# RATING PREDICTION


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Internship-29

# ACKNOWLEDGMENT

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I would also like to thank my academic "Data Trained Education" and their team who has helped me to learn Machine Learning and NLP.

Working on this project was an incredible experience as I learnt more from this Project during completion.

# INTRODUCTION

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

## 2. Conceptual Background of the Domain Problem

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.

## 3. Review of Literature

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.

## 4. Motivation for the Problem Undertaken

To build an application which can predict the rating by seeing the review.

# Analytical Problem Framing

## 1. Mathematical/ Analytical Modelling of the Problem

1) Used web scraping to scrap data from different websites and
2) Used Panda's Library to save data into excel file
3) Cleaned Data by removing irrelevant features
4) Pre-processing of text using NLP processing
5) Used Lemmatization
6) Used Text Normalization – Standardization
7) Used Word Counts
8) Used Character Counts
9) Removed Outliers
10) Used TF-IDF Vectorizer
11) Splitted data into train and test
12) Built Model
13) Hyper parameter tunning

## 2. Data Sources and their formats

There are two data-set in excel format: **Rating_Review.xlsx**. Features of this dataset are:

- Unnamed: 0 - contains serial no
- Review_title- Title of Reviews on multiple shopping websites
- Review_text- Comments Reviews from multiple shopping websites
- Ratings- Ratings of products from multiple shopping websites

## 3. Data Pre-processing:

a) Checked Top 5 Rows of Dataset

```
rating.head()
```

| | Unnamed: 0 | Review_title | Review_text | Ratings |
|---|---|---|---|---|
| 0 | 0 | After 6 monts used of zebronics Worst watch co... | Don't waste your money, power button not worki... | 1.0 out of 5 stars |
| 1 | 1 | Watch | Firstly thanks to Amazon for day Delivery. Thi... | 5.0 out of 5 stars |
| 2 | 2 | .. | This watch is the best in this price segment a... | 5.0 out of 5 stars |
| 3 | 3 | Nice and very sporty watch | Very good in hand and looks very cool to wear ... | 5.0 out of 5 stars |
| 4 | 4 | Nice watch | I likes the fitting of this watch and it has l... | 5.0 out of 5 stars |

b) Checked Total Numbers of Rows and Column

```
rating.shape
```

```
(53363, 4)
```

c) Checked All Column Name

```
rating.columns
```

```
Index(['Unnamed: 0', 'Review_title', 'Review_text', 'Ratings'], dtype='object')
```

d) Checked Data Type of All Data

```
rating.dtypes
```

```
Unnamed: 0       int64
Review_title    object
Review_text     object
Ratings         object
dtype: object
```

e) Checked for Null Values

```
rating.isnull().sum()
```

```
Unnamed: 0         0
Review_title    3463
Review_text     3655
Ratings         3460
dtype: int64
```

There is null value in the dataset in all 3 columns except one.

f) Checking if "-" values present in dataset or not

```
(rating=='-').sum()
```

```
Unnamed: 0      0
Review_title    0
Review_text     0
Ratings         0
dtype: int64
```

g) Checked total number of unique values

```
rating.nunique()
```

```
Unnamed: 0       53363
Review_title      8655
Review_text      21097
Ratings             10
dtype: int64
```

h) Information about Data

```
rating.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53363 entries, 0 to 53362
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   Unnamed: 0    53363 non-null  int64 
 1   Review_title  49900 non-null  object
 2   Review_text   49708 non-null  object
 3   Ratings       49903 non-null  object
dtypes: int64(1), object(3)
memory usage: 1.6+ MB
```

i) Data cleaning

- Dropped Column " Unnamed: 0 " as this column contains serial no.

```
#Dropping column 'Unnamed: 0' as it contains only serial no and it is not required
rating.drop(columns=['Unnamed: 0'],inplace=True)
```

## Handling Null Values

```
#Droping rows containing NULL Values
rating.dropna(inplace = True)
```

```
#reseting index no after droping rows
rating.reset_index(inplace=True, drop=True)
```

## Checking all values in of column Rating

```
rating["Ratings"].value_counts()
```

```
5                    22179
4                     6787
5.0 out of 5 stars    3498
1                     3099
1.0 out of 5 stars    3057
4.0 out of 5 stars    2908
3.0 out of 5 stars    2557
2.0 out of 5 stars    2376
3                     2045
2                      733
Name: Ratings, dtype: int64
```

### Handling duplicate value of Column 'Ratings'

```
#Column 'Ratings' contains 5.0 and 5 which means same and like this 4.0, 3.0, 2.0, 1.0
rating["Ratings"]= rating["Ratings"].str.replace('5.0 out of 5 stars', '5')
rating["Ratings"]= rating["Ratings"].str.replace('4.0 out of 5 stars', '4')
rating["Ratings"]= rating["Ratings"].str.replace('3.0 out of 5 stars', '3')
rating["Ratings"]= rating["Ratings"].str.replace('2.0 out of 5 stars', '2')
rating["Ratings"]= rating["Ratings"].str.replace('1.0 out of 5 stars', '1')
```

```
rating["Ratings"].value_counts()
```

```
5    3498
1    3057
4    2908
3    2557
2    2376
Name: Ratings, dtype: int64
```

```
#checking again null values
rating.isnull().sum()
```

```
Review_title        0
Review_text         0
Ratings         34843
dtype: int64
```

```
rating["Ratings"].unique()
```

```
array(['1', '5', '2', '3', '4', nan], dtype=object)
```

```
#checking repeated values in "Embarked" column through mode
print(rating["Ratings"].mode())
```

```
0    5
dtype: object
```

```
#Filling the Null Values with mode method
rating["Ratings"].fillna(rating["Ratings"].mode()[0], inplace=True)
```

```
rating["Ratings"].unique()
```

```
array(['1', '5', '2', '3', '4'], dtype=object)
```

```
#checking again total columns
rating.columns
```

```
Index(['Review_title', 'Review_text', 'Ratings', 'Review'], dtype='object')
```

```
#checking again total rows and columns
rating.shape
```

```
(49239, 4)
```

```
# Now combining the "Review_title" and "Review_text" columns into one single column called "Review"
rating['Review'] = rating['Review_title'].map(str)+' '+rating['Review_text']
rating
```

| | Review_title | Review_text | Ratings | Review |
|---|---|---|---|---|
| 0 | After 6 monts used of zebronics Worst watch co... | Don't waste your money, power button not worki... | 1 | After 6 monts used of zebronics Worst watch co... |
| 1 | Watch | Firstly thanks to Amazon for day Delivery. Thi... | 5 | Watch Firstly thanks to Amazon for day Deliver... |
| 2 | .. | This watch is the best in this price segment a... | 5 | .. This watch is the best in this price segmen... |
| 3 | Nice and very sporty watch | Very good in hand and looks very cool to wear ... | 5 | Nice and very sporty watch Very good in hand a... |
| 4 | Nice watch | I likes the fitting of this watch and it has l... | 5 | Nice watch I likes the fitting of this watch a... |

# 4. Data Inputs- Logic- Output Relationships

## I. Text Pre-Processing

### Visualizing text in first three rows from the newly created "Review" column

```
rating['Review'][0]
```

```
"After 6 monts used of zebronics Worst watch condition Don't waste your money, power button not working after some days, touch not working then battery discharge in 6 to 7 hrs,bluethooth calling  range only 2 to 3 meter. I wasted my money, don't waste yours."
```

```
rating['Review'][1]
```

```
'Watch Firstly thanks to Amazon for day Delivery. This watch comes with a heart rate meter, SPO2 meter, fitness goals, alarm, call rejector, and many more. Battery life is good. This watch gives me battery backup for 6 days and Takes 1.5 hours to charge from 0-100%. Overall good smartwatch. Thanks to Zebronics❤️'
```

```
rating['Review'][2]
```

```
'.. This watch is the best in this price segment as compared to other brands and the battery is awesome. The display is good according to the price. The accuracy of heart rate, Sp02, and step counter is also good. There is no issue with connectivity. Watch Look is stylish. Go for its accuracy. This is the best watch in this price segment.'
```

### Text Processing to remove unwanted punctuations and special characters

```
'''Here I am defining a function to replace some of the contracted words to their full form and removing urls and some unwanted text'''

def decontracted(text):
    text = re.sub(r"won't", "will not", text)
    text = re.sub(r"don't", "do not", text)
    text = re.sub(r"can't", "can not", text)
    text = re.sub(r"im ", "i am", text)
    text = re.sub(r"yo ", "you ",text)
    text = re.sub(r"doesn't", "does not",text)
    text = re.sub(r"n\'t", " not", text)
    text = re.sub(r"\'re", " are", text)
    text = re.sub(r"\'s", " is", text)
    text = re.sub(r"\'d", " would", text)
    text = re.sub(r"\'ll", " will", text)
    text = re.sub(r"\'t", " not", text)
    text = re.sub(r"\'ve", " have", text)
    text = re.sub(r"\'m", " am", text)
    text = re.sub(r"<br>", " ", text)
    text = re.sub(r'http\S+', '', text) #removing urls
    return text
```

```
# Lowercasing the alphabets
rating['Review'] = rating['Review'].apply(lambda x : x.lower())
rating['Review'] = rating['Review'].apply(lambda x : decontracted(x))

# Removing punctuations from the review
rating['Review'] = rating['Review'].str.replace('[^\w\s]','')
rating['Review'] = rating['Review'].str.replace('\n',' ')
# Removing all the stopwords
stop = stopwords.words('english')
rating['Review'] = rating['Review'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
```

## Lemmatization

```
lemmatizer = nltk.stem.WordNetLemmatizer()
```

```
# Defining functiom to convert nltk tag to wordnet tags
def nltk_tag_to_wordnet_tag(nltk_tag):
    if nltk_tag.startswith('J'):
        return wordnet.ADJ
    elif nltk_tag.startswith('V'):
        return wordnet.VERB
    elif nltk_tag.startswith('N'):
        return wordnet.NOUN
    elif nltk_tag.startswith('R'):
        return wordnet.ADV
    else:
        return None

# Defining function to lemmatize our text
def lemmatize_sentence(sentence):
    # tokenize the sentence and find the pos_tag
    nltk_tagged = nltk.pos_tag(nltk.word_tokenize(sentence))
    # tuple of (token, wordnet_tag)
    wordnet_tagged = map(lambda x : (x[0], nltk_tag_to_wordnet_tag(x[1])), nltk_tagged)
    lemmatize_sentence = []
    for word, tag in wordnet_tagged:
        if tag is None:
            lemmatize_sentence.append(word)
        else:
            lemmatize_sentence.append(lemmatizer.lemmatize(word,tag))
    return " ".join(lemmatize_sentence)

rating['Review'] = rating['Review'].apply(lambda x : lemmatize_sentence(x))
```

## Text Normalization - Standardization

```
# Noise removal function
def scrub_words(text):
    # remove HTML markup
    text = re.sub("(<.*?>)", "", text)
    # remove non-ascii and digits
    text = re.sub("(\\W)", " ", text)
    text = re.sub("(\\d)", "", text)
    # remove white space
    text = text.strip()
    return text

rating['Review'] = rating['Review'].apply(lambda x : scrub_words(x))
```

# Word Counts

```
# Creating column for word counts in the review text
rating['Review_Count'] = rating['Review'].apply(lambda x: len(str(x).split(' ')))
rating[['Review_Count', 'Review']].head(10)
```

| | Review_Count | Review |
|---|---|---|
| 0 | 27 | monts use zebronics bad watch condition waste ... |
| 1 | 38 | watch firstly thanks amazon day delivery watch... |
| 2 | 31 | watch best price segment compare brand battery... |
| 3 | 17 | nice sporty watch good hand look cool wear eve... |
| 4 | 16 | nice watch like fit watch lot sport mode easy ... |
| 5 | 19 | vey good smart watch good fitting feel expensi... |
| 6 | 12 | nice watch good fitting feel comfortable easy ... |
| 7 | 16 | smart watch cool watch easy use bright sunligh... |
| 8 | 8 | hand smart watch extra backup look like best |
| 9 | 9 | quality assure best best price range absolutel... |

# Character Counts

```
# Creating column for character counts in the review text
rating['Review_Char'] = rating['Review'].str.len()
rating[['Review_Char','Review']].head(10)
```

| | Review_Char | Review |
|---|---|---|
| 0 | 155 | monts use zebronics bad watch condition waste ... |
| 1 | 225 | watch firstly thanks amazon day delivery watch... |
| 2 | 202 | watch best price segment compare brand battery... |
| 3 | 95 | nice sporty watch good hand look cool wear eve... |
| 4 | 87 | nice watch like fit watch lot sport mode easy ... |
| 5 | 122 | vey good smart watch good fitting feel expensi... |
| 6 | 72 | nice watch good fitting feel comfortable easy ... |
| 7 | 89 | smart watch cool watch easy use bright sunligh... |
| 8 | 44 | hand smart watch extra backup look like best |
| 9 | 59 | quality assure best best price range absolutel... |

## II. Removing Outliers

```
# Applying zscore to remove outliers
z_score = zscore(rating[['Review_Count']])
abs_z_score = np.abs(z_score)
filtering_entry = (abs_z_score < 3).all(axis = 1)
rating = rating[filtering_entry]
print("We have {} Rows and {} Columns in our dataframe after removing outliers".format(rating.shape[0], rating.shape[1]))
```

```
We have 48799 Rows and 6 Columns in our dataframe after removing outliers
```

## 5. State the set of assumptions (if any) related to the problem under consideration

- It was observed that there is one column "Unnamed: 0" which is irrelevant column as it contains serial no, so, have to drop this column.
- It was observed that in columns there are irrelevant values present in comment_text. So, we need to drop, replace and remove those values.
- Also have to convert text (reviews) into vectors using TF-IDF
- By looking into the Target Variable, it is assumed that it is a multiclass classification problem.

## 6. Hardware and Software Requirements and Tools Used

- **Hardware used:**
  - **Processor**: 11th Gen Intel(R) Core (TM) i3-1125G4 @ 2.00GHz 2.00 GHz
  - **System Type**: 64-bit OS

- **Software used:**
  - **Anaconda** for 64-bit OS
  - **Jupyter** notebook

- **Tools, Libraries and Packages used:**

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from scipy.stats import zscore
from sklearn.model_selection import train_test_split, GridSearchCV,cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,classification_report, confusion_matrix
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import BaggingClassifier,AdaBoostClassifier
```

```
import nltk
import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer, WordNetLemmatizer
from nltk.corpus import wordnet
from nltk import FreqDist
import gensim
from gensim.models import Word2Vec
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk import FreqDist
from scipy import stats
from scipy.sparse import hstack
nltk.download('averaged_perceptron_tagger', quiet=True)
from wordcloud import WordCloud
import scikitplot as skplt

import lightgbm
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import MultinomialNB, GaussianNB, BernoulliNB
from lightgbm import LGBMClassifier
from sklearn.linear_model import SGDClassifier

import pickle
import joblib
import warnings
warnings.filterwarnings('ignore')
```

# Model/s Development and Evaluation

## 1. Identification of possible problem-solving approaches (methods)

In this project, we want to differentiate between comments and its categories and for this we have used these approaches:

- Checked Total Numbers of Rows and Column
- Checked All Column Name
- Checked Data Type of All Data
- Checked for Null Values
- Checked for special character present in dataset or not
- Checked total number of unique values
- Information about Data
- Dropped irrelevant Columns
- Replaced special characters and irrelevant data
- Checked all features through visualization.
- Removed unwanted punctuations and special characters
- Converted all messages to lower case
- Removed punctuations
- Removed StopWords
- Used Lemmatization
- Used Text Normalization – Standardization
- Used Word Counts
- Used Character Counts
- Removed Outliers
- Checked loud word using WordCloud
- Converted text into vectors using TF-IDF

## 2. Testing of Identified Approaches (Algorithms)

1. Logistic Regression
2. Linear Support Vector Classifier
3. Bernoulli NB
4. Multinomial NB
5. SGD Classifier
6. LGBM Classifier
7. XGB Classifier

## 3. Run and evaluate selected models

### Splitting the data into train and test datasets

```
state = 42
x_train, x_test, y_train, y_test = train_test_split(train_features, y, test_size = 0.30, random_state = state)

# Lets check the shapes of traning and test data
print("x_train", x_train.shape)
print("x_test", x_test.shape)
print("y_train", y_train.shape)
print("y_test", y_test.shape)
```

```
x_train (34159, 150000)
x_test (14640, 150000)
y_train (34159,)
y_test (14640,)
```

```
# Defining the Classification Machine Learning Algorithms
lr = LogisticRegression(solver='lbfgs')
svc = LinearSVC()
bnb = BernoulliNB()
mnb = MultinomialNB()
sgd = SGDClassifier()
lgb = LGBMClassifier()
xgb = XGBClassifier(verbosity=0)

# Creating a function to train and test the model with evaluation metrics
def BuiltModel(model):
    print('*'*30+model.__class__.__name__+'*'*30)
    model.fit(x_train, y_train)
    y_pred = model.predict(x_train)
    pred = model.predict(x_test)
    accuracy = accuracy_score(y_test, pred)*100
    print(f"ACCURACY SCORE PERCENTAGE:", accuracy)
    # Confusion matrix and Classification report
    print(f"CLASSIFICATION REPORT: \n {classification_report(y_test, pred)}")
    print(f"CONFUSION MATRIX: \n {confusion_matrix(y_test, pred)}\n")
    print("-"*120)
    print("\n")
```

## Training and testing of all the classification algorithms

```
for model in [lr,svc,bnb,mnb,sgd,lgb]:
    BuiltModel(model)
```

```
******************************LogisticRegression******************************
ACCURACY SCORE PERCENTAGE: 77.56147540983606
CLASSIFICATION REPORT:
               precision    recall  f1-score   support

           1       0.71      0.77      0.74      1791
           2       0.66      0.47      0.55       865
           3       0.69      0.53      0.60      1335
           4       0.71      0.63      0.67      2885
           5       0.83      0.91      0.87      7764

    accuracy                           0.78     14640
   macro avg       0.72      0.66      0.68     14640
weighted avg       0.77      0.78      0.77     14640

CONFUSION MATRIX:
 [[1375   85   57   66  208]
 [ 202  404   90   70   99]
 [ 113   59  706  173  284]
 [  72   35   87 1827  864]
 [ 170   31   88  432 7043]]

------------------------------------------------------------------------------
```

```
******************************LinearSVC******************************
ACCURACY SCORE PERCENTAGE: 79.43989071038251
CLASSIFICATION REPORT:
               precision    recall  f1-score   support

           1       0.76      0.77      0.76      1791
           2       0.63      0.56      0.59       865
           3       0.70      0.59      0.64      1335
           4       0.72      0.69      0.70      2885
           5       0.86      0.90      0.88      7764

    accuracy                           0.79     14640
   macro avg       0.73      0.70      0.72     14640
weighted avg       0.79      0.79      0.79     14640

CONFUSION MATRIX:
 [[1371  103   50   69  198]
 [ 152  481   89   68   75]
 [  85   76  794  165  215]
 [  58   49  104 1988  686]
 [ 148   49   95  476 6996]]

----------------------------------------------------------------------
```

```
******************************BernoulliNB******************************
ACCURACY SCORE PERCENTAGE: 69.79508196721311
CLASSIFICATION REPORT:
              precision    recall  f1-score   support

           1       0.65      0.73      0.69      1791
           2       0.47      0.37      0.42       865
           3       0.46      0.41      0.43      1335
           4       0.58      0.60      0.59      2885
           5       0.81      0.81      0.81      7764

    accuracy                           0.70     14640
   macro avg       0.59      0.59      0.59     14640
weighted avg       0.69      0.70      0.70     14640

CONFUSION MATRIX:
 [[1306   94   88   80  223]
 [ 226  324  122   89  104]
 [ 158   89  542  225  321]
 [  97   81  165 1745  797]
 [ 228   99  268  868 6301]]

-------------------------------------------------------------------------------
```

```
******************************MultinomialNB******************************
ACCURACY SCORE PERCENTAGE: 68.54508196721312
CLASSIFICATION REPORT:
              precision    recall  f1-score   support

           1       0.59      0.76      0.67      1791
           2       0.78      0.05      0.09       865
           3       0.79      0.14      0.24      1335
           4       0.69      0.39      0.50      2885
           5       0.70      0.94      0.80      7764

    accuracy                           0.69     14640
   macro avg       0.71      0.46      0.46     14640
weighted avg       0.70      0.69      0.63     14640

CONFUSION MATRIX:
 [[1367    3    5   50  366]
 [ 388   42   20   75  340]
 [ 235    3  189  156  752]
 [ 107    1    9 1136 1632]
 [ 215    5   16  227 7301]]

-------------------------------------------------------------------------------
```

```
******************************SGDClassifier******************************
ACCURACY SCORE PERCENTAGE: 77.15163934426229
CLASSIFICATION REPORT:
               precision    recall  f1-score   support

           1       0.69      0.79      0.74      1791
           2       0.71      0.45      0.55       865
           3       0.72      0.51      0.59      1335
           4       0.71      0.61      0.65      2885
           5       0.82      0.91      0.86      7764

    accuracy                           0.77     14640
   macro avg       0.73      0.65      0.68     14640
weighted avg       0.77      0.77      0.76     14640

CONFUSION MATRIX:
 [[1422   54   43   66  206]
 [ 240  387   75   69   94]
 [ 138   46  677  182  292]
 [  85   22   73 1751  954]
 [ 186   36   77  407 7058]]

--------------------------------------------------------------------------
```

```
******************************LGBMClassifier******************************
ACCURACY SCORE PERCENTAGE: 78.0464480874317
CLASSIFICATION REPORT:
               precision    recall  f1-score   support

           1       0.73      0.77      0.75      1791
           2       0.68      0.54      0.60       865
           3       0.71      0.56      0.63      1335
           4       0.71      0.64      0.67      2885
           5       0.83      0.90      0.86      7764

    accuracy                           0.78     14640
   macro avg       0.73      0.68      0.70     14640
weighted avg       0.77      0.78      0.77     14640

CONFUSION MATRIX:
 [[1374   93   48   69  207]
 [ 161  464   81   60   99]
 [ 102   54  748  167  264]
 [  79   29   85 1839  853]
 [ 177   43   94  449 7001]]

--------------------------------------------------------------------------
```

# Cross validation score for best score models

```
def cross_val(model):
    print('*'*30+model.__class__.__name__+'*'*30)
    scores = cross_val_score(model,train_features,y, cv = 3).mean()*100
    print("Cross validation score:", scores)
    print("\n")

for model in [lr,svc,bnb,mnb,sgd,lgb]:
    cross_val(model)
```

```
******************************LogisticRegression******************************
Cross validation score: 77.24134218455275


******************************LinearSVC******************************
Cross validation score: 78.73931874673873


******************************BernoulliNB******************************
Cross validation score: 68.6878910686223


******************************MultinomialNB******************************
Cross validation score: 67.35179882864419


******************************SGDClassifier******************************
Cross validation score: 76.77206871913532


******************************LGBMClassifier******************************
Cross validation score: 77.45651052834704
```

# HyperParameter Tuning

## Linear SVC with GridSearchCV

```
# Lets select the different parameters for tuning our best model (Linear SVC)
grid_params =  {'C':(0.001, 0.01, 0.1, 1, 10),
                 'penalty':('l1','l2'),
                'loss':('hinge','squared_hinge')}

# Train the model with given parameters using GridSearchCV
LSVC =  GridSearchCV(svc, grid_params, cv=3)
LSVC.fit(x_train, y_train)
```

```
GridSearchCV(cv=3, estimator=LinearSVC(),
             param_grid={'C': (0.001, 0.01, 0.1, 1, 10),
                         'loss': ('hinge', 'squared_hinge'),
                         'penalty': ('l1', 'l2')})
```

```
LSVC.best_params_ # Selecting the best parameters found by GridSearchCV
```

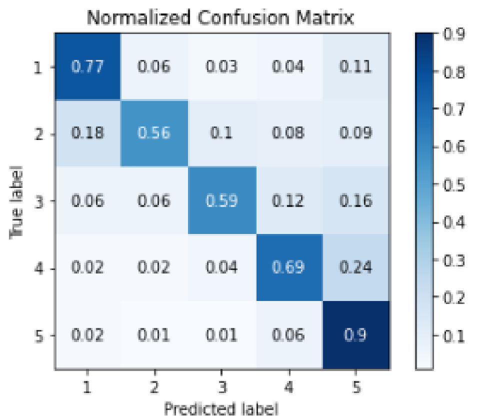
```
{'C': 1, 'loss': 'squared_hinge', 'penalty': 'l2'}
```

```python
# Final Model with the best chosen parameters list
best_model = LinearSVC(C= 1, loss= 'squared_hinge', penalty= 'l2')
best_model.fit(x_train,y_train) # fitting data to the best model
pred = best_model.predict(x_test)
accuracy = accuracy_score(y_test, pred)*100
# Printing the accuracy score
print("ACCURACY SCORE:", accuracy)
# Printing the classification report
print(f"\nCLASSIFICATION REPORT: \n {classification_report(y_test, pred)}")
# Printing the Confusion matrix
print(f"\nCONFUSION MATRIX: \n {confusion_matrix(y_test, pred)}")
```

```
ACCURACY SCORE: 79.43989071038251

CLASSIFICATION REPORT:
               precision    recall  f1-score   support

           1       0.76      0.77      0.76      1791
           2       0.63      0.56      0.59       865
           3       0.70      0.59      0.64      1335
           4       0.72      0.69      0.70      2885
           5       0.86      0.90      0.88      7764

    accuracy                           0.79     14640
   macro avg       0.73      0.70      0.72     14640
weighted avg       0.79      0.79      0.79     14640


CONFUSION MATRIX:
 [[1371  103   50   69  198]
 [ 152  481   89   68   75]
 [  85   76  794  165  215]
 [  58   49  104 1988  686]
 [ 148   49   95  476 6996]]
```

```python
# Creating a normalized confusion matrix here
skplt.metrics.plot_confusion_matrix(y_test, pred, normalize=True)
```

```
<AxesSubplot:title={'center':'Normalized Confusion Matrix'}, xlabel='Predicted label', ylabel='True label'>
```



## • Saving The Predictive Model

```
joblib.dump(best_model, "Rating_Prediction_Model.pkl")
```

```
['Rating_Prediction_Model.pkl']
```

## • Comparing Actual and Predicted

```
Model = joblib.load("Rating_Prediction_Model.pkl")
```

```
# Predicting test data using loaded model
prediction = Model.predict(x_test)
# Analysing Predicted vs Actual results
Rating_Prediction_Model = pd.DataFrame()
Rating_Prediction_Model['Predicted Ratings Review'] = prediction
Rating_Prediction_Model['Actual Ratings Review'] = y
Rating_Prediction_Model
```

| | Predicted Ratings Review | Actual Ratings Review |
|---|---|---|
| 0 | 5 | 1 |
| 1 | 4 | 4 |
| 2 | 5 | 5 |
| 3 | 1 | 4 |
| 4 | 5 | 5 |

## • Saving the model in CSV format

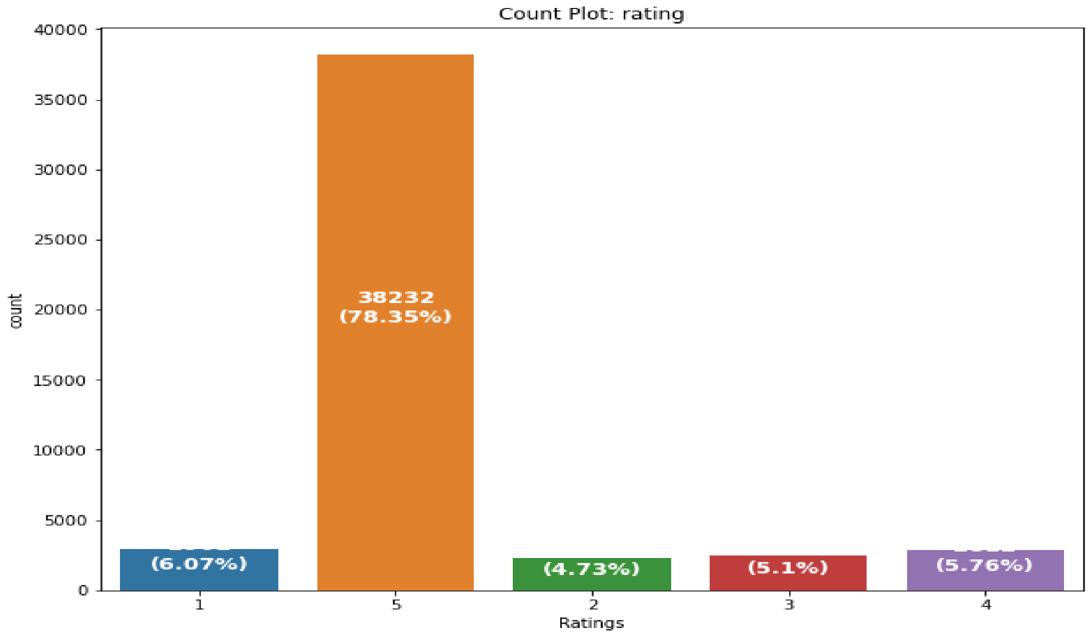
```
# Converting the dataframe into CSV format and saving it
Rating_Prediction_Model.to_csv('Rating_Prediction_Model.csv', index=False)
```

# 4. Key Metrics for success in solving problem under consideration

- Accuracy Score, Precision Score, Recall Score, F1-Score and CV score are used for success. Also, confusion matrix is used for success.

# 5. Visualization

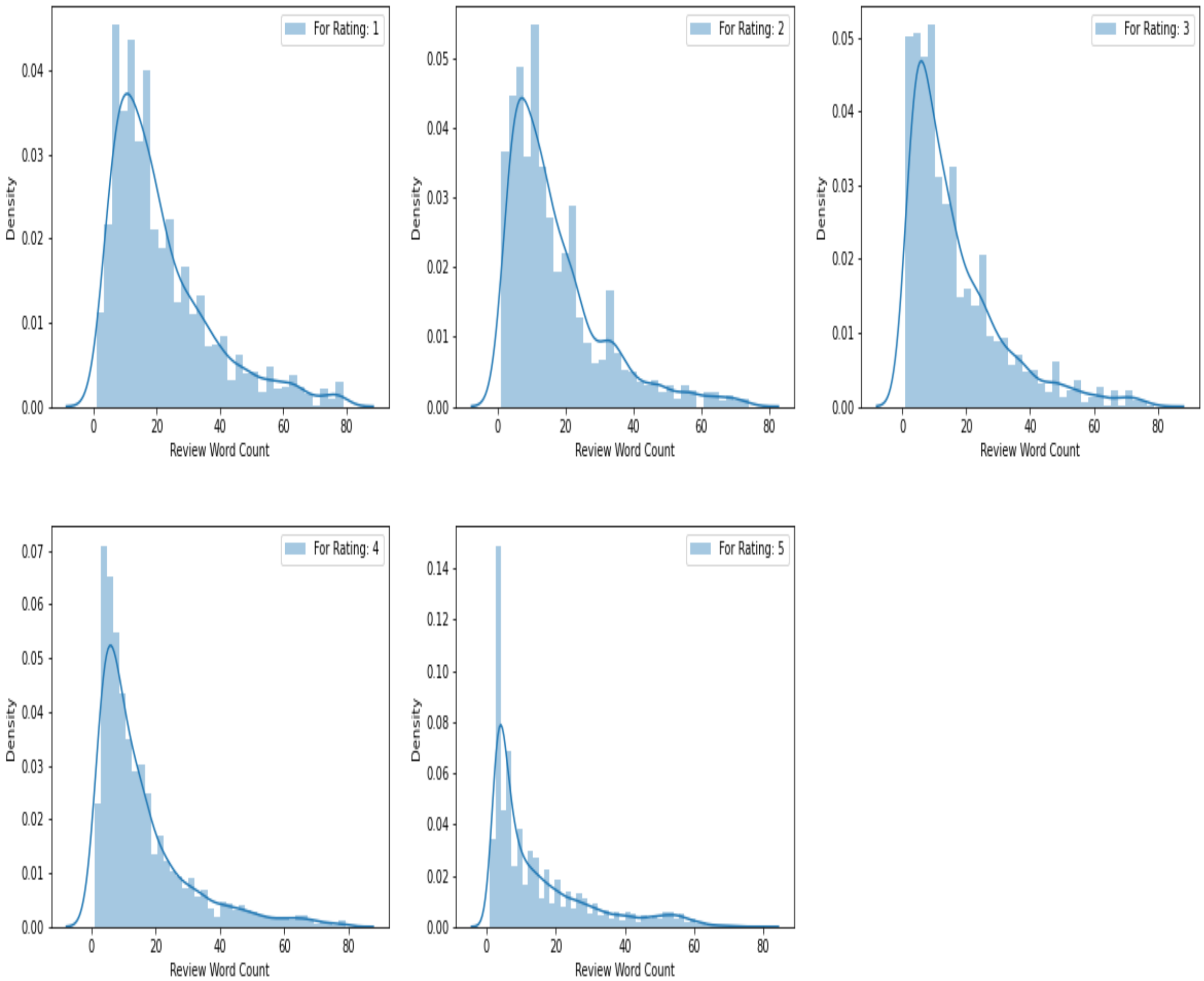
```python
# Checking the ratings column details using count plot
x = 'Ratings'
fig, ax = plt.subplots(1,1,figsize=(10,8))
sns.countplot(x=x,data=rating,ax=ax)
p=0
for i in ax.patches:
    q = i.get_height()/2
    val = i.get_height()
    ratio = round(val*100/len(rating),2)
    prn = f"{val}\n({ratio}%)"
    ax.text(p,q,prn,ha="center",color="white",rotation=0,fontweight="bold",fontsize="13")
    p += 1

plt.title("Count Plot: rating")
plt.show()
```




## Observation:

- We can see that the highest number of customer rating received are for 5 stars then 4 star rating reviews present .
- Then 1 star rating is highest compared to 2 and 3 star rating reviews

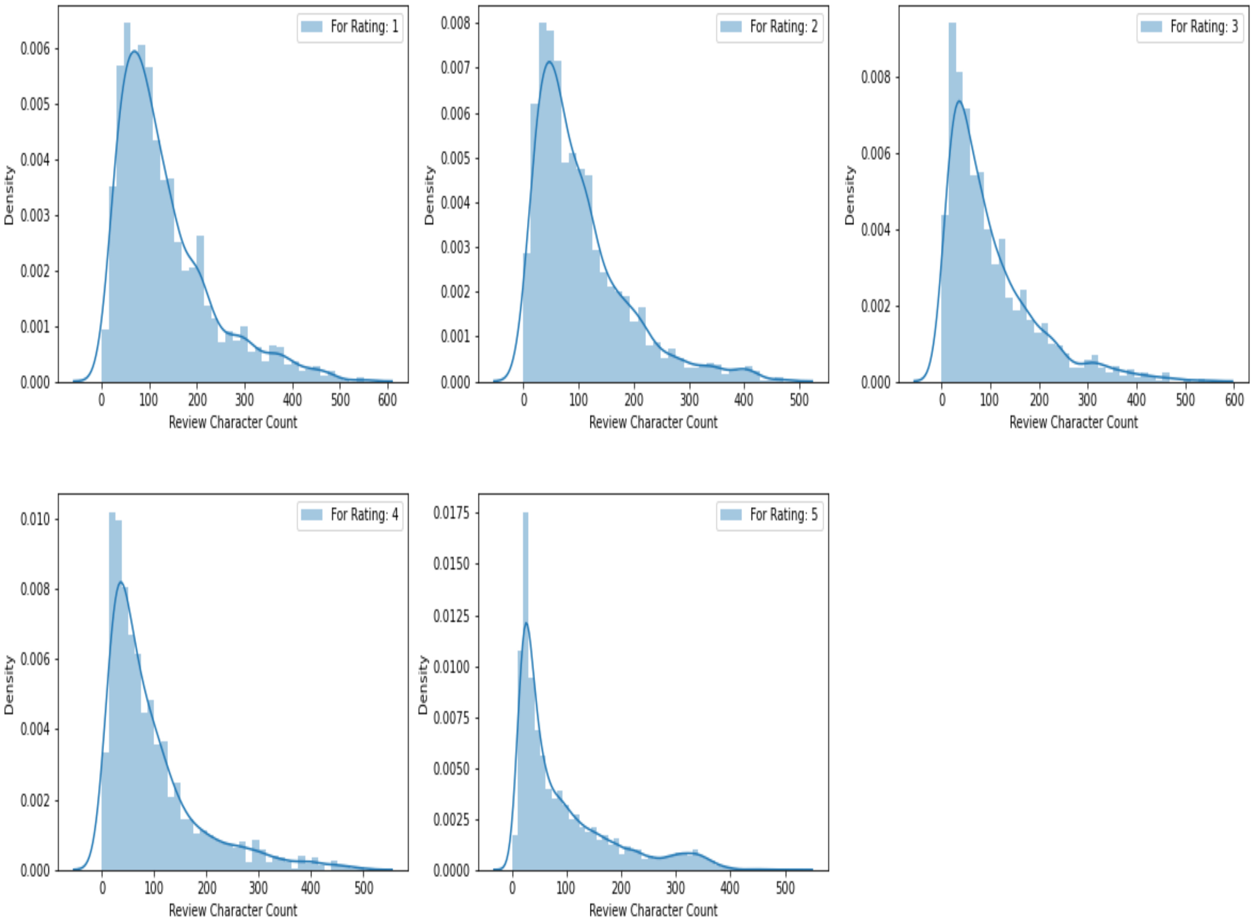
```
# Checking review word count distribution for each rating
ratings = np.sort(rating.Ratings.unique())
cols = 3
rows = len(ratings)//cols
if rows % cols != 0:
    rows += 1

fig = plt.figure(figsize=(20,10))
plt.subplots_adjust(hspace=0.3, wspace=0.2)
p = 1
colors = [(1,0,0,1),(0.6,0.2,0,1),(0.4,0.5,0,1),(0.2,0.7,0,1),(0,1,0.1,1)]
for i in ratings:
    axis = fig.add_subplot(rows,cols,p)
    sns.distplot(rating.Review_Count[rating.Ratings==i], ax=axis, label=f"For Rating: {i}")
    axis.set_xlabel(f"Review Word Count")
    axis.legend()
    p += 1

plt.show()
```




Observation:

The above word count histogram+distributions for each and every rating shows that when people are disappointed with a service they tend to mention a discriptive review as compared to when they are happy they use lesser words to express the joy of having got a great product.

```python
# Checking review character count distribution for each rating
ratings = np.sort(rating.Ratings.unique())
cols = 3
rows = len(ratings)//cols
if rows % cols != 0:
    rows += 1

fig = plt.figure(figsize=(20,10))
plt.subplots_adjust(hspace=0.3, wspace=0.2)
p = 1
colors = [(1,0,0,1),(0.6,0.2,0,1),(0.4,0.5,0,1),(0.2,0.7,0,1),(0,1,0.1,1)]
for i in ratings:
    axis = fig.add_subplot(rows,cols,p)
    sns.distplot(rating.Review_Char[rating.Ratings==i], ax=axis, label=f"For Rating: {i}")
    axis.set_xlabel(f"Review Character Count")
    axis.legend()
    p += 1

plt.show()
```




Observation:

Just as in the case of word count histogram+distribution plots the pattern is quite evident that Rating 5 reviews have lesser character counts on their comments when compared to the lower rating details.

# Displaying loud words with Word Cloud information

```python
# Getting insight of loud words in each rating
cols = 2
ratings = np.sort(rating.Ratings.unique())
rows = len(ratings)//2
if len(ratings) % cols != 0:
    rows += 1
fig = plt.figure(figsize=(15,20))
plt.subplots_adjust(hspace=0.3)
p = 1
for i in ratings:
    word_cloud = WordCloud(height=800, width=1000, background_color="white", max_words=50).generate(' '.join(rating.Review[rating.Ratings==i]))
    axis = fig.add_subplot(rows,cols,p)
    axis.set_title(f"WordCloud for Rating: {i}\n")
    axis.imshow(word_cloud)
    for spine in axis.spines.values():
        spine.set_edgecolor('r')
    axis.set_xticks([])
    axis.set_yticks([])

    plt.tight_layout(pad=5)
    p += 1
plt.show()
```


**Observation:**

- For Rating: 1

It mostly consists of words like watch, use, bad product, waste, time, money, bad experience, issue etc

- For Rating: 2

It mostly consists of words like good, phone, use, watch, poor, issue, waste money, quality good, bad, problem etc

- For Rating: 3

It mostly consists of words like sound quality, good, use, time, camera quality, display, buy, build quality etc

- For Rating: 4

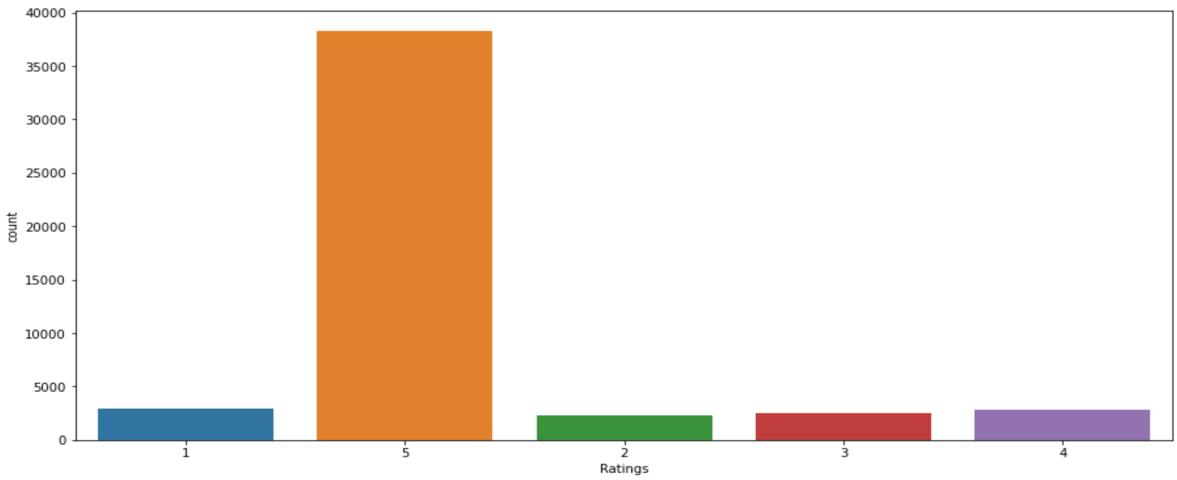
It mostly consists of words like use, buy, phone, watch, good product, good quality, good choice, nice product etc

- For Rating: 5

It mostly consists of words like price range, value money, good product, well, go, simply awesome, perfect product etc

```python
# Checking the count of target column values
plt.figure(figsize=(15,7))
sns.countplot(rating['Ratings'])
print(rating.Ratings.value_counts())
plt.show()
```

```
5    38232
1     2961
4     2812
3     2487
2     2307
Name: Ratings, dtype: int64
```

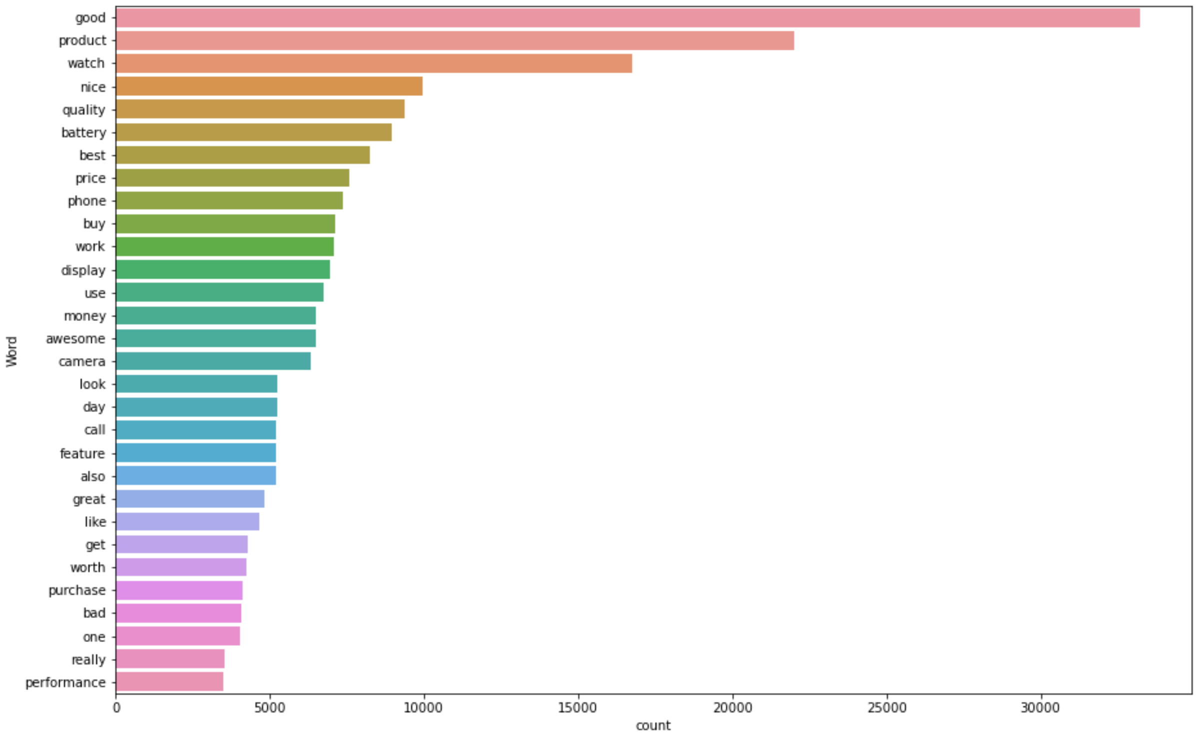



Observation:

- Looking at the above count plot for our target varible (Ratings) we can say that the data set is having most number of reviews rated as 5 star and very less number of reviews rated as 2 star.
- Which will cause the Imbalance problem for our Machine Learning model and make it bias.
- So I am selecting equal number of reviews of each rating as a input for our model to avoid any kind of biasness
- For that first I will shuffle the dataset so that we can select data from both web-sites (Amazon and Flipkart)
- Then I will select equal number of data of every category and ensure that the rating values are balanced

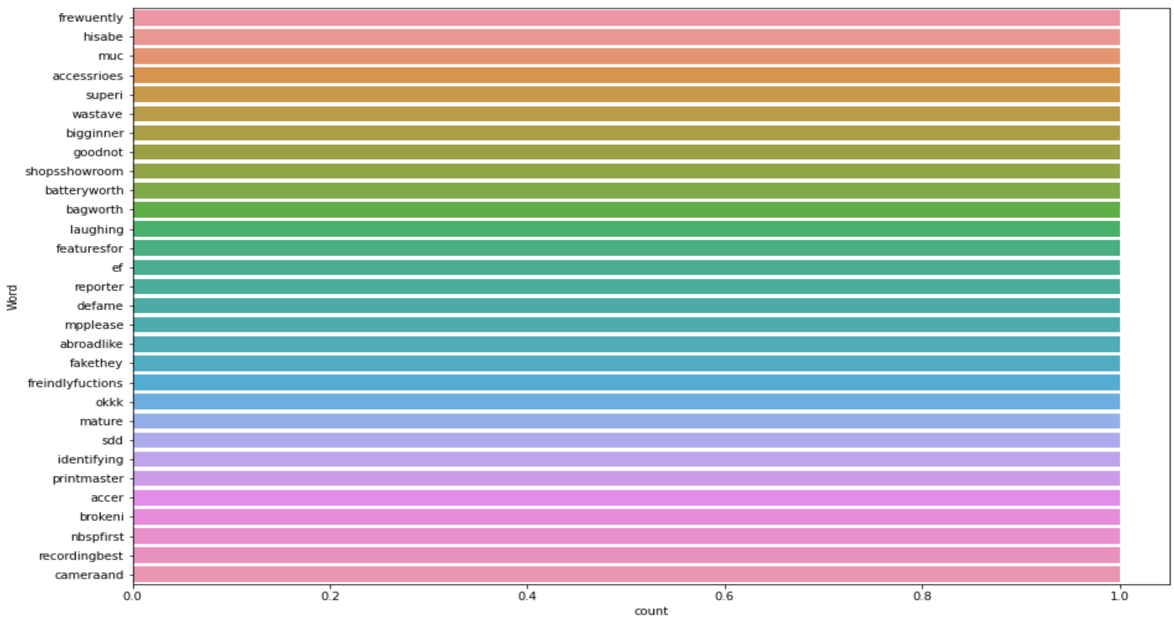
# Top 30 most frequently occuring words

```python
# Function to plot most frequent terms in our Review column
def freq_words(x, terms=30):
    all_words = ' '.join([text for text in x])
    all_words = all_words.split()
    fdist = FreqDist(all_words)
    words_df = pd.DataFrame({'word':list(fdist.keys()),
                             'count':list(fdist.values())})
    # selecting top 30 most frequent words
    dt = words_df.nlargest(columns='count', n=terms)
    plt.figure(figsize=(15,10))
    ax = sns.barplot(data=dt, x='count', y='word')
    ax.set(ylabel = 'Word')
    plt.show()

freq_words(rating['Review'])
```




## Top 30 rarely occuring words

```
# Function to plot least frequent terms in our Review column
def rare_words(x, terms=30):
    all_words = ' '.join([text for text in x])
    all_words = all_words.split()
    fdist = FreqDist(all_words)
    words_df = pd.DataFrame({'word':list(fdist.keys()),
                             'count':list(fdist.values())})
    # selecting top 30 least freq rare words
    dt = words_df.nsmallest(columns='count', n=terms)
    plt.figure(figsize=(15,10))
    ax = sns.barplot(data=dt, x='count', y='word')
    ax.set(ylabel = 'Word')
    plt.show()

rare_words(rating['Review'])
```



## 6. Interpretation of the Results

- Through Pre-processing it is interpretated Converted all reviews to lower case, removed money symbols and parenthesis, removed Punctation, replaced extra space, removed stop-words, Calculated length of sentence and decreased after pre-processing, converted text into vectors using TF-IDF.
- There are 5 types of Ratings in the dataset, Rating: 1, 2, 3, 4 & 5.
- By creating/building model we get best model: Linear SVC.

# CONCLUSION

## 1. Key Findings and Conclusions of the Study

In this project we have collected data of reviews and ratings for different products from amazon.in and flipkart.com. Then we have done different text processing for reviews column and chose equal number of texts from each rating class to eliminate problem of imbalance. By doing different EDA steps we have analyzed the text. We have checked frequently occurring words in our data as well as rarely occurring words. After all these steps we have built function to train and test different algorithms and using various evaluation metrics we have selected Linear-SVC for our final model. Finally, by doing hyperparameter tuning we got optimum parameters for our final model. And finally, we got improved accuracy score for our final model.

## 2. Learning Outcomes of the Study in respect of Data Science

- This project has demonstrated the importance of NLP.
- Through different powerful tools of visualization, we were able to analyse and interpret the huge data and with the help of pie plot, count plot & word cloud, I am able to see the distribution of threat comments.
- Through data cleaning we were able to remove unnecessary columns, values, special characters, symbols, stop-words and

punctuation from our dataset due to which our model would have suffered from overfitting or underfitting.

**The few challenges while working on this project were: -**

- To find punctuations & stop words, which took time to run using NLP.
- The data set is huge it took time to run some algorithms & to check the cross-validation score.

## 3. Limitations of this work and Scope for Future Work

As we know the content of text in reviews is totally depends on the reviewer and they may rate differently which is totally depends on that particular person. So, it is difficult to predict ratings based on the reviews with higher accuracies. Still, we can improve our accuracy by fetching more data and by doing extensive hyperparameter tuning.