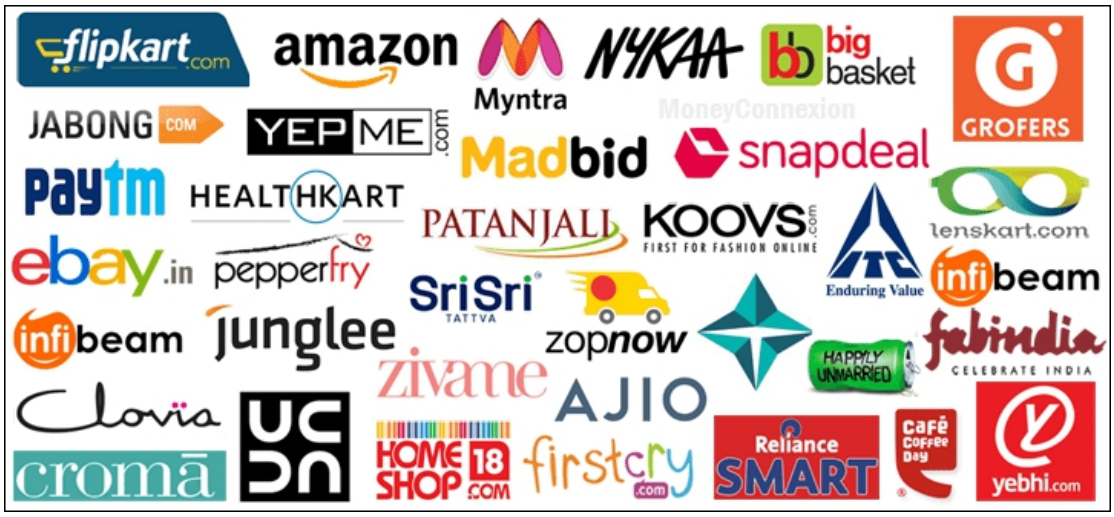
FLIP ROBO

REVIEW RATING PREDICTION



SUBMITTED BY
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INTRODUCTION

Business Problem Framing

It is quite common for e-Commerce companies to introduce new features into their existing e-commerce site. Our client has a website where people write different reviews for technical products. Now they are adding a new feature to their website. The reviewer will have to add stars(rating) as well with the review. The reviewers will be able to add star ratings (1 to 5) with their review. However, the reviews written in past will not have any stars. Hence, our client wants a solution that can predict the star rating by seeing the reviews written in the past.

Conceptual Background of the Domain Problem

The star rating will help new buyers to understand if a product will be useful for them or not. Hence, the star rating features is a good value addition. Being able to predict the star rating for all the past reviews add advantage to the customer in understanding the product.

Motivation for the Problem Undertaken

The star rating is a very useful feature for the customers to quickly understand about a product and decide if to buy it or not. By being able to predict the rating from past reviews, the client can benefit from implementing the ‘add star’ feature in their website for future reviews.

Analytical Problem Framing

Mathematical/ Analytical Modeling of the Problem

The data gave a good result with GradientBoostingClassifier GradientBoostingClassifier is built from an ensemble of Tree based estimators. This model uses Bagging technique.

Data Sources and their formats

The data required for the Rating predictor model is different reviews and ratings from different e-Commerce websites. The data used in this project contains Reviews and the corresponding Ratings. The data is scraped from Amazon, Flipkart sites. The dataset contains 2 columns:

1. 'Reviews', an object data type – contains the reviews of different products.
2. 'Ratings', numeric data type – Contains the ratings of each review. Ratings values are from 1 to 5.

```
[8]  import io
     df = pd.read_excel(io.BytesIO(uploaded['RR_webscraping.xlsx']))
     df
```

	Review	Rating
0	very important tool thank you flipkart nice pr...	5
1	this product was amazing and quality are amazi...	3
2	The Product is awesome at this very price rang...	4
3	Product is nice but not prefect.....for the pr...	3
4	All type of tools are available with good shap...	4
...	...	...
17322	In my case one dumble is 3 kg and other is 2....	3
17323	Good product	1
17324	It's fake product	1
17325	Nice product,	5
17326	Product quality is not well	1

Data Pre-processing

1. Converted all the characters in the ‘Reviews’ column to lowercase.
2. Replaced all email addresses, website links, currencies, phone numbers and any numbers with constant texts link email address, web address, currency amount, phone number and number respectively.
3. Removed all non-alphabetic characters.
4. Replaced all multiple blank spaces with single blank space.
5. Changed the datatype of ‘Reviews’ as ‘str’ and stored as ‘reviews’.
6. Removed the stopwords from the ‘reviews’ column.
7. Used ‘reviews’ and ‘Ratings’ fields for further steps.
10. Used the cleaned ‘reviews’ field to create features using TFIDF with monograms, bigrams and trigrams. Max features restricted to 10,000 to compensate the computation power available.

Data Inputs- Logic- Output Relationships

1. The input data consists of float values which are derived using TFIDF method from the ‘reviews’(cleaned ‘Reviews’) column in the data-set.
2. The TFIDF method uses monograms, bi-grams and tri-grams to create the independent features for the model and the output contains numerical classes.
3. The model approximates the function between the input and the output.

Hardware and Software Requirements and Tools Used

1. Google Colab
2. SKLEARN
3. MATPLOTLIB
4. PANDAS
5. NUMPY

Model/s Development and Evaluation

Identification of possible problem-solving approaches (methods)

1. Scrape the required dataset from different eCommerce websites.
2. Clean the dataset using NLP approaches.
3. Compare different models and identify the suitable model.

Testing of Identified Approaches (Algorithms)

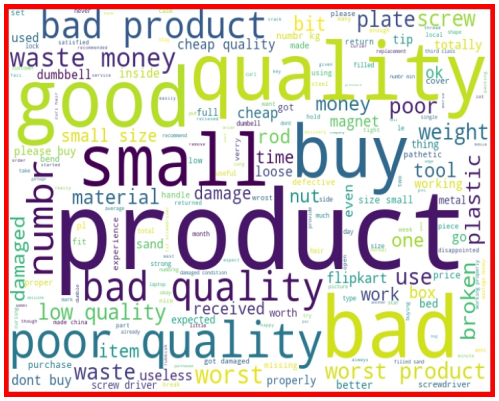
1. 'KNeighborsClassifier'
2. 'DecisionTreeClassifier'
3. 'RandomForestClassifier'
4. 'AdaBoostClassifier'
5. 'MultinomialNB'
6. 'GradientBoostingClassifier'
7. 'BaggingClassifier'
8. 'ExtraTreesClassifier'

Key Metrics for success in solving problem under consideration

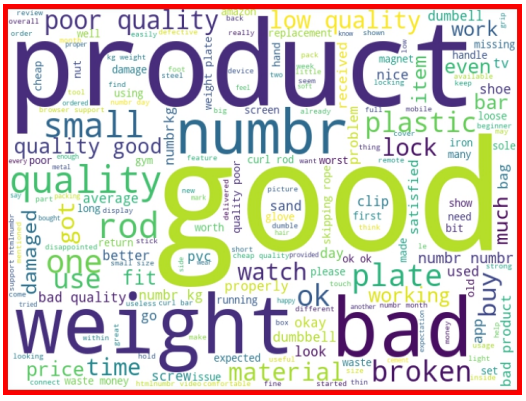
1. Accuracy is used as the key metric for evaluation. Because the dataset used is balanced, Accuracy is a good metric.
2. Classification Report was used so that the Precision, Recall and F1 scores could also be used to evaluate the model.

Observations:

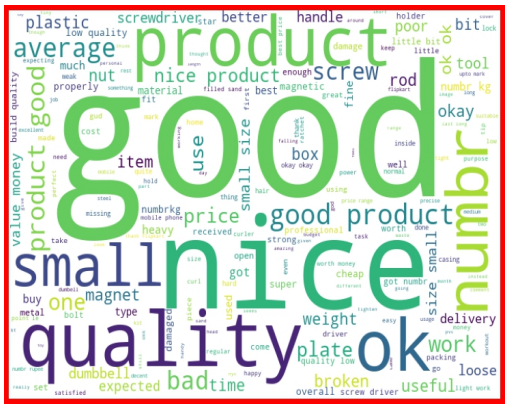
1. The lengths of the cleaned reviews have decreased compared to the lengths of the original reviews.
2. Comparing Ratings 1, 2, 3 4 and 5 word-clouds



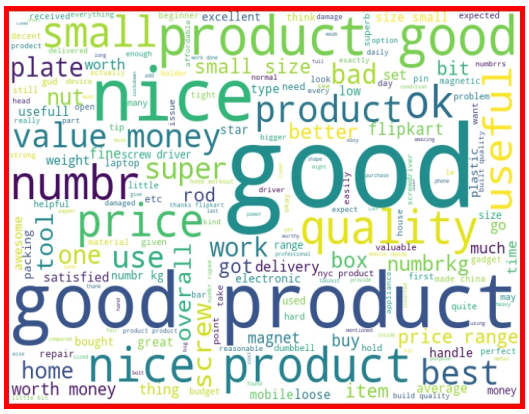
Rating 1



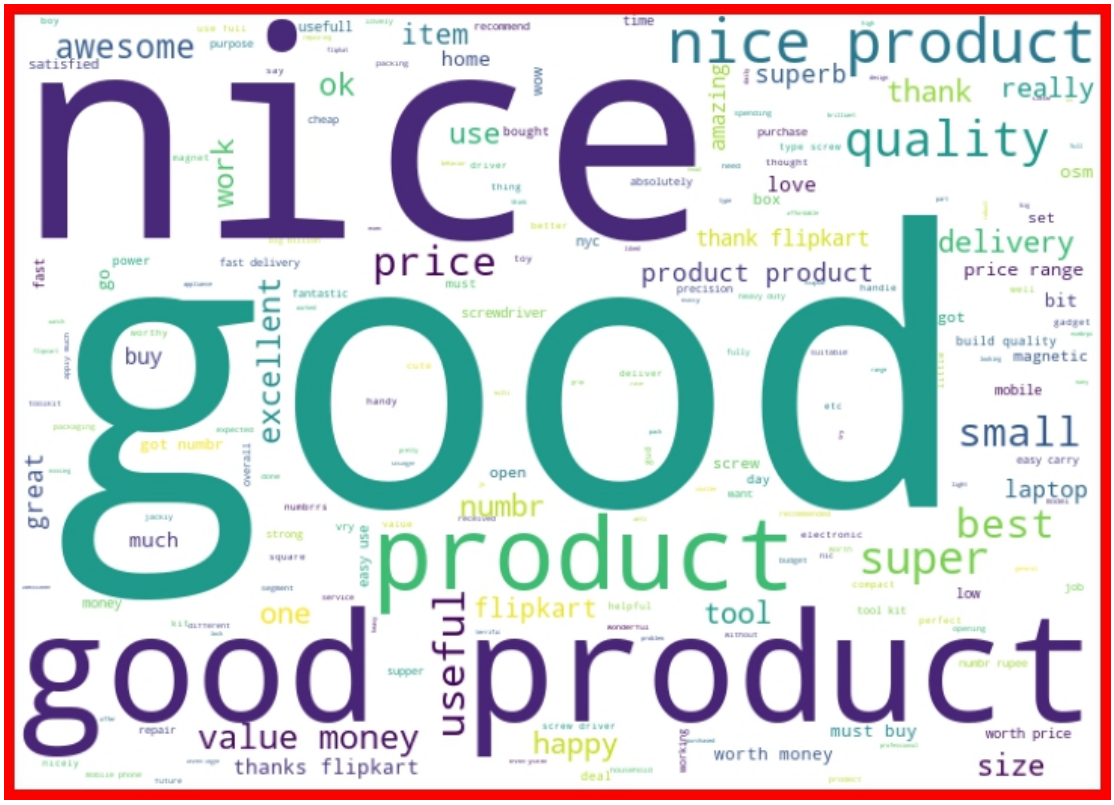
Rating 2



Rating 3



Rating 4



Rating 5

Observations:

1. We can see that there is a clear distinction between the words used in the reviews of Rating 1 and Rating 5.
2. The Rating 1 reviews have many negative words for eg: 'Stopped working', 'waste money', 'bad product', etc,.
3. The Rating 5 reviews have many positive words for eg: 'value money', 'nice product', 'better', 'good quality'.
4. Some of these positive words in Rating 5 reviews are also available in Ratings 3 and 4. Also, there are some other words in the word cloud that are unique to Ratings 3, 4 and 5 respectively.
5. It would make sense to use monogram, bigram and trigram while using TFIDF.

Interpretation of the Results

1. Ratings 3,4 and 5 have many common words. The model could get confused between classifying the records as class 3, 4 and 5. Hence Ensemble techniques will be more effective than basic algorithms.
2. Due to computational limits, only 6,000 features were used from TFIDF. Using more features may increase the model performances.

CONCLUSION

Key Findings and Conclusions of the Study

1. The reviews of the higher ratings contain more positive words than the least ratings.
2. More the data used for training the better the model performed.
3. GradientBoostingClassifier is able to perform well for the data used.

Learning Outcomes of the Study in respect of Data Science

Learned about the up-sampling techniques. Up-sampling is very useful in text/NLP based problems since in these problems, the more text combinations we are able to find the better the model performs.

Limitations of this work and Scope for Future Work

Computational power is the limitation faced in this project. The RAM memory in Google Colab was not enough for certain computations with the whole features.

If there is enough computation power, using more data for training will give better results.