FLIP ROBO

RATINGS PREDICTION PROJECT

Submitted by:

Prerna Jain

ACKNOWLEDGEMENT

The internship opportunity I have with Flip Robo Technologies is a great chance for learning and professional development. I perceive this opportunity as a big milestone in my career development. I will strive to use gained skills acknowledge in the best possible way.

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References: www.scipy.org, Kaggle, Github

INTRODUCTION

- ## Business Problem Framing

  We have a client who has a website where people write different reviews for technical products. Now they are adding a new feature to their website i.e. The reviewer will have to add stars(rating) as well with the review. The rating is out 5 stars, and it only has 5 options available 1 star, 2 stars, 3 stars, 4 stars, 5 stars. Now they want to predict ratings for the reviews which were written in the past and they don't have ratings. So, we have to build an application which can predict the rating by seeing the review.

- ## Conceptual Background of the Domain Problem

  Nowadays, a massive number of reviews are available online. Besides offering a valuable source of information, these informational contents generated by users also called User Generated Contents (UGC) strongly impact the purchase decision of customers. As a matter of fact, a recent survey (Hinckley, 2015) revealed that 67.7% of consumers are effectively influenced by online reviews when making their purchase decisions. More precisely, 54.7% recognized that these reviews were either fairly, very or absolutely important in their purchase decision making. Relying on online reviews has thus become second nature for consumers

- ## Review of Literature

  The rapid development of Web 2.0 and e-commerce has led to a proliferation in the number of online user reviews. Online reviews contain a wealth of sentiment information that is important for many decision-making processes, such as personal consumption decisions, commodity quality monitoring, and social opinion mining. Mining the sentiment and opinions that are contained in online reviews has become an important topic in natural language processing, machine learning, and Web mining.

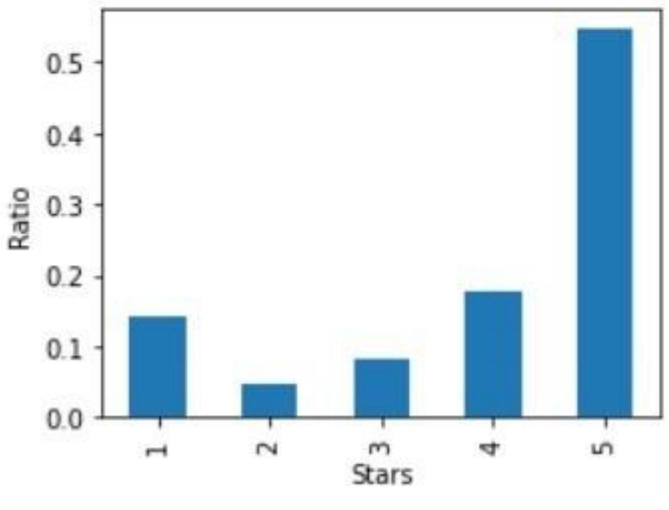
- Motivation for the Problem Undertaken

  Many product reviews are not accompanied by a scale rating system, consisting only of a textual evaluation. In this case, it becomes daunting and time-consuming to compare different products to eventually make a choice between them. Therefore, models able to predict the user rating from the text review are critically important. Getting an overall sense of a textual review could in turn improve the consumer experience.

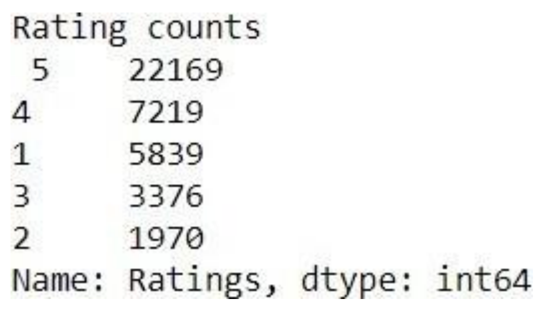
Analytical Problem Framing

- Mathematical/ Analytical Modelling of the Problem

  There are in total 33294 rows and 2 columns of ratings and reviews present in our dataset.
  We found the occurrence of rating ratio as shown below,



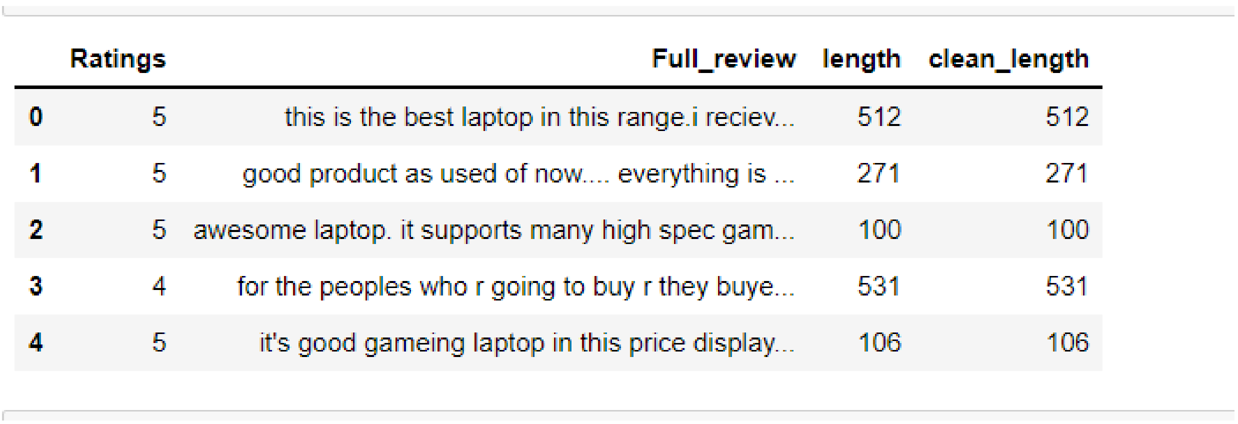
We can observe that our dataset is quite imbalanced.



```
Rating counts
 5     22169
4      7219
1      5839
3      3376
2      1970
Name: Ratings, dtype: int64
```

Maximum, 22169 number of ratings present is of 5 stars and minimum, 1970 is of 2 stars.

We then create two more columns length and clean_leangth based on the lengths of the text before and after cleaning for our analysis purpose.



	Ratings	Full_review	length	clean_length
0	5	this is the best laptop in this range.i reciev...	512	512
1	5	good product as used of now.... everything is ...	271	271
2	5	awesome laptop. it supports many high spec gam...	100	100
3	4	for the peoples who r going to buy r they buye...	531	531
4	5	it's good gameing laptop in this price display...	106	106

- Data Sources and their formats

  The variable features of this problem statement are,

- **Ratings:** It is the Label column, which includes ratings in the form of integers from 1 to 5.
- **Full review:** It contains text data on the basis of which we have to build a model to predict ratings.

- Data Pre-processing Done

We first looked for the null values present in the dataset. We noticed that there were no null values present in our dataset. Then we performed text processing. Data usually comes from a variety of sources and often in different formats. For this reason, transforming your raw data is essential. However, this is not a simple process, as text data often contain redundant and repetitive words. This means that processing the text data is the first step in our solution. The fundamental steps involved in text pre-processing are, Cleaning the raw data Tokenizing the cleaned data.

- Cleaning the Raw Data

This phase involves the deletion of words or characters that do not add value to the meaning of the text. Some of the standard cleaning steps are listed below:
Lowering case Removal

of special characters

Removal of stop words

Removal of hyperlinks

Removal of numbers

Removal of whitespaces

- Lowering Case

Lowering the case of text is essential for the following reasons: The words, ‘TEXT’, ‘Text’, ‘text’ all add the same value to a sentence Lowering the case of all the words is very helpful for reducing the dimensions by decreasing the size of the vocabulary.

- Removal of special characters

This is another text processing technique that will help to treat words like ‘hurray’ and ‘hurray!’ in the same way.

- Removal of stop words

Stop words are commonly occurring words in a language like ‘the’, ‘a’, and so on. Most of the time they can be removed from the text because they don’t provide valuable information.

- Set of assumptions related to the problem under consideration

By looking into the target variable label, we assumed that it was a multiclass classification type of problem. We observed that the dataset was imbalanced so we will have tobalance the dataset for a better outcome.

- Hardware and Software Requirements and Tools Used

This project was done on laptop with i5 processor with quad cores and eight threads with 8gb of ram and latest GeForce GTX 1650 GPU on Anaconda, Jupiter notebook.

The tools, libraries, and packages we used for accomplishing this project are pandas, NumPy, matplotlib, seaborn, word cloud, tiff vectorizer, smote, Grid search, joblib.

Through the pandas library, we loaded our CSV file 'messages' into the data frame and performed data manipulation and analysis.

With the help of NumPy, we worked with arrays.

With the help of matplotlib and seaborn, we did plot variousgraphs and figures and did data visualization.

With word cloud, we got a sense of loud words present in the dataset. Through the TF-IDF vectorizer, we converted text into vectors.

Through smote technique we handled the imbalanced dataset.

Through Gridsearchcv we tried to find the best parameters of the random forest classifier.

Through joblib, we saved our model in CSV format.

Model/s Development and Evaluation

- Identification of possible problem-solving approaches (methods)

  Pre-processing involved the following steps:
  Removing Punctuations and other special characters

  Removing Stop Words

  Stemming and

  Lemmatising Applying tfidf

  Vectorizer

  Splitting dataset into Training and Testing

- Testing of Identified Approaches (Algorithms)

  The algorithms we used for the training and testing are as

  follows: - Decision tree classifier

  Kneighbors classifier

  Multinominal

  Randomforest classifier

  Ad boost classifier

  Gradient boosting

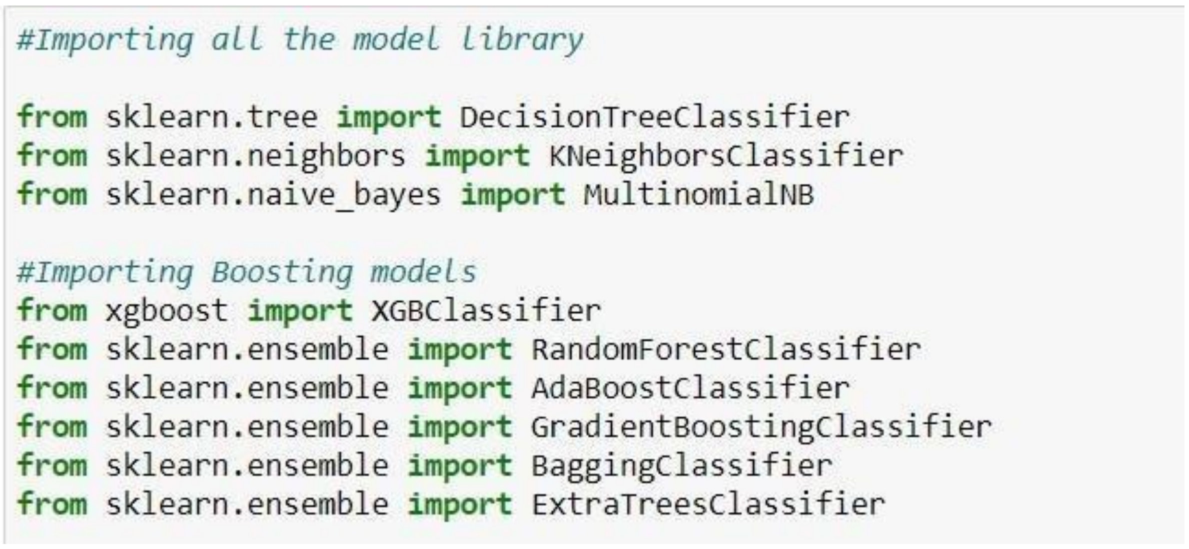
  classifier Bagging

  classifier

  Extra trees classifier

- Run and evaluate selected models

  The algorithms we used are shown in fig,

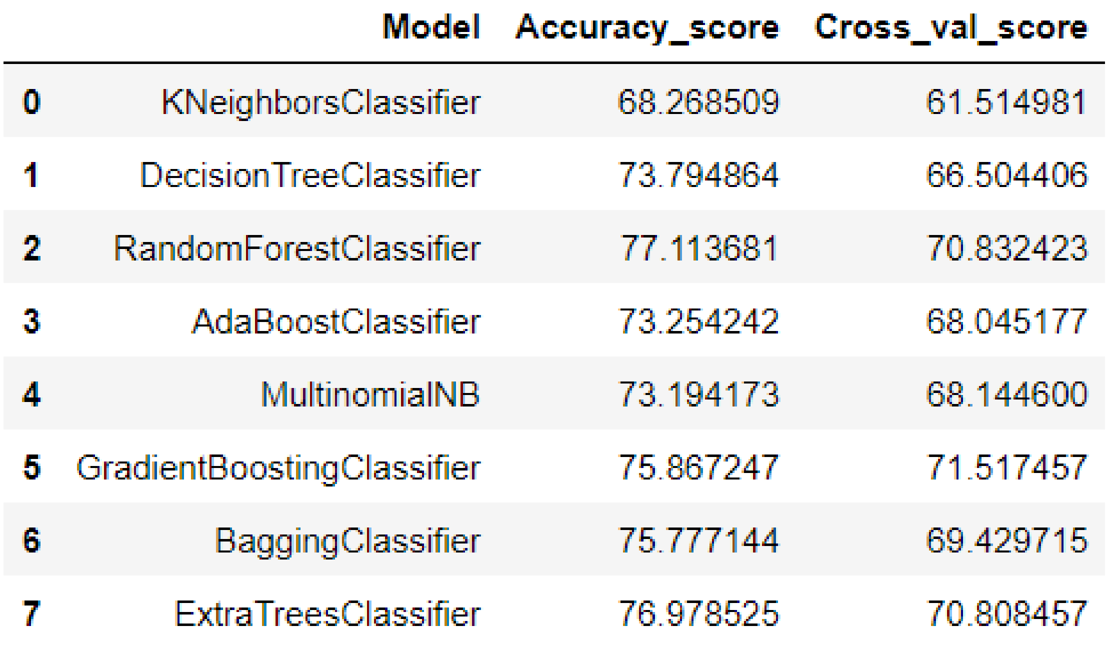


```
#Importing all the model library

from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB

#Importing Boosting models
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import ExtraTreesClassifier
```

The results observed over different evaluation metrics are shown in fig,



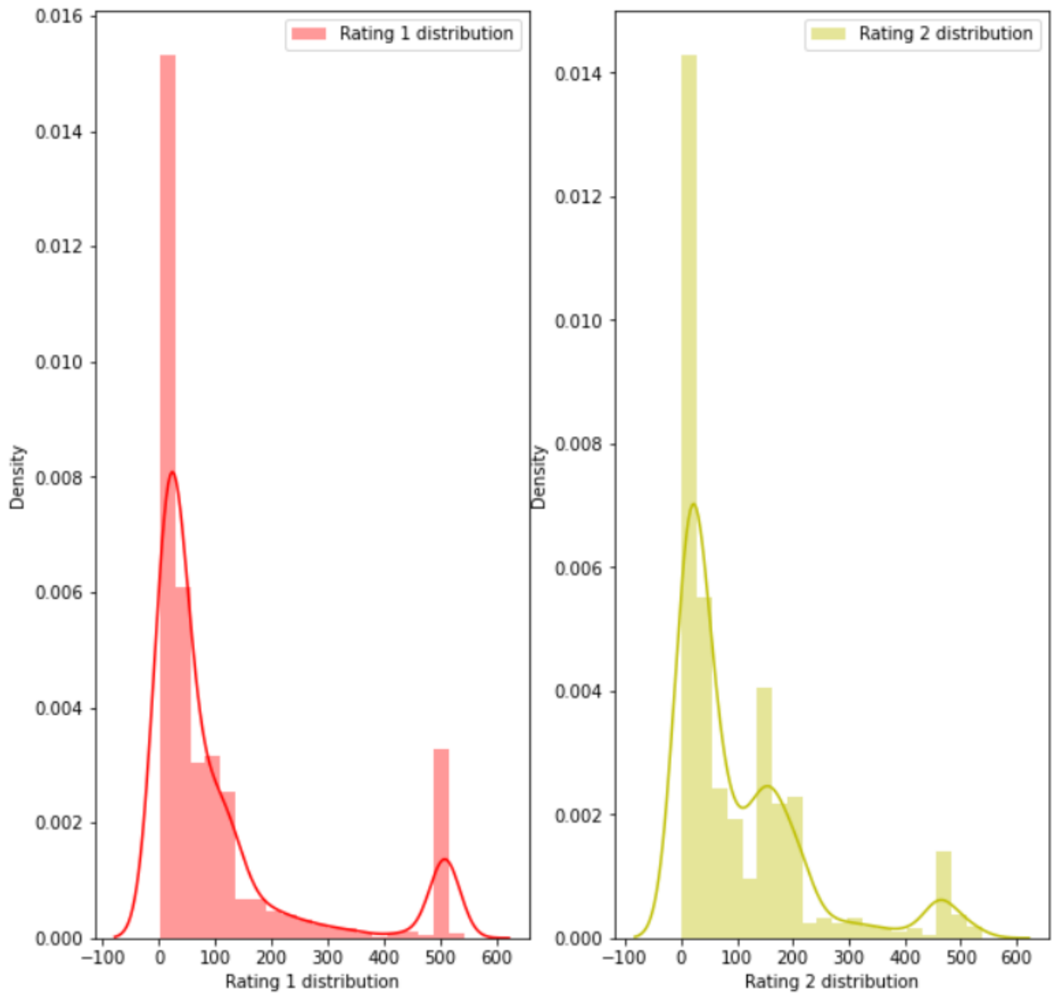
	Model	Accuracy_score	Cross_val_score
0	KNeighborsClassifier	68.268509	61.514981
1	DecisionTreeClassifier	73.794864	66.504406
2	RandomForestClassifier	77.113681	70.832423
3	AdaBoostClassifier	73.254242	68.045177
4	MultinomialNB	73.194173	68.144600
5	GradientBoostingClassifier	75.867247	71.517457
6	BaggingClassifier	75.777144	69.429715
7	ExtraTreesClassifier	76.978525	70.808457

- Key Metrics for success in solving the problem under consideration

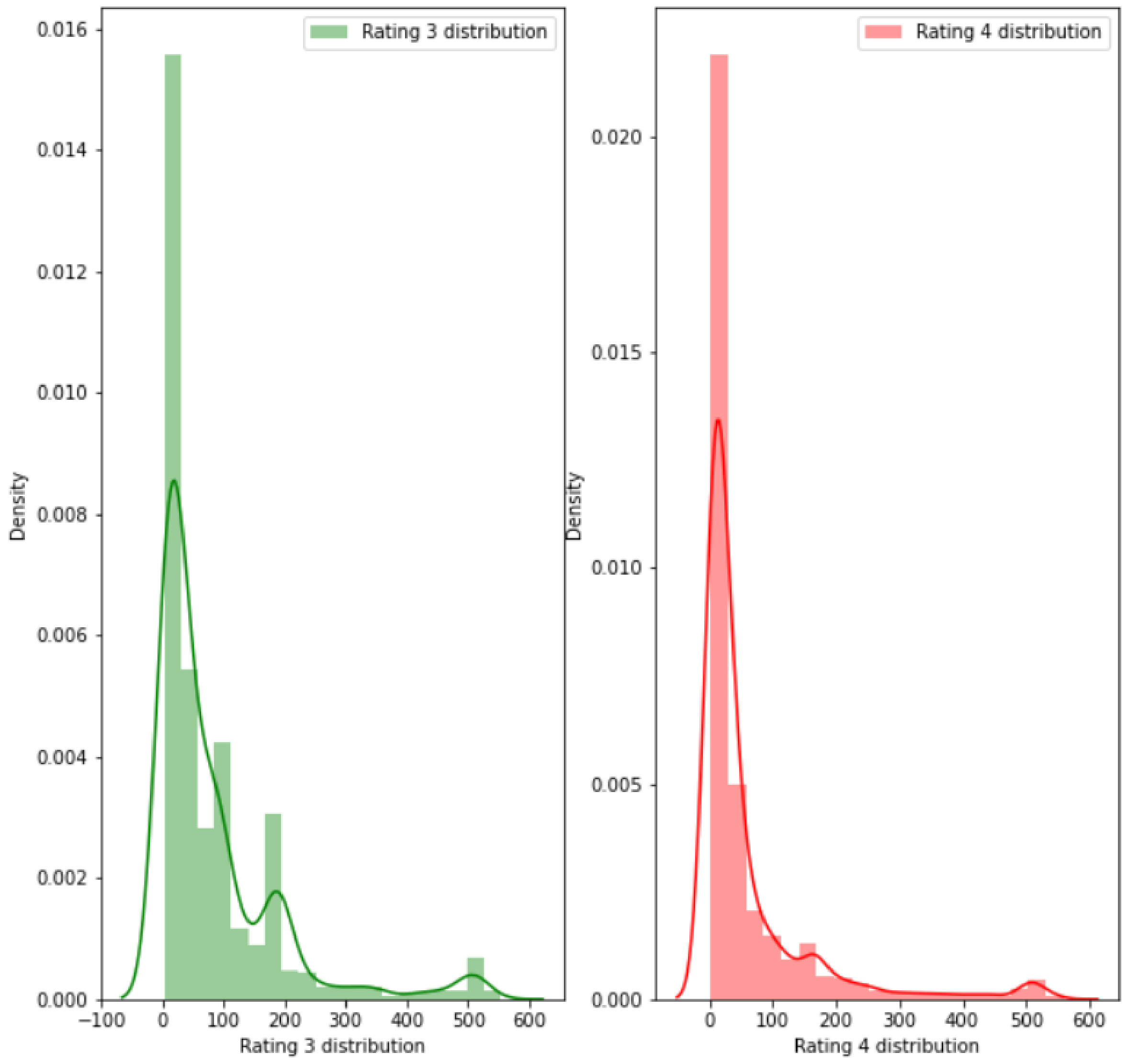
On the basis of the accuracy and confusion matrix, we savetRandom Forest classifier as our final model.

- Visualizations

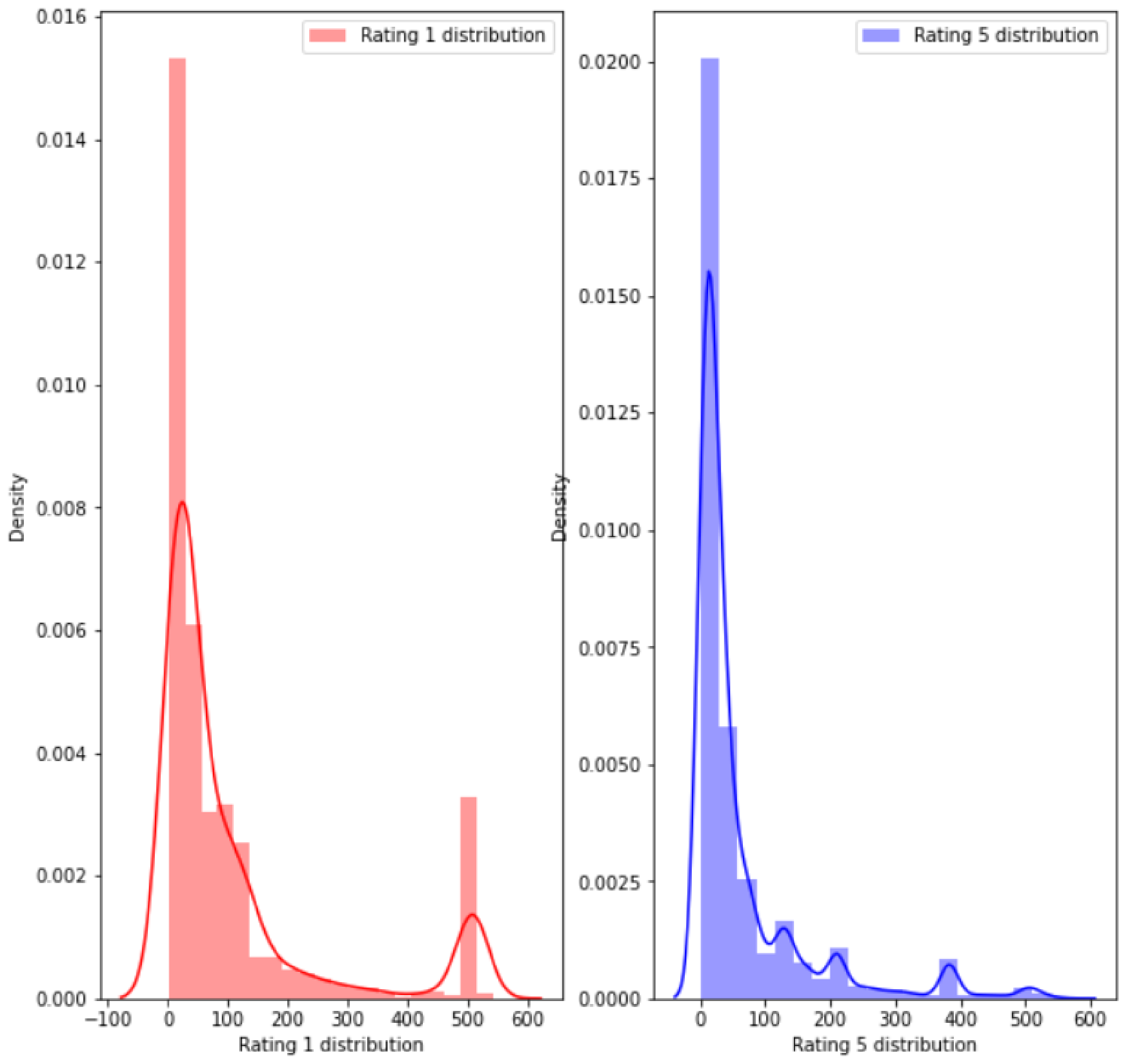
Rating 1 and Rating 2 distribution after cleaning the reviews:



Rating 3 and Rating 4 distribution after cleaning the reviews:

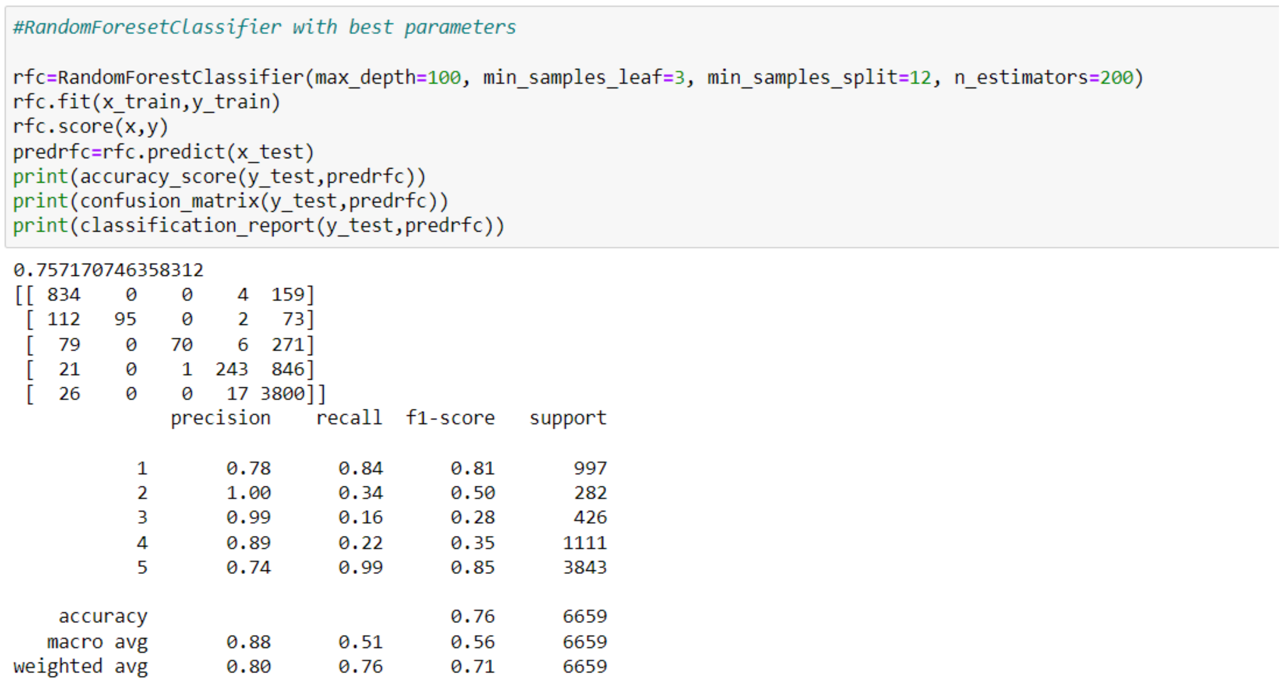


Rating 1 and Rating 5 distribution after cleaning reviews:



- Interpretation of the Results

  We interpreted that Random Forest classifier model was giving us the best results with an accuracy score of 77.11 and a comparatively better f1-score so we saved it as our final model.



```
#RandomForesetClassifier with best parameters

rfc=RandomForestClassifier(max_depth=100, min_samples_leaf=3, min_samples_split=12, n_estimators=200)
rfc.fit(x_train,y_train)
rfc.score(x,y)
predrfc=rfc.predict(x_test)
print(accuracy_score(y_test,predrfc))
print(confusion_matrix(y_test,predrfc))
print(classification_report(y_test,predrfc))
```

```
0.757170746358312
[[ 834    0    0    4  159]
 [ 112   95    0    2   73]
 [  79    0   70    6  271]
 [  21    0    1  243  846]
 [  26    0    0   17 3800]]
              precision    recall  f1-score   support

           1       0.78      0.84      0.81       997
           2       1.00      0.34      0.50       282
           3       0.99      0.16      0.28       426
           4       0.89      0.22      0.35      1111
           5       0.74      0.99      0.85      3843

    accuracy                           0.76      6659
   macro avg       0.88      0.51      0.56      6659
weighted avg       0.80      0.76      0.71      6659
```

CONCLUSION

- ## Key Findings and Conclusions of the Study

In this project, we have tried to detect the Ratings on commercial websites on a scale of 1 to 5 based on the reviews given by the users. We made use of natural language processing and machine learning algorithms to do so. We interpreted that Random Forest classifier model is giving us best results.

- ## Learning Outcomes of the Study in respect of Data Science

Through this project we were able to learn various Natural language processing techniques like lemmatization, stemming, and removal of stopwords.

This project has demonstrated the importance of sampling effectively, modelling and predicting data.

Through different powerful tools of visualization, we were able to analyses and interpret different hidden insights about the data.

The few challenges while working on this project were: -

- Imbalanced dataset
- Lots of text data

The dataset was highly imbalanced, so we balanced the dataset using smote technique.

We converted text data into vectors with the help of tfidf vectorizer.

• Limitations of this work and Scope for Future Work

While we couldn’t reach our goal of maximum accuracy in the Ratings prediction project, we did end up creating a system that can with some improvement and deep learning algorithms get very close to that goal. As with any project, there is room for improvement here. The very nature of this project allows for multiple algorithms to be integrated together as modules and their results can be combined to increase the accuracy of the result. This model can further be improved with the addition of more algorithms into it. However, the output of these algorithms needs to be in the same format as the others. Once that condition is satisfied, the modules are easy to add as done in the code. This provides a great degree of modularity and versatility to the project.