Amazon_reviews_sentiment_analysis

August 18, 2021

[6]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")

import re
from bs4 import BeautifulSoup
from tqdm import tqdm
from nltk.stem import WordNetLemmatizer

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,f1_score, confusion_matrix

from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.layers import Dense , Input , LSTM , Embedding, Dropout ,␣
 ↪Activation, GRU, Flatten
from keras.layers import Bidirectional, GlobalMaxPool1D
from keras.models import Model, Sequential
from keras.layers import Convolution1D
from keras import initializers, regularizers, constraints, optimizers, layers
```

[7]:

```
import io
from google.colab import files
uploaded = files.upload()
df2 = pd.read_csv(io.BytesIO(uploaded['amazon_reviews_1.csv']))
df=pd.read_csv('amazon_reviews_1.csv')
df.head()
```

```
<IPython.core.display.HTML object>
```

```
Saving amazon_reviews_1.csv to amazon_reviews_1 (1).csv
```

[7]:

```
   Unnamed: 0  … review_category
0       35311  …               1
1       44590  …               0
```

```
2       90295  …               0
3       38798  …               0
4       43364  …               0

[5 rows x 16 columns]
```

[8]:

```
df.columns
```

[8]:

```
Index(['Unnamed: 0', 'marketplace', 'customer_id', 'review_id', 'product_id',
       'product_parent', 'product_title', 'product_category', 'star_rating',
       'helpful_votes', 'total_votes', 'vine', 'verified_purchase',
       'review_date', 'review', 'review_category'],
      dtype='object')
```

[9]:

```
l=['marketplace','product_category','verified_purchase','vine','review_category','helpful_vote
 ↪'total_votes']

for i in l:
  print('The unique element in : ', i)
  print('-'*30)
  print(df[i].unique())
  print()
```

```
The unique element in :  marketplace
------------------------------
['UK']

The unique element in :  product_category
------------------------------
['Mobile_Apps' 'Video DVD' 'Music' 'Books']

The unique element in :  verified_purchase
------------------------------
['Y' 'N']

The unique element in :  vine
------------------------------
['N' 'Y']

The unique element in :  review_category
------------------------------
[1 0]

The unique element in :  helpful_votes
------------------------------
[  0   1   3   5  14   2   4  29  32   9   6  13  20  19  17   7  22  15
  18  28  31   8  10  11 190 100  30  16  42  12  38  35 102  95  27  69
  37  49  36  84 133  68 184  62  43  26  24  44  21 419  33  77  25 109
  97  39  76  56 175  46  23  80 166  34  48  63 292  41  86 127  58  70
  53  79  45 229 163  51 380 105  47 297 244  55 117 103  50  75 135 101
  90]

The unique element in :  total_votes
------------------------------
[  1   2   5   0  33  41  10   3   4  19  11  45   8  31   6  84   7  15
  23 134   9  12  14  21  27  18  28  22  13  16  25  29 109  80  26  52
  17  36 128  20 216 113 104  35  30  37  48  34  24  42  38  96  69  50
  82 110  57  46 108  98 121  87  53  91  64  39  60  62  90 142  92 196
  79  94  77  66  59 493  43  89  49  40  56  85  70 219  83  88  44 202
  54  78 178 169  72 147  32  74 305  67  47  97 149  65  55 201 132 112
  71 268  51 189 434 118  58 335 125 290  63  61  75 163 123  68 151 103
 130 222  81]
```

[10]:

```python
l=['product_category','verified_purchase','vine','review_category','helpful_votes','total_votes']

for i in l:
  print('The unique element in : ', i)
  print('-'*30)
  print(df[i].value_counts())
  print()
```

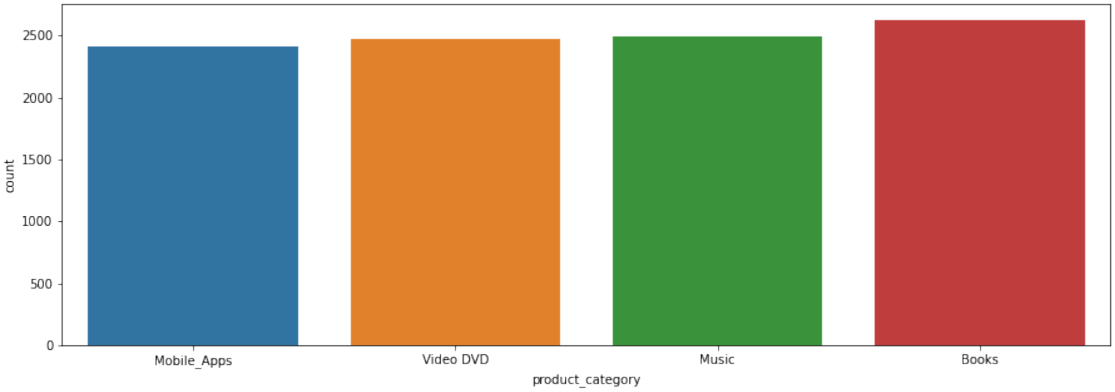
```
The unique element in :  product_category
------------------------------
Books          2624
Music          2493
Video DVD      2469
Mobile_Apps    2414
Name: product_category, dtype: int64

The unique element in :  verified_purchase
------------------------------
Y    8119
N    1881
Name: verified_purchase, dtype: int64

The unique element in :  vine
------------------------------
N    9990
Y      10
Name: vine, dtype: int64

The unique element in :  review_category
------------------------------
0    5046
```

```
1    4954
Name: review_category, dtype: int64

The unique element in :  helpful_votes
------------------------------
0      6891
1      1183
2       475
3       298
4       207
       …
58        1
53        1
77        1
101       1
175       1
Name: helpful_votes, Length: 91, dtype: int64

The unique element in :  total_votes
------------------------------
0      5205
1      1411
2       765
3       431
4       314
       …
202       1
178       1
130       1
82        1
123       1
Name: total_votes, Length: 129, dtype: int64
```

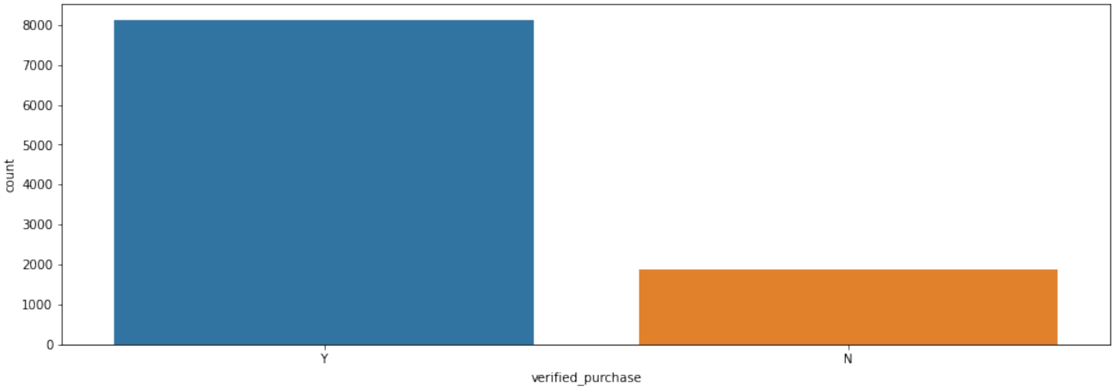
[11]:

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
l=['product_category','verified_purchase','vine','review_category','helpful_votes',␣
 ↪'total_votes']

for i in l:
  print('The count plot of  : ', i)
  print('-'*30)
  plt.figure(figsize=(15,5))
  sns.countplot(df[i])
  plt.show()
  print()
```

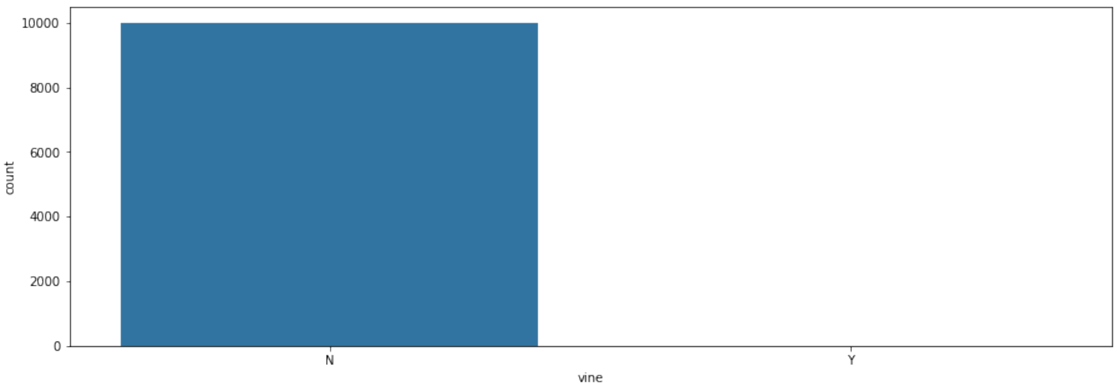
```
The count plot of  :  product_category
------------------------------
```



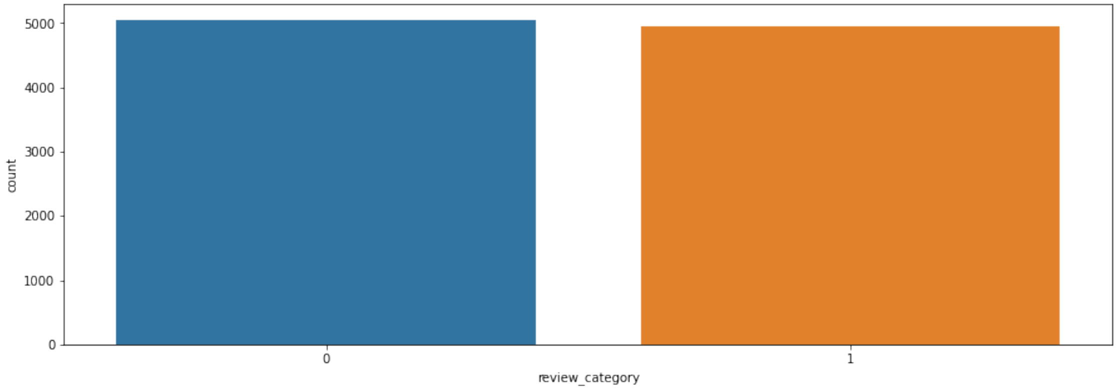
```
The count plot of  :  verified_purchase
------------------------------
```



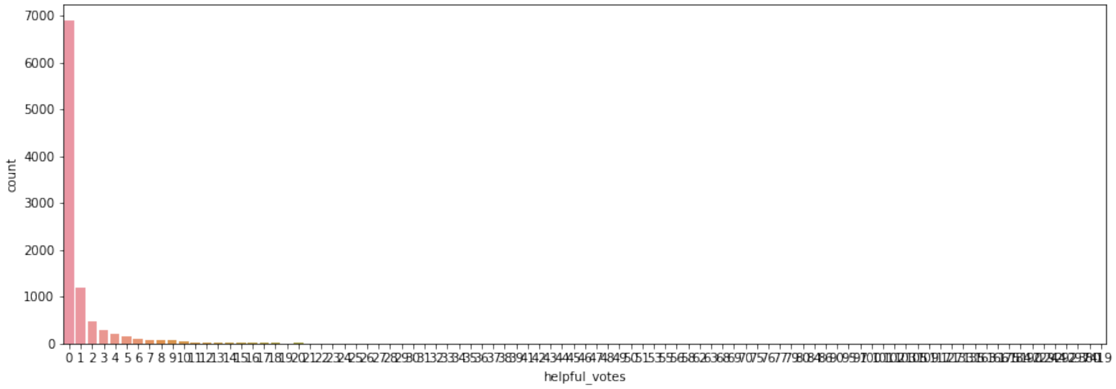
```
The count plot of  :  vine
------------------------------
```



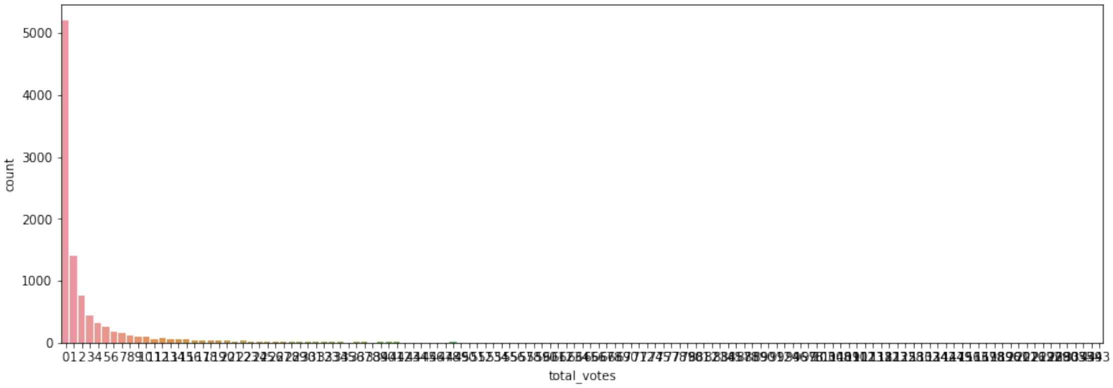
```
The count plot of  :  review_category
------------------------------
```



```
The count plot of  :  helpful_votes
------------------------------
```



```
The count plot of  :  total_votes
------------------------------
```



[12]:
```
df_new=df[['star_rating','review']]
df_new.head()
```

[12]:
```
   star_rating                                             review
0            5  Addictive game Very good game, the graphics ar…
1            2  Where to start? I came on here because I wante…
2            3  Really Disappointed in this Film I have to say…
3            1  Rubbish game When I tried to open it, it said …
4            1                                  One Star Come on
```

[13]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   star_rating  10000 non-null  int64
 1   review       9999 non-null   object
dtypes: int64(1), object(1)
memory usage: 156.4+ KB
```

[14]:
```
df_new.dropna(inplace=True)
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

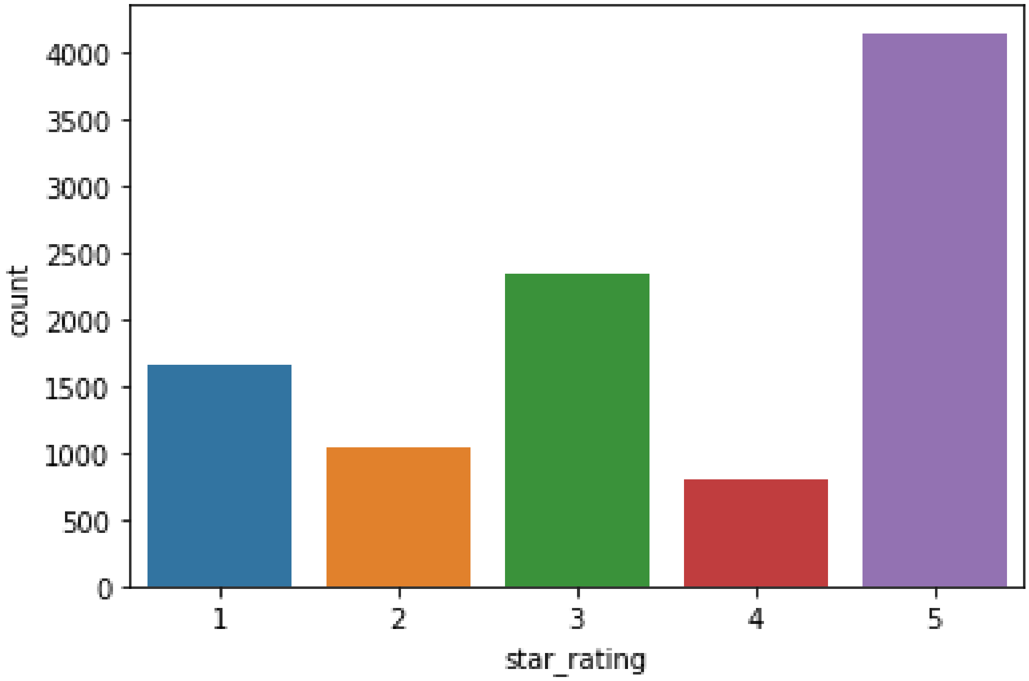
```
Int64Index: 9999 entries, 0 to 9999
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   star_rating  9999 non-null   int64
 1   review       9999 non-null   object
dtypes: int64(1), object(1)
memory usage: 234.4+ KB
```

[15]:
```
df_new['star_rating'].value_counts()
```

[15]:
```
5    4149
3    2350
1    1661
2    1035
4     804
Name: star_rating, dtype: int64
```

[16]:
```
#show the visualizing count of target feature.
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

sns.countplot(df_new['star_rating'])
```

[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb70247e6d0>
```



[17]:
```
df_new.head(1)
```

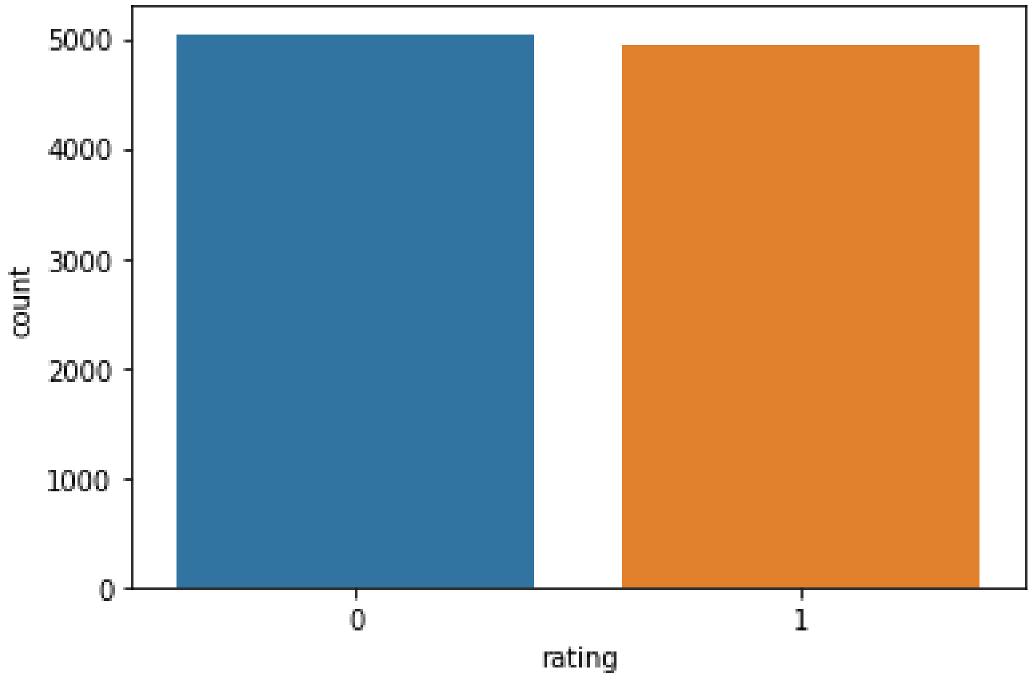
[17]:
```
   star_rating                                             review
0            5  Addictive game Very good game, the graphics ar…
```

[18]:
```
df_new["rating"] = df_new["star_rating"].apply(lambda x : 1 if x>3 else 0)
df_new.head(3)
```

[18]:
```
   star_rating                                             review  rating
0            5  Addictive game Very good game, the graphics ar…       1
1            2  Where to start? I came on here because I wante…       0
2            3  Really Disappointed in this Film I have to say…       0
```

[19]:
```
#show the visualizing count of target feature.

sns.countplot(df_new['rating'])
```

[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb7023e2e90>
```



4. Text preprocessing In this step, following operations are performed on the review text

- Removing website links
- Removing html tags
- Decontracting(expanding from the original form)

- Removing the words with numeric digits
- Removing non-word characters
- Converting to lower case
- Removing stop words
- Performing Lemmatization

[20]:

```
def decontract(text):
    text = re.sub(r"won\'t", "will not", text)
    text = re.sub(r"can\'t", "can 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)
    return text
```

[21]:

```
lemmatizer = WordNetLemmatizer()
import nltk
nltk.download('stopwords')
nltk.download('wordnet')
from nltk.corpus import stopwords
stopwords=set(stopwords.words('english'))
def preprocess_text(review):
    review = re.sub(r"http\S+", "", review)          # removing website links
    review = BeautifulSoup(review, 'lxml').get_text()    # removing html tags
    review = decontract(review)                      # decontracting
    review = re.sub("\S*\d\S*", "", review).strip()     # removing the words␣
 ↪with numeric digits
    review = re.sub('[^A-Za-z]+', ' ', review)         # removing non-word␣
 ↪characters
    review = review.lower()                          # converting to lower␣
 ↪case
    review = [word for word in review.split(" ") if not word in stopwords] #␣
 ↪removing stop words
    review = [lemmatizer.lemmatize(token, "v") for token in review]␣
 ↪#Lemmatization
    review = " ".join(review)
    review.strip()
    return review
df_new['cleaned_text'] = df_new['review'].apply(lambda x: preprocess_text(x))
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data…
[nltk_data]   Unzipping corpora/wordnet.zip.
```

[22]:
```
df_new.head(20)
```

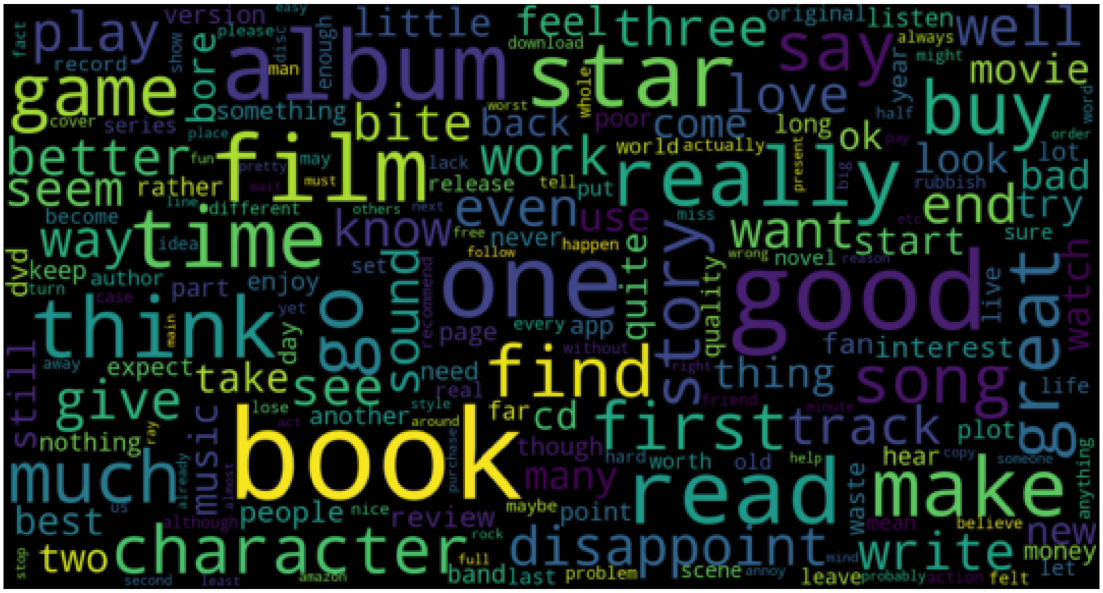
[22]:
```
    star_rating  …                                   cleaned_text
0             5  …  addictive game good game graphics brilliant gr…
1             2  …  start come want get flappy bird saw think basi…
2             3  …  really disappoint film say look forward remake…
3             1  …      rubbish game try open say stop fix higher rat
4             1  …                                    one star come
5             5  …         five star brilliant fast postage fab thank
6             5  …  five star cd excellent wish review system woul…
7             1  …  worth buy family huge matt damon fan especiall…
8             5  …                               five star good buy
9             1  …                                    one star like
10            1  …  hand hold shakey camera rubbish big monster at…
11            5  …  fantastic film great especially original end d…
12            5  …                                   love love game
13            5  …            five star great book recommend anyone
14            4  …     four star really make difference try complete
15            5  …           five star beautiful cd would recomened
16            3  …                             worth alook good hop
17            1  …  disappointingly flat album take hostile muse a…
18            3  …  bone booth happy families bone booth settle ha…
19            5  …  best booko ever best book ever love read chang…

[20 rows x 4 columns]
```

[23]:
```
df_final=df_new[['rating','cleaned_text']]
df_final.head()
```

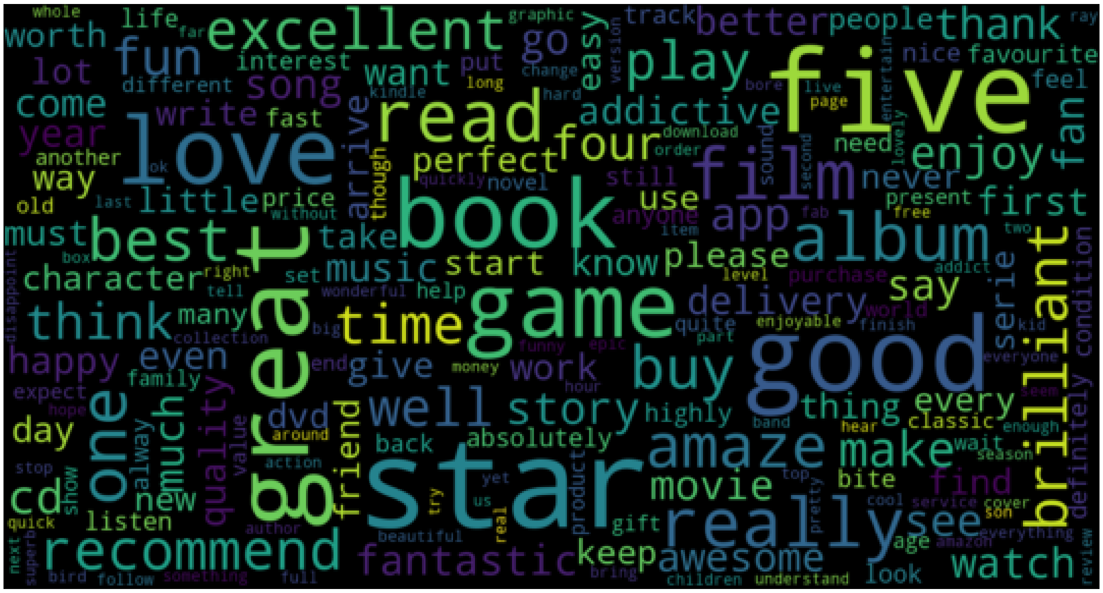
[23]:
```
   rating                                       cleaned_text
0        1  addictive game good game graphics brilliant gr…
1        0  start come want get flappy bird saw think basi…
2        0  really disappoint film say look forward remake…
3        0      rubbish game try open say stop fix higher rat
4        0                                    one star come
```

[24]:
```
#most common words used
from wordcloud import WordCloud

for i in range (0,2):
  print('When star Rating is : ', i)
  print('_'*30)
  print()
  text = df_final[df_final['rating'] == i]
  all_words = ' '.join([text for text in text.cleaned_text])
  wordcloud = WordCloud(width= 1500, height= 800,
                            max_font_size = 170,
                                        collocations = False).generate(all_words)
  plt.figure(figsize=(10,7))
  plt.imshow(wordcloud, interpolation='bilinear')
  plt.axis("off")
  plt.show()
```

```
When star Rating is :  0
------------------------------
```

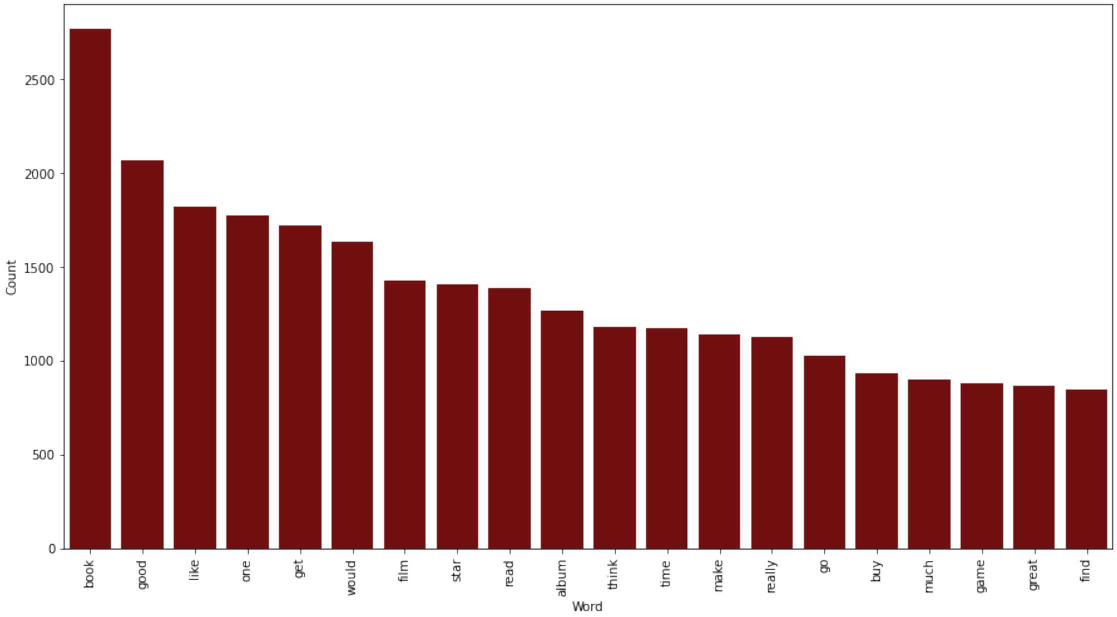


```
When star Rating is :  1
------------------------------
```

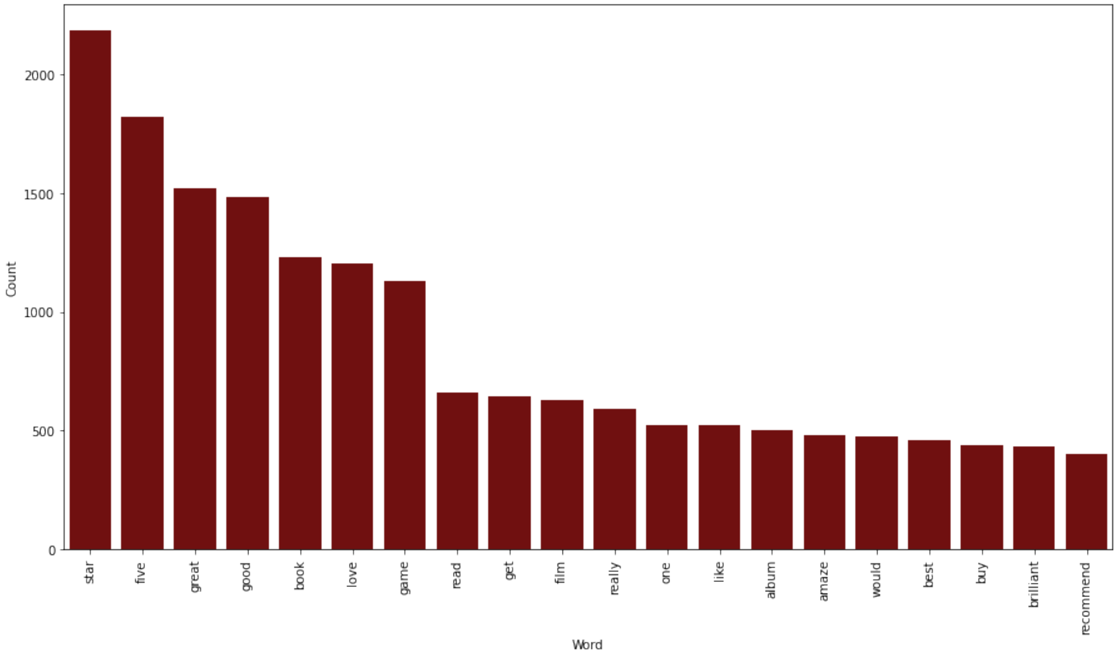


```
[25]: from nltk import tokenize
      token_space = tokenize.WhitespaceTokenizer()
      def counter(text, column_text, quantity):
          all_words = ' '.join([text for text in text[column_text]])
          token_phrase = token_space.tokenize(all_words)
          frequency = nltk.FreqDist(token_phrase)
          df_frequency = pd.DataFrame({"Word": list(frequency.keys()),
                                         "Frequency": list(frequency.values())})
          df_frequency = df_frequency.nlargest(columns = "Frequency", n = quantity)
          plt.figure(figsize=(15,8))
          ax = sns.barplot(data = df_frequency, x = "Word", y = "Frequency", color =␣
        ↪'maroon')
          ax.set(ylabel = "Count")
          plt.xticks(rotation='vertical')
          plt.show()


      for i in range(0,2):
        print('When star Rating is : ', i)
        print('_'*30)
        print()
        counter(df_final[df_final['rating'] == i], 'cleaned_text', 20)
        print()
```

```
When star Rating is :  0
______________________________
```



```
When star Rating is :  1
------------------------------
```



[26]:

```
train_df, test_df = train_test_split(df_final, test_size = 0.2, random_state =␣
 ↪42)
print("Training data size : ", train_df.shape)
print("Test data size : ", test_df.shape)
```

```
Training data size :  (7999, 2)
Test data size :  (2000, 2)
```

6. Model Building 6.1 Fitting LSTM with Embedding layer

[27]:

```
top_words = 6000
tokenizer = Tokenizer(num_words=top_words)
tokenizer.fit_on_texts(train_df['cleaned_text'])
list_tokenized_train = tokenizer.texts_to_sequences(train_df['cleaned_text'])

max_review_length = 130
X_train = pad_sequences(list_tokenized_train, maxlen=max_review_length)
y_train = train_df['rating']
```

[28]:

```
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(top_words+1, embedding_vecor_length,␣
 ↪input_length=max_review_length))
model.add(LSTM(200))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
model.summary()
```

```
Model: "sequential"

-----------------------------------------------------------------
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 130, 32)           192032

-----------------------------------------------------------------
lstm (LSTM)                  (None, 200)               186400

-----------------------------------------------------------------
dense (Dense)                (None, 1)                 201
=================================================================
Total params: 378,633
Trainable params: 378,633
Non-trainable params: 0

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

[29]:

```
model.fit(X_train,y_train, epochs=20, batch_size=8, validation_split=0.2)
```

```
Epoch 1/20
800/800 [==============================] - 30s 12ms/step - loss: 0.5203 -
accuracy: 0.7483 - val_loss: 0.2719 - val_accuracy: 0.8900
```

```
Epoch 2/20
800/800 [==============================] - 8s 10ms/step - loss: 0.2259 -
accuracy: 0.9153 - val_loss: 0.2742 - val_accuracy: 0.8894
Epoch 3/20
800/800 [==============================] - 8s 10ms/step - loss: 0.1381 -
accuracy: 0.9510 - val_loss: 0.3179 - val_accuracy: 0.8806
Epoch 4/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0926 -
accuracy: 0.9682 - val_loss: 0.3316 - val_accuracy: 0.8850
Epoch 5/20
800/800 [==============================] - 8s 11ms/step - loss: 0.0615 -
accuracy: 0.9797 - val_loss: 0.3978 - val_accuracy: 0.8844
Epoch 6/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0546 -
accuracy: 0.9843 - val_loss: 0.4403 - val_accuracy: 0.8813
Epoch 7/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0662 -
accuracy: 0.9794 - val_loss: 0.4784 - val_accuracy: 0.8719
Epoch 8/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0332 -
accuracy: 0.9906 - val_loss: 0.5904 - val_accuracy: 0.8756
Epoch 9/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0230 -
accuracy: 0.9937 - val_loss: 0.5682 - val_accuracy: 0.8737
Epoch 10/20
800/800 [==============================] - 8s 11ms/step - loss: 0.0176 -
accuracy: 0.9950 - val_loss: 0.6010 - val_accuracy: 0.8675
Epoch 11/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0248 -
accuracy: 0.9927 - val_loss: 0.6227 - val_accuracy: 0.8606
Epoch 12/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0176 -
accuracy: 0.9965 - val_loss: 0.7198 - val_accuracy: 0.8662
Epoch 13/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0124 -
accuracy: 0.9961 - val_loss: 0.5921 - val_accuracy: 0.8650
Epoch 14/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0152 -
accuracy: 0.9952 - val_loss: 0.7029 - val_accuracy: 0.8687
Epoch 15/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0156 -
accuracy: 0.9954 - val_loss: 0.6552 - val_accuracy: 0.8644
Epoch 16/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0111 -
accuracy: 0.9961 - val_loss: 0.8154 - val_accuracy: 0.8650
Epoch 17/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0043 -
accuracy: 0.9986 - val_loss: 0.7481 - val_accuracy: 0.8656
```

```
Epoch 18/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0089 -
accuracy: 0.9978 - val_loss: 0.8074 - val_accuracy: 0.8687
Epoch 19/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0065 -
accuracy: 0.9978 - val_loss: 0.7939 - val_accuracy: 0.8694
Epoch 20/20
800/800 [==============================] - 8s 10ms/step - loss: 0.0055 -
accuracy: 0.9988 - val_loss: 0.8488 - val_accuracy: 0.8637
```

[29]:

```
<keras.callbacks.History at 0x7fb6fdc73650>
```

0.1 Adding dropout

[30]:

```python
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(top_words+1, embedding_vecor_length,␣
 ↪input_length=max_review_length))
model.add(Dropout(0.3))
model.add(LSTM(100))
model.add(Dropout(0.3))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 130, 32)           192032
_________________________________________________________________
dropout (Dropout)            (None, 130, 32)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 100)               53200
_________________________________________________________________
dropout_1 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101
=================================================================
Total params: 245,333
Trainable params: 245,333
Non-trainable params: 0
_________________________________________________________________
```

[31]:

```python
model.fit(X_train,y_train, epochs=5, batch_size=64, validation_split=0.2)
```

```
Epoch 1/5
```

```
100/100 [==============================] - 4s 19ms/step - loss: 0.6247 -
accuracy: 0.6407 - val_loss: 0.3311 - val_accuracy: 0.8644
Epoch 2/5
100/100 [==============================] - 1s 12ms/step - loss: 0.3325 -
accuracy: 0.8688 - val_loss: 0.2945 - val_accuracy: 0.8781
Epoch 3/5
100/100 [==============================] - 1s 12ms/step - loss: 0.2581 -
accuracy: 0.8956 - val_loss: 0.2759 - val_accuracy: 0.8813
Epoch 4/5
100/100 [==============================] - 1s 13ms/step - loss: 0.1736 -
accuracy: 0.9353 - val_loss: 0.2735 - val_accuracy: 0.8844
Epoch 5/5
100/100 [==============================] - 1s 13ms/step - loss: 0.1403 -
accuracy: 0.9505 - val_loss: 0.2966 - val_accuracy: 0.8800
```

```
[31]: <keras.callbacks.History at 0x7fb6f0423e50>
```

6.2 Evaluating model performance on test data

```
[32]: list_tokenized_test = tokenizer.texts_to_sequences(test_df['cleaned_text'])
      X_test = pad_sequences(list_tokenized_test, maxlen=max_review_length)
      y_test = test_df['rating']
      prediction = model.predict(X_test)
      y_pred = (prediction > 0.5)
      print("Accuracy of the model : ", accuracy_score(y_pred, y_test))
      print('F1-score: ', f1_score(y_pred, y_test))
      print('Confusion matrix:')
      confusion_matrix(y_test,y_pred)
```

```
Accuracy of the model :  0.8765
F1-score:  0.8711528429838289
Confusion matrix:
```

```
[32]: array([[918, 111],
             [136, 835]])
```

1 ML

```
[33]: df_final.head(2)
```

```
[33]:    rating                                       cleaned_text
      0       1  addictive game good game graphics brilliant gr…
      1       0  start come want get flappy bird saw think basi…
```

```
[34]: x=df_final['cleaned_text']
      y=df_final['rating']
      print(x[:5])
      print(y[:5])
```

```
0    addictive game good game graphics brilliant gr…
1    start come want get flappy bird saw think basi…
2    really disappoint film say look forward remake…
3        rubbish game try open say stop fix higher rat
4                                        one star come
Name: cleaned_text, dtype: object
0    1
1    0
2    0
3    0
4    0
Name: rating, dtype: int64
```

[35]:
```
#countvectoriser with stemming

from sklearn.feature_extraction.text import CountVectorizer
CV=CountVectorizer(max_features=5000, ngram_range=(2,2))
x_stem=CV.fit_transform(x).toarray()
x_stem
```

[35]:
```
array([[0, 0, 0, …, 0, 0, 0],
       [0, 0, 0, …, 0, 0, 0],
       [0, 0, 0, …, 0, 0, 0],
       …,
       [0, 0, 0, …, 0, 0, 0],
       [0, 0, 0, …, 0, 0, 0],
       [0, 0, 0, …, 0, 0, 0]])
```

[36]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test= train_test_split(x_stem,y,test_size=0.2)
```

[37]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[37]:
```
((7999, 5000), (2000, 5000), (7999,), (2000,))
```

[38]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import SGDClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import ExtraTreesClassifier

from sklearn import metrics
```

[39]:

```
clf_logit_pca = LogisticRegression()
clf_tree_pca = DecisionTreeClassifier()
clf_svm_pca = SVC(probability = True)
clf_rf_pca= RandomForestClassifier(n_estimators=100)
clf_gb_pca= GradientBoostingClassifier(n_estimators=100)
clf_bag_pca= BaggingClassifier(n_estimators=100)
clf_nb_pca= GaussianNB()
clf_sgd_pca= SGDClassifier(loss='modified_huber',shuffle=True, random_state=101)
clf_knn_pca= KNeighborsClassifier(n_neighbors=15)
clf_etc_pca= ExtraTreesClassifier(n_estimators = 5,
                                        criterion ='entropy', max_features = 2)
```

[40]:

```
classifiers = ['LogisticRegression', 'DecisionTreeClassifier', 'SVC',␣
 ↪'RandomForestClassifier',
               'GradientBoostingClassifier', 'BaggingClassifier', 'GaussianNB',␣
 ↪'SGDClassifier',
               'KNeighborsClassifier', 'ExtraTreesClassifier' ]
```

[41]:

```
models = {clf_logit_pca: 'LogisticRegression',
          clf_tree_pca: 'DecisionTreeClassifier',
          clf_svm_pca: 'SVC',
          clf_rf_pca: 'RandomForestClassifier',
          clf_gb_pca: 'GradientBoostingClassifier',
          clf_bag_pca: 'BaggingClassifier',
          clf_nb_pca: 'GaussianNaiveBayes',
          clf_sgd_pca: 'StochasticGradientDescent',
          clf_knn_pca: 'KNN',
          clf_etc_pca: 'ExtraTreesClassifier'}
```

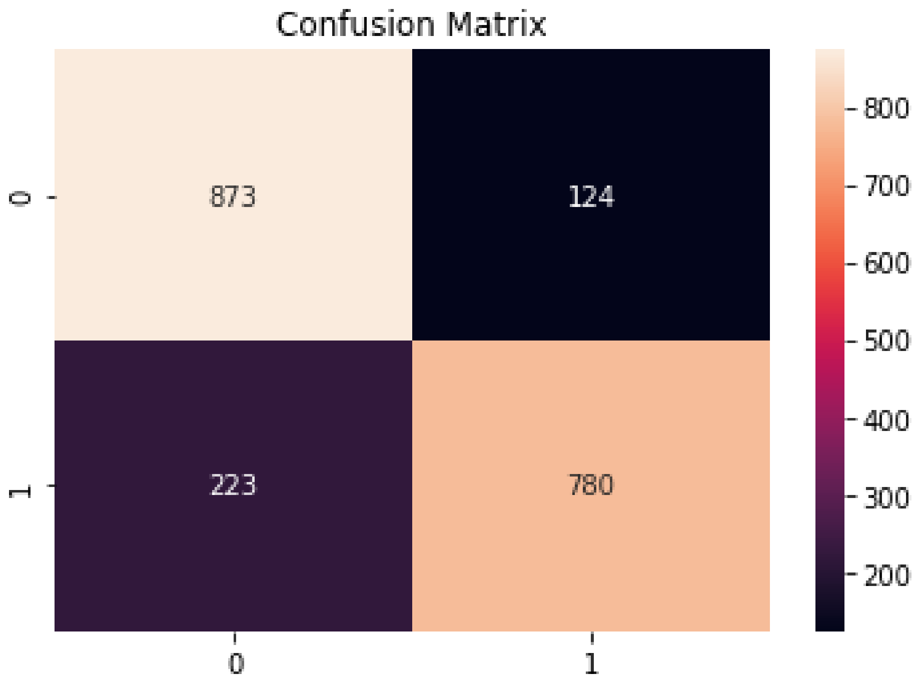
[42]:

```
def train(algo, name, X_train, y_train, X_test, y_test):
    algo.fit(X_train, y_train)
    y_test_pred = algo.predict(X_test)
    return y_test_pred


def performance(algo, name, X_test, y_test, y_test_pred):
    # Accuracy Score
    score = metrics.accuracy_score(y_test, y_test_pred)
    print('Accuracy score for', name, ':', score)

    # Confusion Metrics
    sns.heatmap(metrics.confusion_matrix(y_test, y_test_pred), annot=True,␣
 ↪fmt='d')
    plt.title("Confusion Matrix")
    plt.show()

    # Classification Report
    print(metrics.classification_report(y_test, y_test_pred))

    # ROC AUC Score
    prob = algo.predict_proba(X_test)
    prob = prob[:, 1]
    roc_auc = metrics.roc_auc_score(y_test, prob)
    print(roc_auc)

    # Plotting ROC Curve
    fpr, tpr, thresholds = metrics.roc_curve(y_test, prob)
    plt.plot([0, 1], [0, 1], linestyle='--')
    plt.plot(fpr, tpr, marker='.')
    plt.show()

    return roc_auc


def main(models):
    auc = []
    for algo, name in models.items():
        print('#'*40, name, '#'*40)
        y_test_pred = train(algo, name, X_train, y_train, X_test, y_test)
        roc_auc = performance(algo, name, X_test, y_test, y_test_pred)
        auc.append(roc_auc)
    return auc
```

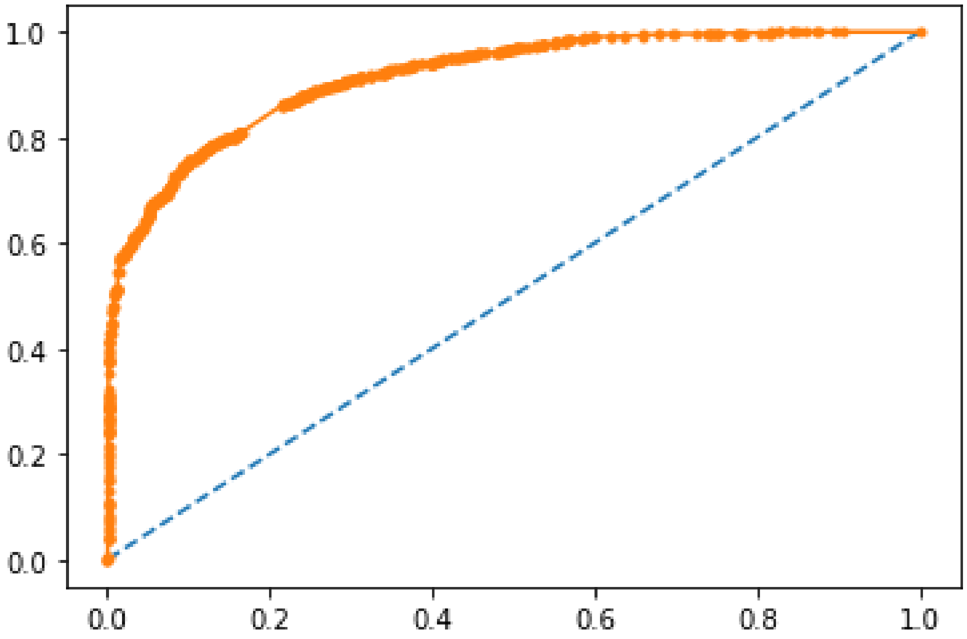
[43]:

```
%%time

auc = main(models)
```

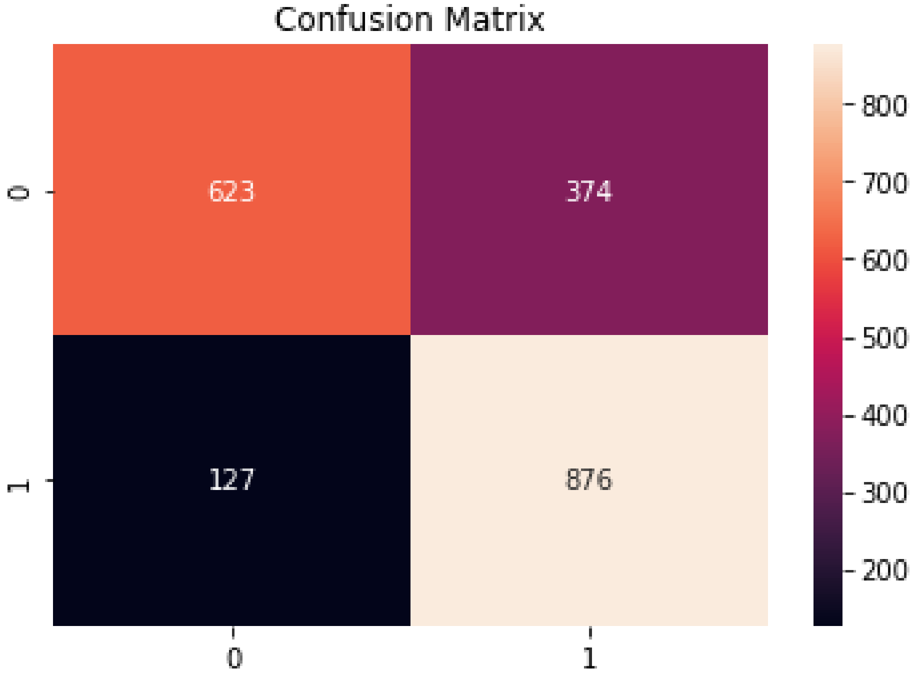
```
######################################## LogisticRegression
########################################
Accuracy score for LogisticRegression : 0.8265
```



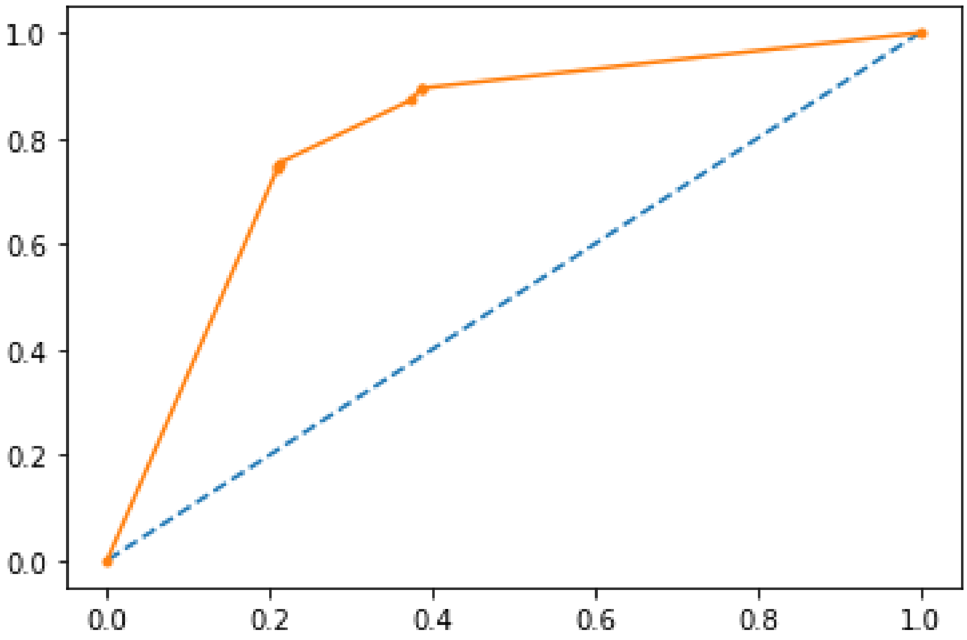
```
              precision    recall  f1-score   support

           0       0.80      0.88      0.83       997
           1       0.86      0.78      0.82      1003

    accuracy                           0.83      2000
   macro avg       0.83      0.83      0.83      2000
weighted avg       0.83      0.83      0.83      2000

0.9162422461802157
```



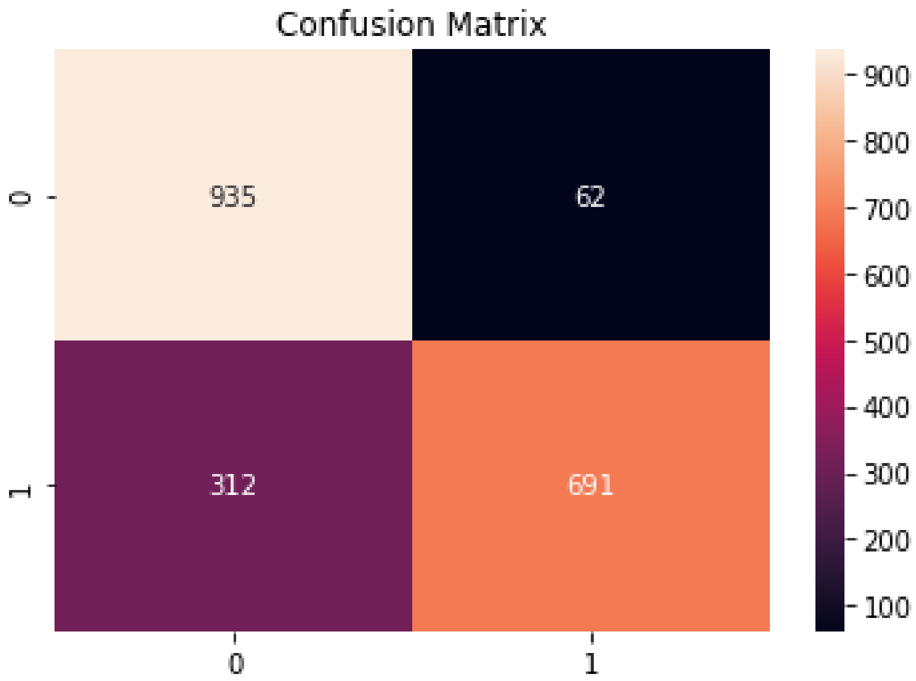
```
######################################## DecisionTreeClassifier
########################################
Accuracy score for DecisionTreeClassifier : 0.7495
```



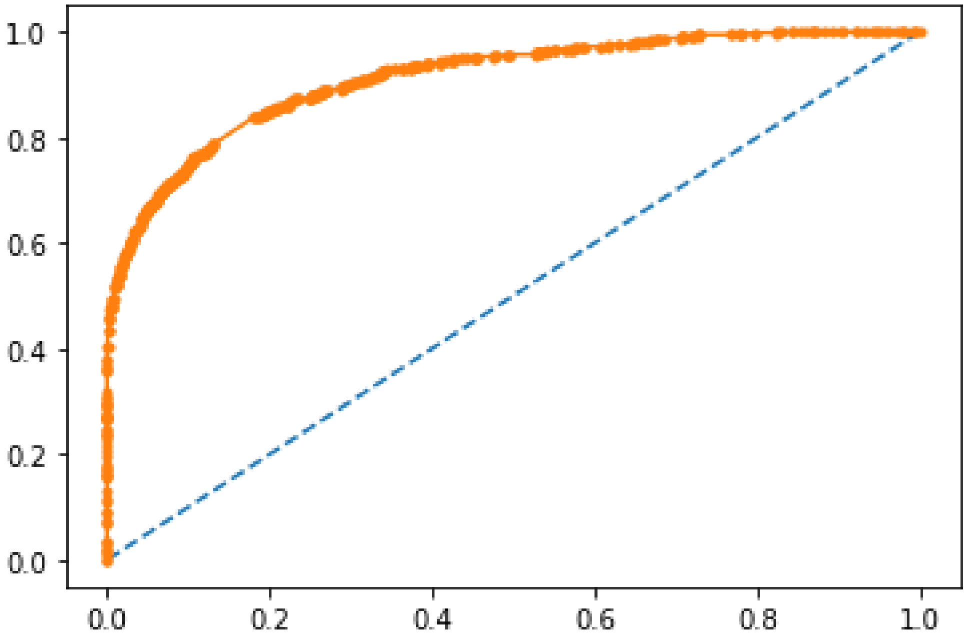
```
              precision    recall  f1-score   support

           0       0.83      0.62      0.71       997
           1       0.70      0.87      0.78      1003

    accuracy                           0.75      2000
   macro avg       0.77      0.75      0.75      2000
weighted avg       0.77      0.75      0.75      2000

0.8037397336576029
```



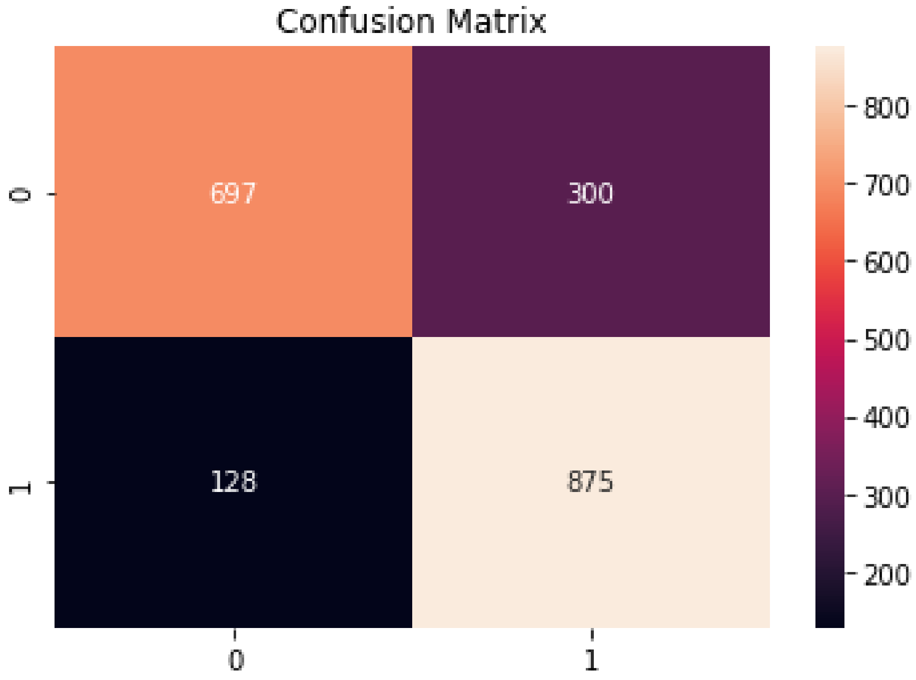
```
######################################## SVC
########################################
Accuracy score for SVC : 0.813
```



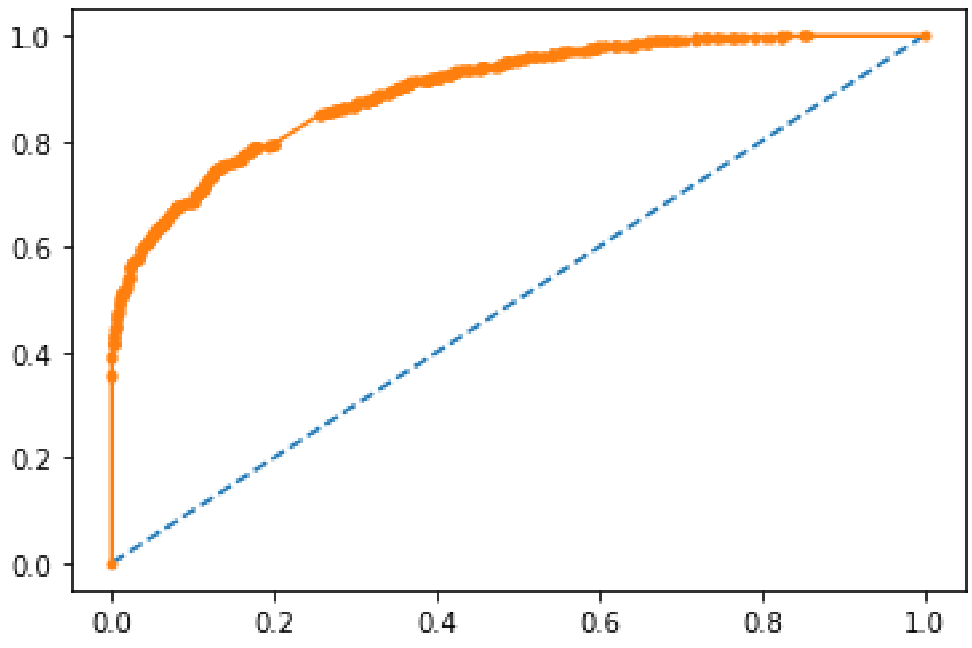
```
              precision    recall  f1-score   support

           0       0.75      0.94      0.83       997
           1       0.92      0.69      0.79      1003

    accuracy                           0.81      2000
   macro avg       0.83      0.81      0.81      2000
weighted avg       0.83      0.81      0.81      2000

0.9135582220239982
```



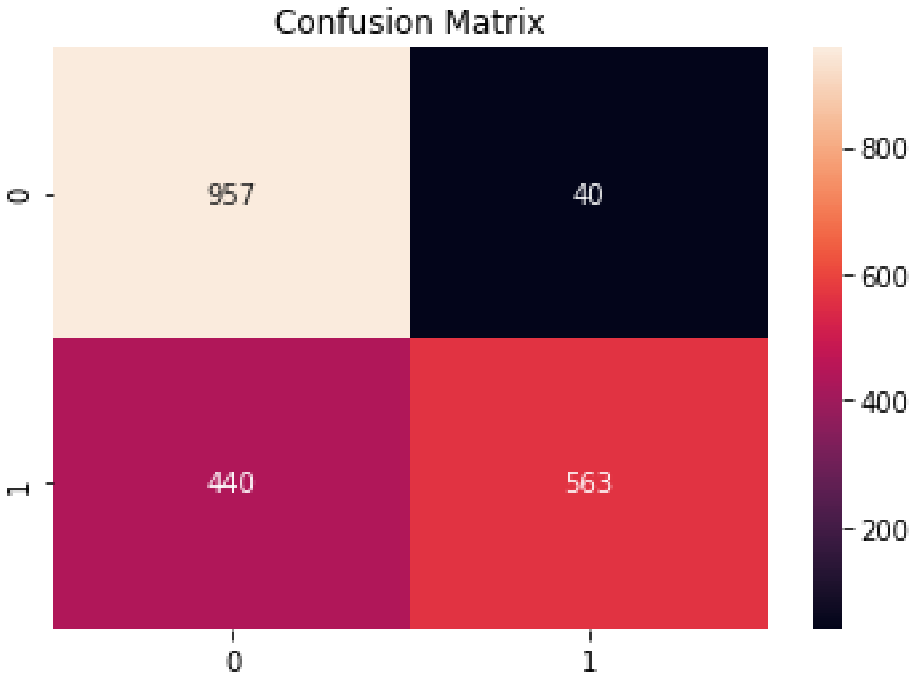
```
######################################## RandomForestClassifier
########################################
Accuracy score for RandomForestClassifier : 0.786
```



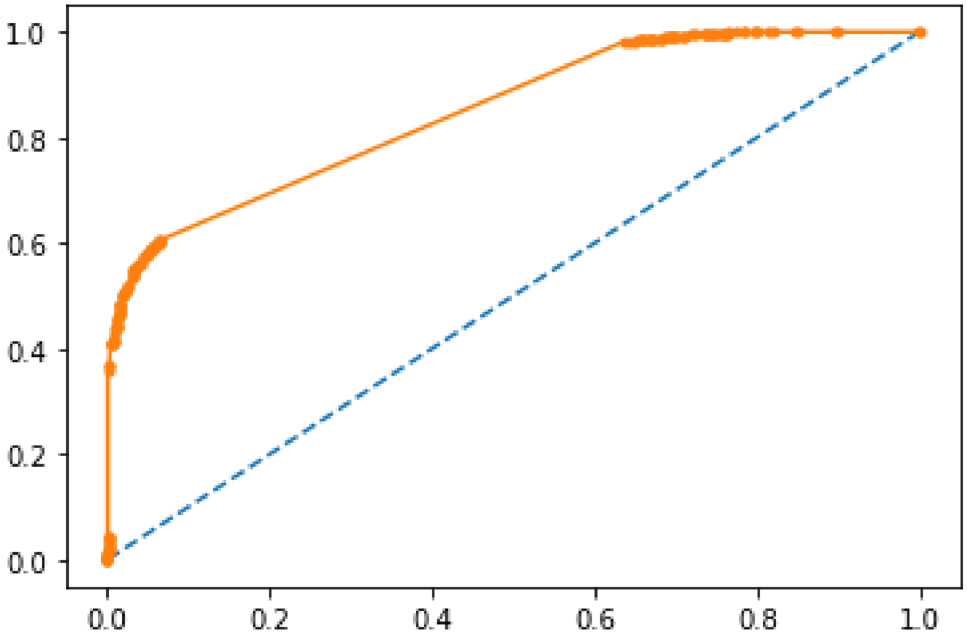
```
              precision    recall  f1-score   support

           0       0.84      0.70      0.77       997
           1       0.74      0.87      0.80      1003

    accuracy                           0.79      2000
   macro avg       0.79      0.79      0.78      2000
weighted avg       0.79      0.79      0.78      2000

0.8985515869642827
```



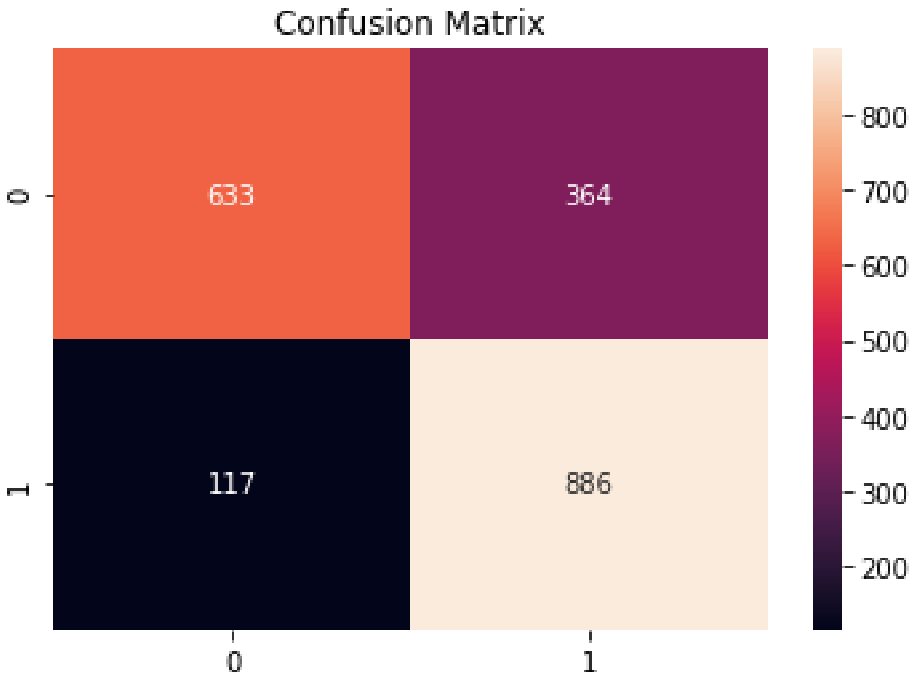
```
######################################## GradientBoostingClassifier
########################################
Accuracy score for GradientBoostingClassifier : 0.76
```



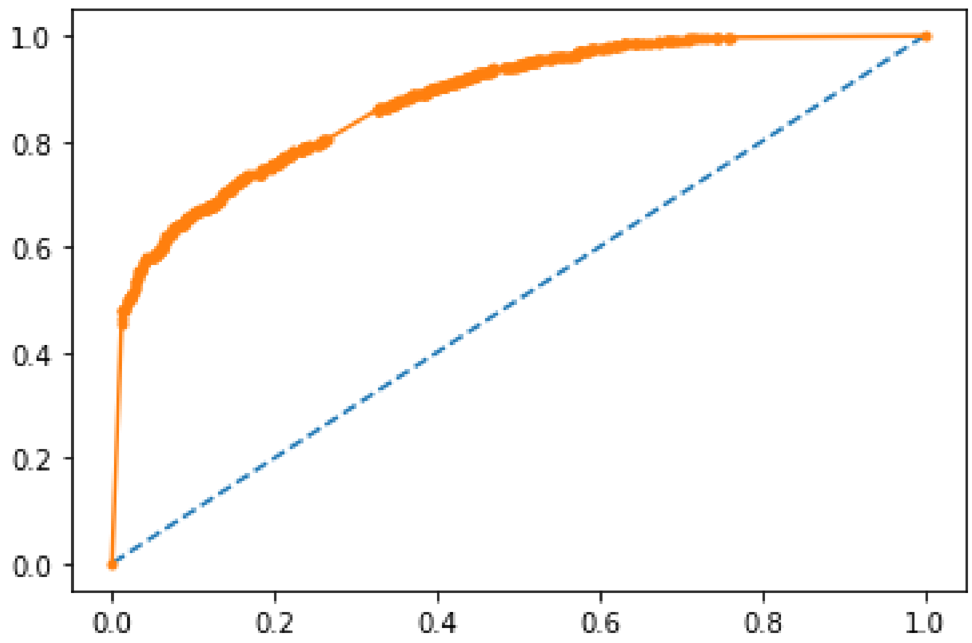
```
              precision    recall  f1-score   support

           0       0.69      0.96      0.80       997
           1       0.93      0.56      0.70      1003

    accuracy                           0.76      2000
   macro avg       0.81      0.76      0.75      2000
weighted avg       0.81      0.76      0.75      2000

0.8493766443897995
```



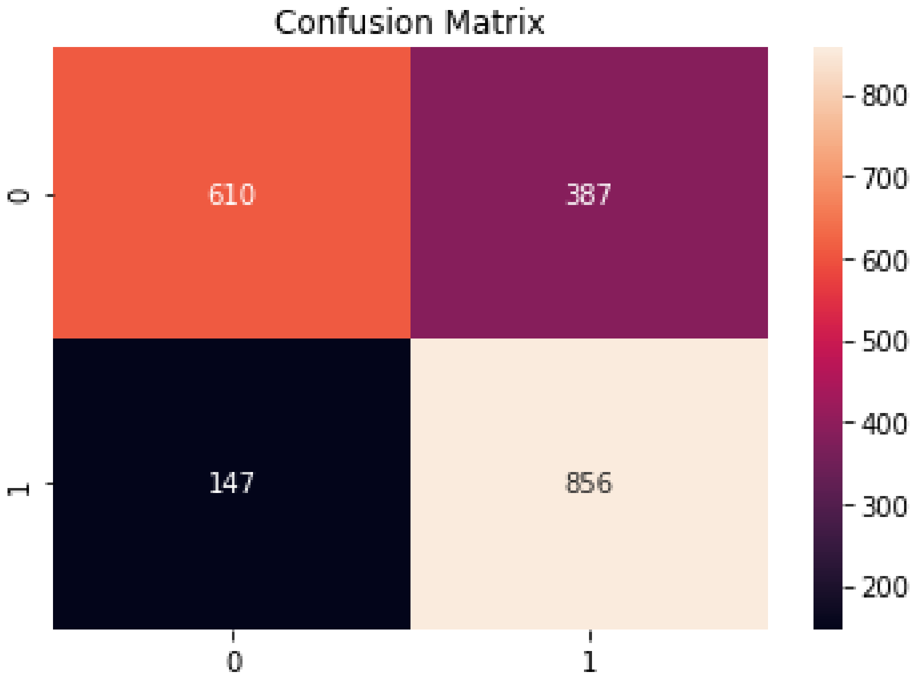
```
######################################## BaggingClassifier
########################################
Accuracy score for BaggingClassifier : 0.7595
```



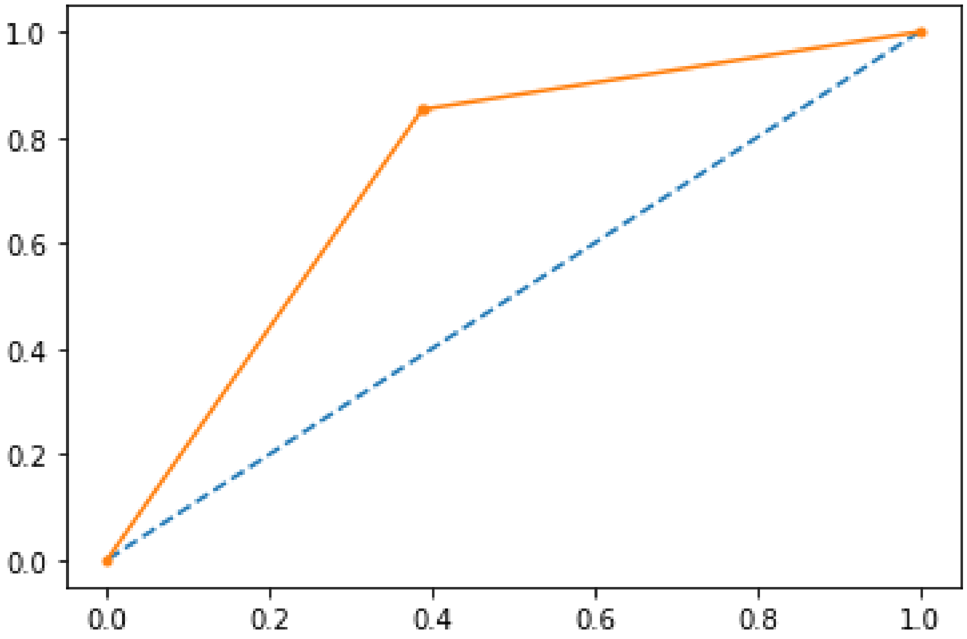
```
              precision    recall  f1-score   support

           0       0.84      0.63      0.72       997
           1       0.71      0.88      0.79      1003

    accuracy                           0.76      2000
   macro avg       0.78      0.76      0.76      2000
weighted avg       0.78      0.76      0.76      2000

0.8789239103151927
```



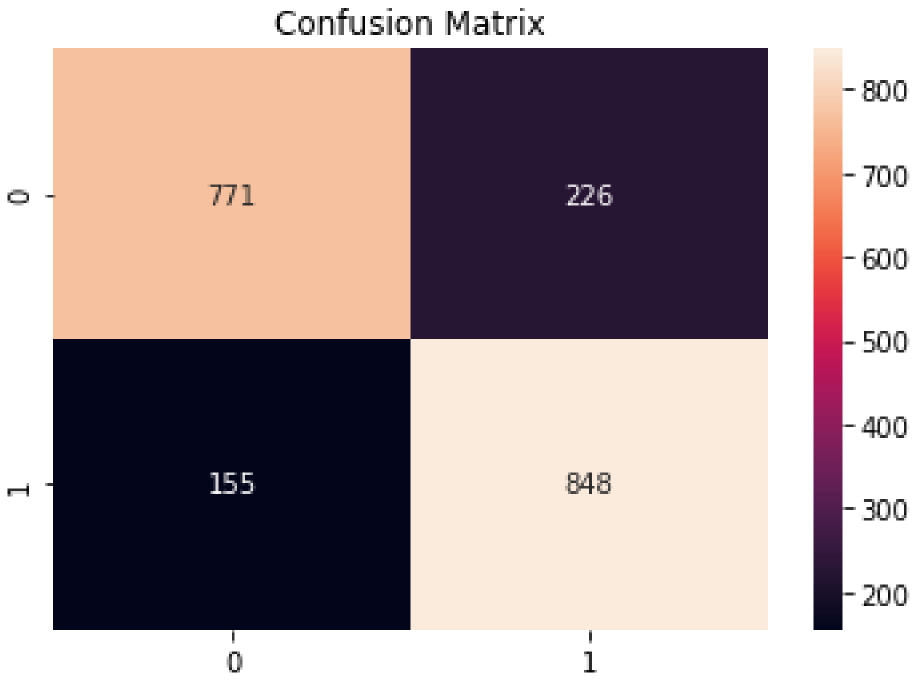
```
######################################## GaussianNaiveBayes
########################################
Accuracy score for GaussianNaiveBayes : 0.733
```



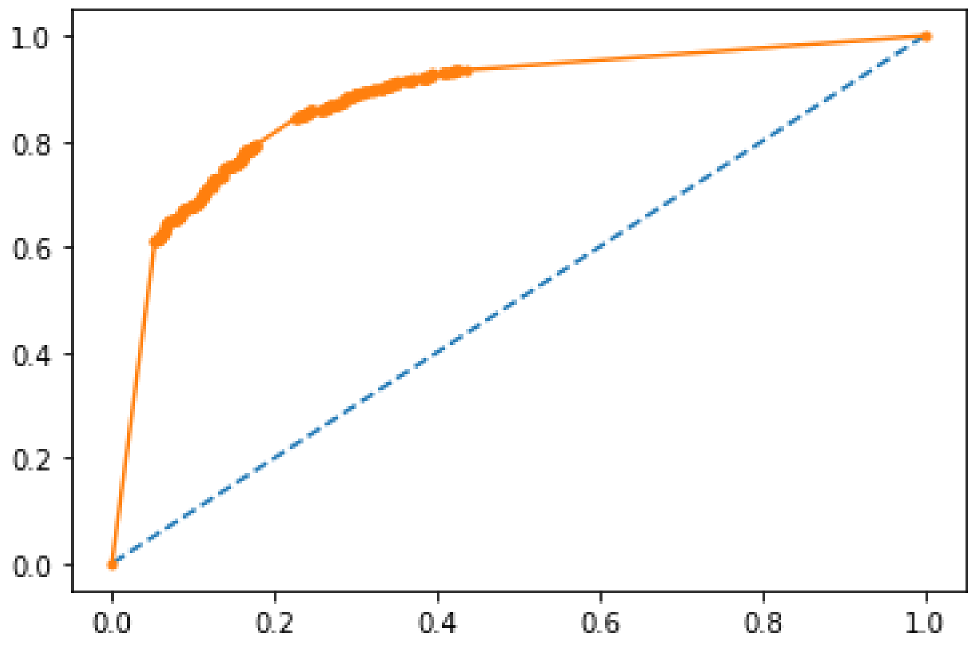
```
              precision    recall  f1-score   support

           0       0.81      0.61      0.70       997
           1       0.69      0.85      0.76      1003

    accuracy                           0.73      2000
   macro avg       0.75      0.73      0.73      2000
weighted avg       0.75      0.73      0.73      2000

0.7325640930768378
```



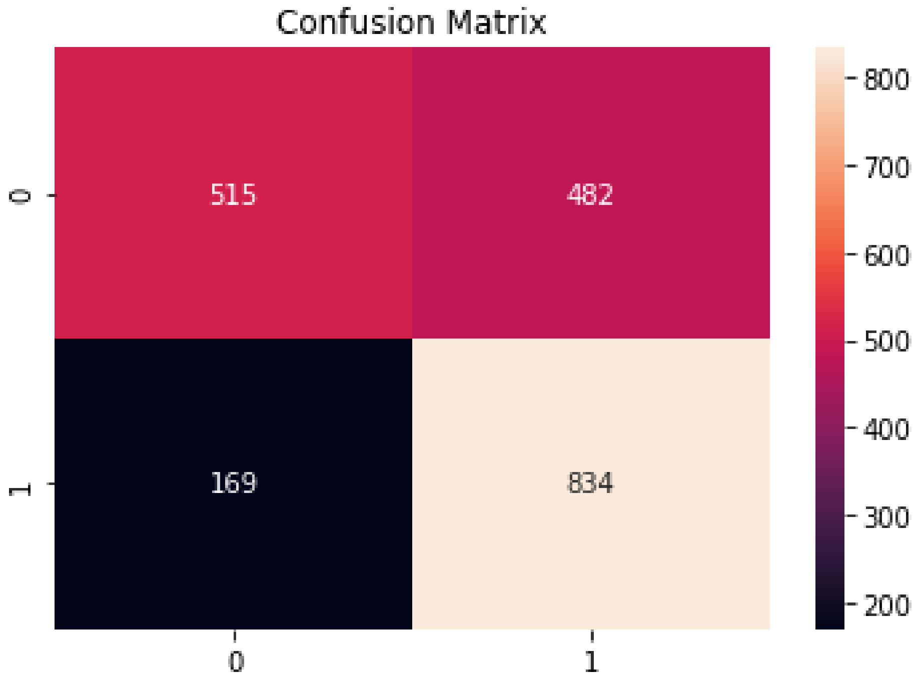
```
######################################## StochasticGradientDescent
########################################
Accuracy score for StochasticGradientDescent : 0.8095
```



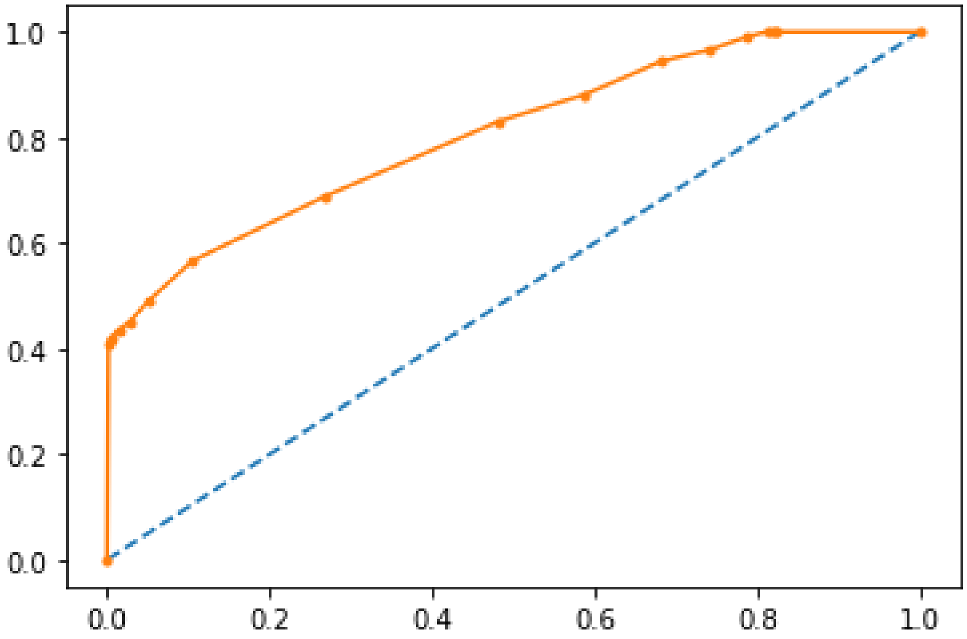
```
              precision    recall  f1-score   support

           0       0.83      0.77      0.80       997
           1       0.79      0.85      0.82      1003

    accuracy                           0.81      2000
   macro avg       0.81      0.81      0.81      2000
weighted avg       0.81      0.81      0.81      2000

0.8780164021476193
```



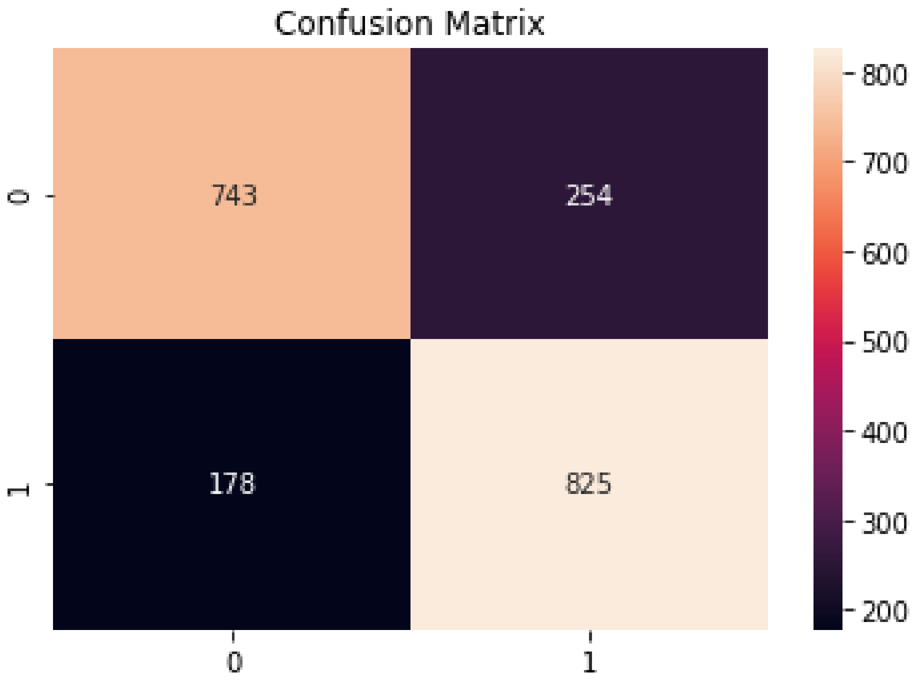
```
######################################## KNN
########################################
Accuracy score for KNN : 0.6745
```



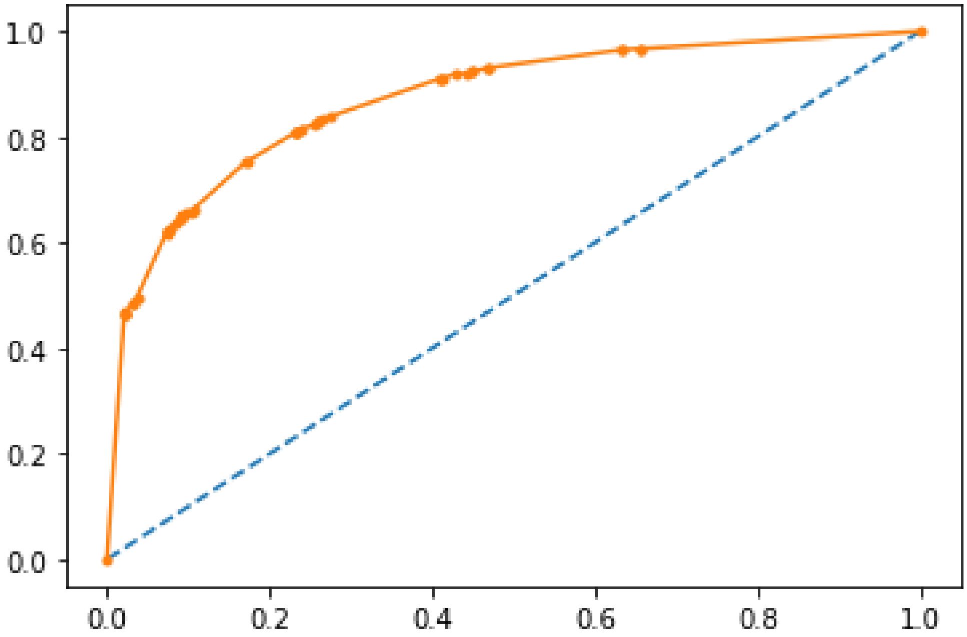
```
              precision    recall  f1-score   support

           0       0.75      0.52      0.61       997
           1       0.63      0.83      0.72      1003

    accuracy                           0.67      2000
   macro avg       0.69      0.67      0.67      2000
weighted avg       0.69      0.67      0.67      2000

0.806555759001831
```



```
######################################## ExtraTreesClassifier
########################################
Accuracy score for ExtraTreesClassifier : 0.784
```



```
              precision    recall  f1-score   support

           0       0.81      0.75      0.77       997
           1       0.76      0.82      0.79      1003

    accuracy                           0.78      2000
   macro avg       0.79      0.78      0.78      2000
weighted avg       0.79      0.78      0.78      2000

0.8714433429900871
```



```
CPU times: user 1h 11min 9s, sys: 4.89 s, total: 1h 11min 14s
Wall time: 1h 10min 49s
```

[44]:
```
model_comp_df = pd.DataFrame(auc, columns = ['ROC AUC'], index = classifiers)

model_comp_df.sort_values(by='ROC AUC', ascending=False)
```

[44]:
```
                             ROC AUC
LogisticRegression          0.916242
SVC                         0.913558
RandomForestClassifier      0.898552
BaggingClassifier           0.878924
SGDClassifier               0.878016
ExtraTreesClassifier        0.871443
GradientBoostingClassifier  0.849377
```

```
KNeighborsClassifier          0.806556
DecisionTreeClassifier        0.803740
GaussianNB                    0.732564
```

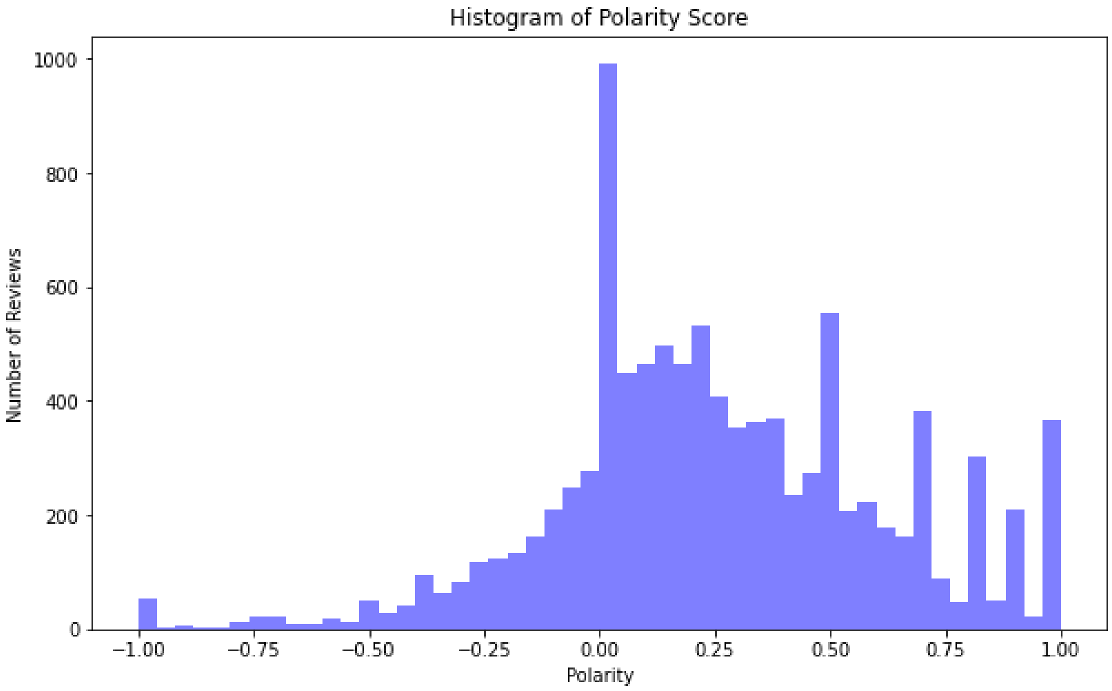
```
[45]: from textblob import TextBlob
```

```
[46]: df_new.columns
```

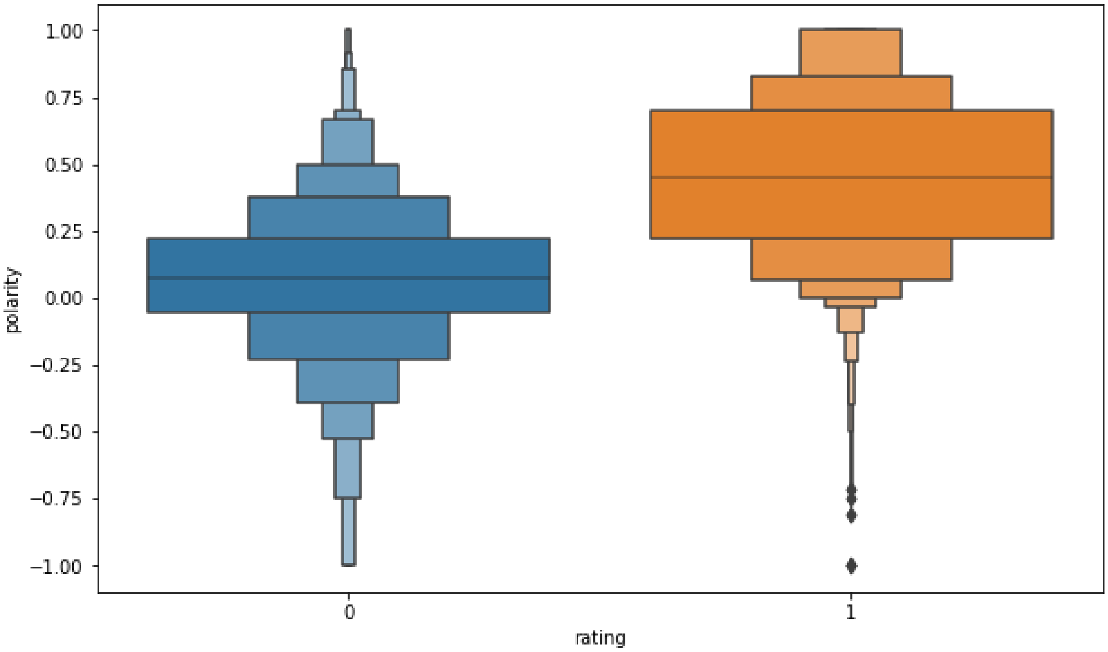
```
[46]: Index(['star_rating', 'review', 'rating', 'cleaned_text'], dtype='object')
```

#polarity

```
[47]: df_new['review']= df_new['review'].astype(str) #Make sure about the correct␣
       ↪data type
      pol = lambda x: TextBlob(x).sentiment.polarity
      df_new['polarity'] = df_new['review'].apply(pol)
      import matplotlib.pyplot as plt
      import seaborn as sns
      num_bins = 50
      plt.figure(figsize=(10,6))
      n, bins, patches = plt.hist(df_new.polarity, num_bins, facecolor='blue',␣
       ↪alpha=0.5)
      plt.xlabel('Polarity')
      plt.ylabel('Number of Reviews')
      plt.title('Histogram of Polarity Score')
      plt.show();
```



[48]:
```
plt.figure(figsize=(10,6))
sns.boxenplot(x='rating', y='polarity', data=df_new)
plt.show();
```



#subjectivity

[49]:
```
sub = lambda x: TextBlob(x).sentiment.subjectivity
df_new['subjectivity'] = df_new['review'].apply(sub)
df_new.sample(10)
```

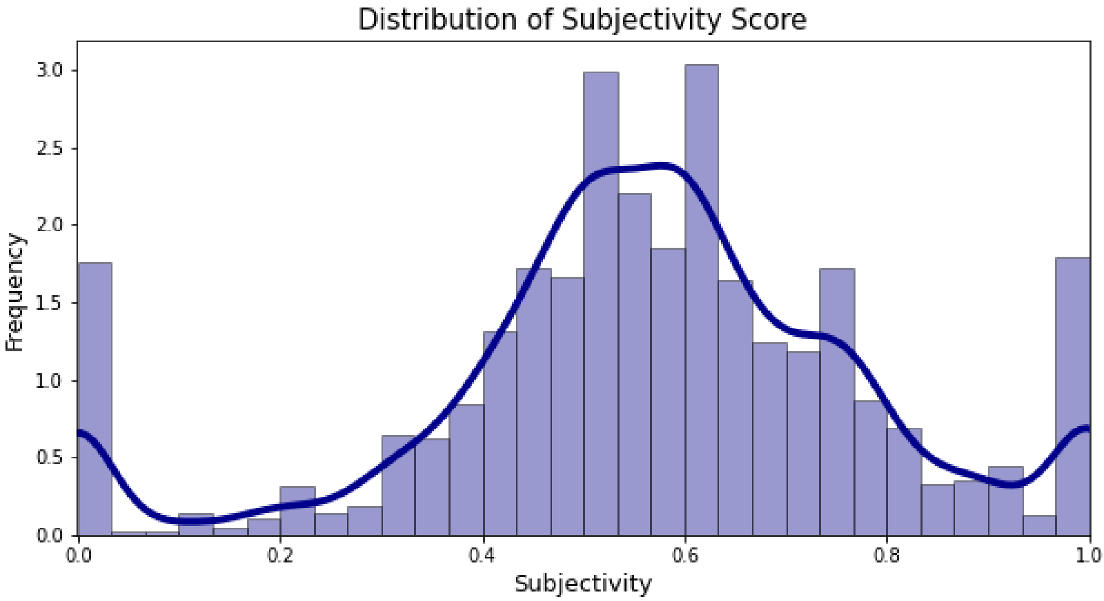
[49]:
```
      star_rating  … subjectivity
5047            5  …     0.755952
3181            4  …     1.000000
8899            5  …     0.625000
3156            1  …     0.426667
733             5  …     1.000000
9311            3  …     0.058333
8475            3  …     0.416667
4765            2  …     0.408333
9542            4  …     0.640000
8668            3  …     0.341667

[10 rows x 6 columns]
```

[50]:

```
# Density Plot and Histogram of subjectivity
plt.figure(figsize=(10,5))
sns.distplot(df_new['subjectivity'], hist=True, kde=True,
bins=int(30), color = 'darkblue',
hist_kws={'edgecolor':'black'},
kde_kws={'linewidth': 4})
plt.xlim([-0.001,1.001])
plt.xlabel('Subjectivity', fontsize=13)
plt.ylabel('Frequency', fontsize=13)
plt.title('Distribution of Subjectivity Score', fontsize=15)
```

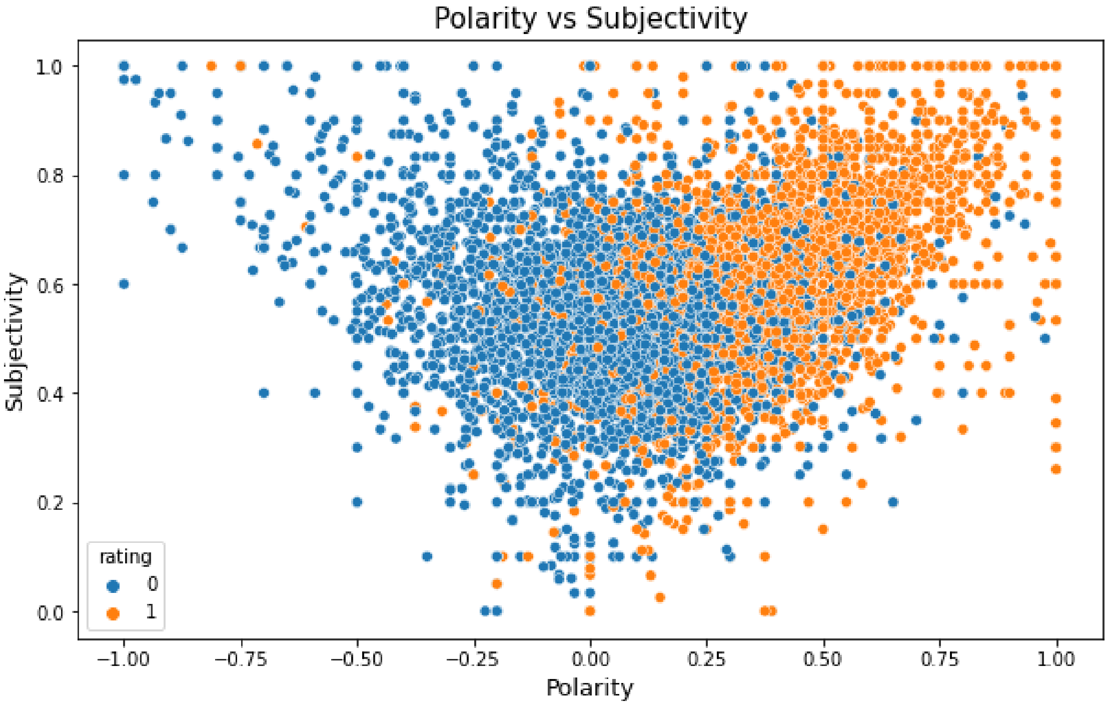
[50]:

```
Text(0.5, 1.0, 'Distribution of Subjectivity Score')
```



[51]:

```
plt.figure(figsize=(10,6))
sns.scatterplot(x='polarity', y='subjectivity', hue="rating", data=df_new)
plt.xlabel('Polarity', fontsize=13)
plt.ylabel('Subjectivity', fontsize=13)
plt.title('Polarity vs Subjectivity', fontsize=15)
plt.show();
```


Polarity vs Subjectivity
Subjectivity
Polarity
1.0
0.8
0.6
0.4
0.2
0.0
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
rating
● 0
● 1

[51]:

```

```