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Einblick- A Sentimental Analysis And Opinion Mining System For Mobile Networks

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ABSTRACT

Sentimental analysis and popular legal opinion mining are one among the foremost agile research areas in natural language processing and is additionally widely studied in data processing, web mining and text mining. The growing grandness of sentimental analysis coincide with the rise of social medium like reviews, forum discussion, blog, micro blog, Twitter and social electronic networks. A system to implement this technology in mobile network sectors can be very much helpful for any mobile network for quicker interaction with their subscribers as well as enriching their reach of advertisement. Thus ensuring effective and optimized use of their resources to yield desired public response within a proposed time limit. Sentimental analysis helps to decide whether a statement is positive ,neutral or negative. It also helps data analyst to collect public opinion and do research based on that. In sentimental analysis we breakdown text into small parts and then we will identify each statement bearing phrase or components and will assign a score to each component.

Key words: Sentimental Analysis, Logistic Regression, Accuracy, mobile networks, Opinion Mining

1. INTRODUCTION

With the blowing-up of Web 2.0, platforms like blogs, e-commerce sites, peer-to-peer networks and social media, consumers have a wide platform and limitless power to share their experiences in the form of reviews. In this project an aspect based opinion mining arrangement is proposed which segregate reviews as positive and negative. Two aspects in a review are dealt with in this system. When we compare with other techniques experimental results which are done using reviews of mobile phones show an accuracy of 75%. This is a project which mainly concentrate on sharing of posts in the application more efficiently, effectively and effortlessly. In this application, users can share their posts whether it can be images or any others. This application gives a special feature i.e.., when one of the user shares a post in the application, all the other users who have registered can see the post and leave a comment to the post. By this, all users can easily also show how any comment is helpful or not to them by liking or disliking a comment. Mobile networks have been an indistinguishable part of our daily lives since past few years. Besides from the need of technical advancements in the products and services they are also facing challenges like effective customer interactions, Competition in digital marketing,etc. So the current times demand the employment of methods like sentiment analysis and opinion mining for the mobile networks to understand the tastes and preferences of their subscribers and adapt according to the changing needs and trends so as to be updated. Besides from saving time this could also help in decreasing the human effort and adding up the efficiency in customer management and organizing the plans and services according to the different category of users classified on basis of their preferences and even complaints.

2. LITERATURE SURVEY

Sentiment analysis of reviews on mobile commerce platforms includes extraction, classification, retrieval, and induction of sentiment data [1]. There have machine□learning and knowledge□based approaches. The latter uses a sentiment lexicon and grammar rules for sentiment analysis. The paper [2] proposed a totally distinctive sentiment analysis technique action reviews of product features by employing an ancient sentiment words library. Then, this technique integrated context data with sentiment reviews to predict the sentiment polarity of a product, increasing prediction accuracy. In [3] it is analyzed the characteristics of metaphysics and Chinese on□line reviews and planned a text mining model supported sentiment vocabulary metaphysics to make a match of opinion target. This model attracts attention to the mobile commerce enterprises. Similarly, [4] analyzed the sentiment tendency within the dependencies of goods and opinion□supported metaphysics models. This technique integrated syntax with linguistics data thus on quantify sentiment price, which had nice business price within the application. In paper [5] the authors created grammar rules by adopting noun pruning and frequency by filtering technology to extract review corpus. The sentiment mining technique supported machine learning, that is extraordinarily completely different from the knowledge□based, needs additional coaching time, and so the model is simply too complex [6]. Therefore, the author improved the normal sentiment mining method and engineered a text sentiment opinion mining model on the basic concept of binary language model and gray theory to understand quality sentiment□oriented mining [7]. In addition, considering the quality of the machine□learning technique, [8] extracted goods options offline according to the utmost entropy and trained the model victimization corpus□tagged library. Finally, they extracted product options of on□line opinions by victimization traditional auxiliary goods data. The model reduced learning time and achieved smart prejudging results.

Some researchers have found that similar preferences of music are often matched by analyzing sentiment options. On one hand, paper [9] centered on sentiment characteristics of users who had common musical interests once calculating similarity of users. Similarly, in [10] it is found that sentiment characteristics among completely different users by analyzing options of theme music in the picture show and engineered a user interest of music model supported sentiment tendency to achieve correct recommendations. On the opposite hand, the authors of [11] proposed cross□domain recommendation to predict the users sentiment tendency in music by analyzing the opinions from Weibo in real time. The authors of [12] conferred a context□aware music recommendation system. They sculptural and classified users' sentiment supported metaphysics language and solved the matter of recommendation knowledge meagerness with context by victimisation the plus matrix factorization technique. in addition,[13] integrated analysis of on□line reviews with users' behavior preference mining. they;ll get better recommendation results through analysis of the users sentiment tendency toward more sensible opinions. Ancient cooperative filtering recommendation method depends on a matrix of "user□review" to calculate user similarity or item similarity. But, it covers restricted data and infrequently ends up in user interest bias due to several factors like context. In [14] it is introduced that the sentiment analysis technique supported topic model into cooperative filtering recommendation, that augmented accuracy by victimisation rich□text review information. In [15] the authors studied sentiment analysis within the film recommendation system. They found out that the user teams of comparable interests through sentiment tendency submitted actively by users so it projected a sentiment aware cooperative filtering technique. Paper [16] projected a technique supported decomposition matrix once scheming the films similarity on the idea of sentiment. They integrated sentiment analysis ends up in the method of collaborative filtering recommendation, assembling users' ratings knowledge of IMDB in 3 stages, that is, before a picture show, throughout a picture show, and when a picture show. Then, this technique utilised users' sentiment reviews revealed on Twitter for improving the formula of cooperative filtering recommendation and accurately statement the box workplace.

3. PROPOSED SYSTEM

In the proposed system the users will be able to easily find the status of the comment for their post by a user. The user can also save a lot of time. The user can easily find the status of their post with in no time and with less effort by analyzing comments, ratings and their helpfulness. Besides from determining the status the popular keywords in comments classified under star rating values can be also seen, which helps in determining the scenario even better.

3.1 System Features

- **Automated opinion mining:** The collection of user reviews and complaints through the posts and complaint box is done by the system and it is analyzed to determine the overall opinion of the subscribers about a particular product or service within a short span of time. So the admin can make change of plans more timely and effectively.
- **Post monitoring :** The administrator can view the status of each post even before a preset time limit finishes.
- **Comment History :** A log of all comments made by individual users can be made to display by admin privileges. The user can be blocked under suspicious activities.
- **Automatic Complaint resolutions :** In case of common type of complaints being reported by any user, the system recommends solutions from its previous experiences.

3.2 Feasibility Study

- The system may not recognize verbal styles like figure of speech, Sarcasm , Proverbs ,etc initially. So it must be trained so much as to cope up with such cases. And it should also be trained for trending keywords and references regularly.
- Operational Feasibility: The system runs automatically without human help in normal scenario.
- Schedule Feasibility: The project can be implemented within a couple of months. But more time is required for the initial set up of the back end development and the stability depends on training done.

4. IMPLEMENTATION DETAILS

4.1 Model Details

Model type: Classifier

Feature extraction methods used : ngrams (1,2)

Model used : Logistic Regression

Training data source: Network review websites- mouthshut.com and trustpilot.com

4.2 Data Collection

The first and foremost step is to collect data to train the model. The sources of these data is confined to Public websites on mobile network reviews and a manually made dataset focused on advanced level of training. To ensure only proper English is used, the web scrapping is done manually and ensured the encoding is utf-8 for all comment texts.

4.3 Data Frame

Pandas being a popular library provides provisions to read csv file from source location, is used to acquire and create a data frame consisting of the data including an additionally calculated helpfulness percentage and upvote percentage. The data frame is displayed to monitor during the pre modeling phase.

- **Heat Map**

The sklearn library function heatmap is used to display the type of user comments classified under the category: positive, neutral and negative.s The high density of colors in heatmap table gives the intensity of polls and the skewing of comments by all users collectively.The helpfulness % is plotted against the Score %.The insufficiency of data specifically in case of upvotes and downvotes (Helpfulness Denominator and Helpfulness Numerator) Where, Helpfulness Denominator = Helpfulness Denominator + (Helpfulness Numerator). The heat map is plotted as a figure of sufficient dimensions to display.

- **Heat Map Of Reviews**

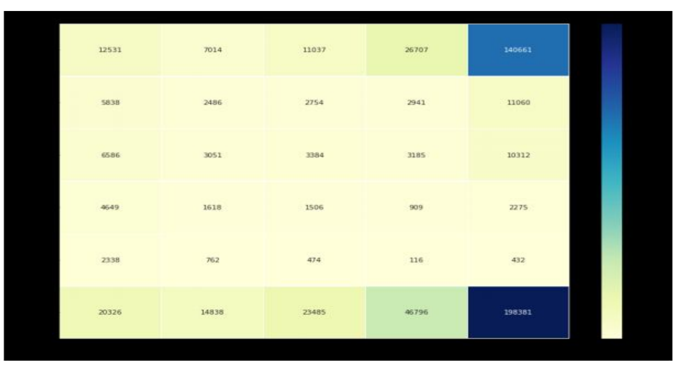


Figure 1: Heat map of reviews

- **Neutral Comment Removal**

The comments with score values exactly 3 are neutral comments as testified by the user who wrote the particular comment. Such comments are of not concerns for the system. So the comments of neutral types are removed logically by comparing their score values are 3 or not.

- **Stop Word Removal**

Removing stop words is an necessary step in NLP text processing. It usually require straining out words that adds little or no semantic value or meaning to a sentence, for example, to which, for, is, etc. Here we use Count Vectorizer function from sklearn for stop word removal. As the proposed system is confined to Sentimental analysis in English language, We provide 'english ' as argument to the stop-word parameter of function CountVectorizer aliased by a variable 'C' for easy use in regards to optimization.

5. EXPERIMENTAL RESULTS

Considering the difficulty in distinguishing sentiments from data acquired from user comments, Choosing from the best and popular models available like SVM and logistic regression, Along with feature extraction methods. To verify this scientifically we conducted different experiments on the given dataset. Considering the limitations of a dataset with fewer data records and additional database with enormous number of data records were also used to study the process, in cases where the data insufficiency was a notable problem. Besides the additional dataset data resampling was also used to ensure all features of the data being exploited once for all.

5.1 Experiment one (Logistic regression model on word count)

The test,train data and logistic regression model is given with word count obtained from CountVectorizer, both imported from sklearn library ,with stop_words from the language English specified as an argument to the function. The output is obtained. Accuracy is around 83.7% - not bad. However we notice that some of those significant coefficients are not meaningful, e.g. 4g.

- **Experiment one (base line accuracy)**

Instead of logistic regression model the DummyClassifier model imported from sklearn is used along with same data and word count is tested for base line accuracy (predicting with positive class). Accuracy is now 50.6%.

5.2 Experiment two (Logistic regression model on TFIDF)

As like before the test is conducted but this time using TFIDF vectorizer imported from sklearn used for tokenizing ,learning vocabulary and inverse frequency weightings, on logistic regression model instead of word count. Accurancy is 70.46%. However we notice that the significant words make much more sense now.

5.3. Experiment three (Logistic regression model on TFIDF + ngram)

The previous experiment is repeated adding a new ngram parameter.ngram is text mining technique to get co occuring sequence of words, imported from the NLTK for data mining. Here the ngram is given a range of (1,3).So the ngram gives 1,2&3gram words. Adding ngram parameter, we are able to understand phrase like "best network","bad network",etc. And accuracy is 71%.

5.4 Experiment four (Logistic regression model on word count)

The data from the dataset is randomly resampled and the new test,train data and logistic regression model is given with word count obtained from CountVectorizer, both imported from sklearn library ,with stop_words from the language English specified as an argument to the function. And the output is obtained.The words look no sense at all(like “3GB”), and the coefficients are very small. And accuracy is 60%. Which is not more than that of previous test.

5.5 Experiment five (Logistic regression model on TFIDF + ngram)

The previous experiment is repeated adding a new ngram parameter. But unlike previous experiments here the ngram is given a range of (1,2).So the ngram gives only 1gram and 2 gram words limiting the features. Similar to count metric, the accuracy isn't very high and words are not meaningful.

5.6. Experiment six (Study on non-context features)

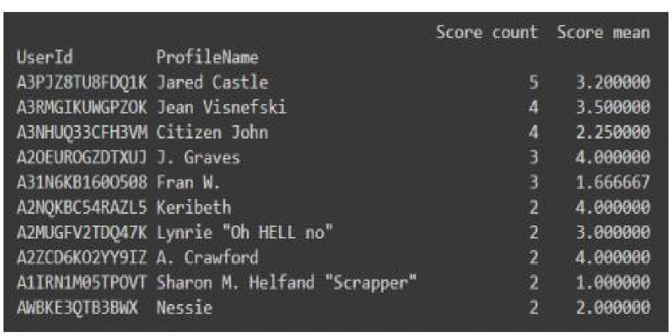
Now extracting some possible features like mean of word count,number of ‘?’ sign,number of ‘!’ sign,etc we see:Mean value for number of question marks and exclamation marks occurances as we see. But this is common and usual with small datasets like ours.And moreover not so important.

5.7 Experiment Seven (Training the model to predict)

Accuracy is lower than context features we tried above meaning the feature is not good enough to predict the target.

5.8 In-depth study on user behavior

This analysis will be carried out to focus on one specific user, on what he / she likes in terms of fine food, based on the reviews he / she had given in the past. So that it can be expanded to all users later on. First looking at how many reviews each user gave in the past:



UserId	ProfileName	Score count	Score mean
A3PJZ8TU8FDQ1K	Jared Castle	5	3.200000
A3RMGIKUWGPZOK	Jean Visnefski	4	3.500000
A3NHUQ33CFH3VM	Citizen John	4	2.250000
A2OEUROGZDTXUJ	J. Graves	3	4.000000
A31N6KB160O5O8	Fran W.	3	1.666667
A2NQKBC54RAZL5	Keribeth	2	4.000000
A2MUGFV2TDQ47K	Lynrie "Oh HELL no"	2	3.000000
A2ZCD6KO2YY9IZ	A. Crawford	2	4.000000
A1IRN1M05TPOVT	Sharon M. Helfand "Scrapper"	2	1.000000
AWBKE3QTB3BWX	Nessie	2	2.000000

Figure 2: User List

The user with most frequent reviews are "Jared Castle" with 5 reviews and average score 3.2. So looking at his review distribution: To have a graphical analysis on the data the user id of Jared Castle, which is “A3PJZ8TU8FDQ1K” as observed is used to plot a bar graph with his score values and their occurances mapped from the dataframe.(userid == score).The plotting is done using pyplot from matplot library.

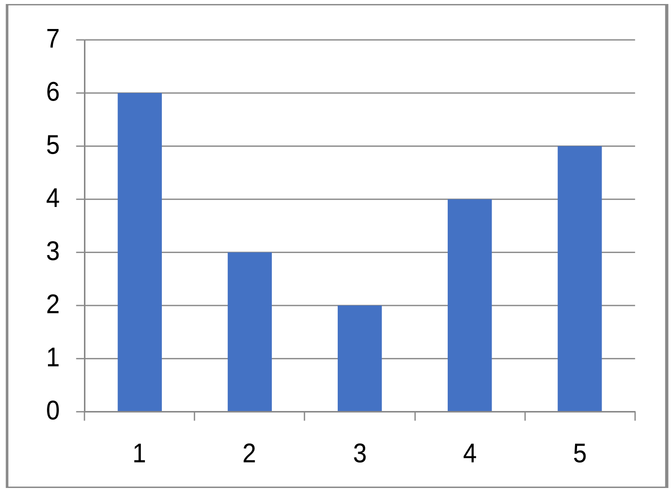


Figure 3: Score distribution of user Jared Castle review, X axis shows user scores and in Y axis is the frequency

It looks like user " Jared Castle " is a good choice. But still for the procedure ,testing him being of diverse opinions: Now we filter the data for only Score mean<3.5 and Score Mean>2.5. Higher score count and average mean.So target confirmed. To make deeper analysis on the target user’s review we follow the basic algorithm :

Table 1: Algorithm for extracting combined bi-grams-trigrams

Step 1: Start Step 2: input userid,score,dataframe Step 3: if userid ≠ all : Step 4: df= dataframe values where userid == userid,score=given score Step 5: else : Step 6: df = dataframe values where score=given score Step 7: endif Step 8: count = length of the dataframe Step 9: total_text = text from dataframe after being tokenized and lemmatized Step 10: Stop

Now using ngrams 2,3 grams (combined bigrams-trigrams) of total_text is acquired and for each score value from 1 to 5 the data frame values in total_text received after executing the above algorithm with Jared Castle’s userid and score = 0.25, is displayed (sorted by Count value in descending order). From the result we can make inferences like Mr.Castle has found a Service provider as india’s best network operator.etc,If that sound interesting we can read that in detail. Now looking at full picture instead of just one user: Same algorithm is executed but this time with no userid and score =0.03 as input. And output is obtained. Not much useful discoveries except mentioning of network names and senti words, since people are very different in texting style. So focusing on popular single adjective word people used for different score. Initially modifying the algorithm a bit for easier implementation.

Table 2: Algorithm for extracting popular single adjective words

Step 1: Start
Step 2: input userid,score,dataframe
Step 3: if userid ≠ all :
Step 4: df= dataframe values where userid == userid,score=given score
Step 5: else :
Step 6: df = dataframe values where score=given score
Step 7: endif
Step 8: count = length of the dataframe
Step 9: stop = stop words from English from nltk corpus
Step 10: total_text = text from dataframe after being tokenized and lemmatized
Step 11: remove words common in total_text and stop from total_text
Step 12: Stop

Now using ngrams 2,3 grams (combined bigrams-trigrams) of total_text is acquired and for each score value from 1 to 5 the data frame values in total_text received after executing the above algorithm with Jared Castle's userid and score = 0.05, is displayed (sorted by Count value in descending order) : then trying this algorithm for all users (input without any specific userid).

6. OBSERVATION AND INFERENCE

Table 3: Observations

Experiment	Accuracy	Remarks
SVM model and logistic regression	40	Low accuracy
Logistic regression on TFIDF ngram on resampled data	40	Low accuracy Words are not meaningful
Logistic regression on word count for resampled data	60	The word look no sense at all(like "3GB") The coefficients are very small
Logistic regression model on TFIDF + ngram	71	Able to understand phrase like "best network"
Logistic regression model on TFIDF	70	Significant words make much more sense now, Higher coefficient magnitude
Base line accuracy	50	Dummy classifier
Logistic regression model on word count	83	Some of those significant coefficients are not meaningful, eg.4g.

From the seven tests conducted above it is found Logistic regression model on TFIDF + ngram method gives meaningful words as output along with comparatively fair accuracy (71%). The human accuracy of sentimental analysis is found between 80-85% [17][18].Dispite insuffficiet data in dataset the model gives an accuracy nearer to the expected value.The same model is tested with a rich data set of Amazon food reviews containing 568454 record. Now the accuracy has increased to 94%.Which is beyond desired value.So, despite the fact that using the more training data brings with it the more accuracy results, it is obvious that it is expensive, time consuming and sometimes impossible to use a considerable amount of training data.So the current method is selected. Similarly the popular single adjective word method is chosen for overall pattern analysis by monitoring single adjective positive and negative words popularly used by all users classified by the score values.

7. CONCLUSION

The project 'Sentimental Analysis and opinion Mining for Mobile networks' provides effortless and quick opinion on the comments made on the posts uploaded by the users in the application. This application also helps to saves a lot of time and effort for users in searching the status of the post and give real time feedback from the users about plans, products and services. The System also helps in understanding the tastes of each and every subscribers with the help of user profile which gives an overview about his/her personality and attributes for different aspects.

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