Ranking products from online customer reviews

Anushka Gupta
anushka21114@iiitd.ac.in
MTech,IIIT Delhi

Nitin Khatkar
nitin21133@iiitd.ac.in
MTech,IIIT Delhi

Shoumik Bhattacharya
shoumik21144@iiitd.ac.in
MTech,IIIT Delhi

ABSTRACT

Online customer reviews on E-commerce websites plays a very important role in the whole buying decision process. Whenever we try to decide to buy a product, we are likely to get the opinions of different customers via their reviews, who had previously purchased that product.Nowadays, there are lots of customer reviews available on various online shopping platforms, which can be referred by the customers to get a better understanding about the product, they wish to purchase.But going through each and every review to decide the optimal product is a very tedious and time consuming task. Therefore, there is a need of an automated system, which can process all the reviews from various websites and can provide ranking of the products to the user based on how different customers have rated that product and its features.

1 INTRODUCTION

With numerous products launching in almost all e-commercial giants every now and then, and user with limited amount of time in hand, nobody likes to visit each and every website and then, read reviews about it and then again repeat the same task for other product and then, decide which product to buy (**Refer Figure** 1), wouldn't it be easier if there existed a website which could do all this for you. To make this process hassle free, what we intend to solve these problems and provide user with one stop solution where user can enter products which are in his/her mind, and then we would be able to rank those products while comparing their aspect-based rating on various parameters related to the product.

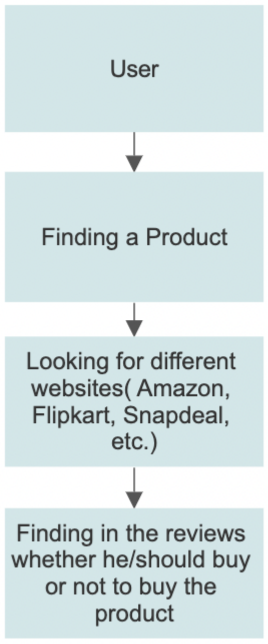

User
Finding a Product
Looking for different websites(Amazon, Flipkart, Snapdeal, etc.)
Finding in the reviews whether he/should buy or not to buy the product

Figure 1: How user need to search different websites and compare products manually

2 LITERATURE REVIEW

Literature review of some of the existing work in the domain of our problem.

- Gobi et. al.[4] used customer reviews of mobile phones and cameras from Amazon dataset. They applied a four step approach which included Pre-processing the dataset, Feature extraction, Context Identification and Fuzzy Ranking. The Pre-processing of data included Tokenisation and PoS Tagging. The Feature Extraction step included extracting the Explicit and Implicit Features such as Battery life, price, camera and Size, Weight etc. respectively. They took all synonyms of explicit features and clubbed them under a common category. For implicit features they took the count of each feature and the most frequently occurring one was assigned as implicit feature to the opinion word. The adjectives in the pre-processed reviews represent opinion words. In the Context Identification step Linguistic rules were used to handle opinion words. For example, "the battery life is very long". It is not clear whether "long" means a positive or a negative opinion on the product feature "battery life". "This camera takes great pictures, but has a short battery life." Here the word "but" changes the opinion of the sentence. "Great" represents a positive opinion and "short" has a negative opinion. Then they applied Fuzzy Topsis Ranking in which the opinion words were classified into five categories such as very good, good, medium, poor and very poor based on the semantic similarity between them. Then Five triangular fuzzy numbers are used for scoring the features. They obtained Precision, Recall and F-measure values of 0.795, 0.562 and 0.658 respectively and provided an efficient ranking system based on the customer reviews.
- Karthik R.V. et. al.[5] devised a new method algorithm called Feature Based Product Ranking and Recommendation Algorithm(FBPRRA) for recommending products to the users. They wanted to make a generalized sentimental analysis for the same for handling of all varied type of input, unstructured data from review blogs and social networking sites with customer specific recommendation. Occasion(anniversary, birthday) and actual reviewer information(mainly age) is identified from the review blogs or reviews given, then according to user inputted occasion and user age, they identified the correct product for the user entered occasion and age for the end user. Then user interested features and weightage calculation is automatic. Took online reviews and target user age

as input, then identified correct reviewers from the lot and calculated weightage(that is, positive, negative or neutral) and then according to occasion they filtered them further and gave recommendation on basis of that. Processing of reviews is in the order of tokenizer, filter tokens, filter stop words, transform cases and then applying FBPRRA algorithm to it. In the proposed algorithm they got a accuracy of about 81.23 percent which was higher than the other learning techniques namely SVM, Decision Tree, Naive Bayes, KNN and Random Forest. Further they applied the same algorithm to amazon dataset taken and found out that out of total data for given products nearly only 30 percent filtered out to be useful for applying information retrieval according to given target user for a given occasion. Hence, on basis of end user's information mainly age and other factors like occasion, they calculated weight for each feature and create a ranking and recommendation system.

- Ping et. al.[2] reviewed two types of sentiment analysis: Lexicon-based sentiment analysis and Sentiment analysis based on machine learning. They found that a combination of both techniques could be found in existing literature. They stated to make effective decisions refined accurate analysis is required. They proposed information fusion to add some information from consumers for which ranking is to be done using sentiment analysis. The approach of using information fusion in ranking products is based on intuitionistic fuzzy theory, use of weighted directed graphs and hesitant fuzzy theory, providing viable and effective product rating algorithms. The approach they proposed performed accurate analysis on a large number of product reviews from the internet.
- Lokhande et. al. [3] proposed a real time search engine where users can find the best product after comparing multiple e-commerce websites like Flipkart, Amazon and Snapdeal. The system compares the price of the product among different websites and then ranks them in descending order. They have 2 possible cases- One, if the product is searched for the first time. This case requires a lot of computational power. The second case is that if the product already exists in the database. In such a case, only the product prices are updated every hour by web crawlers which is a very quick process. The Product ranking algorithm ranks the products based on popularity, prices, ratings and review counts. Sentiment analysis is performed on the user reviews using Word Cloud. Naive Bayes was used for Text classification. First the user entered the product which needs to be searched, then Web crawler crawls web pages based on certain parameters and filtered out the unnecessary products, selected products are stored in a csv file and in the database, then products are ranked in decreasing order based on the ranking algorithm which considers all the parameters and then displayed to the user.
- T. Saranya et. al.[7] identified that a large number of customers have shifted to the online mode of shopping from various E-commerce websites like Amazon, Flipkart, Myntra, etc because they are more convenient, require less time and are cost effective. As a result, customers post product reviews in the E-commerce websites, expressing their reviews and opinions about the product. But, at the same time, it has become very difficult for the customers to purchase products based on their pictures and short descriptions, since they can't judge the quality and performance of the product by merely looking at its image. To tackle this issue, one solution is to rank each product based on the features obtained from the customer reviews. To implement this, they proposed a method "feature-based opinion summarization of reviews" which involves mining of the product features, on which customers have given their opinions and then ranking them based on their frequency of appearance in the reviews. The paper focuses on product reviews on various websites like amazon, etc. They collected the reviews of a product and loaded into the database, which is then fed to the product ranking system. First they extracted product feature followed by categorizing them into implicit and explicit features. Then, they pruned irrelevant features and labelled sentence involving subjective and comparative sentences followed by assigning sentiment orientation to the sentences. Then, they used Ranking algorithm 'Prank' to rank the products. Finally they calculated performance of the ranking system is evaluated using Precision and Recall. They ranked system to produce better results comparing to previously existing system, where the products were ranked based on their overall quality and the features mentioned by the user.
- Syamala et al.[6] used an amazon product URL to get all the reviews on that product and then these reviews are preprocessed. They calculated the polarity of each word and then calculated the sum of polarities. This total words polarity score was then normalized using the formula Normalized Polarity = Polarity MIN (Product-rating).(MAX-MIN), where Product rating is the rating on that review out of 5. Next they used Principal Component Analysis for feature selection. This normalized polarity score and a vector of features was then fed to Ada boost and Random Forest Classifiers for Prediction and Classification of results.
- Bhatt et al.[1] took reviews of iPhone 5s on Amazon and applied four different types of processing. The first method was based on ratings on the review. They classified the review score as 1 if the rating on the review was 4 or 5, the review score was 0 if the rating was 3 and the review score was -1 if the rating was 1 or 2. In second methodology they calculated a polarity score of the entire review. In third methodology, they extracted all the words in the review after the word "NOT" and then preprocessed the string and calculated the polarity score of the words after "Not". Then they inverted it since those words are prefixed by a "Not". In the fourth methodology, they preprocessed the whole review by removing the stopwords, converting to lowercase, removing numerics, whitespaces and special characters and then calculated the sum of polarity scores of all words in the review and classified them. They gave equal weightage to all the four types and then calculated the overall polarity of the review and classified them as positive, negative or neutral.

3 BASELINE RESULTS

First Baseline Model

Methodology -

(1) Create a text file consisting of different mobile phone Urls on amazon. Read this text file and extract data from amazon on these urls.
(2) Create a dataframe consisting of product title, product price, overall rating, total reviews, availability.
(3) Calculate product popularity based on answered questions on the product and append a column for popularity on the dataframe.
(4) Clean the data where there is NA present in the dataframe and drop those rows.
(5) Extract the ratings and total review counts as float values and append to the dataframe.
(6) Now we will normalize the values of four columns- popularity, ratings, price and total review count.
(7) After normalization, give equal weightage to all four attributes and rank the products. Here, we will subtract the value of price, because the lower the price the better the product, where the higher the number of reviews, ratings and popularity, the better is the product.
(8) Create a sorted dataframe based on the above point and this dataframe is used for ranking the products.
(9) Extract top 5 products from the ranked list of products.
(10) Use web scraping to Get all reviews on the top 5 products. Create a dataframe consisting of customer name, review title, rating and review text.
(11) Extract only the review text from the above dataframe and plot a wordcloud consisting of reviews of each product in top 5.
(12) Next, we will do sentiment analysis on reviews using Naive Bayes.
(13) On each review of each top 5 products, get the polarity score and save in a column in the dataframe.
(14) Preprocess each review. Convert to lowercase, Remove stopwords, numerics, special characters and whitespaces and store the preprocessed string in a column in a dataframe.
(15) Based on the polarity score, classify the review as positive if polarity>0, negative if polarity<0 and neutral if polarity=0.
(16) Split the dataset into training and testing with feature matrix as preprocessed query and target matrix as polarity score.
(17) Vectorize the query and train the Multinomial Naive Bayes model.
(18) Apply the model on the test data for predicting the sentiment.
(19) Get the total number of positive and negative review counts for each product.
(20) Calculate the sentiment score by dividing total number of positive and negative reviews with total reviews and giving a score of 1 and -1 respectively.
(21) Give equal weightage to buying probability based on raking and the sentiment score of reviews and get Total score.
(22) Sort the products based on final score.

Result - Naive bayes classification score 90 percent.

Second Baseline Model

Methodology -

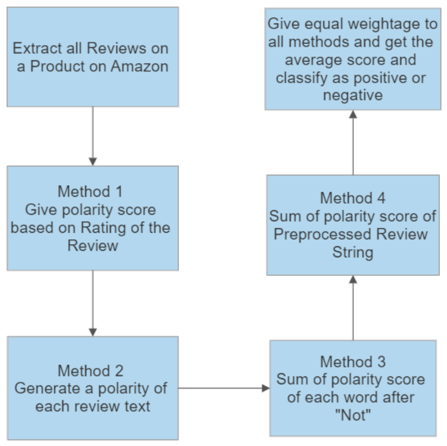
(1) Extracted all reviews on Redmi 9 on Amazon and created a dataframe consisting of Customer Name, Review Title, Rating and Review text.
(2) Extracted the Ratings as a float value and appended a separate column in the dataframe.
(3) **Method 1** - Give a score of 1 to the review if the rating on a review is 4 or 5, give a score of 0 if the rating on a review is 3, and give a score of -1 if the rating is 0 or 1. Append this score in a new column in the dataframe.
(4) **Method 2** - Generate a polarity of each review text. If the polarity>0, give a score of 1, if the polarity<0, give a score -1, and if 0, give a score of 0. Append this score as a new column in the dataframe.
(5) **Method 3** - Extract all the reviews which have the word "Not" in them. Now get all the words in the review after the word "Not". Preprocess this string after the "Not" by converting to lowercase, removing numerics, special characters and stopwords and whitespaces. Now get the polarity score of each word and sum it. If the sum >0, give a score of 1, else -1 and if the sum is 0, then 0. Now invert these signs because this string is prefixed with a "Not" so it has the opposite sentiment. Append this score in a new column in the dataframe.
(6) **Method 4** - Preprocess the whole review text string by converting to lowercase, removing stopwords, numerics, special characters and whitespaces. Now calculate the polarity of this preprocessed words and get the sum of polarities of the words. If the sum>0, give a score of 1, if sum<0 give a score -1 and if the sum is 0, give a score of 0. Append this score in a new column in the dataframe.
(7) Give equal weightage to all the above 4 methodologies and get the average score of each review. If the average score is positive, the review is positive, else negative, and neutral if the average score is 0.
(8) Get the total number of positive and negative reviews on a product and advice the user based on the positive and negative count.

Result - based on the positive and negative review count we advice the user to either buy or not buy the product. Refer to Figure 2

Third Baseline Model

Methodology -

(1) Get all reviews on Redmi 9 Active on Amazon and create a dataframe consisting of Customer Name, Review Title, Rating and Review text.
(2) Extracted the Ratings as a float value and appended a separate column in the dataframe.
(3) Get the polarity of each review and if polarity>0 give a score 1, if polarity<0 give a score -1, and 0 if polarity is 0.



Extract all Reviews on a Product on Amazon
Method 1 Give polarity score based on Rating of the Review
Method 2 Generate a polarity of each review text
Method 3 Sum of polarity score of each word after "Not"
Method 4 Sum of polarity score of Preprocessed Review String
Give equal weightage to all methods and get the average score and classify as positive or negative

Figure 2: Workflow of the Second baseline model

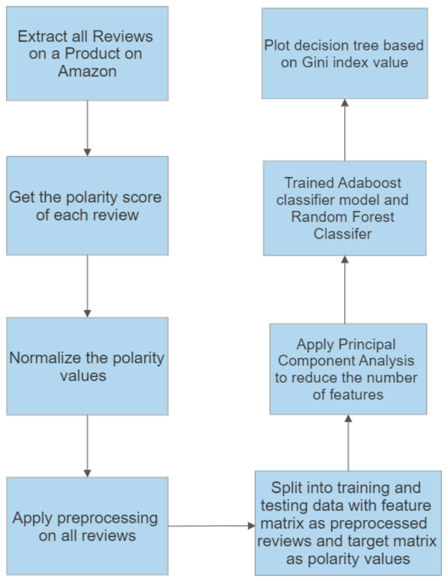
(4) Normalize the polarity values using the formula- Normalized Polarity = Polarity MIN (Product-rating).(MAX-MIN)
(5) Append the Normalized Polarity values in a separate column in the dataframe.
(6) Apply preprocessing on all reviews by converting to lowercase, removing stopwords, numerics, special characters and whitespaces. Append this preprocessed review string in a separate column in the dataframe.
(7) Split into training and testing data with feature matrix as preprocessed reviews and target matrix as polarity values.
(8) Vectorize the review text to numbers.
(9) Apply Principal Component Analysis to reduce the number of features.
(10) Trained Adaboost classifier model and Random Forest classifier and predicted the reviews as positive or negative. Predicted on the test data to get the results.
(11) Plotted a decision tree based on Gini index value.

Result - Random Forest Classifier gave a score of 87.5 percent. Refer to Figure 3

4 PROPOSED METHODOLOGY

We intend to solve our identified problem in following phased manner. Refer to Figure 4

(1) Fetched four URL's for each product- One is the amazon product URL, Flipkart product URL, Amazon All reviews URL of the respective product and Flipkart all reviews of the respective product.
(2) We created a Text file for all 4 URLs of Each product. (Each product will have a separate Text file).
(3) Now using the Product URL, we fetch the Name, Price, Availability, Rating and the Number of Total reviews on that product. Same was done for the Flipkart Product URL.
(4) We combined the dataframe for Amazon and Flipkart of the same product into a single dataframe and Appended a column which specifies the website name and product id.



Extract all Reviews on a Product on Amazon
Get the polarity score of each review
Normalize the polarity values
Apply preprocessing on all reviews
Split into training and testing data with feature matrix as preprocessed reviews and target matrix as polarity values
Apply Principal Component Analysis to reduce the number of features
Trained Adaboost classifier model and Random Forest Classifer
Plot decision tree based on Gini index value

Figure 3: Workflow of the Third baseline model

(5) Next we cleaned this data- removed NaN and Null entries, removed punctuations, and converted the ratings etc. to float values. (Correct data types as required).
(6) Next, we fetch all Reviews on the respective Product using the "See all Reviews" URL from the text file. This was also done for both Amazon and Flipkart URLs. We used web scraping using BeautifulSoup library and going class by class over each element.
(7) We also combined the reviews from Amazon and Flipkart for the same product into a single dataframe and Appended a column which specifies the website name from which the reviews were fetched and also appended a column specifying the ID of the product.
(8) Next we cleaned this review data- removed NaN and Null entries and removed punctuations.
(9) Next we also combined the dataframes of Multiple products that we want to compare. This was also done for both dataframes, one for product details and one for reviews.
(10) By now, we have our data ready- which consists of Two dataframes- one specifying product details of all the products and one containing all reviews of all the products
(11) **METHOD 1**- Take the Product details dataframe and Normalized the Price, Rating and Total number of reviews columns using the formula- Normalized Value=(Value- Min) / (Max-Min).
(12) We now calculated a score using these normalized values using the formula - Score= Ratings + Reviews - Price.
(13) **METHOD 2**- Aspect Based Ranking- We took different aspects of Mobile Phones like- design, display, software, performance, battery life, value for money and camera. We Processed the review dataframe constructed in (10) and extracted all reviews which contains these specific keywords/aspects.

(14) Next we processed these reviews and fetched a polarity score of those reviews for that particular aspect.
(15) We stored this information of aspect based score by creating a dictionary which has the particular aspect as the Keys and the polarity score of that review as the value. This was created for each review.
(16) Now we iterated this dictionary for each product and calculated the average polarity of that aspect for the respective product.
(17) We appended this aspect based polarity columns in the dataframe.
(18) **Method 3** - We iterated through each review from the concatenated dataframe, and pre-processed each review by first converting to lower case, removing numerics, remove whitespaces, stripping white spaces left and right, remove stopwords and finally stemming the review, then on the pre-processed review we checked polarity using textblob.
(19) Then, for each device we extracted polarity review score for the device, and calculated average polarity of the device and stored in the dataframe.
(20) **Method 4** - We splitted the review in training and testing, for the training reviews we pre-processed the reviews and then labeled it's polarity in terms of positive, negative and neutral as the labelled data, then applied naive bayes on the training data as it is one of the most accurate algorithm in case of classification of supervised data in text classification. We achieved an accuracy of 82.23 on validation data.
(21) Then, for the rest of the data, we generated polarity score of it, using the already trained model, and stored all the results in an extra column in our already created dataframe.
(22) Finally we calculated cumulative score by calculating the average of scores obtained in all of the four methods mentioned above.
(23) On basis of score we ranked our products.

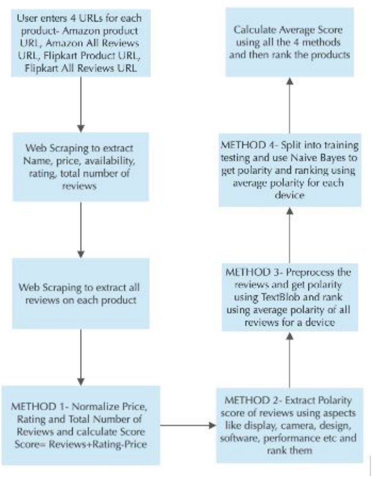

User enters 4 URLs for each product- Amazon product URL, Amazon All Reviews URL, Flipkart Product URL, Flipkart All Reviews URL
Web Scraping to extract Name, price, availability, rating, total number of reviews
Web Scraping to extract all reviews on each product
METHOD 1- Normalize Price, Rating and Total Number of Reviews and calculate Score Score= Reviews+Rating-Price
METHOD 2- Extract Polarity score of reviews using aspects like display, camera, design, software, performance etc and rank them
METHOD 3- Preprocess the reviews and get polarity using TextBlob and rank using average polarity of all reviews for a device
METHOD 4- Split into training testing and use Naive Bayes to get polarity and ranking using average polarity for each device
Calculate Average Score using all the 4 methods and then rank the products

Figure 4: Planned Workflow for the project

5 EXPLORATORY DATA ANALYSIS

5.1 Length of Review V/S Rating

This signifies that most users with rating 4.0 are the one which write descriptive review as compared to others, hence most information could be extracted out of it.**Refer to Figure** 5

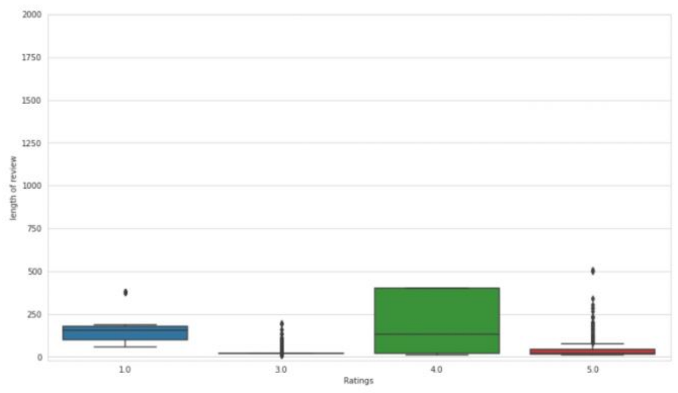


Figure 5: Length of Review V/S Rating

5.2 Number of Ratings V/S Ratings

This signifies reviews with the rating; hence we can interpret from here that most reviews are for rating 1 hence, mostly negative reviews out there for the selected devices.**Refer to Figure** 6

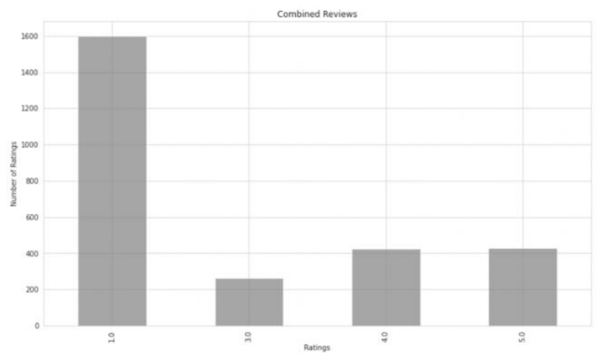


Figure 6: Number of Ratings V/S Ratings

5.3 Count of Features V/S Features

This is the pictorial representation of which feature is repeated how many times in the complete database.**Refer to Figure** 7

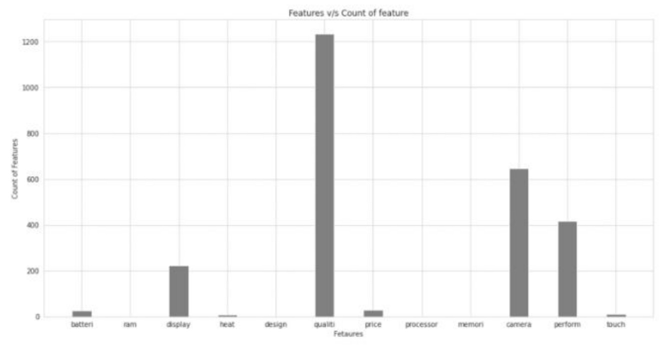
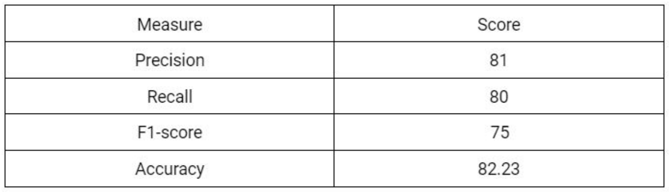


Figure 7: Count of Features V/S Features

6 EVALUATION METRIC

We applied Naive Bayes model to predict polarity of the sentence in terms of positive, negative or neutral polarity; model was trained on sample of reviews with labelled polarity calculated using textblob, then the same model was applied to predict polarity for the remaining of reviews.

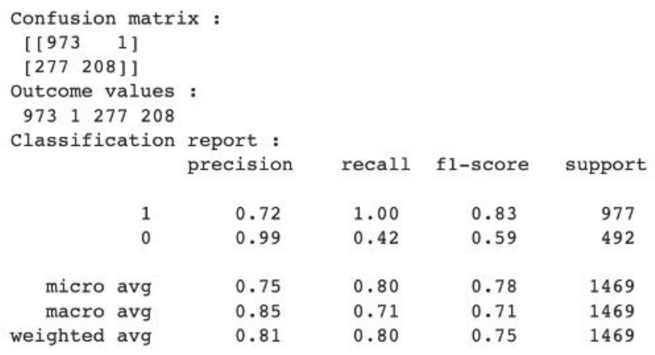
On the validation data, we got an accuracy of 82.23. We got precision, recall and f1-score of 81, 80 and 75 percent respectively. Evaluation metric is noted as follows. **Refer to Figure** 8



Measure	Score
Precision	81
Recall	80
F1-score	75
Accuracy	82.23

Figure 8: Scores of Different Evaluation Metrics used

Screenshot for the same is attached as follows. **Refer to Figure** 9



```
Confusion matrix :
 [[973   1]
 [277 208]]
Outcome values :
 973 1 277 208
Classification report :
              precision    recall  f1-score   support

           1       0.72      1.00      0.83       977
           0       0.99      0.42      0.59       492

   micro avg       0.75      0.80      0.78      1469
   macro avg       0.85      0.71      0.71      1469
weighted avg       0.81      0.80      0.75      1469
```

Figure 9: Confusion Matrix and Classification Report

7 CONCLUSION

Our ranking of devices are novel in its approach because of we considered ranking of products based on all amalgamation of features such as product price, overall rating, total reviews, different aspects of the device (design, display, software, performance, battery life, value for money and camera), sentiment polarity and polarity calculated on basis of naive bayes model.

Since it is combination of all kind of features it is ranking devices using every minute aspect and hence, giving better results as compared to other high level models.

REFERENCES

[1] Aashutosh Bhatt, Ankit Patel, and Kiran Gawande Harsh Chheda. “Amazon Review Classification and Sentiment Analysis”. In: *International Journal of Computer Science and Information Technologies* 6 (2015), pp. 5107–5110.

[2] Zhi-Ping Fan, Guang-Ming Li, and Yang Liu. “Processes and methods of information fusion for ranking products based on online reviews: An overview”. In: *Information Fusion* 60 (Feb. 2020). DOI: 10.1016/j.inffus.2020.02.007.

[3] Suyash Lokhande et al. “Product Rank Algorithm Along with Sentiment Analysis on Reviews of E- Commerce Websites”. In: 2021.

[4] Gobi Natesan and A. Rathinavelu. “Analyzing cloud based reviews for product ranking using feature based clustering algorithm”. In: *Cluster Computing* 22 (May 2019). DOI: 10.1007/s10586-018-1996-3.

[5] Karthik R V, Ganapathy Sannasi, and Kannan Arputharaj. “A Recommendation System for Online Purchase Using Feature and Product Ranking”. In: Aug. 2018, pp. 1–6. DOI: 10.1109/IC3.2018.8530573.

[6] Maganti Syamala and Nattanmai Jeganathan Nalini. “A Filter Based Improved Decision Tree Sentiment Classification Model for RealTime Amazon Product Review Data”. In: *International Journal of Intelligent Engineering and Systems* 13 (Feb. 2020), pp. 191–202.

[7] T.Saranya. “Mining Features and Ranking Products From Online Customer Reviews”. In: *International Journal of Engineering Research Technology* 2 (Oct. 2013), pp. 643–648.