

# **Ratings Prediction Project**

**Submitted by:** 

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## **ACKNOWLEDGMENT**

The project entitled "RATINGS PREDICTION PROJECT" is done by me during my internship with Flip Robo Technologies. I am grateful to Data Trained and Flip Robo Technologies for their guidance during this project. Other reference websites used to complete this project are:

- 1. Stackoverflow.com
- 2. Towardsdatascience.com
- 3. Medium.com

#### INTRODUCTION

## **Conceptual Background of the Domain Problem**

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

## **Problem Statement**

**Ratings Prediction:** We have to predict ratings of all the products based on the reviews given by customers which will be pre-processed and trained.

# **Analytical Problem Framing**

#### **Data Collection Phase**

• We have to scrape at least 20000 rows of data. You can scrape more data as well, it's up to you. More the data better the model In this section you need to scrape the reviews of different laptops, Phones, Headphones, smart watches, Professional Cameras, Printers, monitors, Home theater, router from different e-commerce websites. Basically, we need these columns: 1) reviews of the product. 2) rating of the product. You can fetch other data as well, if you think data can be useful or can help in the project. It completely depends on your imagination or assumption. Hint: – Try fetching data from different websites. If data is from different websites, it will help our model to remove the effect of over fitting. - Try to fetch an equal number of reviews for each rating, for example if you are fetching 10000 reviews then all ratings 1,2,3,4,5 should be 2000. It will balance our data set. - Convert all the ratings to their round number, as there are only 5 options for rating i.e., 1, 2, 3, 4, 5. If a rating is 4.5 convert it 5.

### **Model Building Phase**

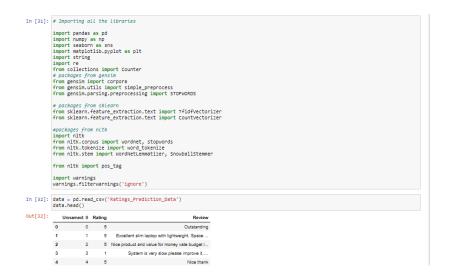
- After collecting the data, you need to build a machine learning model.
   Before model building, do all data pre-processing steps involving NLP.
   Try different models with different hyper parameters and select the best model. Follow the complete life cycle of data science. Include all the steps like
  - 1. Data Cleaning
  - 2. Exploratory Data Analysis
  - 3. Data Pre-processing
  - 4. Model Building
  - 5. Model Evaluation
  - 6. Selecting the best model
- Firstly we have collected data i.e, we did webscraping of a website Flipcart and passed collected all the reviews and ratings of products that we wanted to scrape such as: ['laptops', 'Phones', 'Headphones', 'smart

watches', 'Professional Cameras', 'Printers', 'monitors', 'Home theater', 'router'].

Finally we created a dataframe and stored the ratings and reviews in it and also saved it in csv format. Sample data is as shown below:



 The data is that we saved in csv format we imported it using pandas and to further proceed with the pre-processing steps.



 Then we further checked more about data using info(), shapes using .shape, value counts using value\_counts(), null values using .isnull. .sum().sum(), and further visualize it through heatmap as follows:



From this we can observe that 63% data has rating 5.

#### **Data Pre-Processing**

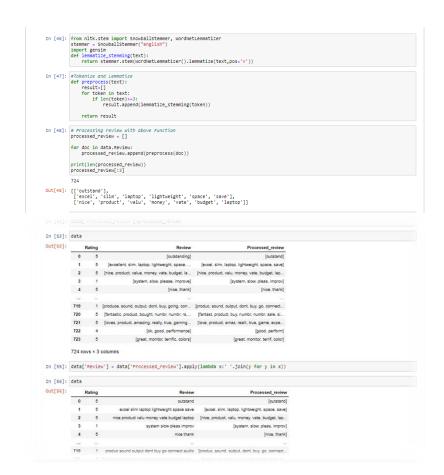
• In this we will be performing data cleaning such as removing html tags, special characters, converting everything to lowercase, replace email addresses with 'email', URLs with 'webaddress', money symbols with 'moneysymb', 10 digit phone numbers (formats include paranthesis, spaces, no spaces, dashes) with 'phonenumber', numbers with 'numbr', whitespace between terms with a single space, removing leading and trailing whitespace and punctuations. We also removed Stopwords.

```
In [41]: # 1. Remove HTML tags #Regex rule : '<.*?>
                   def clean(text):
    cleaned = re.compile(r'<.*?>')
    return re.sub(cleaned,'',text) # substring replace with ''(space)
                    data.Review = data.Review.apply(clean)
data.Review
Out[4]: 0

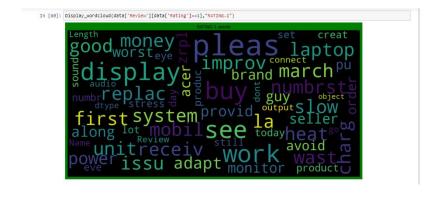
1 Excellent slim laptop with lightweight. Space ...
2 Nice product and value for money vate budget l...
3 System is very slow please improve it.....
4 Citchank
                  719 It doesn't produce any sound output... Don't bu...
720 Fantastic product & have bought it for 14,499 ...
721 I LOVES THIS PRODUCT..ITS AMAZING. REALLY TBU...
722 OK good performance
723 Great monitor with terrific colors..
Name: Review, Length: 724, Otype: Object
In [42]: # 2. Remove special characters def is_special(text):
                        ef is_special(text):
    rem = ''
    for i in text:
        if i.isalnum():
            rem = ren + i
        else:
            rem = ren + ''
    return rem
                    data.Review = data.Review.apply(is_special)
data.Review
                        Excellent slim laptop with lightweight Space ...
Nice product and value for money vate budget l...
                  718 It doesn't produce any sound output Don't bu...
728 Fantastic product have bought if for 14-499 ...
721 I LOVES THIS PRODUCT ITS AMELIN RELLY TRU...
722 OK good performance
723 Great monitor with terrific colors
Name: Review, Length: 724, dtype: Object
In [43]: # 3. Convert everything to Lowercase
def to_lower(text):
    return text.lower()
                   data.Review = data.Review.apply(to_lower)
data.Review
Out[43]: e outstanding
1 excellent slim laptop with lightweight space...
2 nice product and value for money vete budget l...
3 system is very slow please improve it
ince thank
                    719 it doesn t produce any sound output dont bu...
720 fantastic product have bought it for 14 499 ...
721 i loves this product its amazing really tru..
722 ok good performance
723 great monitor with terrific colors
Name: Review, Length: 724, dtype: object
In [44]: # Replace email addresses with 'email' data['Review'] = data['Review'].str.replace(r'^.+@[^\.].*\.[a-2]{2,}$', 'emailaddress')
                     # Replace money symbols with 'moneysymb' (E can by typed with ALT key + 156) data['Review'] = data['Review'].str.replace(r'f|\$', 'dollers')
                    # Replace 10 digit phone numbers (formats include paranthesis, spaces, no spaces, dashes) with 'phonent data['Review'] = data['Review'].str.eplace(r'^\(?\d](3))?(\s-]?(\d](3)\s-)?(\d](4)s', 'phonenumber')
                     # Replace numbers with 'numbr'
data['Review'] = data['Review'].str.replace(r'\d+(\.\d+)?', 'numbr')
                     # Remove punctuation
data['Review'] = data['Review'].str.replace(r'[^\w\d\s]', '')
                     # Replace whitespace between terms with a single space
data['Review'] = data['Review'].str.replace(r'\s+', ' ')
                     # Remove Leading and trailing whitespace
data['Review'] = data['Review'].str.replace(r'^\s+|\s+?$', '')
In [45]: # 4. Remove stopwords

def rem_stopwords(text):
    stop_words = set(stopwords.words('english'))
    words = word_tokenize(text)
    return [w for w in words if w not in stop_words]
                     data.Review = data.Review.apply(rem_stopwords)
data.Review
                            [excellent, slim, laptop, lightweight, space, ...
[nice, product, value, money, vate, budget, la...
[system, slow, please, improve]
```

 Then we performed stemming using Snowball Stemmer and WordNetLemmatizer. Then we further pre-process the text and save the final processed data in processed\_review.



To get sense of loud words in Review corresponding to each rating i., 1,
 2, 3, 4 and 5 we have used wordcloud and visualized it as follows:



```
total touch fetur numbrm basic descent realitibackup time alw per tu orm soft expect wast prospect phone laptop moving system phone laptop moving system basic descent realitibackup time alw per tu orm soft expect wast prospect phone laptop moving system phone laptop moving system basic descent realitibackup time alw per tu orm soft expect wast prospect phone laptop moving build face system phone laptop moving system phone laptop moving system phone laptop moving the paper paper paper per to buy backup the said in the
```

```
budgetpixel bound to the second of the secon
```

```
fast Name—
realling good damage time money realling good damage time money numbr confuse mentiontft overheatlaptop numbr perform tintelquit buy stand fabuldecent hey speed batteri product panel display height sound place look adjust first numbrstar
```

```
work product fantast

work product fantast

budget numbr money space

budget numbr money space

budget numbr money space

amaz

buy object good

amaz

savecolor backlit en b

dydtype laptoptrue thank super

alightweight Name

vate

vate

terrif nice

reallilove
```

# **Model/s Development and Evaluation**

Review column have been converted to tokens using TFidfVectorizer.
 Then using train\_test\_split we split the data into training and testing dataset.

```
In [65]: from sklearn.feature_extraction.text import Tfidfvectorizer

tf_vec = Tfidfvectorizer()
features = tf_vec.fit_transform(data['Review'])

X = features
y = data['Rating']
print("X.shape = "X.shape)
print("Y.shape = "X.shape)

X.shape = (724, 1726)
y.shape = (724, 1726)
y.shape = (724, 1726)
y.shape = (724, 1726)
y.shape = (724, 1726)
from sklearn.ansive_layers import inlitenomables
from sklearn.ansive_layers import inlitenomables
from sklearn.ansive_layers import inlitenomables
from sklearn.nesemble import togisticRegression
from sklearn.nesemble import togistorsed.

### Transition of the transitio
```

 We have used following algorithms such as: RandomForestClassifier, AdaBoostClassifier, MultinomialNB, DecisionTreeClassifier and KNeighborsClassifier.

```
In [68]: # Creating instances for different classifiers

arc.dandombrorestclassifier()
AAA-Adabootclassifier()
(MM-multionialNe()
OT.DecisionTreclassifier()
(NW-melgiphorsclassifier()
(NW-melgiphorsclassifier()

In [69]: # List of Models

models.append("fandombrorestclassifier", &FC()
models.append("disabootclassifier", &FC()
models.append("disabootclassifier", AFC()
models.append("disabootclassifier", AFC()
models.append("disabootclassifier", AFC()
models.append("DecisionTreclassifier", AFC()
models.append("De
```

 We have formed a loop where all the algorithms will be used one by one and their corresponding accuracy\_score, cross\_val\_score and classification report will be evaluated.

Key metrics used for finalising the model was accuracy\_score, cross\_val\_score. Since in case of RandomForestClassifier it was giving us maximum score among all other models and it's performing well. It's cross\_val\_score is also satisfactory and it shows that our model is neither underfitting/overfitting.

```
Accuracy_score= 0.7018348623853211
Cross_Val_Score= 0.6656513409961686
Accuracy_score= 0.6422018348623854
Accuracy_score= 0.6376146788990825
```

```
Accuracy_score= 0.6284403669724771
Cross_Val_Score= 0.5868869731800765
classification report precision
           0.41 0.41
0.62 0.63
KNeighborsClassifier()
Accuracy_score= 0.6238532110091743
Cross_Val_Score= 0.5551819923371648
classification report precision
                    recall f1-score support
           0.62
0.39 0.35 0.36
0.57 0.62 0.59
```

## **Model Summary:**

```
In [74]: result=pd.DataFrame({'Model': Model,'Score': score,'Cross_Val_Score':cvs})

Out[74]: Model Score Cross_Val_Score

0 RandomForestClassifier 70.183486 66.565134

1 AdaBoostClassifier 64.220183 63.950192

2 MultinomialNB() 63.761468 63.397510

3 DecisionTreeClassifier 62.844037 58.688897
```

4 KNeighborsClassifier 62.385321 55.518199

 Since RandomForestClassifier was giving us maximum score we applied hyper parameter tuning on it to further improve the result using GridSearchCV.

```
In [76]: from sklearn.ensemble import RandomForestClassifier
            from sklearn.model_selection import GridSearchCV
           rf=RandomForestclassifier()
parameters={'n_estimators':[50,100,150,200,250,300,350,400,450,500],'max_depth':[5, 8, 15, 25, 30]}
           parameters={'n_estimators':[50,100,19]
clf=GridSearchCV(rf,parameters,cv=5)
          clf.best_params
Out[76]: {'max_depth': 30, 'n_estimators': 200}
In [77]: rf=RandomForestClassifier(n_estimators=200,max_depth=30)
           rf.fit(x_train,y_train)
predrf=rf.predict(x_test)
           print(accuracy_score(y_test,predrf))
print(confusion_matrix(y_test,predrf))
           print(classification_report(y_test,predrf))
               8 0 0 0 10]
2 0 0 0 3]
0 0 0 0 12]
                              1 13711
                   0 0
                                           recall f1-score support
                                                         0.00
                                              0.00
                                                          0.16
                accuracy
                                                          0.68
                                                                       218
           macro avg 0.45 0.31
weighted avg 0.66 0.68
                                                          0.31
```

- Since it didn't show any improvement in result even after hyperparameter tuning. Hence, we will be choosing the RandomForestClassifier Model with default values that we got earlier.
- We will further use that model to predict our test data set as follows:

# **CONCLUSION**

- We have got the accuracy score of 70% using RandomForestClassifier. Hence, our model is working well.
- Since the data was quite imbalanced as it contained more than 60% ratings as 5.
- We had less data.
- I have included one more additional work folder in the zip file where I have scraped data from amazon as well. Hence it contains data from two websites i.e., amazon and flipcart.