Predicting Sentiments on Shopee Reviews Using Machine Learning Models

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ABSTRACT

In the growing field of e-commerce, delivering an exceptional online shopping experience to the public is important. This study addresses the challenge of efficiently analyzing sentiments expressed in Shopee reviews, one of the leading e-commerce platforms in the country. Using machine learning models such as Logistic Regression, Naive Bayes and Support Vector Machine on the training data, we developed a system capable of predicting sentiments, categorizing reviews into positive or negative. Utilizing a dataset of 6000 Shopee reviews from the Google Play Store, our system has trained models to recognize patterns within textual features and associate them with sentiments.

The aim of the system is to provide a practical and automated tool for businesses and platform administrators to easily categorize reviews, gaining insights into customer satisfaction and areas for improvement. Motivated by the need to streamline review analysis processes, our research contributes to the broader field of sentiment analysis in the context of e-commerce. The outcomes of this study offer a valuable resource for Shopee and similar platforms, enabling data-driven decision-making, product optimization, and enhanced user experiences.

KEYWORDS
Oral reading fluency, prosody, Filipino language, children speech

1 INTRODUCTION

In the growing field of e-commerce, delivering an exceptional online shopping experience to the public is important. Shopee has played an important role in the growth of e-commerce in Southeast Asia. Shopee is a platform tailored for Southeast Asia providing customers with an easy, secure, and fast online shopping experience through strong payment and fulfillment support.

Shopee's number of users has continually been increasing since its release. It had 375 million users last 2022 and the number of users and devices installing the app is constantly increasing. As students and as users of the app, we recognize the significance of understanding customer sentiments in aiming for customer satisfaction. For this project, we created a system that performs a sentiment analysis for its input review. The system used a dataset from kaggle consisting of Shopee reviews that are taken from the Google Play Store app and utilized 6,000 of those reviews.

Identifying sentiments in customer reviews helps Shopee understand the experience of the users. Positive sentiments highlight the aspects that the customers appreciate and find amiable. Meanwhile negative sentiments point to areas where improvements may be needed. Sentiment analysis helps in enhancing the overall user experience.

It could also be used as a basis for a competitive analysis against Shopee's leading competing brand. It provides them insights on how they are performing relative to their competitors.

1.1 **Problem Statement**
Shopee has played an important role in the growth of e-commerce in Southeast Asia. The mobile app has surpassed millions of users as of 2022 and the number of users are increasing till today.

As such, it is important to enhance Shopee's online shopping experience. This can be given by identifying the sentiments of the customers and understanding the users' pain points. However with the sheer volume of user reviews, a manual analysis would be a burden and costly. A system that automatically analyzes the sentiments of these user reviews is necessary to help solve this problem.

1.2 Objectives of the Study
The primary objective is to understand and categorize customer sentiments expressed in the reviews by distinguishing them between Positive and Negative.

Through the use of Classical Machine Learning and Natural Language Processing (NLP) techniques, we aim to extract the valuable insights of the users from their reviews. This can help refine and enhance the shopping experience for a diverse customer base.

II. Methodology

The research process of this project consisted of the following phases: data collection, data cleaning, data preprocessing, exploratory data analysis, classification modeling, and model evaluation. An overview of the methodology is shown in Figure 1.

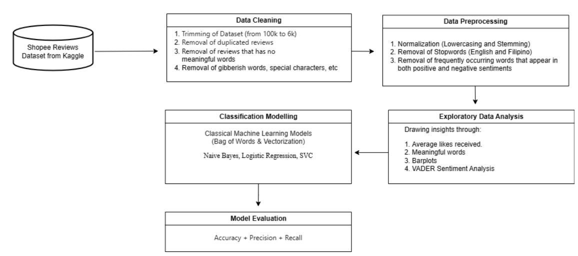


Figure 1. Overview of Methodology

2.1 Data Collection
The dataset used in this study was a subset of the corpus of Shopee App Reviews posted on Kaggle, scraped from the Google Play Store by user BwandoWando between 2015 - 2023. The original dataset contained features such as: user reviews, user ratings (1–5), review likes (the amount of users that agreed with a particular review), App Version, Author Id, Author Name, Review Date. For the sentiment analysis, only the said features were utilized: user reviews, user ratings (1–5), and review likes

2.2 Data Cleaning

To clean the data before preprocessing, the size of the dataset was trimmed down to 6,000 reviews due to limited memory, performance issues, and time constraints. As running all 100,000 reviews in different Machine Learning models would take an ample amount of time. Duplicates were also removed to ensure that we train and test our model on unique reviews

2.2.1 Target Labeling

In the process of categorizing app reviews as either positive or negative, a classification approach based on user ratings was employed. Reviews that have ratings ranging from 1 to 3 were labeled as Class 1, indicating a negative sentiment. Conversely, reviews with ratings of 4 or 5 were assigned to Class 0, signifying a positive sentiment.

	review_text	review_rating	review_likes
0	napaka bulok an tagal mag load ng tracking ord...	1	0
1	so unfair how about the student that have an p...	1	0
2	this is my favorite online store eversince.	5	0
3	love ko talaga ang shopee.kasi ni minsan hindi...	5	0

Figure 2. Before adding a target variable

	review_text	review_rating	review_likes	target
0	napaka bulok an tagal mag load ng tracking ord...	1	0	1
1	so unfair how about the student that have an p...	1	0	1
2	this is my favorite online store eversince.	5	0	0
3	love ko talaga ang shopee.kasi ni minsan hindi...	5	0	0

Figure 3. After adding a target variable

2.3 Data Preprocessing

To ensure that the data is in good shape for training models, data preprocessing is done to get rid of irrelevant information, handling missing values, and cleaning up text data. This enhances accuracy, making the model more effective in understanding patterns and making predictions. The preprocessing techniques done are as follows: (a) Normalization (Lowercasing and Stemming), (b) Removal of Stopwords (English and Filipino), (c)Removal of frequently occurring words that appear in both positive and negative sentiments

Before normalizing the dataset, reviews were further cleaned by removing HTML tags, special characters and numbers.

2.3. 1 Normalization of Data

To normalize the dataset, the cleaned reviews were first converted into lowercase characters. Additionally, Natural Language Toolkit (NLTK) – a Python library for working with human language data, was employed to apply stemming, reducing words to their root form. The decision to use stemming instead of lemmatization was driven by the model's improved accuracy when stemming was applied.

2.3.2 Removal of stopwords and frequently occurring words in both positive and negative sentiments

Stopwords are a set of commonly used words in a language. These are words that are generally considered to be of little value in terms of conveying meaningful information in a text. Examples are: *"and," "the," "is," and "in,".* These words frequently occur in a text but often do not contribute much to the understanding or interpretation of the content. To remove English stop words, NLTK was utilized.

As the dataset also contained Filipino reviews, Tagalog stopwords like *'ako', 'sa', 'akin', 'ko', 'aking', etc.* were also removed. The tagalog stopwords were taken from spaCy(), a library for advanced Natural Processing in Python and Cython, and also from Stopwords ISO().

Furthermore, to enhance the accuracy of our model, words that frequently appear in both positive and negative reviews such as *"app", "item", "shopee", "seller"* were removed.

Table 1. Data Preprocessing

Original text of the first review in our dataset
'*napaka bulok an tagal mag load ng tracking order page aabot pa ata ng isang taon bago mag load bwisit, ayusin nyo naman to mga bugok'*
Pre-processed text
'*bulok tagal mag load track order page aabot ata taon mag load bwisit ayusin bugok'*

2.3.3 Removal of reviews that without meaningful words

After the dataset was pre-processed, certain reviews returned a length of 0. These reviews yielded empty fields as they mostly consist of emojis and other non meaningful characters.. Recognizing that these reviews contribute no value to the training of the model, they were consequently removed from the dataset.

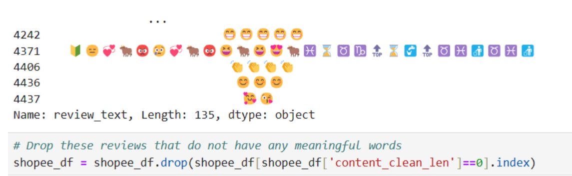


Figure 4. Example of reviews with no meaningful words

3.3 Exploratory Data Analysis

Exploratory Data Analysis (EDA) is the initial phase of data analysis, involving exploration, visualization, and summary of dataset characteristics. It helps uncover insights, detect patterns, and identify outliers, providing a foundation for informed decision-making in subsequent analyses. (IBM, nd) As such, to draw insights from our training set, EDA was performed.

3.3.1 Number of likes received from reviews

To show dissatisfaction with an app's service, users may express their sentiments by writing reviews. These reviews can serve as valuable sources of feedback, providing insights into user experiences, identifying specific issues, and highlighting areas for improvement in the application. Higher likes on a certain review may suggest that other users agree with the sentiments expressed in that review.

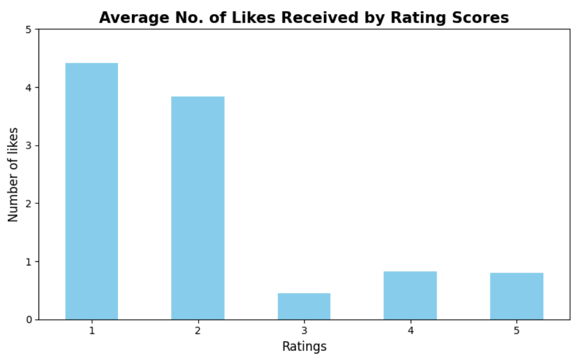


Figure 5. Average number of likes received by rating scores

The figure above illustrates the average number of thumbs up (likes) received by rating scores. Negative reviews with 1 or 2–star ratings generally receive more likes on average, than positive reviews. This hints at the possibility that other users might be encountering similar issues as expressed in these negative reviews.

	review_text	review_likes	review_rating
2903	all you need is here. great app and has a lot ...	1426	5
1887	immediately tags your product review as irrele...	866	1
1592	average app, needs a lot of improvenents.	379	1
498	i cant use the shopee up! every time i'm tryin...	273	1
323	your shopping cart is soooooo laggy i can't de...	265	1

Table 2. Average number of likes received by rating scores

3.3.2 Word Cloud for Most Frequently Used

In order to determine the most frequently used words in both negative and positive reviews, a word cloud was generated.

Figure 6. WordCloud for Most Frequently Used words among Negative Reviews

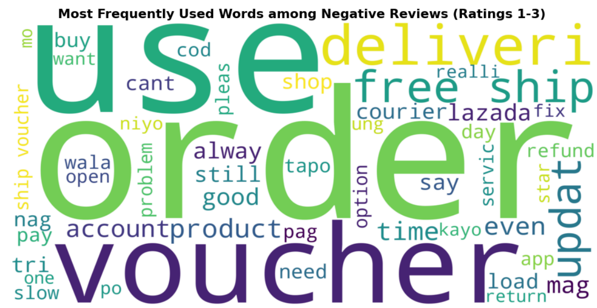
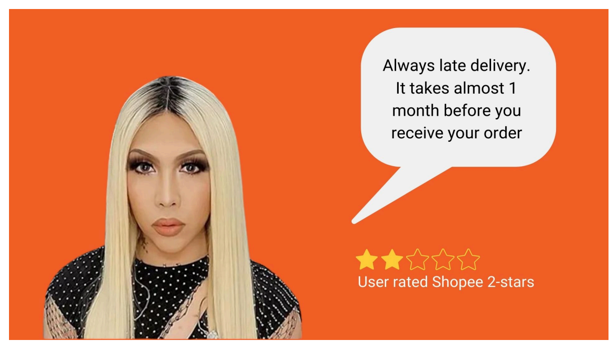


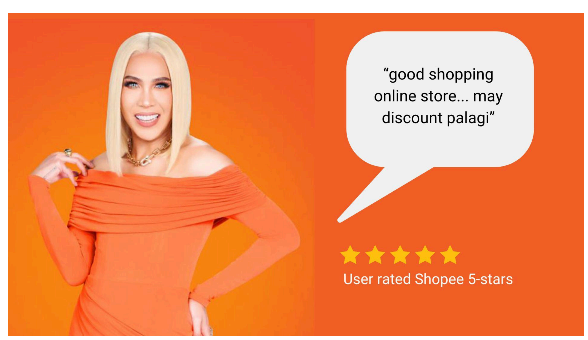
Figure 7. WordCloud for Most Frequently Used words among PositiveReviews

As seen in Figure 6, *'use', 'order', and 'voucher'* are the top occurring words used among negative reviews. Consequently, *'thank', 'good', and 'nice'* are the top words used among positive reviews.

A **negative** review with the word **"Order'**



A **positive** review with the word **"Good"**



3.3.3 Number of Meaningful Words

In order to compare the length of the reviews among positive vs negative sentiments, the distribution of the length of positive and negative reviews were plotted.

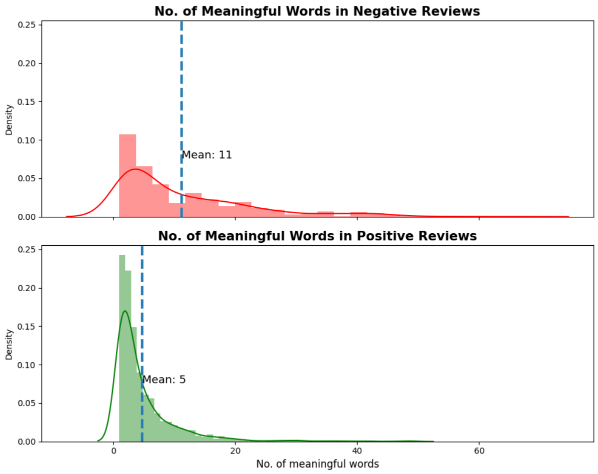


Figure 8. Number of Meaningful Words in Negative and Positive Reviews

In Figure 8, the distribution of meaningful words in both negative and positive reviews exhibits a right-skewed pattern. Notably, the average number of meaningful words in a negative review (11 words) is higher than that in a positive review (5 words).

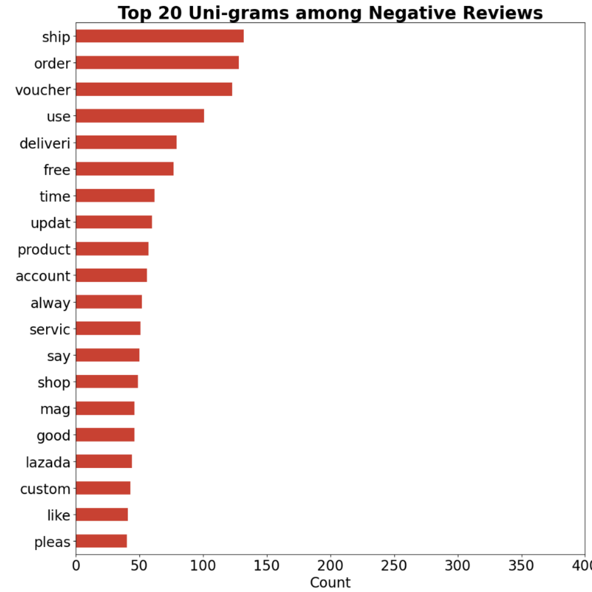
Negative Reviews have higher variance in the number of meaningful words. This means that customers that are dissatisfied with the app are more inclined to express their grievances through longer and more detailed reviews than those satisfied customers.

3.3.4 Barplots

In order to tokenize the textual data and generate bar plots for the top uni-grams and bi-grams seen in both negative and positive review, CountVectorizer was utilized. This tool identifies distinctive words that differentiate between positive and negative sentiments, or, in some instances, identifies words common to both sentiments.

3.3.4.1 Unigram and Bigram

In the unigram below, the three most frequently occurring words in negative reviews are : *'Order', 'Ship' and 'Voucher'*. As for the bi-gram, words such as “free-shipping”, “Shipping voucher”, and “customer service” emerge most frequently. This implies that users commonly express dissatisfaction in Shopee’s free-shipping, vouchers, and customer service.



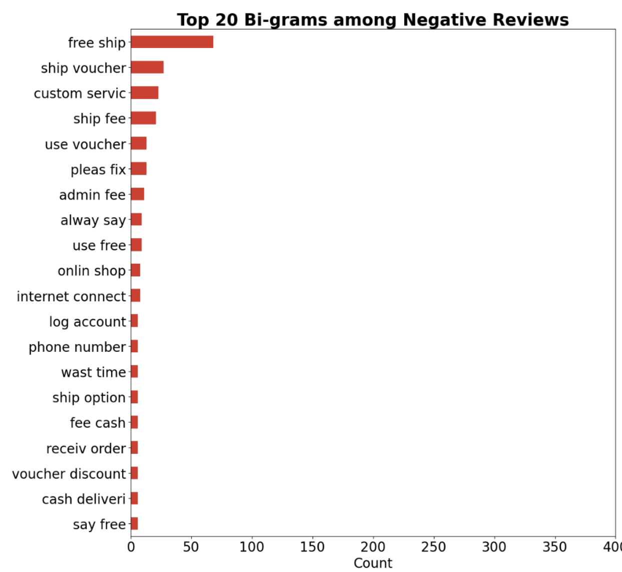
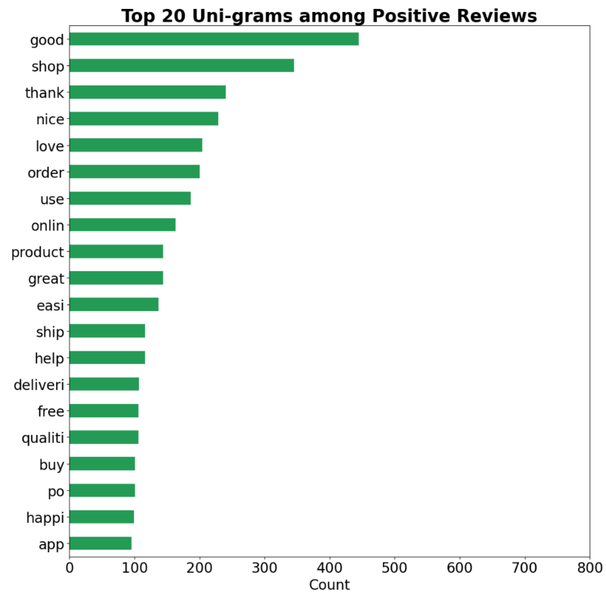
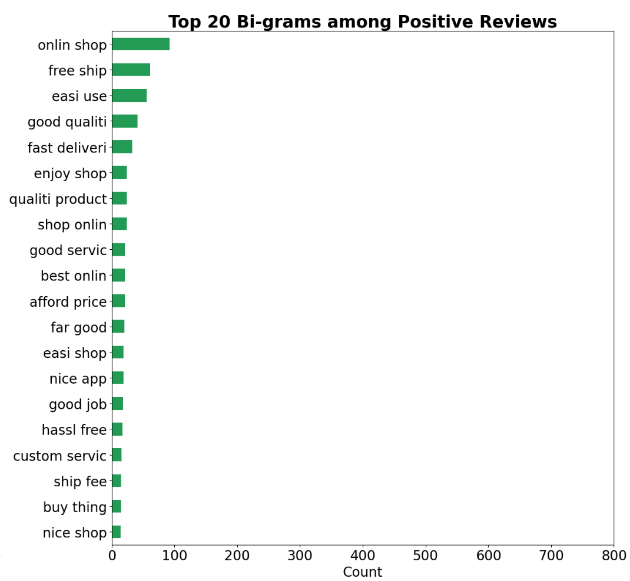


Figure 9. Top 20 Unigram and Bigram for Negative Reviews

In positive reviews, the three most frequently used words are *'Good,' 'Shop,' and 'Thank.'* In the bi-gram analysis, phrases like "online shop," "free shipping," and "easy use" are the most prevalent. This indicates that users express contentment with Shopee's online shopping feature, allowing them to shop conveniently from their phones. Additionally, positive sentiments are associated with the availability of free shipping and ease of use.

Figure 10. Top 20 Unigram and Bigram for Positive Reviews





3.4 Pre-Modeling

After the Exploratory Data Analysis was conducted, the dataset was splitted into Test and Training Set in order to train and test the model's hyperparameters.

```
[ ] # Perform train test split so that we can train, score and tune our models' hyperparameters
    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

[ ] X_train.shape

    (2797,)

[ ] X_val.shape

    (700,)
```

```
[ ] # Assuming X_train and X_val are your training and validation sets
    X_train = X_train.dropna()
    y_train = y_train.loc[X_train.index]

    X_val = X_val.dropna()
    y_val = y_val.loc[X_val.index]

[ ] X_train = X_train.fillna('')
    X_val = X_val.fillna('')

[ ] # Use count vectorizer to check how many unique words there are
    cvec = CountVectorizer(stop_words='english')
    cvec_df = pd.DataFrame(cvec.fit_transform(X_train).todense(), columns=cvec.get_feature_names())
    cvec_df.shape

    # Write a function that takes in the actual y value and model predictions,
    # and prints out the confusion matrix and classification report
    # Dataset: Validation or test set

    def cmat(actual_y, predictions, dataset):

        # Create a classification report
        print('Classification report for', dataset)
        print(classification_report(actual_y, predictions))
        print('')

        # Create a confusion matrix
        cm = confusion_matrix(actual_y, predictions)
        cm_df = pd.DataFrame(cm, columns=['Predicted Positive Review','Predicted Negative Review'], index=['Actual Positive Review', 'Actual Negative Review'])
        print('Confusion matrix for', dataset)
        print(cm_df)
```

Figure 11. Pre Modeling: Splitting of Dataset into Training and Test Set

3.5 Classification Modeling

Classical machine learning will be used for sentiment analysis. The machine learning models used are the following: Voting Classifier (TF-IDF Logistic Regression & TF-IDF Naive Bayes), TF-IDF & SVC, Countvectorizer & Naïve Bayes, TF-IDF & Logistic Regression, TF-IDF & Naïve Bayes, Countvectorizer & Logistic Regression, Countvectorizer & SVC.

Before the modeling process, Bag of Word (BAW) was conducted to extract features from text. This was done through vectorization, specifically the CountVectorizer and TF-IDF Vectorizer. CountVectorizer tokenizes and counts the word occurrences in the corpus. Whereas, tokenization: splits the text into single words. TF-IDF tells us which words are important to one document, relative to all other documents. After vectorizing, Logistic Regression, Naive Bayes and Support Vector Machine were fitted on the training data.

Table 3. Difference between Tokenization and Vectorization

Tokenization	"This is a nice app"	["This", "is", "a", "nice", "app"].
Vectorization	["This", "is", "a", "nice", "app"]	[0,1,2,3,4]

3.6 Model Evaluation

The production model will be selected based on accuracy and recall on the validation set.

RESULTS AND DISCUSSION

Table 4 provides an overview of the models' performance, based on accuracy and recall on the validation and training set.

Table 4. Summary of the Model Evaluation Metrics

	Accuracy on Training	**Accuracy on Validation**	**Accuracy on Recall**
Voting Classifier (TF-IDF Logistic Regression & TF-IDF Naive Bayes	0.908	0.868	0.51
TF-IDF & SVC	0.789	0.781	0.03
Count Vectorizer & Naïve Bayes	0.888	0.878	0.64
TF-IDF & Logistic Regression	0.902	0.858	0.48
TF-IDF & Naïve Bayes	**0.907**	**0.871**	**0.54**
Count Vectorizer & Logistic Regression	0.853	0.838	0.32
Count Vectorizer & SVC	0.872	0.842	0.36

1. **Voting Classifier (TF-IDF Logistic Regression & TF-IDF Naive Bayes)** – This model combines the predictions of a TF-IDF Logistic Regression model and a TF-IDF Naive Bayes model using a voting mechanism. The training accuracy is 90.8%, the validation accuracy is 86.8%, and the recall is 51%.

2. **TF-IDF & SVC:** This model uses the TF-IDF vectorization technique along with Support Vector Classification (SVC). The training accuracy is 78.9%, the validation accuracy is 78.1%, and the recall is 3%.

3. **Count Vectorizer & Naïve Bayes:** This model utilizes the Count Vectorizer to convert text data and Naïve Bayes for classification. The training accuracy is 88.8%, the validation accuracy is 87.8%, and the recall is 64%.

4. **TF-IDF & Logistic Regression:** Here, TF-IDF is used for vectorization, and Logistic Regression is employed for classification. The training accuracy is 90.2%, the validation accuracy is 85.8%, and the recall is 48%.

5. **TF-IDF & Naïve Bayes:** This model employs TF-IDF for vectorization and Naïve Bayes for classification. The training accuracy is 90.7%, the validation accuracy is 87.1%, and the recall is 54%.

6. **Count Vectorizer & Logistic Regression:** Using the Count Vectorizer and Logistic Regression, this model achieves a training accuracy of 85.3%, a validation accuracy of 83.8%, and a recall of 32%.

7. **Count Vectorizer & SVC:** This model utilizes the Count Vectorizer along with Support Vector Classification (SVC). The training accuracy is 87.2%, the validation accuracy is 84.2%, and the recall is 36%.

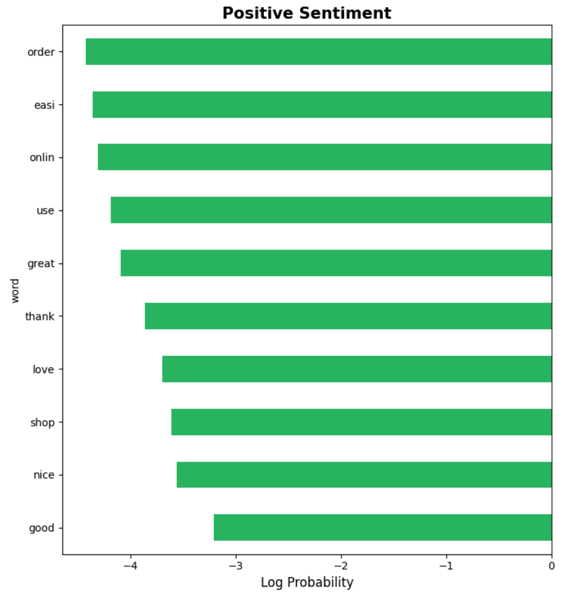
Among all the classification models, TF-IDF & Naïve Bayes was selected as the production model as it achieved the highest accuracy and recall on the training and validation set. It attained an accuracy of 0.907 on the training and an accuracy of 0.871 on the validation data and a recall of 0.87

Evaluate Production Model on Test Set

Since TF-IDF & Naïve Bayes was selected as the production model, the model was then evaluated on the Test Set. The results demonstrated the model's continued efficacy, achieving an accuracy of 0.875– surpassing the performance on the training set. However, it's noteworthy that the recall rate stood at 0.56, which, while slightly lower than the training set

Production Model's Most Predictive Words

In Naive Bayes, including Multinomial Naive Bayes, the log probabilities are used to make predictions. The higher the log probability for a specific class, the more indicative the feature is of that class. In other words, a higher log probability suggests that the presence of the feature makes the observation more likely to belong to that class.



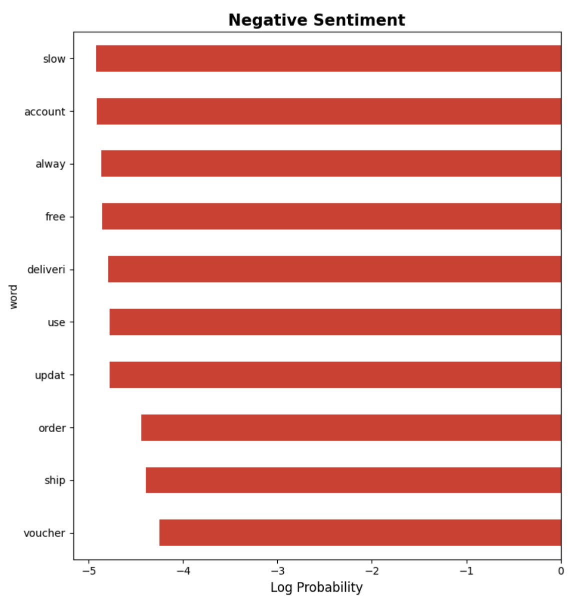


Figure12. Naive Bayes' Top 10 Most Predictive Words for Positive and Negative Sentiments

As seen in the figure above, key indicators of positive sentiment in the analyzed data include terms such as 'order,' 'easy,' 'only,' and 'online.' These words likely denote the positive user experience associated with Shopee's user-friendly online shopping platform, enabling users to conveniently shop using their mobile devices. Conversely, terms like 'slow,' 'account,' and 'always' are most closely associated with negative sentiment, shedding light on potential pain points or areas of concern expressed by users in their feedback.

Model Demo:

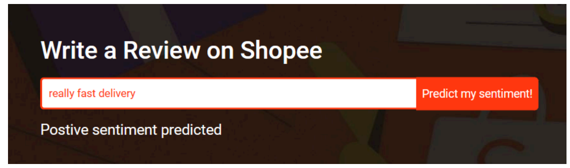


Figure 13. Positive Sentiment Prediction

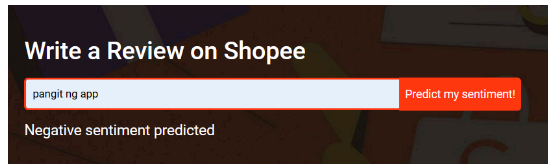


Figure 14. Negative Sentiment Production

Above is a demonstration of the running model. On Figure 13, a positive review saying *"really fast delivery"* is entered, afterwards, it prompts the text 'Positive Sentiment Predicted'. This justifies that positive sentiment prediction was a success. In Figure 14, a negative review saying *"pangit ng app"* is entered, then it prompts the text 'Negative sentiment predicted' right after. This justifies that the negative sentiment prediction was a success as well.

Limitations:

Despite the model's relatively high performance, misclassifications still tend to occur especially when users leave mixed reviews.

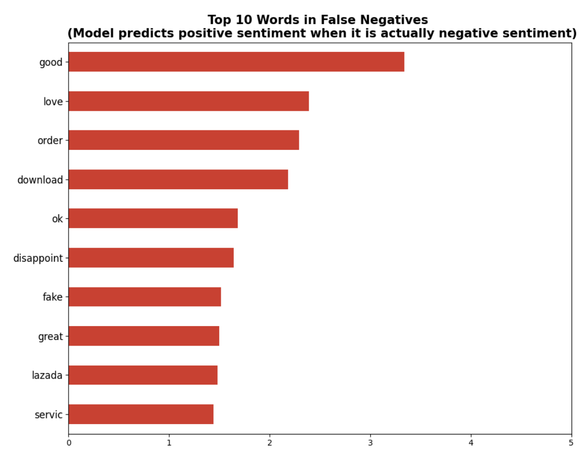


Figure 15. Top 10 Words in False Negatives

Based on the preceding data, the term 'good' is predominantly linked to positive sentiments. Nonetheless, considering that the term 'good' is most prevalent in false negatives, the model is prone to inaccurately categorize these reviews as expressing a positive sentiment. The figure below shows an example of a False Negative that has the words 'good' in it.

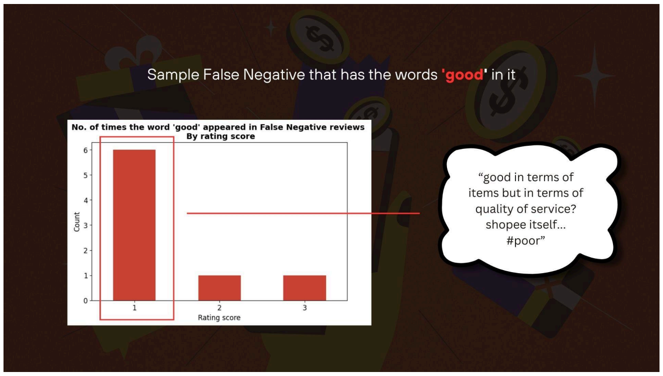


Figure 16. Sample false negative that has the word “good”

As depicted in Figure 17, it is noticeable that a number of users have written reviews containing the term 'good' while giving it a rating of 1. Due to the model being trained to associate the word 'good' with positive sentiment, it erroneously classifies these reviews as positive.

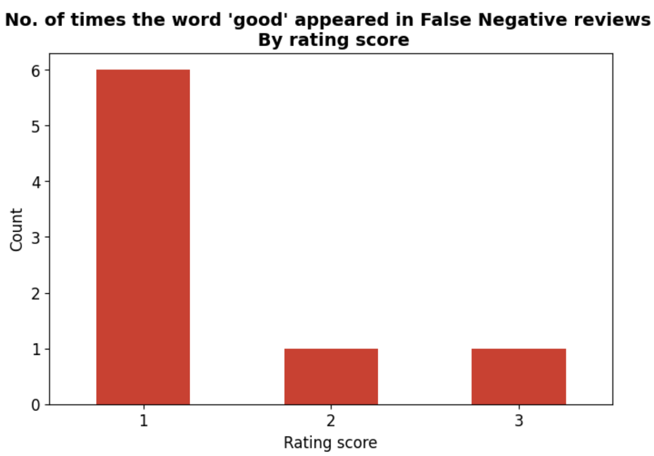


Figure 17. Number of times ‘good’ appeared in False Negative reviews by rating scores

As per further assessment, misclassification of reviews tend to occur due to the following reasons:

- User leaves a positive review but rates the app 1-star. For example, “good app with reasonable pice”. These kinds of misclassifications are unavoidable and even a human will interpret it to be positive sentiment
- User writes a review that mentions Shopee is ‘good’ in one aspect, but indicates that there are other areas of improvement.
  Misclassifications of this sort can be reduced if the model was trained on more negative sentiment. Given the limited pool of negative reviews on Google Play, we can look into training the model on negative reviews from the Apple App Store in the future.
- Given that we have removed stopwords like ‘not’ and ‘no’ during the pre-processing, the word ‘goog’ rather that ‘not good’ will be fed into the model. As these reviews typically contain very few words and do not provide feedback on how Shopee can improve the app experience, there are no dire consequences to such misclassifications.

CONCLUSION

With the sheer volume of user reviews on an app resulted by the increasing number of users, a manual analysis on Shopee user reviews would be a burden and costly. This project successfully addressed the challenge of efficiently analyzing sentiments expressed in the Google Play Store Shopee reviews. Using machine learning models including Logistic Regression, Naive bayes, and Support Vector Machine, on a dataset of 6,000 Shopee reviews, a system was developed that is capable of predicting sentiments and categorizing reviews into positive and negative.

This system aims to provide a practical business tool for businesses and platform administrations to categorize reviews easily, and gain insights for customer satisfaction, and areas for service and app improvement. This system can further contribute to the broader field of sentiment analysis in the field of e-commerce, offering a valuable resource for Shopee and other similar platforms.

The utilization of Classical Machine Learning techniques for the modeling, and the aid of Natural Language Processing methods for data cleaning to ensure the dataset's integrity by addressing issues such as duplicates and irrelevant information, enabled the extraction of valuable insights from user reviews. Moreover, the preprocessing steps, including target labeling, normalization, removal of stopwords, and handling of frequently occurring words laid the groundwork for the training data's effective model training.

Exploratory Data Analysis (EDA), helped in recognizing valuable insights into the user sentiments. It highlighted patterns in the data such as highlighting the patterns in the data such as the average number of likes received by rating scores and the distribution of meaningful words in negative and positive reviews. These observations added contextual understanding to the sentiment analysis.

The classification modeling phase started with the division of the dataset into training and test sets for model and training evaluation. Classical learning models including Logistic Regression, Naive Bayes, and Support Vector Machine were applied using techniques such as Bag of Words (BoW), CountVectorizer, and TF-IDF Vectorizer.

Upon model evaluation, considering the accuracy and recall on the validation set, the TF-IDF & Naive Bayes model with an accuracy on training of 90.7%, an accuracy on validation of 87.1% and a recall of 54% has been selected as the production model.

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