Comparative Analysis of Machine Learning Classifiers on US Airline Twitter Dataset

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Abstract - *One of the main problems in carrying out sentiment analysis using machine learning is the choice of an appropriate classifier that would yield best possible result. In order to solve this problem, the paper analyses the performance of five different classifiers taken one at a time and compares their performance. The dataset under consideration is US airline review data, which consists of Twitter data of reviews on various US airlines and is publicly available. The ensemble classifiers are found to give much better accuracy as against individual classifiers. when used for improving accuracy of the model as against using a particular classifier individually. Results indicate that usage of machine learning ensemble classifiers is justified when the datasets under consideration are smaller in size and much computation demanding classification mechanisms such convolutional neural networks (CNN), Recurrent Neural Networks (RNN), Auto Encoders etc. are unnecessary.*

***Key Words*: Sentiment analysis, random forest classifier, machine learning, ensemble classification**

1. INTRODUCTION

With the rise of social media, people are found to discuss various topics among each other online. Interactions occur between people by exchanging texts, photos, and videos. The topics are related to a wide range of fields. The discussions could be important to the interests of the governments, organizations, and businesses. On a positive note, such organizations can improve their performance and address the queries of the people in a much efficient manner, the reason as to why sentiment analysis on social media is used.

However, it has been seen in recent times that due to the large volumes of available social media data, several techniques like machine learning are used to handle the sentiment analysis task. A key problem, in this case, is choosing the appropriate machine learning based classifier that one should choose when developing a sentiment analysis model.

To help people, make this choice we carry out an experiment that involves various classifiers namely Naïve Bayes, SVM, Decision tree, K means and Random forest classifier, taken one at a time to reach to a conclusion as to which classifier has the best performance and which one is having the worst. We perform the experiments on US airline dataset which consists of Twitter data of reviews on various US airlines.

The rest of the paper is organised as follows: Literature review, brief description of various classifiers, dataset, experiment, results, and conclusion.

2. Literature review

Sentiment analysis is a general term and it could be applied to a wide range of subjects. That is why Aloufi et al. [7] discuss the need for having a domain-specific sentiment analysis approach. In this case, the authors develop a dataset by themselves. For that, they collect football-specific tweets and label them manually. They are thus able to produce a domain-specific sentiment lexicon. For classification purpose, SVM, random forest classifier and Naïve Bayes are used by them. Extending it further Bouazizi et al. [11] state the need to perform sentiment analysis on social media. Furthermore, authors use Multi-class sentiment analysis system wherein the exact sentiment of a Tweet or post is found rather than just sentiment polarity. This provides a more in-depth focus on the analysis of a particular piece of text. Xu et al. [30] uses Naïve Bayes classifier along with extended sentiment dictionary for sentiment analysis of comments on social networks.

Social media itself brings different challenges that are needed to be addressed. In social media, there is extensive usage of languages as users communicate with each other. Language is complicated in many different ways. One such complication is that it consists of metaphors. By definition, metaphor is a figure of speech in which a word or phrase is applied to an object or action to which it is not literally applicable. Zhang et al. [1] discuss certain schemes to tackle the problem of metaphor usage.

Using a self-annotated dataset of metaphors in Chinese language, authors use both machine learning and deep learning to check the efficacy by which the problem could be handled. Support vector machine is used in this process. Also, language consists of several dialects. As the same language is spoken over a large geographical area by people of different backgrounds, the language reflects some changes as we call it change of dialect. The problem of changing dialects in a particular language for all the discrepancies it raises and the need to address it is highlighted by Abo et al. [4]. Authors specifically considered Arabic language as the language of interest and also mentioned that some languages such as Arabic need special attention as it also follows right to left writing paradigm unlike most of the languages. Similar work is done by Cui et al. [13] where a system is developed in which the expression and tone of the text are considered.

Large scale use of social media platform by people of different locations, ethnicities, religions and beliefs has made it possible to have conflicts in social media. This has indeed given rise to hate speech online. Watanabe et al. [28] discuss the problem and the need to address this. Authors use unigrams as features to train and test a machine learning algorithm. They receive satisfactory accuracy in detecting hate speech.

Sometimes, it is likely that some data is encountered which might be multi-class and ordinal which needs to be dealt with accordingly. Such as the performance of an employee in a firm. It might consist of categories such as poor, fair, excellent, more than mere two exact options to choose from like "good" or "bad". Sentiment analysis in such kind of scenario is discussed by Saad et al. [24] where Support vector machine, Decision tree and random forest classifier are used to carry out analysis of data. Such data apart from the fact that they are multiclass, they are also following an order from low to high or small to large. When it comes to the type of data that is been dealt with, there is also a problem in dealing with the multi-source and multi-domain type of data. The problem is highlighted by Abdullah et al. [3] where they discuss underlying problems associated with such type of data.

Information obtained from sentiment analysis of social media data has a wide range of application. The results obtained could be used in recommendation systems, stock price prediction, decision making, improving organisational or political strategies etc. Chen et al. [12] discuss a concept of emotional vocabulary. Authors developed a suggestion system based on machine learning techniques. The system known as RESOLVE suggests users with synonymous emotional words based on the text. Similarly, stock prices are very volatile and it largely depends on the sentiment of the public. Since these days people discuss markets online on social media, a prediction could be done regarding stock prices in future by considering the sentiment of shareholders at a particular time. Ren et al. [21] developed such a system, where they predict stock prices of future using sentiments of social media users online.

Some focus has also been given to improving the efficiency of the sentiment analysis. To make sentiment analysis more efficient, Bibi et al. [10] uses dimensionality reduction in Twitter data by developing a system that uses Naïve Bayes and SVM classification. Similarly, Huang et al. [16] found that filtering sentiment topics from reviews help improve sales prediction. The literature survey of various classifier is presented in Table 1.

Table 1. Survey of various classifiers

Sr. No.	Paper	Author	Publisher	Methodology	Dataset	Remarks
1.	Chinese micro-blog sentiment analysis based on multiple sentiment dictionaries and semantic rule sets.	Wu et al. [29]	IEEE	Multiple sentiment dictionaries and semantic rule sets.	Chinese microblog data.	Multiple sentiment dictionaries are constructed
2.	Detection and classification of social media-based extremist affiliations using sentiment analysis techniques	Ahmad et al. [5]	Springer	Long Short term memory and Convolutional Neural Networks	Twitter API	Classification done with two classes, namely extremist and non-extremist Classes by using a LSTM + CNN model and some other ML and DL classifiers.

3.	Sentiment analysis and machine learning in finance: a comparison of methods and models on one million messages	Thomas Renault [22]	Springer	Naïve Bayes	StockTwits	Increasing complexity of algorithms might not increase the classification accuracy
4.	Solving the twitter sentiment analysis problem based on a machine learning-based approach	Kermani et al. [32]	Springer	Naïve Bayes and Support Vector Machine	Stanford testing dataset, STS-Gold dataset, Obama-McCain Debate dataset, and Strict Obama-McCain Debate dataset	Vector space model is used in order to represent the features of the tweets. Time complexity is not good.
5.	Predicting supervise machine learning performances for sentiment analysis using contextual-based approaches	Aziz et al. [2]	IEEE	Random forest, Multinomial Naïve Bayes	Amazon and IMDB review data	Changing words from one domain to another are the reason why there is low predictability when Machine learning is used. The mechanism called Contextual analysis (CA) can detect that.
6.	Emotion and sentiment analysis from Twitter text	Sailunaz et al. [25]	Elsevier	Naïve Bayes	Twitter API, ISEAR dataset	Personalised recommendation system is built
7.	Sentiment analysis based on improved pre-trained word embeddings	Rezaeinia et al. [23]	Elsevier	Parts of speech (POS) tagging, Bag of words (GloVe, Word2Vec)	Movie review (MR) dataset, Rotten Tomatoes dataset, Stanford Sentiment Treebank (SST), Customer Reviews dataset	Improved Word Vectors (IWV) is used, which increases the accuracy of already trained word embeddings during sentiment analysis.
8.	Lexicon-enhanced Long Short term memory (LSTM) with attention for general sentiment analysis.	Fu et al. [15]	IEEE	Long Short Term Memory (LSTM)	Chinese and English text	LSTM has strong ability in modelling short sequences
9.	Sentiment analysis of big data: methods, applications, and open challenges	Shayaa et al. [26]	IEEE	Random forest classifier, Support Vector machine	Twitter, Amazon, TripAdvisor API	Technical aspects of opinion mining and sentiment analysis (OMSA) are discussed
10.	Applying data mining and machine learning techniques for sentiment shifter identification	Rahimi et al. [20]	Springer	Weighted association rule mining (WARM) based on pattern recognition	Drug domain dataset (www.druglib.com)	A semantic-based model both for shifter identification and polarity classification is used

11.	Sentiment analysis: a review and comparative analysis over social media	Singh et al. [27]	Springer	Random Forest	Twitter sentiment corpus dataset	Addresses the problems of the excessive simplicity while classification of words.
12.	Social media analysis of user's responses to terrorism using sentiment analysis and text mining	Samah Mansour [18]	Elsevier	Term frequency – Inverse document frequency (TF-IDF)	Twitter API	Sentiment analysis of Twitter data to know the opinion on a topic based on the number of times a word has been used
13.	Using long short-term memory deep neural networks for aspect-based sentiment analysis of Arabic reviews	Al-Smadi et al. [8]	Springer	Long Short term memory (LSTM), Random field classifier (a descriptive classifier which means decision boundary is kept between different classes)	Arabic hotel reviews dataset	Aspect based sentiment analysis is carried out. To aspect based means to break text into parts and performing sentiment analysis of each part individually.
14.	Sentiment analysis in tourism: capitalizing on big data	Alaei et al. [6]	SAGE	Lexicon based approach	Sander's Twitter dataset	Review paper on analysis pf methods on sentiment analysis of social media users regarding tourism sector.

3. Classifiers

3.1 Naïve Bayes

A Naive Bayes classifier [31] is a probabilistic machine learning model that is associated to a family of simple probabilistic classifiers centered on a common assumption that all features are independent of each other. The core of the classifier is based on the Bayes theorem. When the predictors take up a continuous value and are not discrete, it is expected that these values are sampled from a Gaussian distribution. Naive Bayes algorithms are mostly used in sentiment analysis, spam filtering, and recommendation systems, etc.

3.2 Support vector machine

A Support Vector Machine [9] is a linear discriminative classifier properly defined by a separating hyperplane. For a given labelled training data (supervised learning), the algorithm yields an optimal hyperplane which categorizes new examples. In two dimensional space this hyperplane is a line dividing a plane in two parts where each class lay in either side.

3.3 Decision tree

Decision tree [19] learning is a method for approximating discrete-valued functions, in which a decision tree represents the learned function. Learned trees are represented as sets of if-then rules in order to improve human readability. Decision tree classifiers are used as a well-known classification technique in various pattern recognition issues, like image classification and character recognition. Decision tree classifiers work more successfully, specifically for complex classification problems, due to their high adaptability and computationally effective features. Besides, decision tree classifiers surpass expectations over numerous typical supervised classification methods.

3.4 K nearest neighbour

K Nearest Neighbor (KNN) is a very simple, easy to understand and one of the top machine learning algorithms. KNN used in the variety of applications such as finance, healthcare, political science, handwriting detection, image and video recognition. In Credit ratings, financial institutions will forecast the credit rating of customers. In loan disbursement, banking institutes will foretell whether the loan is safe or unsafe. In political science, classifying potential voters in two classes, will vote or won't vote. KNN algorithm is used for both classification [17] and regression problems. KNN algorithm is based on feature similarity approach.

3.5 Random forest

Random forest classifier [14] is an ensemble tree-based learning algorithm. It is a set of decision trees from randomly selected subset of training set. It aggregates the votes from different decision trees to decide the final class of the test object.

4. Dataset

There are a few benchmark datasets used in the field of sentiment analysis. Twitter US airline dataset is one of them, the dataset that we are using in our study. It consists of tweets by customers on 6 major US Airlines of February 2015. The tweets are classified into positive, negative and neutral tweets. For example, a tweet containing "rude service" or "delayed" will be classified as negative whereas "good experience" or "food was great" would be classified as a positive tweet. It is available for free in .csv format in Kaggle. It is one of the major benchmark datasets used for performance analysis of models on sentiment analysis. The dataset contains a total of 14,640 Tweets.

5. Experimental study

Scikit-learn is an open source and easy to use machine learning library for the Python programming language. It provides various classification, regression and clustering algorithms. After the dataset has been selected, graphs are plotted to gain an insight into the data. Before we could apply the classifiers, data is needed to be cleaned. Special characters and single characters are removed. Multiple spaces are converted into single spaces. All the characters are converted to lower case letters. The text after cleansing is converted to numeric form. Data is split into two parts. 80% assigned for training and 20% for testing. The pre-processing and classification model is presented in Figure 1.

In case of Naïve Bayes classifier, no parameters are set during the experiment since GaussianNB() accepts no parameter from the user. Support vector machine is a linear classifier. It has particularly one parameter which needs to be defined, it is the gamma value. The value of the gamma parameter in the support vector machine classifier is the inverse of the radius of influence of the classifier on the sample of data. The low value of gamma reflects higher influence or far reachability whereas higher gamma value reflects lower influence or lesser reachability. In the experiment, the value of gamma is set to auto, which means it is left to self-adjust. In decision tree classifier, two parameters are set, Max_depth and random_state. By default, max_depth of decision tree classifier is none, but in the experiment, it was set to 2. If max_depth happens to be none, the classifier is likely to expand the nodes until all the leaves are either pure or all leaves contain less than minimum sample split required. Another parameter random_state is kept 0, the same as the default value it holds. The problem of learning in a decision tree is known to be an NP-complete problem as far as optimality is concerned. Decision tree algorithm is based on a heuristic algorithm such as greedy algorithm. A decision is taken at every node. Therefore, a sub-optimal greedy algorithm is repeated several times using random selections of features and samples. Random_state parameter allows us to control these choices. So, it is to be noted that a random algorithm will be used in any case in decision tree classifier. Passing any value, whether int type, 0 or RandomState instance will not change anything. The only rationale for passing an int value is to make the outcome consistent across calls. For K nearest neighbour classifier, n_neighbors parameter defines the number of neighbours of each element. By, default it is 5. In the experiment, the n_neighbors value is set to 3. In the case of random forest classifier, the random_state parameter is defined as 0 which is the case by default as well. The reason is the same as that of decision tree classifier which is discussed above. Another parameter is n_estimators which define the number of trees present in the random forest. By default, the value is set as 100. In the experiment, it is changed to 200. In case of the random forest classification algorithm, any number of trees can be used for classification and the model would not overfit. It is to be learnt that, more number of trees in random forest classifier would demand more CPU power and the results would not be significantly different with varying number of trees. Thus, 200 is taken as a favourable number in the experiment.

For ensemble classification, voting classifier is used for combination of more than one classifier.

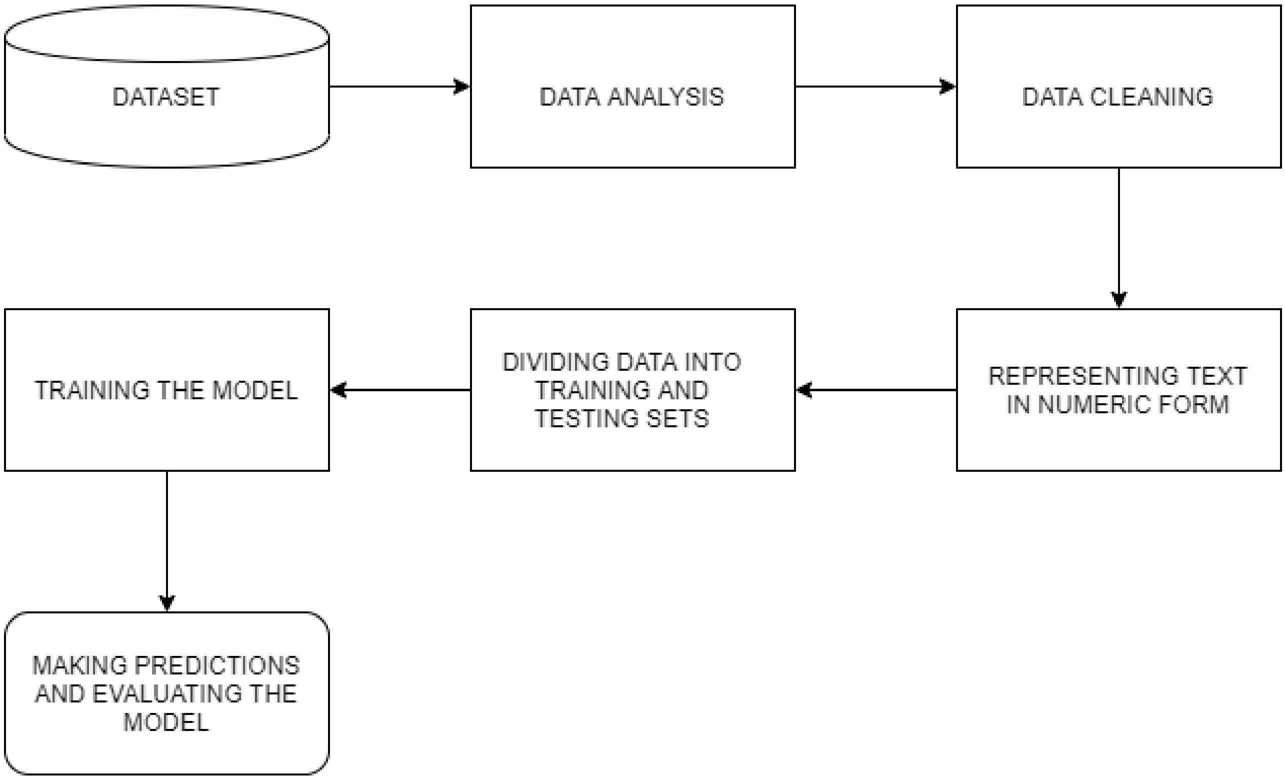

Figure 1. Pre-processing and classification model

6. Results

Results of various classifiers on Twitter dataset are demonstrated in Table 2. The highest accuracy is achieved by Random forest classifier (an ensemble classifier) (76%) and the lowest is achieved by Naïve Bayes classifier (41%). K nearest neighbour (68%) and Decision tree classifier (67%) are having nearly the same accuracy. Support vector machine classifier (64%) finished fourth among the group but have significantly better accuracy as against Naïve Bayes classifier.

The self-formed ensemble classifiers (Decision Tree + K nearest neighbour classifier, K nearest neighbour + Naïve Bayes classifier) also shows

Table 2. Performance analysis of various classifiers on Twitter dataset

Classifier used	accuracy
Naïve Bayes	41%
Support vector machine	64%
Decision tree classifier	67%
K nearest neighbour classifier	68%
Random forest classifier	76%
Decision Tree + K nearest neighbour classifier	67.69%
K nearest neighbour + Naïve Bayes classifier	70.56%

7. Conclusion

For the dataset that has been used in the experiment, Random forest classifier appears to be the one providing the highest accuracy. The random forest classifier (ensemble classifier) has given 9% more accuracy than decision tree, which shows that random forest holds to its main conceptual difference that it is a collection of more than one decision trees and prediction of each decision tree is used to achieve a predicted class. Other ensemble classifiers (Decision Tree + K nearest neighbour classifier) and (K nearest neighbour + Naïve Bayes classifier) also shows improvement in accuracy as against the cases where the classifiers were used individually. This shows that using an ensemble classifier gives promising results when used for improving accuracy of the model as against using a particular classifier individually. This is more beneficial when the datasets are smaller in size and much computation demanding classification mechanisms such convolutional neural networks (CNN), Recurrent Neural Networks (RNN), Auto Encoders etc. are unnecessary. In future, some other dataset might also be used to evaluate the difference in the performance of the classifiers or if the current order of performance holds.

8. Declaration of conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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