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Aspect-Based Sentiment Analysis on Product Reviews

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ABSTRACT

The focus of this paper was on product reviews. The goal of this is to study two (NLP) for evaluating product review sentiment analysis. Customers can learn about a product's quality by reading reviews. Several product reviews characteristics, such as quality, time of evaluation, material in terms of product lifespan and excellent client feedback from the past, will have an impact on product rankings. Manual interventions are required to analyse these reviews, which are not only time-consuming but also prone to errors. As a result, automatic models and procedures are required to effectively manage product reviews. (NLP) is the most practical method for training a neural network in this era of artificial intelligence. First, the Naive Bayes classifier was used to analyse the sentiment of consumers in this study. The (SVM) has categorised user sentiments into binary categories. The goal of the approach is to forecast some of the most important characteristics of product reviews, and then analyse Customer attitudes about these aspects. The suggested model is validated using a large-scale real-world dataset gathered specifically for this purpose. The dataset is made up of thousands of manually annotated product reviews. After passing the input via the network model, (TF) and (IDF) pre-processing methods were used to evaluate the feature. Aspect-based sentiment analysis is also predicted using some approaches. The outcomes precision, recall and F1 score are very promising.

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1. INTRODUCTION

With a powerful remark, the credibility of an internet product with a high number of positive reviews is established. The absence of reviews, books, or any other thing on the internet creates a sense of distrust among potential customers. Pre-processing is used in this study to minimise the Multi-Domain Sentiment Dataset's dimensionality of the features applied. Following that, any frequent words above a certain threshold value are considered characteristics.

This paper displays the results of the polarisation analysis of classic schemes based on user reviews on the Amazon e-commerce website. Compositional sentiment criteria were established by Zhang et al. To figure out how much textual sentiment there is. The system produced a clear use of machine learning. In this work, movie reviews were classified into binary classes using an (SVM) and a Naive Bayes classifier. The accuracy of Naive Bayes models has improved, while SVM models have been extended. To summarise, there has been no research that compares the (SVM) to the Naive Bayes classifier. A comparison of two (NLP) approaches for analysing the sentiment of Amazon product evaluations is presented in this study.

Amazon is the largest online retailer in the world, as well as a significant cloud computing service provider (Talha *et al*., 2020; Aljabre, 2012). The company began as a bookseller, but has now evolved to include a wide range of consumer items and digital media, including the Kindle e-reader, Kindle Fire tablet, and Fire TV., a streaming media adaptor is among the company's own electronic devices (Abubakar *et al*., 2021). People nowadays prefer to trade things on an e-commerce website rather than at a physical store because of the time savings and convenience (Bhatt *et al*., 2015; Hooda & Aggarwal, 2012; Taher, 2021). Before purchasing a product, it is usual to practise reading the product review. The consumer's opinion of the product has been swayed either positively or negatively by the reviews. Thousands of reviews were read, on the other hand, is an unnatural feat. In this era of ever-improving natural language processing algorithms, it takes time to wade through hundreds of comments to identify a product that uses a polarised review of a specific category to assess its popularity among consumers all around the world. This project aims to categorise customers' positive and negative product reviews, as well as construct a supervised learning model to polarise a wide range of reviews. According to an Amazon study from last year, 88% of customers from the internet trust reviews as much as a personal suggestion.

2. METHODS

Amazon, as seen by the numerous evaluations accessible, is one of the most well-known e-commerce companies. The dataset was unlabelled, thus it needed to be labelled before it could be used in a supervised learning model.[8] Only Amazon product feedback, specifically book feedback, was used for this study activity. To evaluate polarisation, about 1, 47,000 book evaluations were analysed. Data collecting was completed as the first step in the data labelling process. Manual labelling is impractical for a human to do because the dataset contains a high number of reviews. The term (TF) and (IDF), elimination of relevant nouns and frequent noun identifier methods were used to extract the dataset's features. TF-IDF: TF-IDF is a retrieval strategy that considers the frequency of a phrase (TF) as well as the (IDF). TF and IDF scores are assigned to each word or phrase. The TF and IDF product results of a term, on the other hand, refer to the TF-IDF weight of that term. As a result, the TF of a word represents its frequency, whereas the IDF is a metric for what percentage of the corpus is occupied by a term. The content will always be among the top search results if words have a high TF-IDF

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content weight, allowing anyone to avoid stop words while also effectively locating words with a higher search volume but a lower level of competition (Fang & Zhang, 2015).

3. RESULTS AND DISCUSSION

The purpose of this part is to assess the experiment's performance. Evaluating metrics is important in determining classification efficiency, and assessing accuracy is the easiest way to do so. The system is assessed using three widely used statistical measures: The F-measure, which is generated from a confusion matrix, is derived from recall, precision, and the F-measure. The confusion matrix is divided into four categories True Positive, True Negative, False Positive, and False Negative. True positive describes a situation in which the system accurately anticipates the positive class. False-positive highlights a situation in which the scheme predicts the positive class inaccurately. Tabulator form is used to show the (SVM) confusion matrix and the Naive Bayes Classifier A separate tabular format is used to display both the statistical measurement and the results. For this matter, SVM confusion matrix was used (see **Table 1**).

Table 1. Initial data.

Description	Number
Positive	3694
Neutral	158
Negative	90

As shown in **Table 1**, in the training dataset, we have 3694 (~95.1%) sentiments labelled as positive, 158 (~4%) sentiments labelled as Neutral and 90(~2.35%) sentiments as Negative. So, it is an imbalanced classification problem.

The next step is the use of Naive Bayes as shown in the following matrix:

[[0 0 24]
[0 0 39]
[0 0 937]]

Then, the results are shown in **Table 2**.

Table 2. Results from Naïve Bayes with the accuracy of 93.7%. Precision refers to the ratio of predicted positive cases to total positive instances indicated by the equation.

	Precision	recall	f1-score	support
0	0.00	0.00	0.00	24
1	0.00	0.00	0.00	39
2	0.94	1.00	0.97	937
Micro avg	**0.94**	**0.94**	**0.94**	**1000**
Macro avg	**0.31**	**0.33**	**0.32**	**1000**
Weighted avg	**0.88**	**0.94**	**0.91**	**1000**

TF/IDF Vectorizer and logistic regression for under-sampled data are estimated based on the following matrix:

[[10 6 8]
[15 7 17]
[314 195 428]]

The results from TF/IDF Vectorizer and logistic regression for under-sampled data are then classified, shown in **Table 3**.

Table 3. Results from TF/IDF Vectorizer.

	Precision	recall	f1-score	support
0	0.03	0.42	0.06	24
1	0.03	0.18	0.06	39
2	0.94	0.46	0.62	937
Micro avg	**0.45**	**0.45**	**0.45**	**1000**
Macro avg	**0.34**	**0.35**	**0.24**	**1000**
Weighted avg	**0.89**	**0.45**	**0.58**	**1000**
Accuracy	**44.50**			

Characteristics of logistic regression of under-sampled data are shown in **Figure 1**. This figure shows the correlation between the true positive rate and the false positive rate.

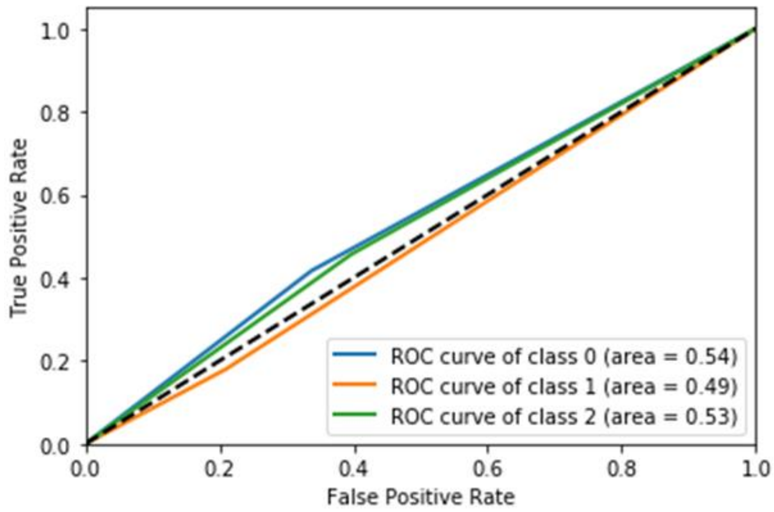

Figure 1. Characteristics of logistics of under-sampled data.

TF/IDF and Logistic regression for over-sampled data is calculated using the following matrix:

[[13 3 8]
[10 10 19]
[214 171 552]]

The results from TF/IDF Vectorizer and logistic regression for over-sampled data are then classified, shown in **Table 3**. Logistic Regression on over-sampled data is performing better than under-sampled data.

Table 3. Data from over-sampled data.

	Precision	recall	f1-score	support
0	0.05	0.54	0.10	24
1	0.05	0.26	0.09	39
2	0.95	0.59	0.73	937
Micro avg	**0.57**	**0.57**	**0.57**	**1000**
Macro avg	**0.35**	**0.46**	**0.31**	**1000**
Weighted avg	**0.90**	**0.57**	**0.69**	**1000**
Accuracy	**27.49**			

Characteristics of logistic regression of over-sampled data are shown in **Figure 2**. This figure shows the correlation between the true positive rate and the false positive rate.

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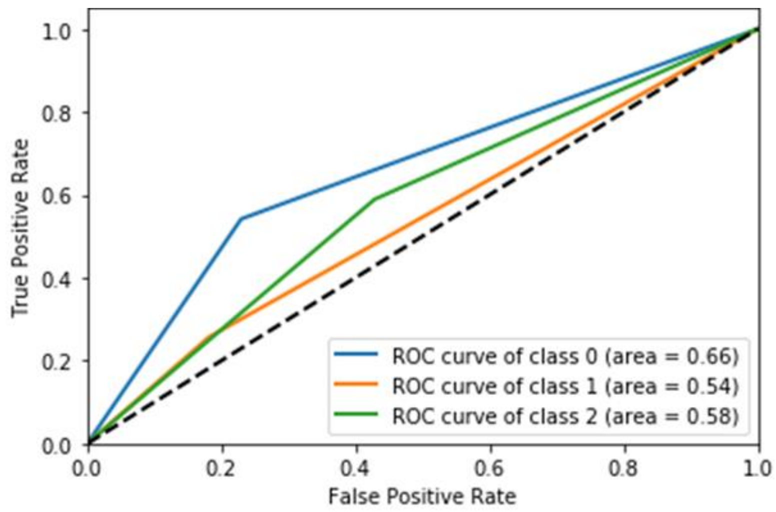

Figure 2. Characteristics of logistics of over-sampled data.

The neural network is calculated using the following matrix:

[[9 2 13]
[0 12 27]
[2 8 927]]

Then the results are shown in **Table 4**. **Table 4** shows the correlation of some data in the precision. It is found that the use of class weights does not improve the performance.

Table 4. Data from Neural network.

	Precision	recall	f1-score	support
0	0.82	0.38	0.51	24
1	0.55	0.31	0.39	39
2	0.96	0.99	0.99	937
Micro avg	**0.95**	**0.95**	**0.95**	**1000**
Macro avg	**0.77**	**0.56**	**0.63**	**1000**
Weighted avg	**0.94**	**0.95**	**0.94**	**1000**

4. CONCLUSION

To investigate the polarisation of Amazon product ratings, this study was able to compare SVM and Naive Bayes classifiers. Following the pre-processing step, almost 2250 features and over 6000 datasets were used to train the models. The SVM classifier in this system has a precision of 0.00%, a recall of 0.00%, f1 score of 0.00%. The model yields SVM and Naive Bayes with 93.7% accuracy, respectively, which is confirmed to be superior to traditional approaches. With a higher accuracy rate, the (SVM) can polarise Amazon product feedback, according to the findings of experiment. https://github.com/MukundAabha/Sentiment_ analysis_ AmazonreviewDataSet/blob/main/AI-Capstone-Ecommerce.ipynb.

5. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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