
# Rating Prediction Project

Submitted by:

PUNEET JAWA

# ACKNOWLEDGMENT

I want to thanks our SME Miss. Khushboo Garg for providing the Dataset and helping us to solve the problem and addressing out our Query in right time.

# 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 rating. So we, we have to build an application which can predict the rating by seeing the review.

## Conceptual Background of the Domain Problem

Nowadays, a massive amount of reviews is 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 a 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.

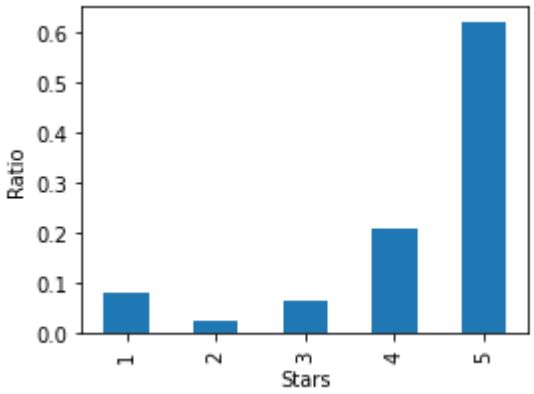
## Motivation for the Problem Undertaken

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 in order 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 consumer experience.

# Analytical Problem Framing

## Mathematical/ Analytical Modelling of the Problem

There are in total 15766 rows and 3 columns of ratings and reviews are present in our dataset. We found the occurrence of ratings ratio as shown below.




We can observe that our dataset is quite imbalanced.

```
Rating counts
 5    9753
4    3283
1    1253
3    1062
2     415
Name: Ratings, dtype: int64
```

Maximum, 9753 number of ratings present is of 5 star and minimum, 415 is of 2 star. We then create two more columns length and clean. length on the basis of the lengths of the text before and after cleaning for our analysis purpose.

:

| | Review_title | Review_text | Ratings | length |
|---|---|---|---|---|
| 0 | Terrific | I am writing this review after using the lapto... | 5 | 361 |
| 1 | Simply awesome | Delivery : Due to some reasons the delivery go... | 5 | 507 |
| 2 | Just wow! | Flipkart, you rock!\nHowever, this is the 1st ... | 5 | 463 |
| 3 | Fair | Have bought this laptop but performance is ver... | 3 | 386 |
| 4 | Wonderful | Delivery was on time and nicely packaged. Got ... | 4 | 510 |

## 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.

Review_text: 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 contains redundant and repetitive words. This means that processing the text data is the first step in our solution. The fundamental steps involved in text preprocessing 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 stopwords

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** Stopwords 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 dataset was imbalance so we will have to balance the dataset for better outcome.

**Hardware and Software Requirements and Tools Used**

The tools, libraries and packages we used for accomplishing this project are pandas, numpy, matplotlib, seaborn, wordcloud, tfidf vectorizer, smote, Gridsearchcv, joblib. Through pandas library we loaded our csv file 'messages' into dataframe 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 various graphs and figures and done data visualization. With wordcloud we got sense of loud words present in the dataset. Through tfidf vectorizer we converted text into vectors. Through smote technique we handled the imbalanced dataset. Through Gridsearchcv we tried to find the best parameters of random forest classifier. Through joblib we saved our model in csv format.

**Model/s Development and Evaluation**

Identification of possible problem-solving approaches (methods) Preprocessing 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

Random forest classifier

Adaboost classifier

Gradient boosting 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


#Importing Boosting models

from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
```

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

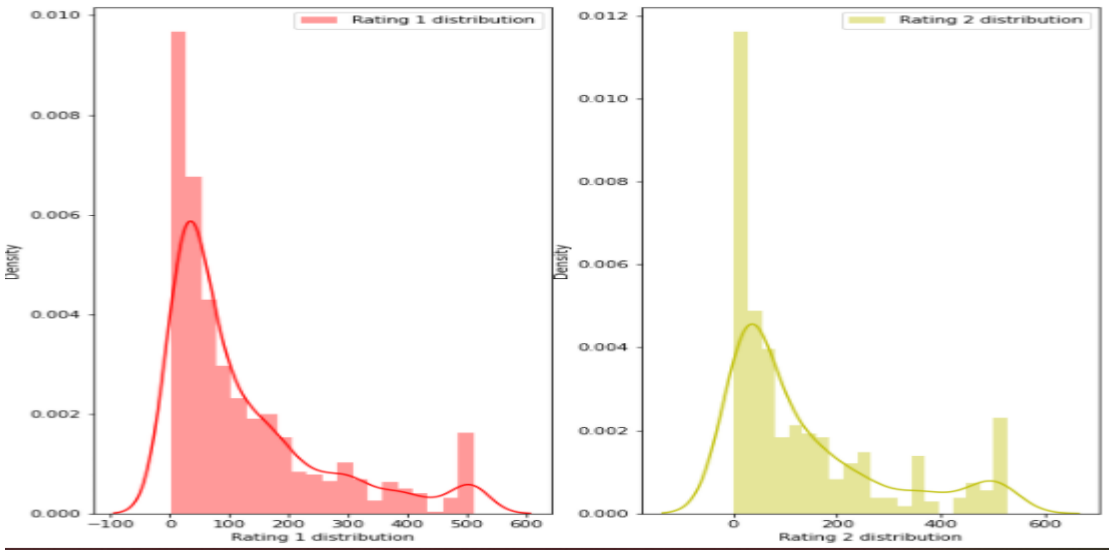
| | Model | Accuracy_score | Cross_val_score |
|---|---|---|---|
| 0 | KNeighborsClassifier | 71.754757 | 63.319985 |
| 1 | DecisionTreeClassifier | 75.877378 | 67.493822 |
| 2 | RandomForestClassifier | 79.725159 | 72.846935 |
| 3 | AdaBoostClassifier | 53.784355 | 65.793432 |
| 4 | GradientBoostingClassifier | 63.128964 | 67.950180 |

**Key Metrics for success in solving problem under consideration**

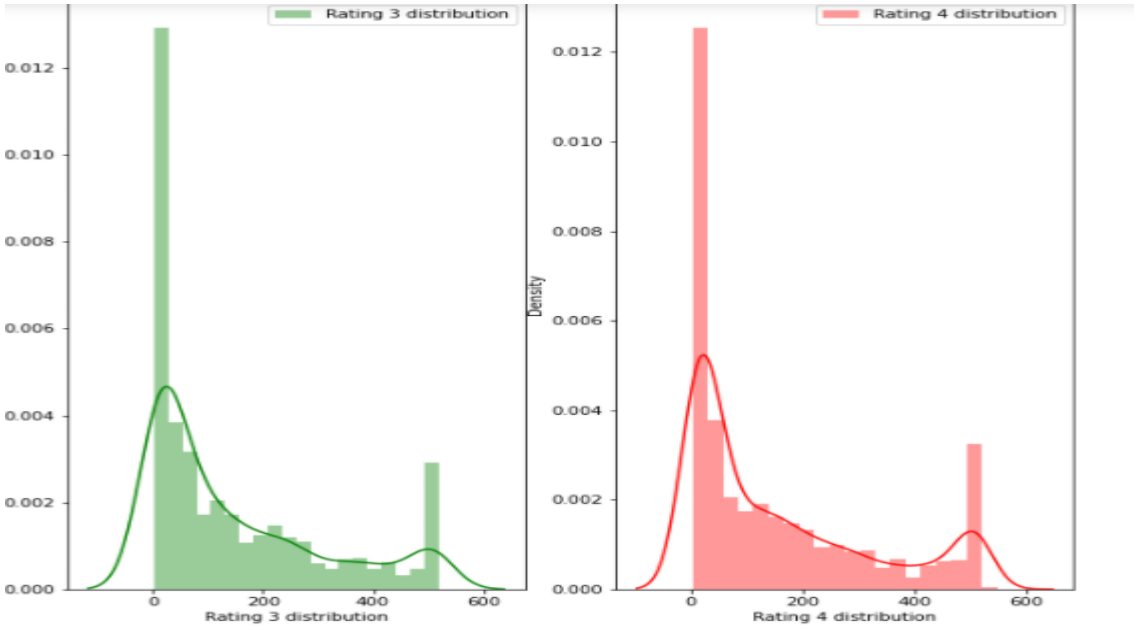
On the basis of accuracy and confusion matrix we save Random forest classifier as our final model.

**Visualizations**

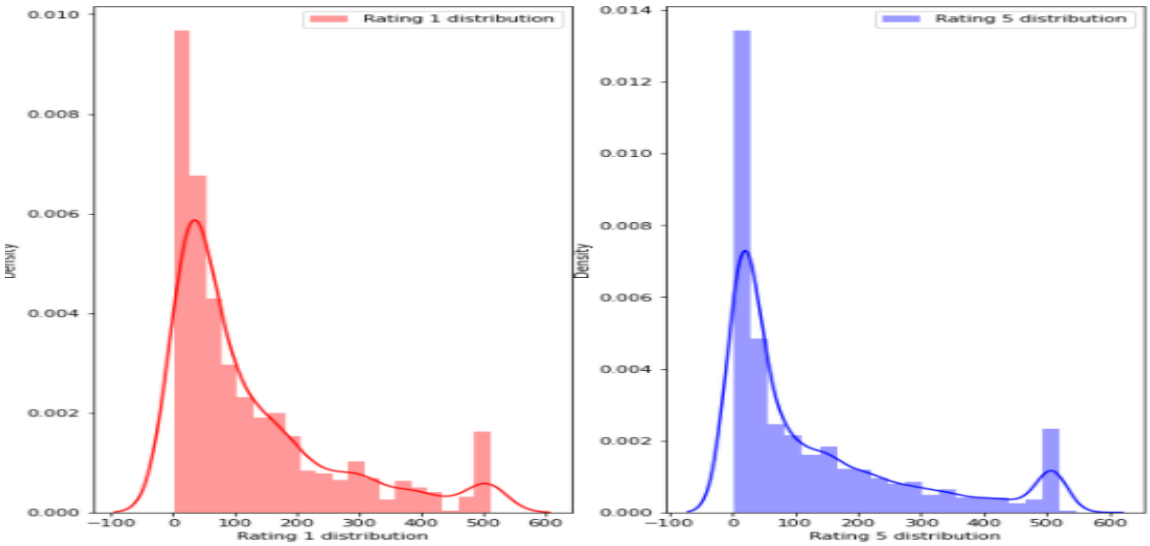
Rating 1 and Rating 2 distribution after cleaning the reviews:



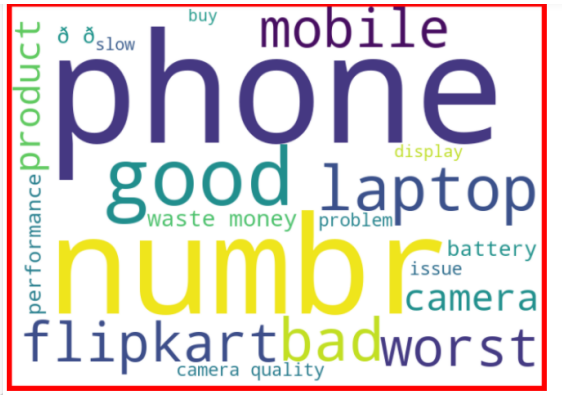

Rating 3 and Rating 4 distribution after cleaning the reviews



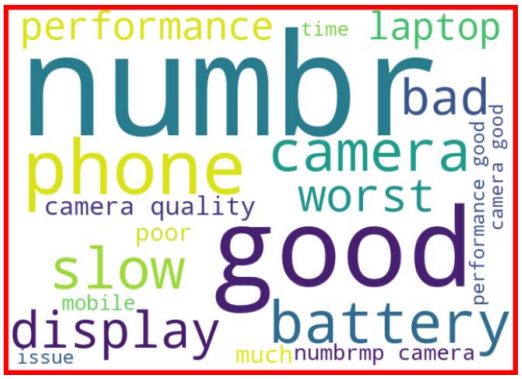

Rating 1 and Rating 5 distribution after cleaning reviews




getting sense of review Loud words in Rating 1:

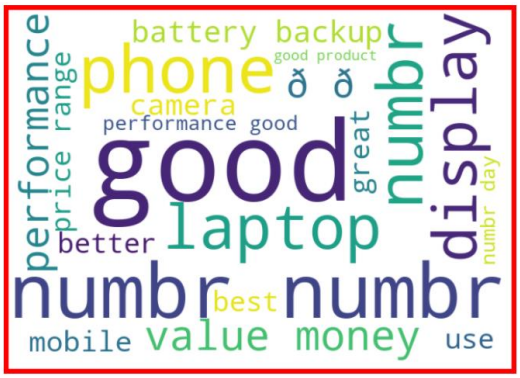



getting sense of review Loud words in Rating 2

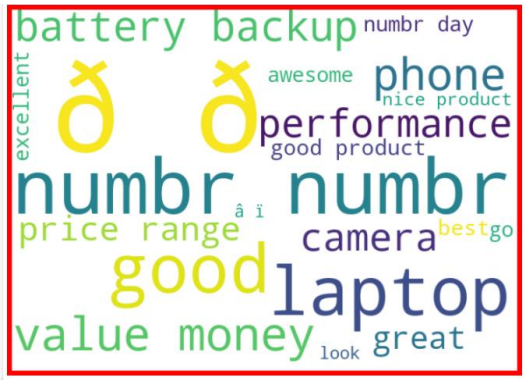



getting sense of review Loud words in Rating 3:


getting sense of review Loud words in Rating 4



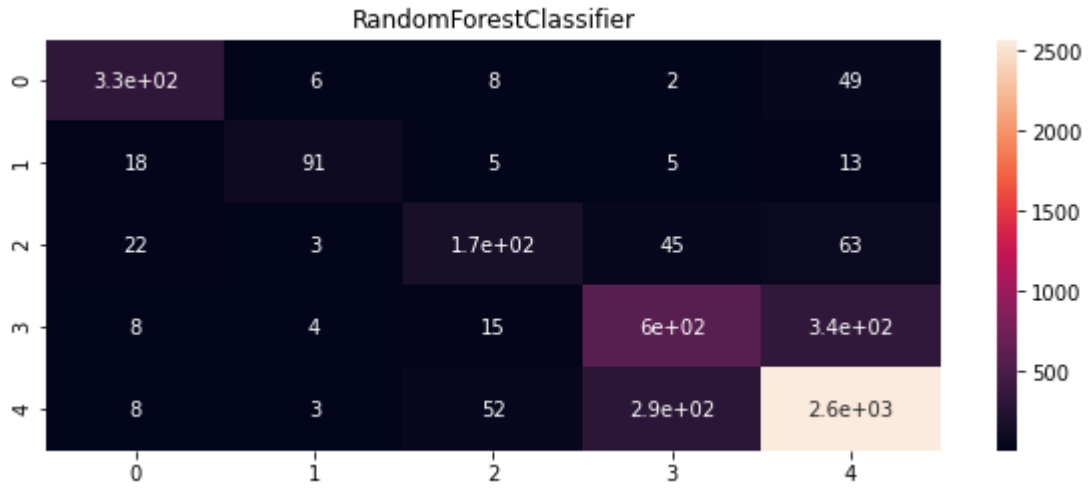

getting sense of review Loud words in Rating 5



## Interpretation of the Results

We interpreted that Random forest classifier model was giving us the best results with the accuracy score of 79.15 and comparatively better f1-score so we saved it as our final model.

```
RandomForestClassifier()


Accuracy_score =  0.7915433403805496


Cross_Val_Score =  0.7290401326875934


classification_report
              precision    recall  f1-score   support

           1       0.84      0.83      0.83       397
           2       0.88      0.69      0.77       132
           3       0.54      0.57      0.56       304
           4       0.67      0.59      0.63       972
           5       0.84      0.88      0.86      2925

    accuracy                           0.79      4730
   macro avg       0.75      0.71      0.73      4730
```



# CONCLUSION

Key Findings and Conclusions of the Study In this project we have tried to detect the Ratings in commercial websites on a scale of 1 to 5 on the basis of the reviews given by the users. We interpreted that Random forest classifier model is giving us best results.

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 out goal of maximum accuracy in 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 final 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.