Twitter Sentiment Analysis

Jimil Desai Machine Learning (CSE523) Machine Learning (CSE523) Ahmedabad University Ahmedabad, India

Khush Kalavadia Ahmedabad University Ahmedabad, India

Tejas Chauhan Machine Learning (CSE523) Machine Learning (CSE523) Ahmedabad University Ahmedabad, India

Hardi Kadia Ahmedabad University Ahmedabad, India

Abstract—With the advancement of social media platforms and its growth there is a huge volume of data present in these platform. Internet has brought the world so close together and provided people a means to express themselves. Social Networking sites like Twitter, Facebook, Instagram are gaining popularity among people as they allow users to express their opinions on variety of topics, have discussions and post messages. This gives rise to opportunities to detect and predict sentiments of people on various topics. There has been a lot of work in the field of sentiment analysis of twitter data. This project mainly focuses on sentiment analysis of twitter data, which is helpful to analyze the information in the tweets where the opinions are highly unstructured and heterogeneous. The aim of this project is to come up various machine learning models to accurately detect sentiment of a tweet.

Index Terms—Sentiment Analysis, Twitter, Machine Learning, Logistic Regression, Naive Bayes, TFIDF Vectorizer

I. INTRODUCTION

The invention of the Internet has revolutionised the world. It has changed the way people think, express their views and opinions. Users find it more convenient and satisfying to express their views via blogs, online forums, social media etc. Internet has given people a new voice. Millions of people use social networking apps like Twitter, Facebook, Instagram etc. on a daily basis to express their opinions. Millions of tweets are posted everyday, where users express their views on variety of topics. Social Media generates a huge volume of sentiment rich data in the form of tweets, blogs, posts etc.

This gives us the opportunity of performing various operations on these data to understand sentiments of the user. Detecting sentiments can help businesses to improve their marketing tactics and advertisements. On the other hand it can also help detect depressions and human emotions. Applications are many.

In this paper, we take a look at twitter data and build models for classifying tweets into positive or negative sentiments. Understanding textual data is a significant task and for that we leverage various NLP (Natural Language Processing) Libraries to learn the vocabulary. After various pre-processing functions we have applied the Multinomial Naive Bayes Classifier and Logistic Regression models to predict the sentiment of a tweet. The rest of the paper discusses the same.

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II. LITERATURE SURVEY

A lot of research and time has gone into Sentiment Analysis and it is handled as a NLP (Natural Language Processing) task at many levels of granularity. Sentiment Analysis is considered a 3 layered approach. Starting from document level classification (Turney, 2002;), it has been handled at sentence level(Hu and Liu, 2004) and more recently at an abstract/phrase level(Wilson et al.2005). As far as the sentiment classification techniques are concerned there have been research going around mainly 3 topics which are Machine learning approach, lexicon based approach and Combination/Hybrid Approach.

Some of the recent results on sentiment analysis of Twitter data are by Go et al. (2009), (Bermingham and Smeaton, 2010). Pak and Paroubek (2010) used distant learning to acquire sentiment data. They built models using Naive Bayes Classifier and Support Vector Machines, reporting that Support Vector Machines outperforms other classifiers.

III. IMPLEMENTATION

A. Dataset Description

Twitter is a social networking microblogging platform that allows users to post short messages called tweets. To apply sentiment analysis on these tweets, we are using **Sentiment140** dataset with 1.6 million tweets, which is obtained from kaggle. The dataset contains 1,600,000 tweets extracted using the twitter api. Each tweet has been annotated (0 = negative)and 4 = positive) for the purpose to detect sentiment.

B. Data Pre-processing

Since the dataset contains text data (tweets), text preprocessing is an important step for NLP tasks. It transforms the given text into a more digestible form for the machine learning algorithms. One of the first tasks of pre-processing that was done was to drop irrelevant columns. The only required columns for the purpose of analysis were "Tweets" column and "Sentiment" column. After removing the unimportant columns, the tweet was pre-processed as follows: a) Lower casing: each tweet was converted to maintain uniformity b) Tweets starting with "http", "https" or "www" are replaced by empty string as they are not important for the sake of analysis. c) "@" and hashtag signs are replaced by empty strings. d) Non-alphanumeric characters are again replaced with a space e) Stop Words removal: Stop words are the english words which do not add much meaning to a sentence. They can be

ignored without sacrificing the meaning of the sentence. f) Lemmatizing: It is important to convert a word to its base form. Lemmatization is the operation that converts a word to its base form. The dataset was divided into training and testing sets with a ratio of 0.95 to 0.05 i.e 0.95 of the data was used for training the model and it was tested on the rest 0.05 of the data.

C. TF-IDF Vectoriser

Term Frequency Inverse Document Frequency (TF-IDF) indicates what the importance of a word is in order to understand the document. This is a very common algorithm to transfrom text into meaningful representation of numbers which is used to fit machine learning algorithm for prediction. This step vectorises the pre-processed text by calculating the frequency of the word in the document and the number of docs the word appear in. TF-IDF Vectorizer converts a collection of raw documents i.e our tweets to a matrix of TF-IDF features, where the features are the words in the tweets. TF-IDF Vectorizer is trained on our training dataset to learn the vocabulary. Then the test and training dataset are transformed into a matrix of TF-IDF Features by using the TF-IDF Vectorizer we trained. Each word is given a weight and prediction is performed on the basis of these weights.

D. Bayes Naive Classification

Sentiment analysis is basically a text classification problem. So it is natural to use classification algorithms to solve the problem. One of the first models that we applied was the bayes naive classification. Naive bayesian is a simple algorithm which uses probability of the events for its purpose. It is based on Bayesian Theorem which assumes that there is no interdependence amongst the variables. The classification is done as per the following formula:

$$P(label|word1, word2, ...) = \frac{P(word1, word2, ...) * P(label)}{P(word1, word2...)} \tag{1} \label{eq:proposed}$$

Here, labels represent the class for which we are calculating the probability, (in our case it is either of positive or negative) and word represent the tf-idf transformed feature vector. In order to calculate the final label we do require a prior, P(label) which calculated from the training data. To be specific we used Multinomial Naive Bayes algorithm to classify the tweets because data generated by tf-idf is discrete. Following steps are performed to predict the correct class:

- Create a frequency table based on the words.
- Calculate the likelihood for each of the classes based on the frequency table
- Calculate the posterior probability of each class
- The highest posterior probability is the outcome of the prediction experiment.

The hyperparameter α , which is the smoothing parameter is calculated via a Grid Search Algorithm, which essentially tests out a bunch of different values for the hyperparameter and selects the value with which the model performs the best i.e

the accuracy is the highest. In our case we got the value for α as 2.

E. Logistic Regression

Logistic Regression is considered as one of the most popular algorithm for classification. In this model, the probability of a tweet being positive or negative is found.

The probability is an outcome of the process which tries to find a plane $(\pi = W^T * X + b)$ that best separates the positive class and negative class. Positive class is the one which is in direction of the plane while negative class is in the opposite direction. A classifier is defined for the best separation of the classes. The classifier which represents the positive class is $W^T * Xi > 0$ and similarly $W^T * Xi < 0$ represents the negative class. Here, Xi represents the input observation which is the weight of the tweet that is a result of TF-IDF Vectorisation. W represents how important that input feature is to the classification decision. Using the same, we are able to achieve the following optimisation function where Y_i is the class label. The positive class has $Y_i = 1$ while negative class has $Y_i = -1$.

$$W^* = argmax(\sum_{i=1}^{n} Y_i W^T X_i)$$
 (2)

Our optimisation function is not robust to handle the outliers. So, we are using the sigmoid function to squish the values of the outliers. We are able to simplify and regularise the above optimisation function to get the following one after using logarithm and converting the function in form of a minimisation function. Here, the regularisation term essentially penalises our model for choosing very large values of W, hence avoiding overfitting.

$$W^* = argmin(\Sigma_{i=1}^n log(1 + exp(-Y_i W^T X_i))) + \lambda W^T W$$
(3)

Now, we have received the optimum set of parameters W. We can plug in the value of W and X_i in the following equation to get the probability of tweet being positive. If the probability is greater than 0.5 than it is considered a positive tweet while the one less having value less than 0.5 is considered a negative tweet.

$$h(X_i, W) = \frac{1}{1 + exp(-W^T X_i)}$$
 (4)

IV. RESULTS

A. Bayes Naive Classifier

Multinomial Bayes Naive Classifier was applied on the training data and was tested on the testing data. The multinomial NB model performs decently well giving us the overall accuracy of 79%. Training accuracy was 82.6% and testing accuracy was 78.9%. Both the accuracy are close to each other, which is a good sign indicating that the model is not overfit.

	precision	recall	f1-score	support
0 1	0.78 0.80	0.80 0.78	0.79 0.79	39989 40011
accuracy macro avg	0.79	0.79	0.79 0.79	80000 80000
weighted avg	0.79	0.79	0.79	80000

Fig. 1. Naive Bayesian Classification Report

| Confusion Matrix | -30000 | | -30000 | | -20000 | | -20000 | | -20000 | | -20000 | | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -200000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -2000

Fig. 2. Naive Bayesian Confusion Matrix

Predicted values

B. Logistic Regression

Logistic Regression was applied on the training data and was tested on the testing data. The logistic regression model performs decently well giving us the overall accuracy of 80%. This model behaves similar to that of Naive Bayesian.

	precision	recall	f1-score	support
Θ	0.81	0.79	0.80	39989
1	0.79	0.82	0.81	40011
accuracy			0.80	80000
macro avg	0.80	0.80	0.80	80000
weighted avg	0.80	0.80	0.80	80000

Fig. 3. Logistic Regression Classification Report

Confusion Matrix

| True Negative | False Positive | 10.63% | -25000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -20000 | -200

Fig. 4. Logistic Regression Confusion Matrix

V. CONCLUSION

Here we have successfully implemented Naive Bayes Classifier and Logistic Regression model on the twitter dataset to

predict sentiments of unseen data. The accuracy were 80% and 80% respectively.

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