an evolving area finds application in all domains. Significant applications of sentiment analysis include retail, movie rating, politics, healthcare, and automobile industry. Sentiment analysis can be implemented in various methods like machine learning methods, syntactic patterns, lexicon based method. Finding the sentiment of e-commerce websites is very important for online customers to buy quality products and timely delivery of their goods and services. This paper compares the e-commerce websites in terms of quality and timely delivery. Sentiment is calculated based on the live tweets generated by twitter on these websites using streaming API.

Key words: Sentiment Analysis, twitter, Over fitting, Accuracy, Feature selection, E-commerce, Real time.


http://www.iaeme.com/IJMET/issues.asp?JType=IJMET&VType=9&IType=2

1. INTRODUCTION

Sentiment analysis is generally appraisal, attitude or subjective. To do sentiment analysis we have to collect opinions from different users, because their opinion will not be the same. Opinion collection collects opinions of different people from social media like Facebook, twitter, forum, blogs. Each of it has unique features. Opinion in twitter will be simple because each tweet is of maximum of 140 characters similarly reviews are also simple, forums are complex because interactive messages will be exchanged between the users. Sentiment analysis is basically a Quadruple (E,S,O,T) where E is the entity on which the opinion is told is the sentiment, either positive or negative is the opinion holder is the time at which the
opinion is given. Ex: User A likes the picture quality of the mobile phone, but its battery life is not good, here Opinion holder is User A, Sentiment is positive on picture quality but negative on battery life, Entity is mobile phone. Entity can be any product, person, service or event. Time component is also important. Ex Sentiment given at this moment is more important than the sentiment given before two years. An Opinion is of two types regular and comparative. Regular opinion is this book is great. Comparative opinion involves comparison between two entities. Ex Mobile X is better than Mobile Y.

In general if users want to buy any product like mobile phone, TV or a dress in e-commerce websites they will see the service ratings in that website. The website maintains only positive ratings so rating will not be helpful to the user. This problem can be solved in twitter by looking into the live tweets generated by the users on e-commerce websites. Twitter is used by millions of people in the world and the no of tweets generated per day is millions. Ex tweet on amazon is the service given by Amazon is awesome in buying apple mobile phone and can compare the services given by the different e-commerce websites so that users can choose which is the best website for buying the products. Our problem is real time sentiment analysis of e-commerce websites using machine learning algorithms. Real time sentiment analysis is a challenging task since the labelled data is difficult to get.

The problem can be solved using different methods
1. Sentiment lexicons.
2. Syntactic analysis.

1.1. Machine Learning Model
Machine learning model [1] includes feature set extraction by removing the irrelevant features then apply machine learning algorithms to train the data and learn, then the model is used to predict the sentiment of the text

1.2. Sentiment Lexicon
Sentiment lexicon[3] uses domain dictionary consists of sentiment words and its synonyms. For any sentence stop words has to be removed and polarity is calculated by first comparing each token presence in the dictionary. If found then its strength of polarity can be found in sentiwordnet. Finally add all the polarity strengths of tokens and based on threshold sentence can be classified as positive or negative.

Generating sentiment lexicons can be done in 3 methods.
2. Thesaurus based.
3. Corpus based.

Manual method is costly in finding all the opinion words and its polarity. J kamps proposed thesaurus based approach to obtain the sentiment lexicon[3] by expanding the adjectives or opinion words with its synonyms’ and antonym’s. For example excellent, good, superb, beautiful all will have positive semantic orientation. Similarly bad, worst, dull will have negative semantic orientation. Corpus[5] based method used to extract the opinion words based on the conjunctions if two sentences are connected by the word “AND” the opinion of
the both words will be positive, otherwise different opinion words if connected by the word “BUT”. E.G. Though the picture quality of camera is good but size is too long. Here the Picture quality has positive semantic orientation, size is having negative semantic orientation.

![Figure 1 Machine learning Model](image)

### 1.3. Syntactic Patterns

Syntactic patterns [2] are used to identify phrases like NN followed by adjective.

<table>
<thead>
<tr>
<th>S.No</th>
<th>First word</th>
<th>Second word</th>
<th>Third word</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>JJ</td>
<td>NN or NNS</td>
<td>Any thing</td>
</tr>
<tr>
<td>2</td>
<td>RB,RBR or RBS</td>
<td>JJ</td>
<td>NNS</td>
</tr>
<tr>
<td>3</td>
<td>JJ</td>
<td>JJ</td>
<td>Not NN nor NNS</td>
</tr>
<tr>
<td>4</td>
<td>NN or NNS</td>
<td>JJ</td>
<td>Not NN nor NNS</td>
</tr>
<tr>
<td>5</td>
<td>RB,RBR, or RBS</td>
<td>VB, VBD, VBN or VBG</td>
<td>Anything</td>
</tr>
</tbody>
</table>

The sentimental analysis approach consists of following steps.
1. Apply parts of speech tagging to the given data set.
2. Extract the patterns using the words given in the above table.
3. Apply Associate rule mining. Frequent item set is words or phrases
4. Extract the Frequent Item sets
   Eg. Digital camera.
5. Find nearby adjectives to know the opinion words.
6. Find the polarity of the extracted phrases.

This method also fails in case of sentiment shifters like ‘NOT’, and ‘but’.

### 2. SENTIMENT ANALYSIS APPLICATIONS-RELATED WORK

This section compares all the existing work done on applications of sentiment analysis and explores the domain of online shopping. Sentiment Analysis for social images is a latest research much focus is on text sentiment analysis. Jyoti Islam, Yanying Zhang[28] proposed a model for sentiment analysis on social images using transfer learning approach with much improved results of the current state of art. Naan Yang and Shufan[14] Zhang proposed a data analysis system for video comments. Comments were extracted from internet and analyses the information using machine learning technique and provides sentiment about the video.
Chih-Hua Tai works on the detecting the intention and intensity of feelings on Social networks. The main idea is building Feeling Distinguisher framework in view of supervised, Latent Dirichlet Allocation (sLDA), Latent Dirichlet Allocation, and SentiWordNet systems for recognizing a person’s feelings and power of emotions through the investigation of the online posts. The performance of FeD is about 1.08–1.18 folds that of SVM and sLDA. Apoorv Agarwal, Vivek Sharma[15] performs opinion mining in news headlines using sentiwordnet. The algorithm works as follows headlines are tokenised into words and apply parts of speech tagger, lemmatise the word to know in which reference it is used, then apply stemming. Finally the output of the resulting word is given to the sentiwordnet which calculates the positive, negative scores and finds the total polarity of the headline.

Huan Chen, Xin-Nan Li[17] worked on sentiment analysis for big data scenario. At present text classification methods such as naïve bayes, SVM, Maximum entropy were used. In this paper text mining analysis based on the big data perspective was proposed. A new text processing service called Cloud based core text processing service has been proposed and finally personalised news recommendation was proposed.

Meghana Ashok, Swathi Rajanna[18] proposed a personalised recommender system using sentiment analysis of social media. Retrieving information from social media is a enormous task. In this paper author proposes a method to retrieve users reviews and comments of restaurants to personalise and rank suggestions based on user preferences.

Yohei Seki studied[19] about the Use of Twitter for Analysis of Public Sentiment for Improvement of Local Government Service. Public sentiment are analysed from their twitter accounts and proved that system is effective in administering the local service. Tweets were analysed on the festival day in Tsukuba city from the public in the year 2014, 2015 then government improved the traffic policies based on the sentiment from the public.

Security Attack Prediction Based on User Sentiment Analysis of Twitter Data by Ado Hernandez, Victor Sanchez [26] used twitter to find the people who uses twitter to express their opinion about security attacks, sentiment analysis is done on the views to predict the security attack. Sentiment analysis of student feedback, A study towards optimal tools by Mohammad aman Ullah[20] used facebook as a platform to collect the feedback from the students and sentiment analysis is done using machine learning algorithms.

In Sentiment and Emotion Analysis for Social Multimedia: Methodologies and Applications by Quanzeng[21] performed sentiment analysis on the visual images of social multimedia. An image is worth of thousand words. Sarah E. Shukri, Rawan I. Yaghi, Ibrahim Aljarah, Hamad Alsawalqah [22] studied about sentiment analysis of automobile industry. Their results show that BMW has more positive polarity than Mercedes.

Latest research on sentiment analysis is using Domain ontology. Domain ontology is used to extract the features of any product and does Aspect level sentiment analysis. Ontology-based Aspect Extraction for an Improved Sentiment Analysis in Summarization of Product Reviews by Ali Marstawi, Nurfadhlin Mohd Sharef, The[23] and Aida Mustapha is based on ontology based sentiment summarisation framework(OBPSS) which outperformed other existing systems in aspect extraction. Ontology Driven Sentiment Analysis on Social Web for Government Intelligence by Akshi Kumar and Arunima Joshi[24] used twitter to collect the opinions of citizens on government rules and policies. Ontology was used to determine the subjects and topics discussed in the tweets. An Ontology is created for ministers of
government of India. Sentiment Learning on Product Reviews via Sentiment Ontology Tree[25] is labelling the product attributes and their associates sentiments in product reviews by hierarchical learning process with a Sentiment ontology tree.

Another major part of research on sentiment analysis is using evolutionary algorithms. A statistical and Evolutionary approach to sentiment analysis by Jonathan Carvalho, Adriana Prado, Alexander Plastino[26] improved the existing statistical method in which polarity of the tweets is identified by the association of product features with set of paradigm words. In this paper Paradigm words are selected from the initial population using genetic algorithms. Results show that there is significant improvement in the accuracy. Adaptive lexicon learning using genetic algorithm for sentiment analysis of micro blogs[27] creates adaptive lexicon from the combining corpus based and lexicon based method and generates new lexicon from the text. The goal is find an optimal sentiment lexicon by using genetic algorithm. A Genetic Algorithm feature selection based approach for Arabic sentiment classification uses genetic algorithm to minimise the no of features in the feature set extraction. Each chromosome is a bag of unigrams, the algorithm randomly generates initial population and fitness function is classification accuracy achieved with the selected words in the chromosome then crossover and mutation is performed to get the selected features for the given data set. Results show that accuracy, precision and recall were improved with the resultant reduced feature set.

Another major implementation model in sentiment analysis is neural networks. Last and the important research in sentiment analysis is identifying sarcastic and comparative sentences. Sarcastic sentence tells about positivity of the sentence but its real intention is negative

2.1. Review
A Minimal work has been done on research of Application of sentiment analysis on e-commerce websites. This paper implements the application of sentiment analysis using nltk twitter API’s and machine learning algorithms

3. IMPLEMENTATION
3.1. Data Collection
Tweets can be downloaded from the twitter using two methods API search key and twitter Streaming API. Twitter streaming API is used to download the live tweets .The basic process of Twitter streaming is

- first create an application in twitter
- Then authenticate the twitter account
- Use stream listener to listen to the live tweets.
- Then use Filter to stream the tweets that user wants.
- Store the tweets in CSV file or in database.

Table 1 Tweets collected for different websites:

<table>
<thead>
<tr>
<th>E-commerce website</th>
<th>Keyword</th>
<th>No of tweets collected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>#amazon</td>
<td>50000</td>
</tr>
<tr>
<td>E-bay</td>
<td>#e-bay</td>
<td>25000</td>
</tr>
<tr>
<td>Alibaba</td>
<td>#Alibaba</td>
<td>25000</td>
</tr>
</tbody>
</table>
Tweets are collected daily from 01/06/17 to 05/06/17 between 4 p.m. to 5 p.m., maximum of 1000 per day so a total of 50,000 tweets in case of amazon, 25,000 in case of E-bay and Alibaba were collected.

![Figure 2: Bar Diagram showing the no of tweets collected.](image)

Twitter application settings are as follows.

![Figure 3 Application settings](image)
API search key is used to download the tweets that user searches in the twitter. Use screen name to know the search content. In this paper tweets are downloaded using streaming API at different times of day by using the search terms ‘Amazon’, ’Ebay’ and ‘Alibaba’.

3.2. Pre-Processing

Tweets downloaded has to be pre-processed. It contains irrelevant information and irrelevant symbols which can be removed manually or using regular expressions in python. In twitter users normally post the urls which has to be removed. Finally stop words like is, was, also to be removed.

![Processing Steps](image.png)

**Figure 5** Preprocessing Steps

<table>
<thead>
<tr>
<th>Sl.no</th>
<th>DESCRIPTION</th>
<th>PURPOSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Remove any url in tweets</td>
<td>URL removal</td>
</tr>
<tr>
<td>2.</td>
<td>Remove RT @username in front of tweets</td>
<td>Retweet tag removal</td>
</tr>
<tr>
<td>3.</td>
<td>Remove #tag at the end of tweets</td>
<td>Hashtag removal</td>
</tr>
<tr>
<td>4.</td>
<td>Remove all prefix(##) in the middle of tweets</td>
<td>Removing special characters</td>
</tr>
</tbody>
</table>

**Table 3**: Tweets before Pre-processing.

**Table 4**: Tweets after Pre-processing.
Real Time Sentiment Analysis of E-Commerce Websites Using Machine Learning Algorithms

<table>
<thead>
<tr>
<th>Sl.no</th>
<th>Tweet</th>
<th>Steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>&quot;RT @CNN: If your child made an in-app purchase on Amazon's app store without your permission, you may get your money back <a href="https://t.co/TdQR">https://t.co/TdQR</a>&quot;</td>
<td>1 to 6</td>
</tr>
<tr>
<td>After Clean up</td>
<td>If your child made an in-app purchase on Amazon's app store without your permission, you may get your money back</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Online retailer Amazon refunding $70M for charges by children without parents knowledge\n\nSTORY; <a href="https://t.co/eUKJYeXMbv">https://t.co/eUKJYeXMbv</a></td>
<td>1 to 6</td>
</tr>
<tr>
<td>After Clean up</td>
<td>Online retailer Amazon refunding $70M for charges by children without parents knowledge\n\nSTORY;</td>
<td></td>
</tr>
</tbody>
</table>

**Figure 6** Sentiment Analysis process

### 3.3. Natural Language Tool kit

The implementation of sentiment analysis of Collected data set is done on NLTK.NLTK provides inbuilt libraries for stemming, tokenisation, and machine learning algorithms, parsing and semantic reasoning.it provides access to more than 50 corpora and lexical resources.NLTK is free and open source supported by all the operating systems.

### 3.4. Feature Selection

Feature selection mainly removes the irrelevant features from the original set. Feature selection model is mainly useful to overcome the problem of over fitting and improving the performance of sentiment analysis and it is cost effective. Different Feature selection methods can be implemented.
**Document Frequency**

Document frequency measures the no of documents in which feature has appeared. It removes the features whose document frequency is less than the predefined threshold value. Research survey suggests that this method is simple, scalable and effective for document classification.

**Information Gain**

Feature selection method used in this paper is Document Frequency (DF) finding the frequent words in the dataset and algorithm learns based on frequent words present in the document. Frequent words are based on the predefined threshold range. Other feature selection methods are Information gain, Gain ratio, CHI squared statistic. Cross-fold validation is used to divide the data set into train set and test set. The algorithm learns in the training phase and predicts the document either negative or positive in test set. Different machine learning algorithms were used to fit a model and compared, like naïve Bayesian classification, Max-entropy classification, decision rule based classification. Maximum accuracy is achieved in Naïve Bayesian classification.

**Naïve Bayesian algorithm**

Naive Bayesian is based on the Bayes theorem

\[
P(x \mid y) = \frac{(P(x) * P(y \mid x))}{P(y)}
\]

If \( F_1, F_2 \ldots F_n \) are Features of the Data set then the algorithm predicts the probability \( P \left( \frac{C_k}{F_1,F_2 \ldots F_n} \right) \) for different clauses \( C_1, C_2, C_3 \). The Class which has the maximum probability will be the correct prediction. Naïve Bayesian is the most powerful and accurate method in machine learning algorithms. It gives Maximum accuracy.

**Maximum Entropy Method**

ME sometimes outperform Naïve Bayesian in standard text classification. Conditional probability is estimated by the exponential form.

\[
P_{Em} (x \mid y) = \frac{1}{Z(y)} EXP \left( \sum_i \lambda_{i,x} F_{i,x} (y,x) \right)
\]

Where \( Z(y) \) is a normalisation function \( F_{i,x} \) is a feature or class function for feature \( f_i \)

This is defined as

\[
F_{i,x} (y,x) = \begin{cases} 
1, & \text{if } r_i(y) > 0 \text{ and } x' = x \\
0, & \text{else}
\end{cases}
\]

Where \( \lambda \) are feature weight parameters. The parameter values are set so that the MaxEnt classifiers increase the entropy of the incited distribution while keeping up the limitations upheld by the training data. The requirement is that the anticipated estimations of the highlight/class capacities as for the model are equivalent to their anticipated values with respect to the training data. Maximum entropy assumes that features are dependent whereas Naïve Bayesian assumes independent.

**Decision Tree**

Decision trees are made by pruning the feature vector space. For each node entropy is calculated, based on the least value of information gain and accordingly split is made. Decision trees is easy to predict. New predictions are made by traversing from the root node to the leaf node.

Information gain = Entropy (parent) – Weighted sum of Entropy (children)
Sentiment of the document is identified using the accuracy. If the accuracy is greater than 0.5 it means that it is positive else negative. In this work, we have used overall accuracy (OA) as performance evaluation metrics. The confusion matrix shown in Table 1 is used for evaluating the performance of classifiers.

**Table 5 Confusion Matrix.**

<table>
<thead>
<tr>
<th>Actual Positive Examples</th>
<th>Predicted Positives</th>
<th>Predicted Negatives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Positive Examples</td>
<td>TP</td>
<td>FN</td>
</tr>
<tr>
<td>Actual Negative Examples</td>
<td>FP</td>
<td>TN</td>
</tr>
</tbody>
</table>

The performance of sentiment classification is evaluated by the Overall Accuracy, which is given by:

\[
\text{Overall Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}
\]

*Recall:* It is the fraction of relevant instances that have been retrieved over total relevant instances in the image. \(\text{Recall} = \frac{TP}{TP + FN}\)

*Precision* (also called positive predictive value) is the fraction of relevant instances among the retrieved instances.

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

*F-measure:* A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score:

\[
F\text{-measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

**Table 6 Overall Document Polarity of different websites**

<table>
<thead>
<tr>
<th>E-commerce website</th>
<th>Polarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>Positive</td>
</tr>
<tr>
<td>E-bay</td>
<td>Positive</td>
</tr>
<tr>
<td>Ali baba</td>
<td>Positive</td>
</tr>
</tbody>
</table>

3.5. **Feature extraction using parts of speech tagging.**

Normally adjectives and adverbs represent polarity words in any domain. So extracting polarity words using parts of speech tagging, then machine learns based on the adjectives present in the document, then classifies the new document. Results for the above method are mentioned in the table 8. Similarly we can use bigrams and trigrams also feature extraction and results will be compared.

4. **RESULTS**

The results show that Amazon has got good accuracy compared with E-bay and Ali-baba. Much of the time NaiveBayesian classification has outperformed the other classification algorithms. Results are compared with Sentiment knowledge discovery in twitter streaming data[29]. We got better results in terms of accuracy.

<table>
<thead>
<tr>
<th>E-commerce website</th>
<th>No of positive tweets</th>
<th>No of negative tweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>46428</td>
<td>3570</td>
</tr>
<tr>
<td>E-bay</td>
<td>21428</td>
<td>3571</td>
</tr>
<tr>
<td>Ali baba</td>
<td>22,011</td>
<td>2989</td>
</tr>
</tbody>
</table>
### Table 7 Accuracy Using Document frequency as Feature selection

<table>
<thead>
<tr>
<th>E-commerce Website</th>
<th>N – no of features</th>
<th>Naïve Bayes Accuracy</th>
<th>Decision tree Accuracy</th>
<th>Max Entropy Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>200</td>
<td>0.8461</td>
<td>0.8461</td>
<td>0.923</td>
</tr>
<tr>
<td>Amazon</td>
<td>300</td>
<td>0.923</td>
<td>0.923</td>
<td>0.923</td>
</tr>
<tr>
<td>Amazon</td>
<td>1000</td>
<td>0.923</td>
<td>0.923</td>
<td>0.923</td>
</tr>
<tr>
<td>E-bay</td>
<td>200</td>
<td>0.8571</td>
<td>0.8334</td>
<td>0.75</td>
</tr>
<tr>
<td>E-bay</td>
<td>300</td>
<td>0.833</td>
<td>0.9166</td>
<td>0.8334</td>
</tr>
<tr>
<td>E-bay</td>
<td>1000</td>
<td>0.9166</td>
<td>0.9166</td>
<td>0.9166</td>
</tr>
<tr>
<td>Alibaba</td>
<td>200</td>
<td>0.8571</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td>Alibaba</td>
<td>300</td>
<td>0.84</td>
<td>0.85</td>
<td>0.86</td>
</tr>
<tr>
<td>Alibaba</td>
<td>1000</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
</tr>
</tbody>
</table>

### Table 8 Accuracy using Parts of speech tag as feature selection method

<table>
<thead>
<tr>
<th>E-commerce Website</th>
<th>N – no of features</th>
<th>Naïve Bayes Accuracy</th>
<th>Decision tree Accuracy</th>
<th>Max entropy Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>200</td>
<td>0.7857</td>
<td>0.7857</td>
<td>0.7857</td>
</tr>
<tr>
<td>Amazon</td>
<td>300</td>
<td>0.7857</td>
<td>0.7857</td>
<td>0.7857</td>
</tr>
<tr>
<td>Amazon</td>
<td>1000</td>
<td>0.7857</td>
<td>0.7857</td>
<td>0.7857</td>
</tr>
<tr>
<td>E-bay</td>
<td>200</td>
<td>0.7142</td>
<td>0.7142</td>
<td>0.7142</td>
</tr>
<tr>
<td>E-bay</td>
<td>300</td>
<td>0.7142</td>
<td>0.7142</td>
<td>0.7142</td>
</tr>
<tr>
<td>E-bay</td>
<td>1000</td>
<td>0.7142</td>
<td>0.7142</td>
<td>0.7142</td>
</tr>
<tr>
<td>Ali baba</td>
<td>200</td>
<td>0.712</td>
<td>0.71</td>
<td>0.71</td>
</tr>
<tr>
<td>Ali baba</td>
<td>300</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>Ali baba</td>
<td>1000</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
</tr>
</tbody>
</table>

### Table 9 Precision using Document frequency as feature selection

<table>
<thead>
<tr>
<th>E-commerce Website</th>
<th>N – no of features</th>
<th>Naïve Bayes Precision</th>
<th>Decision tree Precision</th>
<th>Max entropy Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>200</td>
<td>0.73</td>
<td>0.72</td>
<td>0.76</td>
</tr>
<tr>
<td>Amazon</td>
<td>300</td>
<td>0.73</td>
<td>0.72</td>
<td>0.76</td>
</tr>
<tr>
<td>Amazon</td>
<td>1000</td>
<td>0.73</td>
<td>0.72</td>
<td>0.76</td>
</tr>
<tr>
<td>E-bay</td>
<td>200</td>
<td>0.768</td>
<td>0.768</td>
<td>0.768</td>
</tr>
<tr>
<td>E-bay</td>
<td>300</td>
<td>0.769</td>
<td>0.769</td>
<td>0.769</td>
</tr>
<tr>
<td>E-bay</td>
<td>1000</td>
<td>0.769</td>
<td>0.769</td>
<td>0.769</td>
</tr>
<tr>
<td>Ali baba</td>
<td>200</td>
<td>0.76</td>
<td>0.76</td>
<td>0.76</td>
</tr>
<tr>
<td>Ali baba</td>
<td>300</td>
<td>0.73</td>
<td>0.75</td>
<td>0.76</td>
</tr>
<tr>
<td>Ali baba</td>
<td>1000</td>
<td>0.74</td>
<td>0.75</td>
<td>0.75</td>
</tr>
</tbody>
</table>

![Accuracy for Amazon](chart.png)
5. CONCLUSION AND FUTURE WORK

In this paper the sentiment analysis for different e-commerce websites is compared using machine learning algorithms. Amazon is the preferred entity with good accuracy. There is significant improvement in results using twitter for data set collection instead of Data from the websites which is mostly positive. Currently we are doing sentiment analysis on amazon as an entity in future we can do aspect level sentiment analysis in different e-commerce products and choose the product whose ratings is more in e-commerce website. Using Deep learning we can still improve the accuracy of the machine learning algorithms.

REFERENCES


Real Time Sentiment Analysis of E-Commerce Websites Using Machine Learning Algorithms


