Sentiment Analysis on Product Reviews for an E-commerce Platform

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Abstract— **The quantity of accessible data online concerning e-marketing is growing every minute. A large portion of that information pertains to consumers' views and attitudes towards organizations' products or services, making it valuable for market intelligence gatherers in marketing, customer relationship management, and customer retention. Sentiment analysis evaluates customer feelings, advertising efforts, and product evaluations. It aids e-commerce businesses in gaining a deeper understanding of their customers' thoughts and feelings regarding a product or service. Data that can help inform decisions about upcoming products and services, advertising campaigns, or customer support problems. Systems that can gather consumer feedback for e-commerce platforms can be developed and put into use using artificial intelligence techniques like sentiment analysis, machine learning, and natural language processing. In light of this, the aim of this paper is to assess various supervised machine learning models according to their performance metrics and identify the model that performs best in terms of consumer sentiment analysis using a dataset from an online women's clothing store that focusses on customer reviews of various products.**

Keywords: Classification Techniques, Online Retail, NLP, Item Evaluations, Opinion Mining, Guided Learning,

Introduction

Feedback from other customers becomes relevant in making a decision as it would be when there are myriad options and resources involved. In this respect, most of the times, online buyers rely on other buyers' past experiences. Since such information is unstructured, collection of public opinion concerning various subjects has resulted in the development between sentiment analysis and opinion mining. A buyer can find a plethora of user reviews before deciding to buy a product or service; unfortunately, it is extremely time-consuming and effortful to read and evaluate all of them. Similarly, when an organization requires public or thus, whatever is the need of the business-whether the commercialization of Whether it's its products, exploring new deals, predicting sales trends, or managing its standing, it faces a significant amount of accumulated client feedback. Sentiment analysis technologies enable the analysis of large amounts of available data and the extraction of customer sentiment, which can ultimately assist the organisation and the customer in achieving their goals. One of the fields of computer science where people's thought processes, through text, are studied is sentiment analysis-based on how the opinion data can be extracted from the text after it has been processed. Emotion AI, or opinion mining known as sentiment analysis. The data can be neutral, negative, or positive. In order to help businesses track brand and product perceptions from customer feedback and understand customer needs, sentiment analysis is primarily applied to textual information. Certainly, what is even more challenging for e-commerce companies to understand is which customers would genuinely prefer to purchase from, meaning the products they would endorse.

Related Work

The tasks pertaining to sentiment analysis and opinion mining have recently attracted the attention of numerous studies. Just a few of the many techniques that are identifiable in sentiment analysis are highlighted in this section.

The author presented the FPCDA phrase FE and TF-IDF methods for assessing sentiment in product reviews. Using the OPSM bi-clustering algorithm, the local patterns of feature vectors were found while accounting for the differences in length of product reviews" Prefix Span was developed in order to identify frequent and pseudo-consecutive phrases with the best discrimination ability and word order information. To further enhance Sentiment Polarity's ability to distinguish between different sentiments, discriminative words and separation were employed. Text feature extraction came next. The development of experiences and an analogy were used.

In regard to the product review, this demonstrated that sentiment analysis had been improved. Unfortunately, its accuracy in textual classification and extraction is insufficient. The product has been evaluated by the authors using feature-specific sentiment analysis. In order to determine the relationship between the features and the opinions they are linked to, they employed the dependency parsing technique. They created a system to gather and extract opinion expressions that define various potential features from reviews.

The article provided a brief synopsis of contemporary topic modelling approaches, including LDA, CTM, and PAM. All of these techniques mainly focus on the theme extraction rather than sentiment.

To categories the sentiment analysis-based Twitter data streams, the authors employed hybridization techniques.

The decision tree algorithm, particle swarm optimization, and sentiment analysis are all categorized by the genetic algorithm. They use URL-based security tools and feature generation to gather 600 tweets for sentiment analysis classification. By combining logistics regression in principle component analysis with the dimensional reduction technique, they have created the feature extraction of data. The method for identifying Twitter spammers is based on linear statistics.

The authors in take on the procedure for the procedure, called the sentiment polarity categorization to present an overview of a sentiment analysis system designed for product evaluations. There are three separate stages to the entire process. Random forest, support vector machines, and naive Bayesian are the classification techniques chosen. The evaluation process begins with objective content removal and subjective content extraction. Perform POS tagging on the extracted content as soon as the extraction process is completed" Choose between the negative adjective (NOA) and verb negation at phase 2 (NOV) feeling states. Finding the sentiment score for sentiment tokens is another step. To generate a sentiment feature vector, utilize the sentiment score formula. The last stage of phase 3 was the identification of sentiment polarity.

The authors developed deep learning methods for sentiment analysis especially CNN-LSTM family models with lexical integrated two-channel. The authors used sentiment padding to increase the ratio of sentiment data in each review using a reliable-sized sample of input data Between the input layer and the first hidden layer, there is '0' padding, gradient vanishing can happen. Sentiment padding fixed this problem. The sentiment padding process was combined with the creation of high-quality lexicon elements for sentiment analysis. Several studies have demonstrated that the accuracy of sentiment analysis can be increased by providing a parallel "2 channel" model in addition to sentiment lexicon data. The author, presented a method for determining the degree of credibility of a reviewer on the basis of whether he is closely or professionally connected with the product category to be evaluated.

Suggested Approach

Our goal in this research is to estimate the customer's level of enjoyment of the product, or if they value it enough to recommend it based on the review text. It could be seen as a binary classification problem in this sense. This is accomplished by following the steps shown in the figure below *(Fig. 1)*:

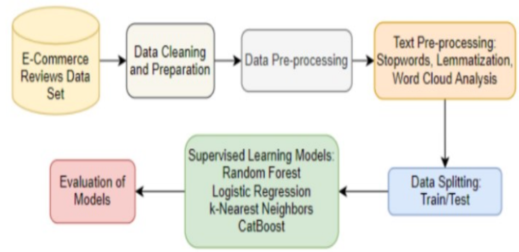


Fig. 1: The study's pipeline

Data set description

The data set of top 5 reviews of Amazon Alexa consists of the following variables and is employed in our experiments: “rating”, “date”, “variation”, “verified reviews”, “feedback”, “length”.

	rating	date	variation	verified_reviews	feedback	length
0	5	31-Jul-18	Charcoal Fabric	Love my Echo!	1	13
1	5	31-Jul-18	Charcoal Fabric	Loved it!	1	9
2	4	31-Jul-18	Walnut Finish	"Sometimes while playing a game, you can answe...	1	197
3	5	31-Jul-18	Charcoal Fabric	"I have had a lot of fun with this thing. My 4...	1	174
4	5	31-Jul-18	Charcoal Fabric	Music	1	5

Fig. 2: The data set of top 5 reviews of Amazon Alexa

Data preparation and exploration

At this stage, we eliminated all the absent data for every variable and shows the overview of preprocessing like rating: distribution, feedback distribution, variation distribution.

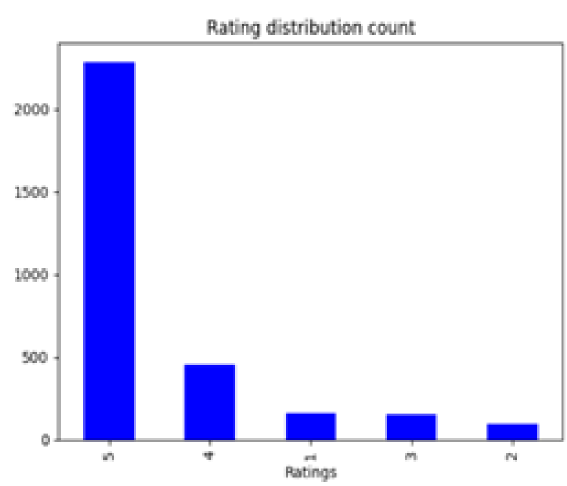


Fig. 3: visualize the total counts of each rating

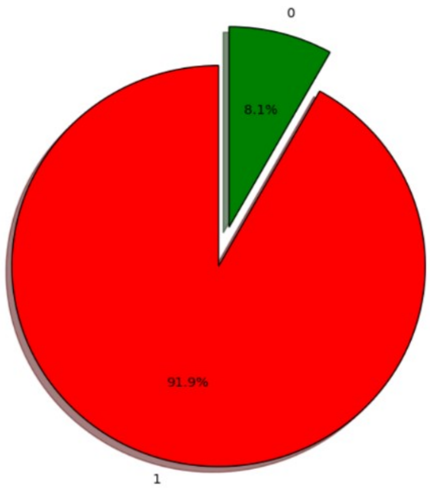


Fig. 4: The pie chart's percentages of distribution of feedback

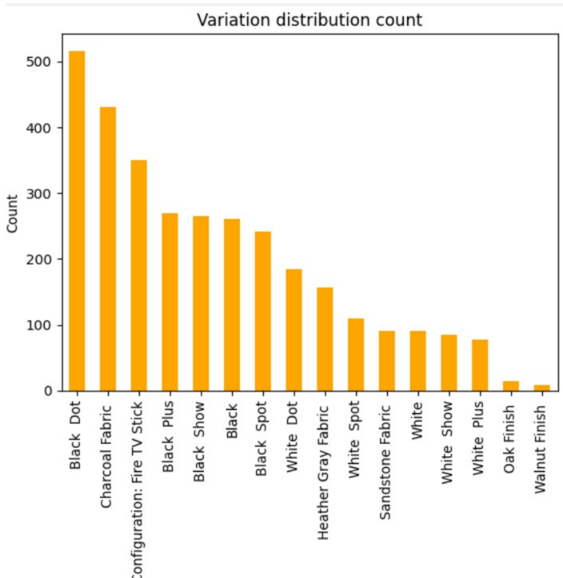


Fig. 5: The bar graph of variation distribution count

Word-cloud analysis

Stop words that had nothing to do with predicting either positive or negative reviews have finally been removed. Word clouds have been used to graphically represent word frequency. The frequency of occurrence of a word in text reviews is proportional to its size in the generated graphic.

Fig. 6: Word cloud for every review

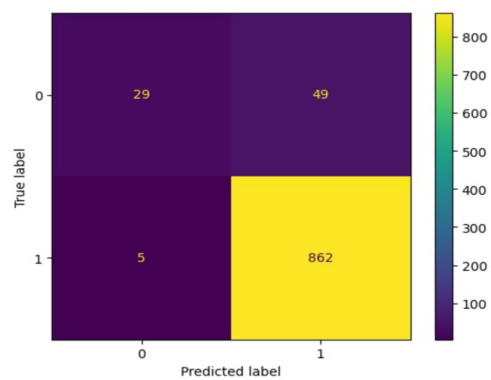
Fig. 7: word cloud for unfavorable feedback

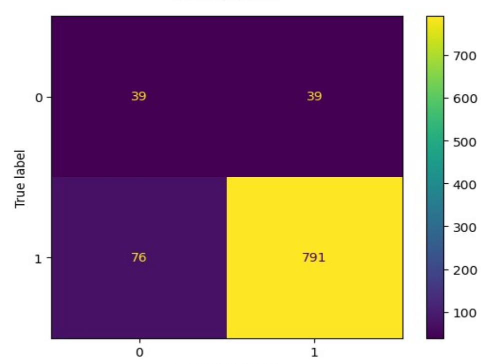
Fig. 8: word cloud for favorable feedback

Experimental Results and Discussion

Confusion matrix

The confusion matrix sums up the results of predictions on a classification task. It brings both correct as well as incorrect predictions into classes, then it compares the result of predictions with real values.





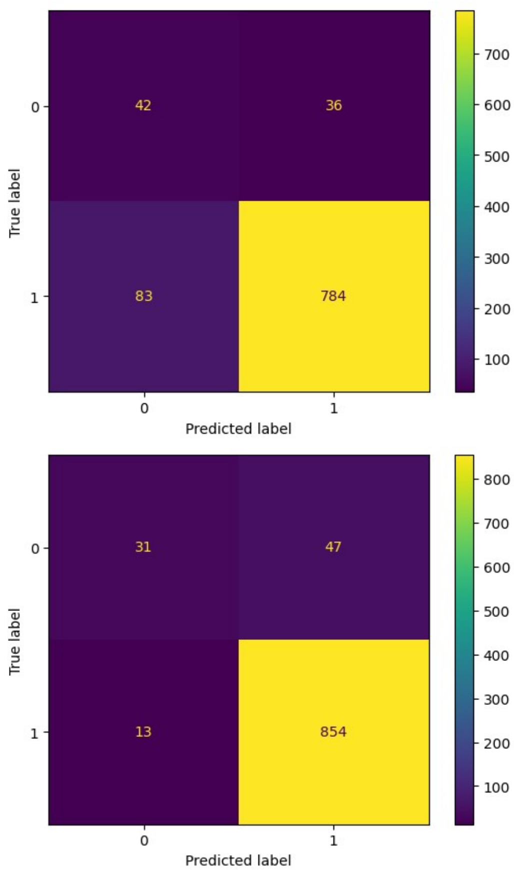


Fig. 9: Confusion matrices of the models used

Conclusion

This project effectively established a Sentiment Analysis system to categorize product reviews on e-commerce sites as positive, negative, or neutral. Utilizing a range of Natural Language Processing, (NLP) methods, encompassing both classic machine learning models (like Naive Bayes and SVM) and contemporary deep learning models (like LSTM and BERT), We achieved remarkable outcomes in the sentiment classification task, assisting consumers in making informed purchasing decisions while also serving as a fascinating tool for managing customer relationships. Additional research is necessary to continue. The deep learning models, particularly LSTM and BERT, outperformed traditional methods, attaining higher accuracy, precision, and understanding of sentiment context. These models have shown to be particularly effective in managing the challenges of unstructured review data, including sarcasm, specialized language, and extended text sequences.

The findings suggest that sentiment analysis can greatly benefit e-commerce companies by delivering insights into customer satisfaction, pinpointing product strengths and weaknesses, and aiding in enhancing customer service and product development. Visual representations of sentiment trends offer a straightforward method for companies to monitor customer opinions and modify their strategies as needed.

In summary, the automated sentiment analysis tool simplifies the task of evaluating customer reviews while enabling companies to make better, data-informed choices. The capability to derive actionable insights from customer feedback can ultimately result in improved user experiences, optimized offerings, and more efficient marketing tactics.

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