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Sentiment Analysis of Customer Reviews

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ABSTRACT

Customer's reactions toward buying a product online are vital for e-commerce companies like Amazon, Flipkart, etc. Now analysing customer reviews to predict accurate sentiments have been proven to be challenging and time-consuming due to high volumes of collected data with untrained rules and random variables due to the nature of the language used by the customers. This paper involves sentiment analysis of the mood and opinion of the customer on a particular product and the need of having structured datasets, standardized solutions and increased focus on emotional expression and detection. The main computational steps in the process are determining the polarity or sentiment of the use of a product and then categorizing them into positive or negative. Naive Bayes, Decision Trees, Random Forests, and Support Vector Machines are the general base classification algorithms in machine learning which are being used to analyse the customer reviews.

Keywords: *Sentiment Analysis; Naive Bayes; Decision Tress; Random Forests; Support Vector Machines; Base Classification Algorithms; Machine Learning.*

INTRODUCTION

The development of computational models of aspects of human language processing is called as Natural Language Processing. The purpose of NLP is to analyze, extract, and present information for better decision-making in businesses. Researchers would use ML models with NLP techniques to process and classify datasets filled with various reviews in their study. Sentiment analysis, also referred to as opinion mining, is an approach to natural language processing (NLP) that identifies the emotional tone behind a body of text. Opinions about a product, service or idea are determined and organized using this sentiment analysis. Sentiment analysis is used as it has to deal with opinion, reality, and decisions that has to be taken. Using advanced text mining techniques, we classify the sentiment of the text in the form of positive, negative and neutral. Challenges in word ambiguity, multi-polarization, detection of negation and sarcasm are to be taken into account while building a sentiment classifier. The evaluation of the models includes audio transcript, voice and text chats from various internal sources along with publicly available social media data sources.

It is not uncommon for people to seek out the opinions of others when making decisions. According to survey, "what other people think" has more impact to a buyer's decision while purchasing products or services. So, for a successful business providing products or services customer satisfaction plays a major role. An analysis of customer opinions is important to understand what the customer wants in terms of sentiment, and also the betterment of a company to grow overtime. So, sentiment analysis is used in this study to look at the ideas of the customers written in their review of a particular product.

The main objective of this paper is to study the existing sentiment analysis methods of customer reviews. This paper has classification of techniques used in sentiment analysis. A number of document-level sentiment analysis approaches and sentence-level sentiment analysis approaches are also expressed.

LITERATURE SURVEY

[1]. Dwivedi, Y., Neogi, A. S., Garg, K. A., & Mishra, R. K. (2021). "Sentiment analysis and classification of Indian farmers' protest using twitter data". International Journal of Information Management Data Insights.

In this article, the public's sentiments concerning framer's protest are understood from the collected data from twitter, a microblogging website. The authors aim to analyze and understand the sentiment of the masses regarding farmers' protest with this research. They extracted 150 tweets related to the protest from each day using the hashtag keyword 'farmers protest'. Understanding the sentiments of the public on farmers' protest shared on Twitter website by incorporating NLP techniques is the main aim of this research. They also aim to analyze the polarity and factuality of the collected data. To conduct a thorough analysis, they used visualization libraries. To convert the textual information to numeric weightage in vector format they used Bag of Words and TF-IDF. Furthermore, they used four classifiers namely, Naïve Bayes, Decision tree, Random Forest and Support Vector Machine for the purpose of prediction. They also determined the study's obstacles and problems and discussed the contribution of this research in possible future. In this paper author used data pre-processing, sentiment classification, Lexicon based sentiment calculation and discovered that Bag of Words performed better than TF-IDF and that Random Forest had the highest classification accuracy.

[2]. P.K. Jain, R. Pamula and G. Srivastava; "A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews" ELSEVIER Computer Science Review 41 (2021)

This paper presents a study to determine the usefulness, scope, and applicability of this association of ML techniques for consumer sentiment analysis (CSA) for online reviews in the domain of hospitality and tourism. The literature surveys they made have focused on ML applications in various domains such as Twitter sentiment, scientific citations, business behavior, and reputation evaluation. CSA extracts consumer sentiment, opinions, and demands from online reviews in a particular domain and identifies their polarity. Researcher's primary objective in CSA is the exchange of consumer feelings through online platforms. A Systematic Literature Review (SLR) was conducted on several research papers, which were based on sentiment classification, predictive recommendation decisions, and fake reviews detection in hospitality and tourism. In this review paper, they have included 68 articles on ML applications in CSA, specifically in hospitality and tourism.

[3]. G.A. Ruz, P.A. Henríquez and A. Mascareño; "Sentiment analysis of Twitter data during critical events through Bayesian networks classifiers" ELSEVIER Future Generation Computer Systems 106 (2020).

In this paper they presented a review of the most commonly used algorithms for sentiment classification. From this review, they have noticed that most algorithms can be considered as black box models that make it difficult to understand how the words (features) interact during the classification process. They analyzed the performance of Bayesian network classifiers, which are probabilistic graphical models that effectively combine the quantitative aspect of the classification task with a qualitative dimension constructed by the probabilistic relationships among the attributes. In this paper, the author assessed the performance with two Twitter datasets from two different critical events, the 2010 Chile earthquake and the 2017 Catalan independence referendum by considering Bayesian network classifiers.

[4]. Chinnalagu A, Durairaj AK. "Context-based sentiment analysis on customer reviews using machine learning linear models". PeerJ Comput Sci. 2021 Dec 19.

This paper discusses about building a model for predicting accurate sentiments from large datasets. This model used the fastText library from Facebook's AI research (FAIR) Lab, Linear Support Vector Machine (LSVM) for classifying of text and word embedding. The fastText works well with large dataset within a minimal configuration of server infrastructure setting. This model is compared with author's custom multi-layer Sentiment Analysis(SA) Bi-directional Long Short-Term Memory (SA-BLSTM) model. So built model obtained a higher accuracy of 90.71% and 20% in performance compared to LSVM and SA-BLSTM models.

[5]. Kastrati, Z.; Dalipi, F.; Imran, A.S.; Pireva Nuci, K.; Wani, M.A. "Sentiment Analysis of Students' Feedback with NLP and Deep Learning: A Systematic Mapping Study". Appl. Sci. 2021, 11, 3986.

Thus, this article aims to map how this research field is structured by answering research questions through a step-wise framework to conduct systematic reviews. In particular, we formulated multiple research questions that cover general issues regarding investigated aspects in sentiment analysis, models and approaches, trends regarding evaluation metrics, bibliographic sources of publications in the field, and the solutions used, among others. A systematic map of 92 primary studies based on the PRISMA framework; An analysis of the investigated educational entities/aspects and bibliographical and research trends in the field; A classification of reviewed papers based on approaches, solutions, and data representation techniques with respect to sentiment analysis in the education domain; An overview of the challenges, opportunities, and recommendations of the field for future research exploration. These are the main contributions of this study. The author used a stepwise PRISMA framework to guide the search process and searched for studies conducted between 2015 and 2020 in the electronic research databases of the scientific literature. They identified challenges and various aspects that need to be considered in order to contribute to the maturity of research and development in the field. The need of having structured datasets, standardized solutions is highlighted and increased focus on emotional expression and detection.

METHODOLOGY

In data pre-processing step, lowercasing all words, removing new lines, punctuation, special characters and stripping recurring headers are needed for neural networks and embedding models. To improve data quality, introduced additional steps which includes stop words removal, text standardization, spelling correction, correcting the negation words, tokenization, stemming, and Exploratory Data Analysis (EDA).

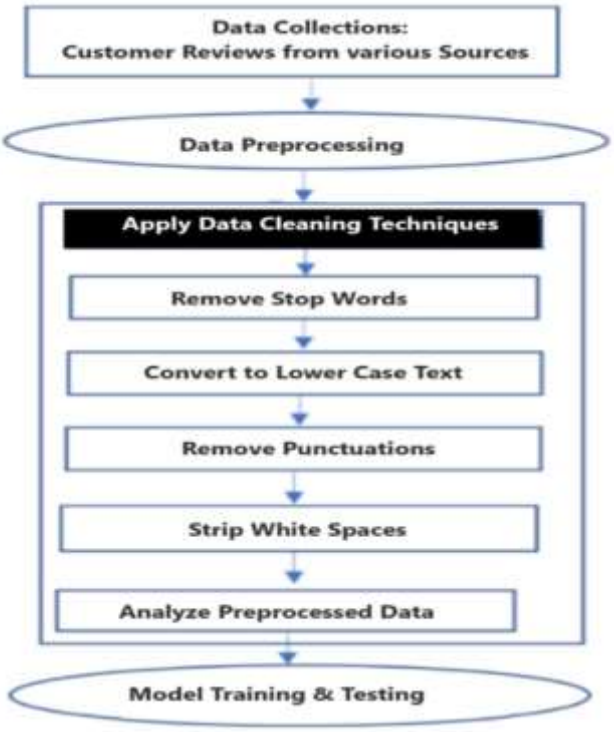

Fig6. Methodology and process flow diagram.

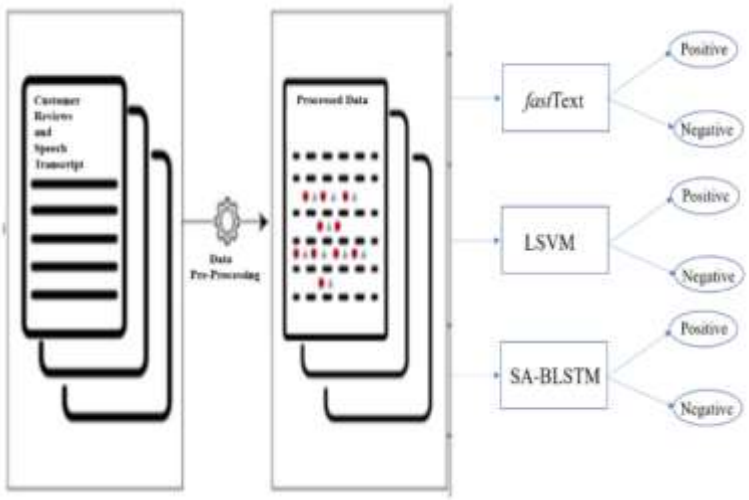

Fig7. Input and model output data flow

Support Vector Machine (SVM) model: SVM is used for text classification problems, this algorithm is viewed as a kernel machine, and the kernel functions can be changes based on the problem. It performs classification by finding the hyperplane that maximize the margin between the two classes. The support vector is the vectors that define the hyperplane.

fastText: Facebook AI research (FAIR) lab release an open-source free library called fastText for text representation and classification. It's a lightweight method and work on standard generic hardware with multicore CPU. In this model text classification pipe-line, raw text documents are processed using data pre-processing steps and processed text data tested using fastText model, the model output classified the output into two classes (Satisfied and Not-Satisfied).

SA-BLSTM model: SA-BLSTM is a sequence processing model. It consists of two LSTM units, one unit taking the input in a forward direction and other unit taking the input in a backward direction. It effectively processes the input and context available to the network. The mixed-language data processing flow, the language detection and translation layers convert the non-English to English and then it embeds the words. Input layer fed the embedded dataset to Bi-LSTM model and it processes vector output of the embedded layer.

RESULT

Among fastText, LVSM, SA-BLSTM models, fastText performed exceedingly well within small duration compared to the other two as fastText is more suitable with large datasets within a server with minimal configuration. The LSVM and fastText are showing similar model accuracy results. SAB-LSTM shows less accuracy. Below table shows the % conversations express the positive and negative score of customer sentiment.

Models	Positive sentiment	Negative sentiment
LSVM	48.31%	51.67%
fastText	48.49%	51.49%
SA-BLSTM	44.67%	55.31%

Table3. Model sentiment score.

Model	Parameters	Accuracy	Recall	Precision	F1
LSVM	Unigram	87.74%	0.88	0.88	0.88
	Bigram	89.96%	0.90	0.90	0.895
	Trigram Kernel=linear	90.11%	0.90	0.90	0.896
fastText	Unigram	88.23%	0.876	0.886	0.868
	Bigram	90.55%	0.896	0.907	0.901
	Trigram epoch = 10, r = 0.01, loss = softmax	90.71%	0.896	0.910	0.902
SA-BLSTM	epoch = 10, lr = 0.01, loss = softmax	77.00%	0.74	0.79	0.76

Table4. Models test and performance measures results with various parameters

It was also noticed that a domain specific dataset training improves the accuracy of the sentiment score when it tested with a particular domain. There is research that is highly essential for the future to explore a framework to build generic models that would be beneficial for industries such as healthcare, retail, and insurance.

However, improvements should be made for the quality of audio text files, as well as for the use of automation scripts to correct text errors in conversations.

CONCLUSION

The results from training the model revealed that fastText performed exceedingly well compared to the LSVM and SA-BLSTM models, and that fastText is much more suitable with large datasets within a server that has minimal configuration. The results of the experiment show fastText model training time duration is less, that it gives more accuracy, and that response time is faster than in the LSVM and SA-BLSTM models. The SA-BLSTM model the authors have built has the ability to integrate fastText for representation of words to provide increased performance, and has the ability to be pre-trained for such industries that could benefit from this. However, improvements should be made for the quality of audio text files, as well as for the use of automation scripts to correct text errors in conversations.