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AN ANALYTICAL STUDY FOR RECOGNISING SENTIMENTUSING MACHINE LEARNING MODELS

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Abstract
Sentiment analysis (SA) is a branch of opinion mining that focuses on obtaining people's thoughts and feelings about a specific subject from systematic, semi-structured, or unorganized text data. In this paper, the efficacy of four ML classifiers i.e. Decision Tree (DT), Random Forest (RF), Logistic Regression (LR) and Multinomial NB is analyzed on IMDB dataset. The main objective of the proposed work is to analyze which classifier shows best results on the given dataset. To achieve this objective, necessary movie review or comment data is taken from IMDB dataset that is available on Kaggle. However, this dataset is not balanced and contains a lot of unnecessary and redundant data that needs to be eliminated, therefore, pre-processing is must. During the pre-processing phase, tokenization, stemming, stop words removal and segregation like techniques are implemented to make the data balanced and normalized. After this, the given dataset is divided into subsets by using k-fold cross validation approach. The main motive for doing so is to train the ML classifiers effectively on various combinations of data so that its accuracy can be enhanced. Finally, the classification is performed by DT, RF, LR and Multinomial NB classifiers as per the training provided to them. The efficacy of the system is analyzed usingMATLAB on IMDB dataset for every fold. Simulation results revealed that LR classifiers is outperforming DT, RF and Multinomial NB in terms of accuracy, precision, recall and F1-Score as well, to prove its supremacy.
Keywords: Sentiment Analysis, ML classifiers, Movie review etc.

Introduction

One of the most emerging and in-demand study areas in text mining and natural language processing (NLP) is sentiment analysis (SA). NLP is basically a part of Artificial Intelligence (AI)and can defined as the system that has capabilityto comprehend the human language (spoken or written) that is often known as natural language. On the other hand, SA can be defined as the NLP technique used to assess the polarity of the data which can be either be positive, negative or neutral. Nonetheless, SA can also be defined as the technique that not only determines the polarity of data but also concentrates on sentiments like angry, pleased, sad etc., urgency and intents as well [1].Because of this, SA is often referred as opinion mining or extraction and review or attitude analysis, and is responsible for extracting, recognizing and categorizing opinions on various domains usually written in text. There are numerous online business sites available where people may discover about various product difficulties.The customers can share their opinions or sentiments regarding any product to general audience by using websites like Amazon, IMDB, yelp or e-commerce. Everyday millions of users write reviews about products, movies or organization which results in huge data that is stored in the form of e-documents. The information stored in these documents can be divided into two categories of facts and opinions. Whilst the facts focus on communication of objective data, opinion purely communicate sentiments [2].Sentiment analysis allows one to gauge customer sentiment toward various aspects of your company without having to read through a massive amount of customer reviews at once.

SA can broadly be classified into two types, one is Lexicon based SA and other is ML based SA. The lexicon technique relies on tokenizing text, calculating the amount of times every word appears, and actually looking every word's significance in a preexisting lexicon.As part of the machine learning methodology, the system becomes increasingly sophisticated by using a training set of data to train several classifiers [3, 4 & 5].Moreover, while determining opinions, SAusually goes under following sub tasks of-- sentiment classification (SC), Sentiment Lexicon Generation (SLG), Sentiment Quantification (SQ), Opinion Extraction (OE), Feature-Based Summary (FBS), and Opinion Spam (OS). The job of the SC is to classify any part of the given text into sentiments. These sentiments can be expressed on any three levels of document, sentence and feature levels. While as, the sentiment lexicon is generated by the SLG by marking words with sentiment polarity. Determining the frequency of various sentiments across a group of texts is the work of SQ. Furthermore, the purpose of OE is to categorize and retrieve every opinion from the components in customer reviews.FBS is concerned with creating a feature description that determine the characteristics, components and other facets of product [6]. Finally, OS identifies the false or bogus content in data like false and untruthful reviews or comments.

Among all the categories, watching movies are considered as most convenient way of entertainment. However, only a small number of films are appreciated and profitable. As mentioned earlier, reviews are brief texts which typically give a viewpoint on films. Therefore, the success of the film is greatly influenced by reviews [7-8].The movie buffs may choose which movies to see and which to skip using one of the various rating websites like IMDB, Rotten Tomatoes etc. The users rate movie on these websites by giving a score out of 10 stars and on the basis of these stars the success of failure rate of the movie is determined. Hence, Reviews play a significant part in bringing audiences to the cinemas in addition to word-of-mouth advertising.To put it another way, SA on movie reviews facilitates Opinion Summarization by capturing the reviewer's emotion. However, with the advancement in technology in the last few years, the researchers are still facing a number of issues in this domain that needs to be resolved. The two main drawbacks are the keywords having different meanings as per their content that leads to ambiguity, and incapability of categorizing reviews that doesn't depict clear emotional keywords. Therefore, it is important to keep these facts in mind while designing a new SA system.

Research Motivation

The impetus for this study originates from the fact that today there are billions of online users around the world today, and it has been seen that the amount of content produced by these people on the web is growing quickly. All kind of textual data, including photographs, video, and videos, can be included in this information. Nevertheless, the majority of consumers even now express their thoughts about brands, movies, and services using sentences. As a result, a substantial amount of information is produced in the form of textual reviews. It is crucial that we analyze and anticipate the reviews because failing to do so will make the data inoperable. In this paper, we are going to analyze the performance of some widely used classifiers specifically for understanding the sentiments of reviews for movies.

The remaining section of the paper is categorized as; Section 2, reviews recent publications for determining sentiments for movies, followed up by the problem statement. The section 3 of this paper describes the proposed work and results obtained are discussed in section 4. Finally, a conclusion of the analytical study is given at the end of paper.

Literature Survey

Over the past few years, a significant number of researchers are paying their attention towards sentiment classification by using various ML and DL algorithms. In this section of the paper, we are going to discuss and review some related papers that particularly use different techniques on IMDB dataset and also what outcomes were obtained. Qaisar et al. [9],proposed a DL based sentiment analysis model wherein they used LSTM classifier for analyzingand categorizing movie reviews. The model preprocesses data and then divided for enhancing the post classification performance. the efficacy of the suggested model was analyzed on IMDB dataset upon which an accuracy of 89.9% was attained.S. Sabba et al. [10],proposed an effective SA system that was based on NLP and Deep CNN models for resolving the various issues faced in user SA. The model was again tested on the IMDB dataset that contained a total of 50,000 reviews and achieved an accuracy of 99 and 89% in training and testing phase respectively. K. Amulya, et al. [11],reviewed the performance of various ML and DL classifiers for identifying sentiments on IMDB dataset. The authors stated that ML only work in single layer that decrease their output value whereas, DL algorithms work on multiple layers to give better results. The given paper aimed at helping the new researchers and scholars to select the best technique for SA. The contrast between machine learning and deep learning methodologies demonstrates that DL algorithms produce precise and effective outcomes.G Donia, et al. [12],analyzed the efficacy of three ML algorithms like ANN, SVM and NB for detecting opinions of users on renowned review datasets including movie, product and smart gadgets of last five years. Through extensive experimentation, it was revealed that ANN produces an accuracy of 90.3% when feature is extracted through Unigram technique. Haque, et al. [13],evaluated and compared the effectiveness of three DL classifiers i.e. CNN and LSTM and hybrid of CNN-LSTM for extracting sentiments from texts. The efficiency of the suggested model was analyzed on IMDB dataset to determine which framework generates more accurate results. Results simulated that CNN outperforms LSTM and CNN-LSTM models and other standard models with an F-Score of 91% on IMDB movie review database. Similarly, R. Bandana,[14], integrated ML and lexicon-based features along with supervised algorithms (NB and linear SVM) to develop a new sentiment analysis model. The outcomes obtained from the work stated that proposed heterogenous feature and hybrid SA system outperforms all other similar models in terms of various performance dependency factors. Furthermore, they also stated that for analyzing large datasets more accurate and effective SA models can be developed by using heterogenous features and DL classifiers. Again Kumar, H. M., [15], showcased the impact of hybrid features by integrating ML features like TF, TF-IDF along with lexicon features on accuracy of SA. The supremacy of the suggested approach was validated over SVM, NB, KNN and maximum entropy in terms of accuracy and complexity.Shaukat, Z., et al. [16],utilized NN that was trained on IMDB dataset in order to extract emotions or sentiments from reviews. The suggested model achieved an accuracy of 91% on the given dataset. A. Yenter et al. [17],proposed another DL based SA model wherein they used CNN along with the LSTM model for extracting opinions from movie reviews. The results obtained highest accuracy on IMDB dataset to prove its supremacy. T İlhan et al. [18],proposed a SA model in which vector space was developed in KNIME analytics platform, upon which classification was implemented by using DT, SVM and NB. The results were analyzed on IMDB and twitter datasets respectively. On IMDB dataset, the suggested model achieved accuracy of 94, 73.20 and 85.50%, whereas, it was only 82.76, 75.44 and 72.50% for DT, NB and SVM classifiers.

From the above literatures, it can be summarized that a number of ML and DL approaches have already been proposed by various researchers for extracting the opinions from movie reviews datasets. However, a number of limitations are faced by scholars while extracting sentiments from IMDB datasets which degraded its performance. Generally, it has been seen accuracy of the SA model decreases when users use keywords with ambiguity meaning. In such cases, the current SA approaches are unable to detect the polarity of the text which in turn results in decreased accuracy. Moreover, the current systems are unable to extract the meaning of slang words or short forms like “LOL”, “ROFL”, etc., in reviews that also is a major challenge in SA. In addition to this, we have seen that majority of researchers are using ML classifiers in their work for analyzing opinions from text, however, each classifier performs differently on different datasets. Moreover, selecting suitable classifier for extracting the polarity of text is still one of the major issues that needs to be resolved. In this regard, an analytical study must be undertaken wherein efficacy of various classifiers should be analyzed on specific dataset.

Present Work

In this paper, an analytical study is conducted specifically for analyzing the sentiments in movie comments or reviews. The main aim of the proposed work is to analyze and understand which classifier shows best accuracy results for a particular movie dataset. To achieve this objective, the proposed model undergoes through various steps of data collection, pre-processing (tokenization, stop word removals and segregation), data segregation, training & testing and finally classification. Initially, the data has been taken from IMDB dataset that comprises a total of 50000 movie reviews for NLP. The detailed description of the given dataset is given in methodology section of this paper. Nonetheless, the data present in this dataset is not normalized and balanced which leads to biased solutions and hence deteriorated accuracy. To overcome this, we have applied a number of techniques like tokenization, stop word removal, stemming and segregating in the pre-processing phase. After this, k-fold cross validation is applied to the given dataset for dividing it into k subsets that are also called as folds. The main reason for doing so is to train classifiers on different various datasets combinations so that accuracy of the system is enhanced. The value of k determines number of subsets that a dataset is divided into. It must be noted here that the classifier is trained on all these subsets but one i.e. (k-1) of the subsets. The one remaining data subset that is not sed in training the classifiers is used for testing its efficacy. Here, we have analyzed the performance of four ML classifiers i.e. Decision Tree (DT), Random Forest (RF), Logistic Regression (LR) and Multinomial NB on the IMDB dataset on 6-fold cross validation technique. The 6-fold cross validation means that classifiers will be trained on 5 folds and the its efficacy is tested on 1 dataset. The results for the given study is obtained in terms of various performance dependency factors like accuracy, precision, recall and Fscorefor 5 folds on IMDB dataset. The general working methodology of the proposed work is given in the next section of this paper.

Methodology

In order to analyze the efficacy of four ML classifiers on the IMDB dataset, the proposed model undergoes through various stages that are described thoroughly here. As mentioned earlier, the proposed work is particularly conducted for analyzing best ML algorithm on IMDB movie dataset.

Data Acquisition: The very first step that is opted in the proposed work is collecting necessary data about movie reviews or comments. Here, we have used IMDB dataset which is one of the popular movie datasets available online on Kaggle.com. The dataset comprises a total of 50K reviews about various movies that is divided into two categories of training and testing. The detailed information of the dataset is given below.

IMDB Dataset

IMDB is a popular movie review dataset that has been utilized by number of researchers in their work for trainingand testing their classifiers. The dataset comprises a total of 50,000 movie review entries that can be used for text analysis and NLP. Basically, the given dataset is binary sentiment classification repository wherein considerably more information is provided than other previous standard datasets. Moreover, the dataset is divided into two categories of training dataset and testing dataset with 25k movie reviews for each. This training data is used for training the classifier and finally the testing data validated its efficacy.

Pre-processing: Nonetheless, the data collected in the previous step is not normalized and balanced which decreases classification accuracy rate. Therefore, it is important to pre-process data before passing it to classifiers for training and testing purpose. During the pre-processing phase, following steps are implemented on the IDB dataset

- Tokenization: This is the first step towards making the dataset balanced and normalized. In this step, the movie reviews or comments present in the dataset are divided into various phrases also called as tokens, symbols and words.
- Stop Word Removal: In this step, pronouns like “I, We, they, she etc.” and other words like “and, the, for, should and so on” are eliminated from the movie reviews. By doing so, only important words that depict the polarity of review are retained which helps in enhancing the model’s efficiency.
- Segregation: it can be defined as the process wherein any special character that’s is present in movie reviews like <, @, &, %, / etc. are removed for making data more informative and effective.
- Stemming: During stemming process, the redundant words are minimized to their basic forms. For an example, the word “dancer” and “dancing” are reduced to their basic root word “dance”.

Data splitting: Once the data is processed, we have divided it into k subsets or folds. The value of k represents the total number of data subsets formed and is 6 in the proposed work. The classifiers used in the proposed model are trained on all subsets of data except one (k-1). It is basically a resampling technique that determines the efficacy of ML algorithms of limited datasets. The process starts by shuffling the given dataset randomly which is then divided into k groups. Each group represents the different combination of data upon which the classifiers are trained and tested for validating their efficacy.

Classification: In this phase, we have analyzed the performance of four ML classifiers, those are—DT, RF, LR and Multinomial NB on IMDB dataset for 6-fold cross validation.The main reason for doing so is to analyze which classifiers shows best results on which subset of data. The four classifiers are trained on various folds and accordingly their performance is analyzed under various performance parameters. The next section of the paper discusses results that are obtained for proposed methodology.

Analytical Results

The usefulness of the proposed study is performed in MATLAB software.The simulated outcomes were obtained in terms of various metrices like Accuracy, precision, recall and Fscore under various folds and overall results. The detailed description of the results is discussed in this section of the paper.

Performance Evaluation

In order to analyze the efficacy of ML classifiers, we firstly analyzed their overall performance in terms of accuracy, precision, recall and F1-score on IMDB dataset. The values obtained for each ML classifier are recorded in tabular form and is shown in table 1. After analyzing the given table, it can be concluded that the value of accuracy came out to be highest in LR with 90.18%, followed up by Multinomial NB with 86.43% and then RF and DT with 84.68% and 72% respectively. Similarly, the value of precision in DT, RF, LR and Multinomial NB was accounted at 71.42%. 84.19%, 89.36% and 88.60% respectively. Moreover, we have analyzed the performance of four classifiers (DT, RF, LR and Multinomial NB) in terms of their recall score and F1-measure as well. The recall outcomes were mounted to 71.80%, 83.64%, 91.22% and 82.90% in DT, RF, LR and Multinomial NB respectively, while as, it was 71.61%, 83.91%, 90.28% and 85.60% for Fscore in four DT, RF, LR and Multinomial NB respectively on IMDB dataset.

Table 1: Specific value of ML classifiers for different parameters

ML model	Accuracy	precision_score	recall_score	f1_score
DecisionTree	72%	71.42%	71.80%	71.61%
RandomForest	84.68%	84.19%	83.64%	83.91%
LogisticRegression	90.18%	89.36%	91.22%	90.28%
MultinomialNB	86.43%	88.60%	82.90%	85.60%

Furthermore, we have also evaluated the efficacy of DT, RF, LR and Multinomial NB on IMDB dataseton every fold in terms of accuracy. From the given results, it has been analyzed that LR classifiers is showing better results for accuracy with 0.89, 0.90, 0.89, 0.896 and 0.892 on fold 0, 1, 2 , 3 and 4 respectively. On the other hand, the value of accuracy was mounted at 0.864, 0.863, 0.862, 0.869 and 0.861 in multinomial NB for 0, 1, 2, 3 and 4 folds. While as, the value of accuracy in DT and RF for IMDB dataset on 0, 1, 2, 3 and 4 folds were 0.719, 0.711, 0.7.31, 0.719 & 0.7154 and 0.842, 0.84, 0.847, 0.841 and 0.844 respectively. The specific value for accuracy obtained in DT, RF, LR and Multinomial NB on IMDB dataset on every fold is given in table 2.

Table 2: Specific value for accuracy on every fold

ML model	fold-0	fold-1	fold-2	fold-3	fold-4
MultinomialNB	0.8643	0.8637	0.8625	0.8697	0.8612
decision Tree	0.719	0.711	0.7031	0.719	0.7154
Logistic Regression	0.8924	0.901	0.8995	0.8968	0.8927
RandomForest	0.8428	0.84	0.8479	0.8411	0.8444

Similarly, the efficacy of Multinomial NB, RF, DT and LR were also analyzed on IMDB dataset for every fold in terms of their Fscore value. The results attained showcased that again LR is showing better results than other ML classifiers in terms of Fscore for every fold. The recall values were 0.859, 0.857, 0.864, 0.858 % 0.859 in multinomial NB, 0.713, 0.716, 0.701, 0.715 and 0.716 in DT and 0.84, 0.837, 0.846, 0.840 and 0.843 in RF. On the other hand, the value of F1-score was mounted at 0.893, 0.902, 0.9, 0.897 and 0.893 in LR classifier on 0, 1,2 3 and 4 folds respectively. The specific values for F1-score attained in each ML classifier for every fold is given in table 3.

Table 3: Specific value for F1-Score on every fold

Classifier	fold-0	fold-1	fold-2	fold-3	fold-4
MultinomialNB	0.859	0.8578	0.8642	0.8581	0.8592
Decision Tree	0.7137	0.7168	0.7012	0.7157	0.7164
Logistic Regression	0.893	0.902	0.9	0.8978	0.8937
Random forest	0.84	0.8379	0.8465	0.8403	0.8436

Likewise, the efficacy of four ML classifiers was also analyzed and verified on every fold of IMDB dataset in terms of their recall values. The specific values obtained for the recall for each classifier is given in table 4. After analyzing the values of table, it can be seen that out of all classifiers LR shows best results for recall with a value of 0.906 for fold-0, 0.911 for fold-1, 0.907 for fold-2 & 3 and 0.9024 for fold-4. While as the recall values were 0.835, 0.831, 0.844, 0.827 and 0.829 in multinomial NB, 0.708, 0.713, 0.709, 0.718 and 0.7226 in DT and 0.84, 0.827, 0.839, 0.8366 and 0.8394 in RF for every fold.

Table 4: Specific value for recall on every fold

Classifier	fold-0	fold-1	fold-2	fold-3	fold-4
MultinomialNB	0.835	0.8316	0.8444	0.8274	0.829
decision Tree	0.7088	0.7132	0.7092	0.7188	0.7226
Logistic Regression	0.9062	0.9116	0.9072	0.9072	0.9024
RandomForest	0.841	0.8272	0.839	0.8366	0.8394

In addition to this, the efficiency of the four ML classifiers (Multinomial NB, DT, LR and RF) was analyzed and determined on every fold in terms of precision. The value of precision was recorded 0.884, 0.885, 0.885, 0.8912 and 0.8917 in Multinomial NB for every fold, 0.7094, 0.72, 0.698, 0.718 and 0.715 for DT on every fold; 0.881, 0.8926, 0.8933, 0.888 and 0.885 for LR on every fold and 0.844, 0.8489, 0.8542, 0.84419 and 0.8478 for RF on every fold. These values specify that LR is showing optimum results for precision as well to prove its supremacy over other classifiers. Table 5 shows the exact values of precision attained in each classifier for very fold.

Table 5: Specific value for Precision on every fold

ML Model	fold-0	fold-1	fold-2	fold-3	fold-4
MultinomialNB	0.8845	0.885811	0.885115	0.8912	0.8917
Decision Tree	0.7094	0.72	0.698	0.718	0.715
Logistic Regression	0.881	0.8926	0.89334	0.888	0.8852
Random forest	0.844	0.8489	0.8542	0.84419	0.8478

After analyzing the results attained in the form of tables, it can be concluded that out of four ML classifiers, LR is showing best results than other three classifiers (Multinomial NB, RF and DT) for all parameters.

Conclusion

In this paper, we have analyzed the performance of four ML classifiers which included Multinomial NB, RF, DT and LR on IMDB dataset by varying folds to see which classifier gives best results. The analysis of the proposed model is performed in MATLAB software under various metrices for every fold. The simulated outcomes revealed that LR classifiers was showing best results than other three ML classifiers. With an accuracy of 90.18% LR showcased its performance over DT, RF and Multinomial NB models whose accuracy rate was only 72%, 84.68% and 86.43% respectively. Moreover, when we analyzed the performance of four classifiers in terms of their precision as well, it came out to be 71.42% in DT, 84.19% in RF, 89.36% in LR and 88.60% in Multinomial NB models respectively. Similarly, the efficacy of four classifiers was also analyzed and validated in terms of their Recall score that acme out to be highest in LR with 91.22%, followed up by RF with 83.64%, followed up by multinomial NB with 88.90% and finally DT with 71.80% respectively. Furthermore, the F1-score values were 71.61%, 83.91%, 90.28% and 85.60% in DT, RF, LR and Multinomial NB classifiers respectively. In addition to this, we also analyzed the efficacy of given classifiers on every fold and results simulated revealed that LR is outperforming DT, RF and Multinomial NB on every fold in terms of accuracy, precision, recall and F1-score respectively to prove its efficiency.

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