
## About Dataset

### Context

> This dataset consists of reviews of fine foods from amazon. The data span a period of more than 10 years, including all ~500,000 reviews up to October 2012. Reviews include product and user information, ratings, and a plain text review. It also includes reviews from all other Amazon categories.

## Data includes:

- Reviews from Oct 1999 - Oct 2012
- 568,454 reviews
- 256,059 users
- 74,258 products
- 260 users with > 50 reviews dataset_source= ['https://www.kaggle.com/datasets/snap/amazon-fine-food-reviews']

```
#!pip install tqdm
```

## Importing Necessary Libraies

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style="whitegrid")
import  warnings
warnings.filterwarnings('ignore')
from tqdm.notebook import tqdm
colors = ['deeppink','royalblue','lightgreen','yellow','grey']
```

## Loading and reading the Dataset

```
dataset_path='Reviews.csv'
df = pd.read_csv(dataset_path)
```

```
df =df.head(10000)
df
```

| | Id | ProductId | UserId | ProfileName | HelpfulnessNumerator | HelpfulnessDenominator | Score | Time | Summary | Text |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | B001E4KFG0 | A3SGXH7AUHU8GW | delmartian | 1 | 1 | 5 | 1303862400 | Good Quality Dog Food | I have bought several of the Vitality canned d... |
| **1** | 2 | B00813GRG4 | A1D87F6ZCVE5NK | dll pa | 0 | 0 | 1 | 1346976000 | Not as Advertised | Product arrived labeled as Jumbo Salted Peanut... |
| **2** | 3 | B000LQOCH0 | ABXLMWJIXXAIN | Natalia Corres "Natalia Corres" | 1 | 1 | 4 | 1219017600 | "Delight" says it all | This is a confection that has been around a fe... |
| **3** | 4 | B000UA0QIQ | A395BORC6FGVXV | Karl | 3 | 3 | 2 | 1307923200 | Cough Medicine | If you are looking for the secret ingredient i... |
| **4** | 5 | B006K2ZZ7K | A1UQRSCLF8GW1T | Michael D. Bigham "M. Wassir" | 0 | 0 | 5 | 1350777600 | Great taffy | Great taffy at a great price. There was a wid... |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **9995** | 9996 | B000P41A28 | A3A63RACXR1XIL | A. Boodhoo "deaddodo" | 10 | 15 | 1 | 1204502400 | constipation | we switched from the advance similac to the or... |
| **9996** | 9997 | B000P41A28 | A5VVRGL8JA7R | Adam | 2 | 3 | 5 | 1306368000 | Constipation Not A Problem if... | Like the bad reviews say, the organic formula ... |

```
#df =df.head(10000)
```

## Exploring the Dataset

```
df.isnull().sum()
```

```
Id                        0
ProductId                 0
UserId                    0
ProfileName               0
HelpfulnessNumerator      0
HelpfulnessDenominator    0
Score                     0
Time                      0
Summary                   0
Text                      0
dtype: int64
```

```
# we don't need 'ProfileName', 'Summary'
df = df.drop(['ProfileName', 'Summary',],axis=1)
```

```
df.shape
```

```
(10000, 8)
```

```
df.info()
```

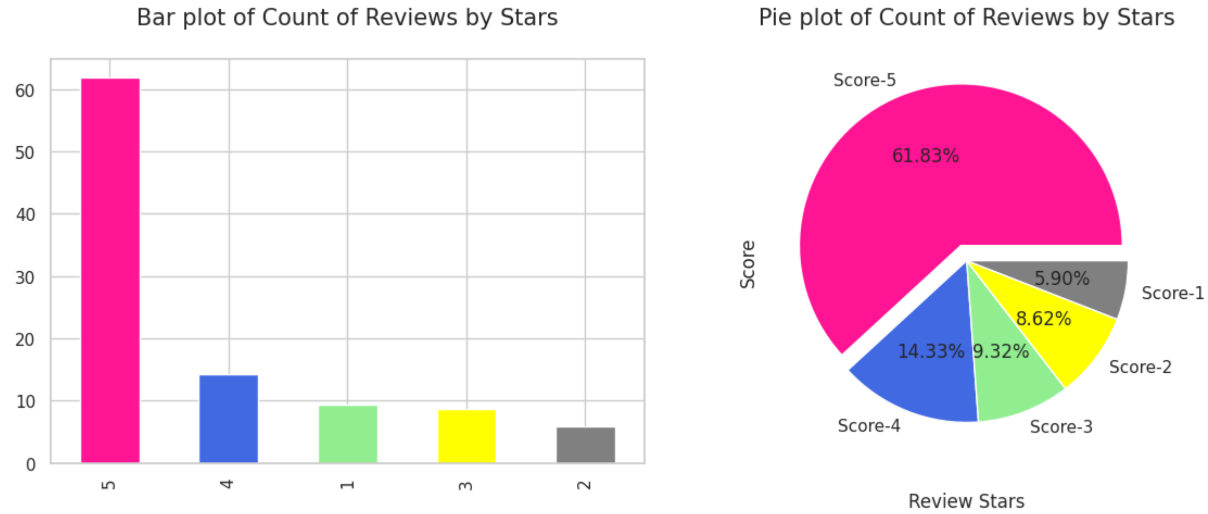
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 8 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Id                      10000 non-null  int64 
 1   ProductId               10000 non-null  object
 2   UserId                  10000 non-null  object
 3   HelpfulnessNumerator    10000 non-null  int64 
 4   HelpfulnessDenominator  10000 non-null  int64 
 5   Score                   10000 non-null  int64 
 6   Time                    10000 non-null  int64 
 7   Text                    10000 non-null  object
dtypes: int64(5), object(3)
memory usage: 625.1+ KB
```

```
df.duplicated().sum()
```

```
0
```

```
score_value_counts = df.Score.value_counts()*100/len(df)
print(score_value_counts)
print('---'*65)
fig, axs = plt.subplots(1,2, figsize=(12,5))
score_value_counts.plot(kind='bar', color =colors, ax=axs[0] )
plt.ylabel('Score Count')
plt.xlabel('\nReview Stars')
axs[0].set_title('Bar plot of Count of Reviews by Stars\n', fontsize = 15)
labels = ['Score-5', 'Score-4', 'Score-3', 'Score-2','Score-1']
score_value_counts.plot.pie(autopct='%1.2f%%',labels = labels, colors=colors, explode=[0.1,0.,0.,0.,0.],ax=axs[1] )
axs[1].set_title('Pie plot of Count of Reviews by Stars\n', fontsize = 15)
plt.tight_layout()
plt.show()
```

```
5    61.83
4    14.33
1     9.32
3     8.62
2     5.90
Name: Score, dtype: float64
------------------------------------------------------------------------------------------------------------------------
```




```
#df.nunique().sort_values().plot(kind='bar')
df.nunique().sort_values()
```

```
Score                          5
HelpfulnessNumerator          58
HelpfulnessDenominator        64
ProductId                   1422
Time                        1952
UserId                      9015
Text                        9513
Id                         10000
dtype: int64
```

```
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import sent_tokenize, word_tokenize
from nltk.stem import WordNetLemmatizer
from nltk.stem.porter import PorterStemmer
nltk.download('stopwords') # for pronouns
nltk.download('vader_lexicon') # for +ve and -ve words used for sentiment
nltk.download('punkt')  # For abbriviation  and any shortform
nltk.download('averaged_perceptron_tagger')
```

```
nltk.download('wordnet')
nltk.download('words')
nltk.download('omw-1.4')
# nltk.data.path.append("/path/to/nltk_data")
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package words to /root/nltk_data...
[nltk_data]   Unzipping corpora/words.zip.
[nltk_data] Downloading package omw-1.4 to /root/nltk_data...
True
```

# Text preprocessing

- [x] Removing non-alphabet characters
- [x] Convert to lowercase
- [x] Tokenization
- [x] selecting stopwords
- [x] Filtering stopwords (Remove stopwords using NLTK's English stopwords list)
- [x] Lemmitization (choosing root words ( removing suffixes or prefixes))

```
corpus = []

# Loop through each message in the df['Text']

for i in tqdm(range(len(df)), desc="Processing Text"):
#     text = df['Text'][i]
#     cleaned_text = re.sub(r'[^a-zA-Z]', ' ', text)  # Remove non-alphabet characters
#     cleantext = cleaned_text.lower()             # Convert to lowercase
#     words = word_tokenize(cleantext)  # selecting words
#     stop_words = set(stopwords.words('english')) # unique stopwords
#     filtered_words = [word for word in words if word not in stop_words]  # Remove stopwords using NLTK's English stopwords list

#     lemmatizer = WordNetLemmatizer()
#     lemmatized_word = [lemmatizer.lemmatize(word) for word in filtered_words]  # root form ( removing suffixes or prefixes)
#     processed_text = ' '.join(lemmatized_word)  # Join the words back into a sentence
# #     ps = PorterStemmer()
# #     stem_words = [ps.stem(word) for word in filtered_words]
# #     processed_text = ' '.join(stem_words)  # Join the words back into a sentence
#     corpus.append(processed_text)
  text = df['Text'][i]
  if isinstance(text, str):
        cleaned_text = re.sub(r'[^a-zA-Z]', ' ', text)  # Remove non-alphabet characters
        cleantext = cleaned_text.lower()             # Convert to lowercase
        words = word_tokenize(cleantext)            # Tokenize words
        stop_words = set(stopwords.words('english')) # Unique stopwords
```

```
        filtered_words = [word for word in words if word not in stop_words]  # Remove stopwords using NLTK's English stopwords list

        lemmatizer = WordNetLemmatizer()
        lemmatized_word = [lemmatizer.lemmatize(word) for word in filtered_words]  # Root form (removing suffixes or prefixes)
        processed_text = ' '.join(lemmatized_word)  # Join the words back into a sentence

        corpus.append(processed_text)
    else:
        # Handle cases where 'text' is not a string, e.g., if it's NaN
        corpus.append('')  # Append an empty string or handle it as needed
```

Processing Text: 100% 10000/10000 [00:09<00:00, 1477.06it/s]

```
df['processed_text'] = corpus
df
```

| | Id | ProductId | UserId | HelpfulnessNumerator | HelpfulnessDenominator | Score | Time | Tex |
|---|---|---|---|---|---|---|---|---|
| **0** | 1 | B001E4KFG0 | A3SGXH7AUHU8GW | 1 | 1 | 5 | 1303862400 | I hav boug several the Vital canne d |
| **1** | 2 | B00813GRG4 | A1D87F6ZCVE5NK | 0 | 0 | 1 | 1346976000 | Produ arrive labeled a Juml Salte Peanut |
| **2** | 3 | B000LQOCH0 | ABXLMWJIXXAIN | 1 | 1 | 4 | 1219017600 | This is confectio that ha bee around fe |

## Sentiment Analysis using Vader

```
from nltk.sentiment.vader import SentimentIntensityAnalyzer
```

```
sia = SentimentIntensityAnalyzer()
```

```
example = df['processed_text'][0]
example
```

```
'bought several vitality canned dog food product found good quality product look like stew processed meat smell bette
r labrador finicky appreciates product better'
```

```
sia.polarity_scores(example)
```

```
{'neg': 0.0, 'neu': 0.503, 'pos': 0.497, 'compound': 0.9413}
```

```
# res = {} # initialising an empty dictionary to store sentiment score

# for index, row in df.iterrows():
# #     text = row['Text']
#     text = row['processed_text']
#     res[index] = sia.polarity_scores(text)
```

```
res = {} # initialising an empty dictionary to store sentiment score
for index,row in tqdm(df.iterrows(),total= len(df)):
    text = row['processed_text']
    res[index] = sia.polarity_scores(text)
```

100% 10000/10000 [00:05<00:00, 1819.93it/s]

```
vaders = pd.DataFrame(res).T
vaders.reset_index().rename(columns={'index' : 'Id'})
vaders
```

| | neg | neu | pos | compound |
|---|---|---|---|---|
| **0** | 0.000 | 0.503 | 0.497 | 0.9413 |
| **1** | 0.129 | 0.762 | 0.110 | -0.1027 |
| **2** | 0.132 | 0.576 | 0.292 | 0.8624 |
| **3** | 0.000 | 0.854 | 0.146 | 0.4404 |
| **4** | 0.000 | 0.369 | 0.631 | 0.9468 |
| **...** | ... | ... | ... | ... |
| **9995** | 0.149 | 0.753 | 0.098 | -0.5267 |
| **9996** | 0.108 | 0.593 | 0.298 | 0.8360 |
| **9997** | 0.030 | 0.760 | 0.210 | 0.9371 |
| **9998** | 0.096 | 0.616 | 0.288 | 0.5859 |
| **9999** | 0.068 | 0.670 | 0.263 | 0.9728 |

10000 rows × 4 columns

```
vaders.shape
```

```
(10000, 4)
```

```
df.shape
```

```
(10000, 9)
```

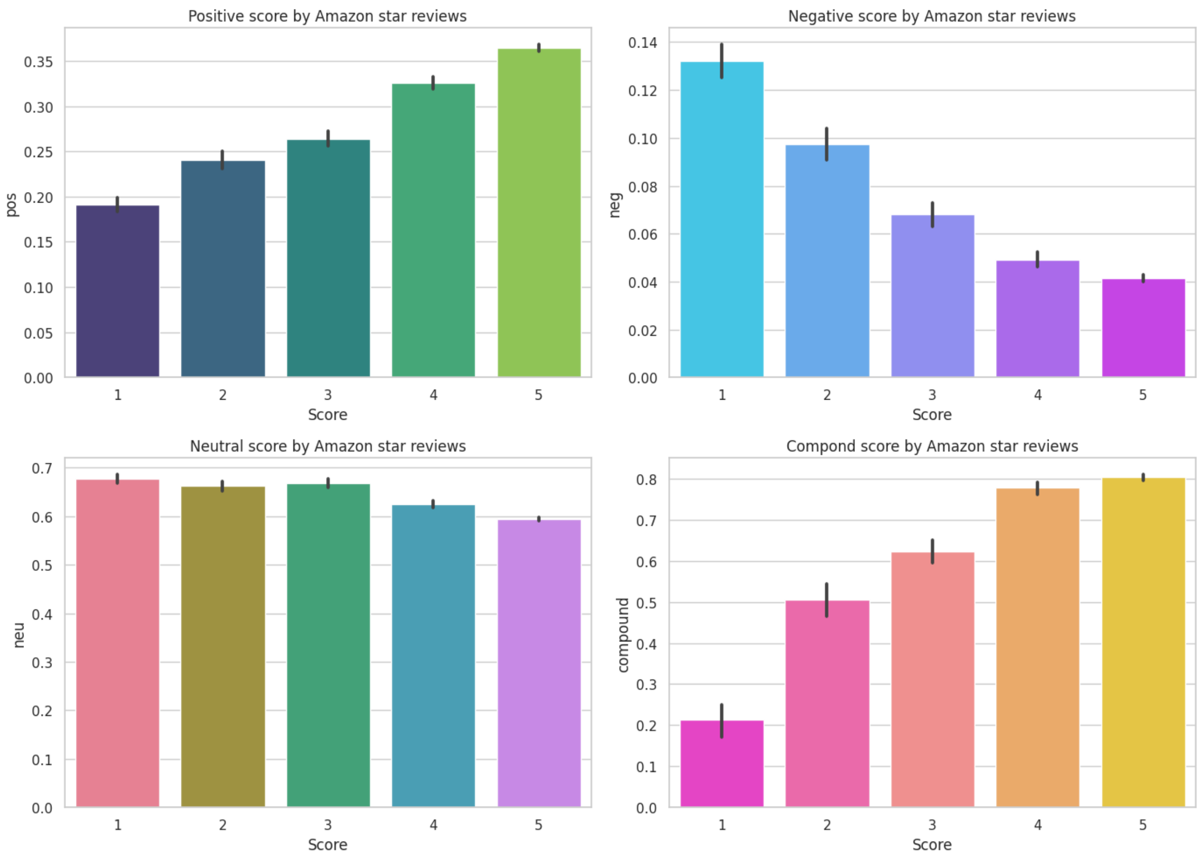
```
new_df = pd.concat([vaders,df], axis=1)
new_df
```

| | neg | neu | pos | compound | Id | ProductId | UserId | HelpfulnessNumerator | HelpfulnessDenominatc |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.000 | 0.503 | 0.497 | 0.9413 | 1 | B001E4KFG0 | A3SGXH7AUHU8GW | 1 | |
| **1** | 0.129 | 0.762 | 0.110 | -0.1027 | 2 | B00813GRG4 | A1D87F6ZCVE5NK | 0 | |
| **2** | 0.132 | 0.576 | 0.292 | 0.8624 | 3 | B000LQOCH0 | ABXLMWJIXXAIN | 1 | |

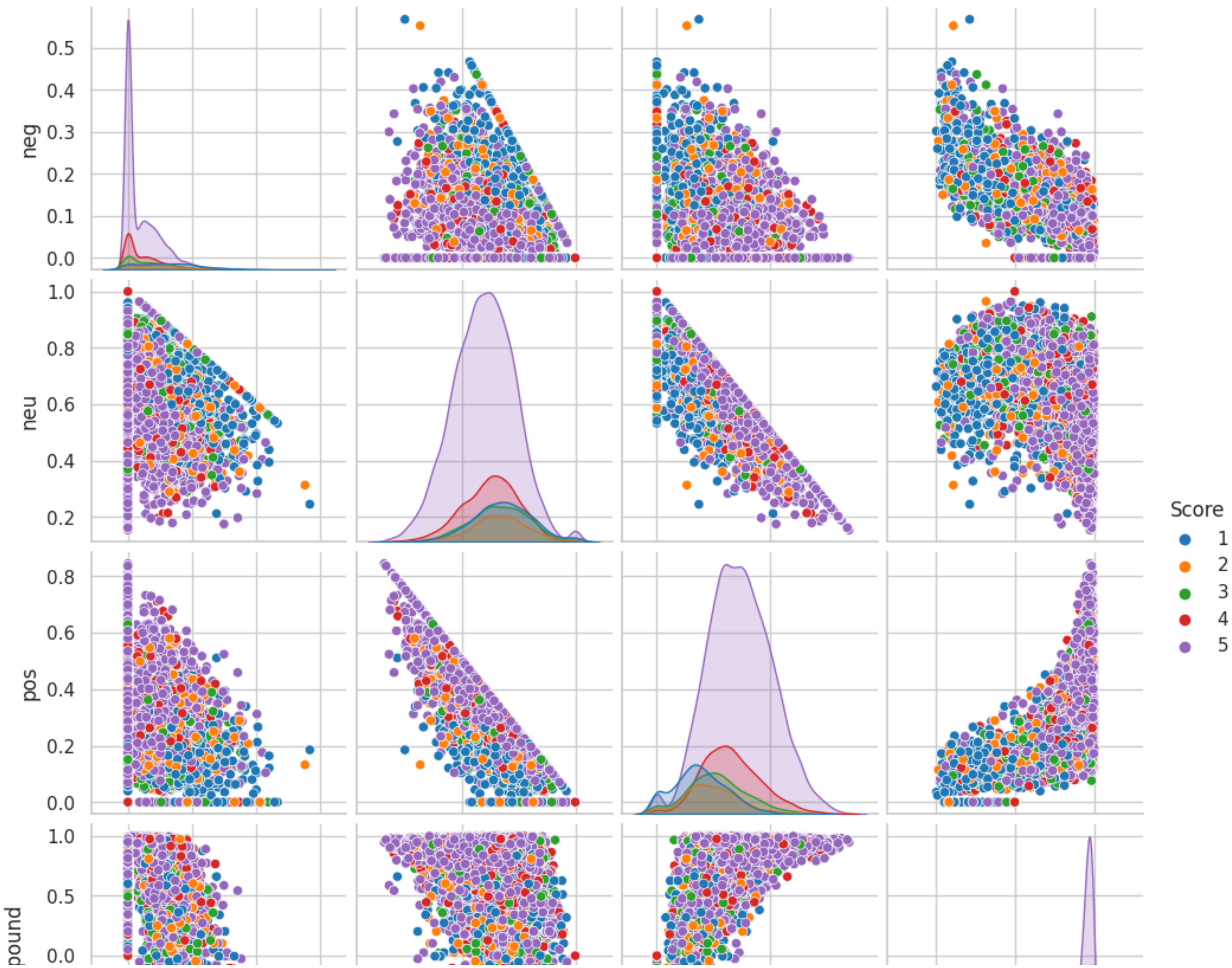
```
new_df.Score.value_counts()
```

```
5    6183
4    1433
1     932
3     862
2     590
Name: Score, dtype: int64
```

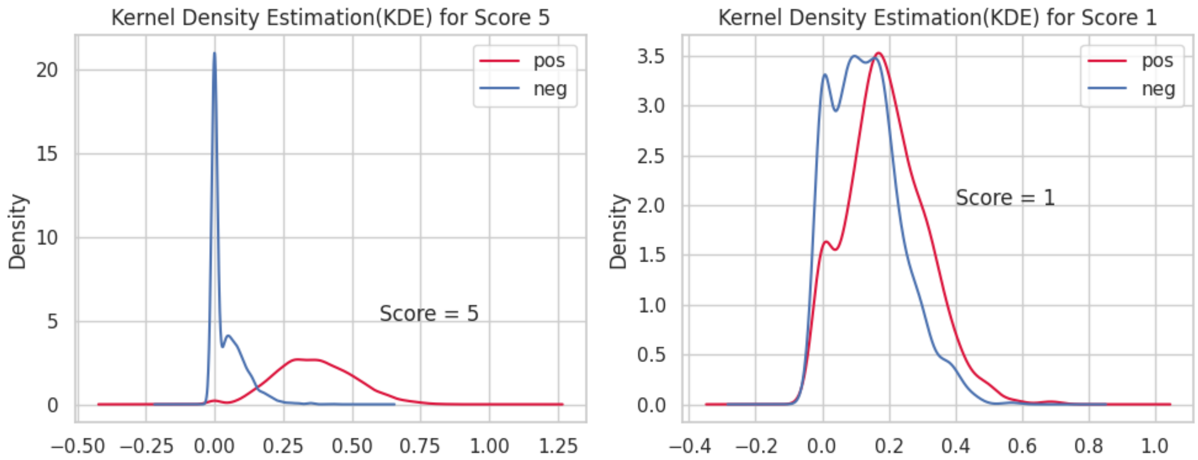
```
plt.figure(figsize =(14,10))
plt.subplot(221)
sns.barplot(data = new_df, x='Score', y='pos', palette='viridis' )
plt.title('Positive score by Amazon star reviews')
plt.subplot(222)
sns.barplot(data = new_df, x='Score', y='neg',palette='cool')
plt.title('Negative score by Amazon star reviews')
plt.subplot(223)
sns.barplot(data = new_df, x='Score', y='neu',palette='husl')
plt.title('Neutral score by Amazon star reviews')
plt.subplot(224)
sns.barplot(data = new_df, x='Score', y='compound',palette='spring')
plt.title('Compond score by Amazon star reviews')
plt.tight_layout()
plt.show()
```



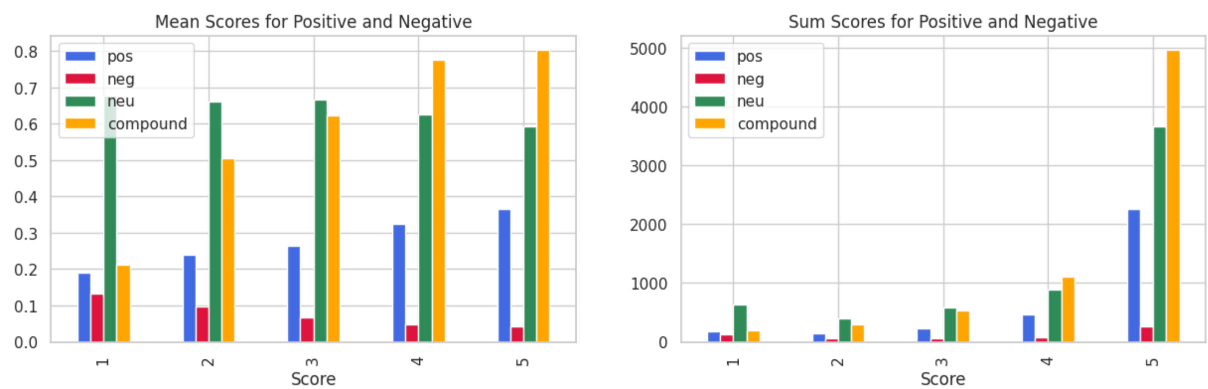

```
sns.pairplot(data= new_df, vars=['neg', 'neu','pos', 'compound'], hue= 'Score', palette='tab10')
plt.show()
```




```
fig, ax = plt.subplots(1,2, figsize=(10,4))
new_df[new_df.Score ==5].sort_values('pos', ascending= False)[['pos']].plot(kind='kde',ax=ax[0], color = 'crimson')
new_df[new_df.Score ==5].sort_values('neg', ascending= False)[['neg']].plot(kind='kde' ,ax=ax[0])
ax[0].set_title('Kernel Density Estimation(KDE) for Score 5')
ax[0].text(0.6, 5.0, 'Score = 5', )
new_df[new_df.Score ==1].sort_values('pos', ascending= False)[['pos']].plot(kind='kde',ax=ax[1],  color = 'crimson')
new_df[new_df.Score ==1].sort_values('neg', ascending= False)[['neg']].plot(kind='kde',ax=ax[1])
ax[1].set_title('Kernel Density Estimation(KDE) for Score 1')
ax[1].text(0.4, 2.0, 'Score = 1', )
plt.tight_layout()
plt.show()
```

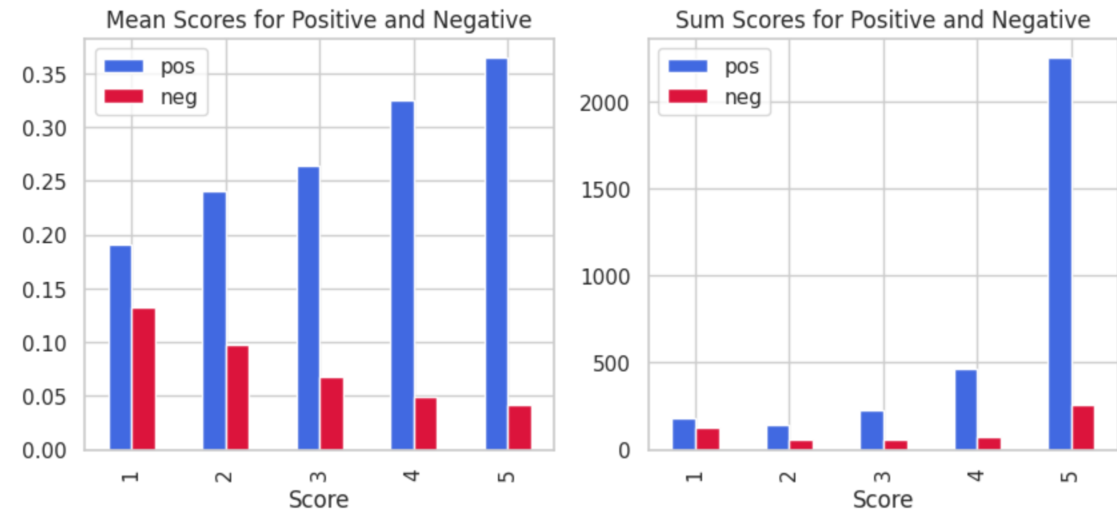



```
fig, ax = plt.subplots(1, 2, figsize=(15, 4))
colors=[ 'royalblue','crimson','seagreen','orange']

new_df.groupby('Score')[['pos', 'neg','neu','compound']].mean().plot(kind='bar', color=colors,ax = ax[0] )
ax[0].set_title('Mean Scores for Positive and Negative')

new_df.groupby('Score')[['pos', 'neg','neu', 'compound']].sum().plot(kind='bar', color=colors, ax =ax[1])
ax[1].set_title('Sum Scores for Positive and Negative')
plt.title
plt.show()
```




```
fig, ax = plt.subplots(1, 2, figsize=(10, 4))

new_df.groupby('Score')[['pos', 'neg']].mean().plot(kind='bar', color=colors,ax = ax[0] )
ax[0].set_title('Mean Scores for Positive and Negative')
```

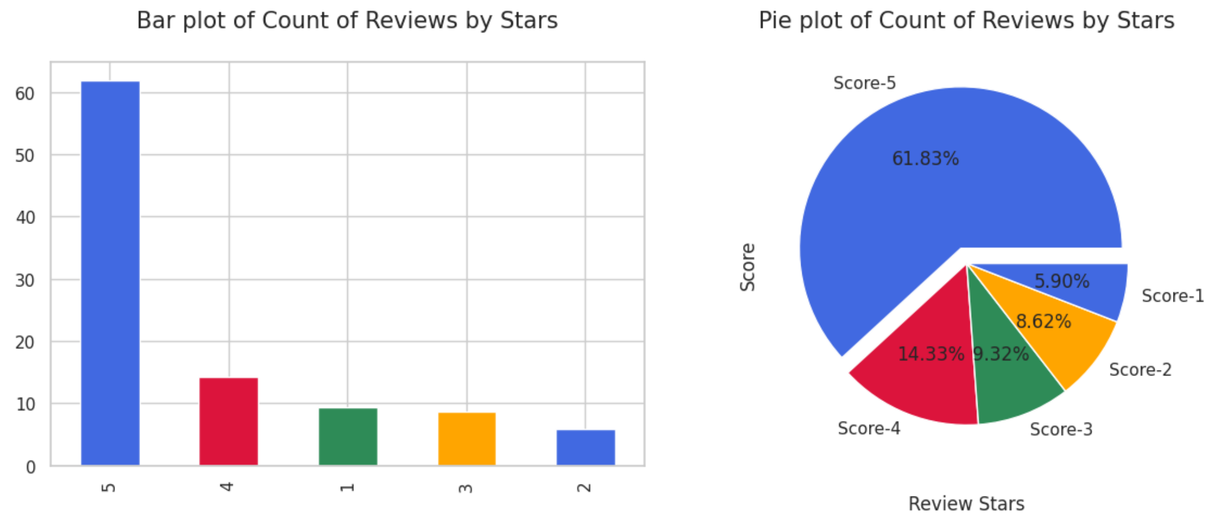
```
new_df.groupby('Score')[['pos', 'neg']].sum().plot(kind='bar', color=colors, ax =ax[1])
ax[1].set_title('Sum Scores for Positive and Negative')
plt.title
plt.show()
print(pd.concat([new_df.groupby('Score')[['pos', 'neg','neu']].mean(),new_df.groupby('Score')[['pos', 'neg','neu']].sum()], axis=1))
print()
```




```
            pos       neg       neu       pos      neg       neu
Score
1      0.191157  0.131986  0.676850   178.158  123.011   630.824
2      0.240517  0.097376  0.662103   141.905   57.452   390.641
3      0.264261  0.068013  0.667703   227.793   58.627   575.560
4      0.325611  0.049172  0.625202   466.601   70.464   895.915
5      0.364733  0.041312  0.593956  2255.142  255.431  3672.428
```

```
score_value_counts = (new_df[new_df['pos']>=0]['Score']).value_counts()*100/len(df)
print(score_value_counts)
print('---'*65)
fig, axs = plt.subplots(1,2, figsize=(12,5))
score_value_counts.plot(kind='bar', color =colors, ax=axs[0] )
plt.ylabel('Score Count')
plt.xlabel('\nReview Stars')
axs[0].set_title('Bar plot of Count of Reviews by Stars\n', fontsize = 15)
labels = ['Score-5', 'Score-4', 'Score-3', 'Score-2','Score-1']
score_value_counts.plot.pie(autopct='%1.2f%%',labels = labels, colors=colors, explode=[0.1,0.,0.,0.,0.],ax=axs[1] )
axs[1].set_title('Pie plot of Count of Reviews by Stars\n', fontsize = 15)
plt.tight_layout()
plt.show()
```

```
5    61.83
4    14.33
1     9.32
3     8.62
2     5.90
Name: Score, dtype: float64
------------------------------------------------------------------------------------------------------------------------
```




```
from wordcloud import WordCloud
wc = WordCloud(width=800,
               height=400,
               min_font_size=2,
               max_font_size=100,
               min_word_length=3,
               max_words=100,
               background_color='white',
               colormap='Reds'
              )
wc1 = WordCloud(width=800,
               height=400,
               min_font_size=5,
               max_font_size=100,
               min_word_length=3,
               max_words=100,
               background_color='white',
               colormap='Blues'
              )


plt.figure(figsize=(25, 8))
plt.subplot(121)
wc_pos = wc.generate(new_df[new_df['neg']==0]['processed_text'].str.cat(sep = " "))
plt.imshow(wc_pos, interpolation='bilinear')
plt.axis('off')
plt.title('Words in Non-Negative Review\n\n', fontsize=15)
```

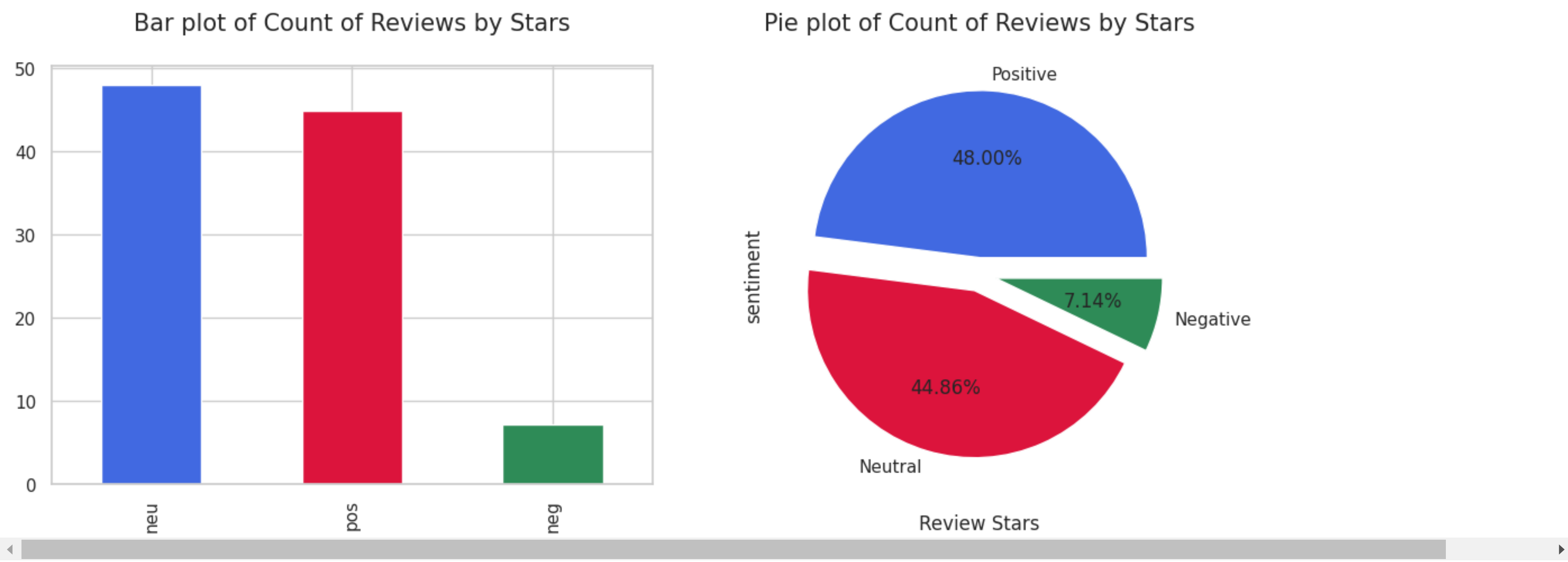
```
plt.subplot(122)

wc_neg = wc1.generate(new_df[new_df['pos']==0]['processed_text'].str.cat(sep = " "))
plt.imshow(wc_neg, interpolation='bilinear')
plt.axis('off')
plt.title('Words in Non-Positive Review\n\n', fontsize=15)
plt.show()
```


```
df1= new_df.copy()
negative_condition = ((df1['compound'] < 0) & (df1['neg']!=0))
positive_condition = ((df1['pos'] != 0) & (df1['neg']==0))
neutral_condition = ((df1['pos'] != 0) & (df1['neg']!=0) | (df1['pos'] == 0) & (df1['neg']==0) )


conditions = [negative_condition, positive_condition, neutral_condition]
values = ['neg', 'pos', 'neu']

df1['sentiment'] = np.select(conditions, values)


df1.sentiment.value_counts()
```

```
neu    4800
pos    4486
neg     714
Name: sentiment, dtype: int64
```

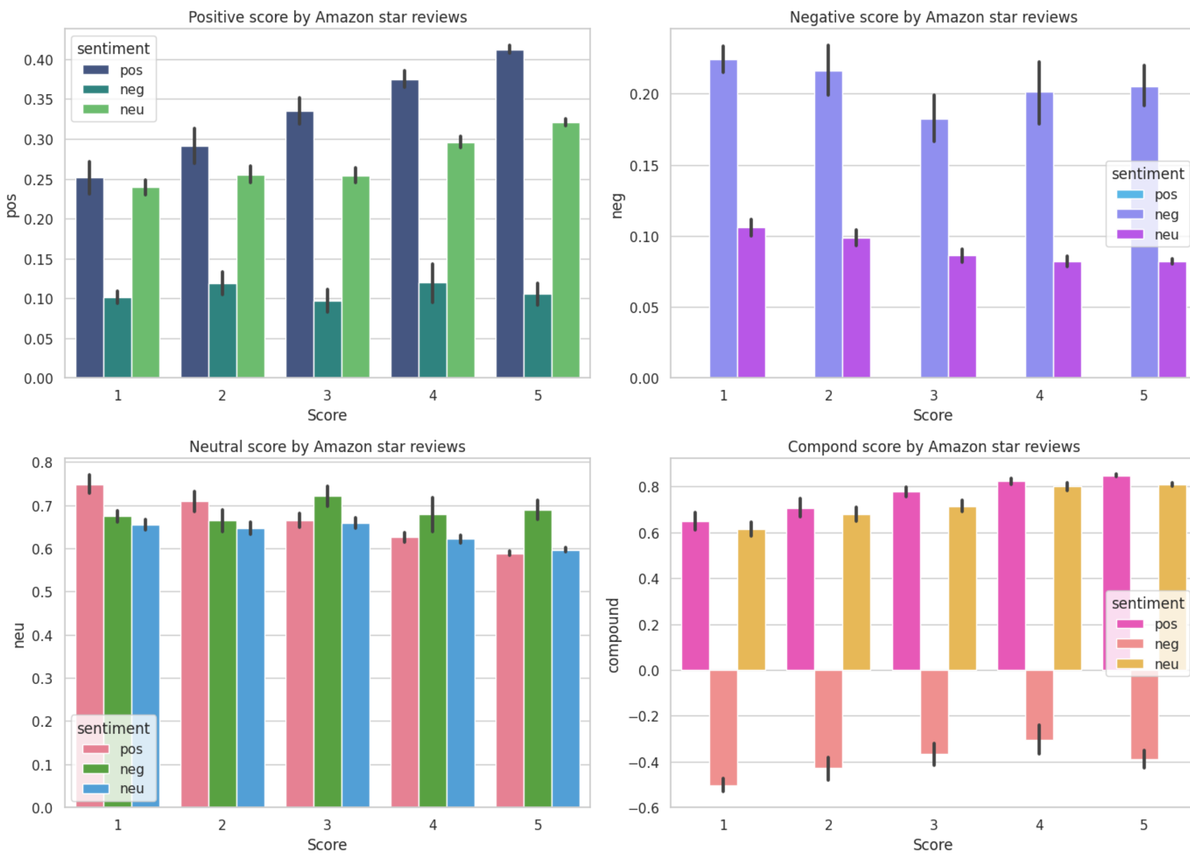
```
sentiment_value_counts = df1.sentiment.value_counts()*100/len(df)
print(sentiment_value_counts)
print('---'*65)
fig, axs = plt.subplots(1,2, figsize=(12,5))
sentiment_value_counts.plot(kind='bar', color =colors, ax=axs[0], )
plt.ylabel('Score Count')
plt.xlabel('\nReview Stars')
axs[0].set_title('Bar plot of Count of Reviews by Stars\n', fontsize = 15)
labels = ['Positive','Neutral','Negative']
sentiment_value_counts.plot.pie(autopct='%1.2f%%',labels = labels, colors=colors, explode=[0.1,0.1,0.1],ax=axs[1] )
axs[1].set_title('Pie plot of Count of Reviews by Stars\n', fontsize = 15)
plt.tight_layout()
plt.show()
```

```
neu    48.00
pos    44.86
neg     7.14
Name: sentiment, dtype: float64
-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------
```




```
plt.figure(figsize =(14,10))
plt.subplot(221)
sns.barplot(data = df1, x='Score', y='pos', palette='viridis', hue= 'sentiment' )
plt.title('Positive score by Amazon star reviews')
plt.subplot(222)
sns.barplot(data = df1, x='Score', y='neg',palette='cool',hue= 'sentiment')
plt.title('Negative score by Amazon star reviews')
plt.subplot(223)
sns.barplot(data = df1, x='Score', y='neu',palette='husl', hue= 'sentiment')
plt.title('Neutral score by Amazon star reviews')
plt.subplot(224)
```

```
sns.barplot(data = df1, x='Score', y='compound',palette='spring', hue= 'sentiment')
plt.title('Compond score by Amazon star reviews')
plt.tight_layout()
plt.show()
```



# Model Building

```
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.naive_bayes import MultinomialNB, GaussianNB, BernoulliNB
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score, roc_curve,roc_auc_score, auc
```

```
from sklearn.feature_extraction.text import CountVectorizer
vc = CountVectorizer()
feature = vc.fit_transform(new_df['processed_text']).toarray()
print(feature.shape)
feature
```

```
(10000, 16106)
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]])
```

```
# Define a function to convert values
def convert_score(score):
    if score >= 3:
        return 1
    else:
        return 0

# new_df['Score'] = new_df['Score'].apply(convert_score)
# new_df['Score'].unique()
```

```
# new_score_count =new_df['Score'].value_counts()*100/len(new_df)

# new_score_count.plot.pie(autopct='%1.2f%%',labels=['good','bad'], colors=colors, explode=[0.1,0.],)
```

```
x=feature
#y=new_df['Score']
y=df1['sentiment']
```

```
y = y.astype('category')
y = y.cat.codes
```

```
y.value_counts()*100/len(y)
```

```
1    48.00
2    44.86
0     7.14
dtype: float64
```

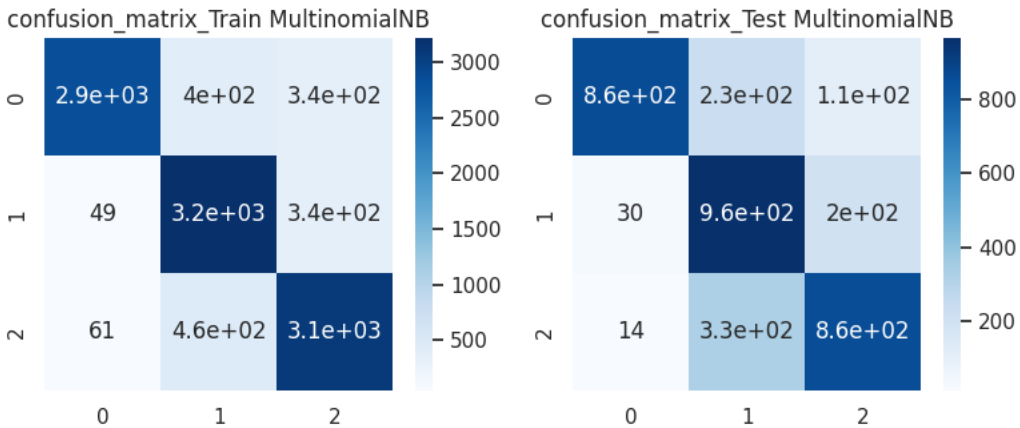
```
from imblearn.over_sampling import  SMOTE
smote = SMOTE()
```

```
x_over, y_over = smote.fit_resample(x,y)


x_train, x_test, y_train, y_test = train_test_split(x_over,y_over,test_size=0.25, random_state=121, stratify=y_over)


mnb=MultinomialNB()
gnb= GaussianNB()
bnb=BernoulliNB()

models =[('MultinomialNB', mnb),('GaussianNB',gnb), ('BernoulliNB',bnb)]

from tabulate import tabulate
print(tabulate(models, headers=['Model name', 'Sklearn models']),)

     Model name     Sklearn models
     -------------  ----------------
     MultinomialNB  MultinomialNB()
     GaussianNB     GaussianNB()
     BernoulliNB    BernoulliNB()



for model_name, model in tqdm(models, desc="Training Models"):
    model.fit(x_train,y_train)
    y_pred_train = model.predict(x_train)
    y_pred_test = model.predict(x_test)

    print('==='*10)
    print(model_name)
    print('==='*10)
#=======================================================
#            Cross Validation
#--------------------------------------------------------
    CV_train_acc =(cross_val_score(model, x_train, y_train, cv =10).mean()).round(2)*100
    #CV_test_acc =(cross_val_score(model, x_test, y_test, cv =10).mean()).round(2)*100

    print(f'▬ Training Accuracy(CrossValidation), {CV_train_acc} %' )


    cm_test = confusion_matrix(y_test, y_pred_test)
    cm_train = confusion_matrix(y_train, y_pred_train)


    fpr, tpr, _ = roc_curve(y_test, y_pred_test, pos_label=1)
    roc_auc = auc(fpr, tpr)

    print(f'Test confusion matrix :\n {cm_test}')
    print()
    print(f'Test ROC-AUC : {roc_auc:.2f}')

    plt.figure(figsize = (8,3.5))

    plt.figure(figsize = (8,3.5))
    plt.subplot(1,2,1)
    sns.heatmap(cm_train, annot = True, cmap= 'Blues')
    plt.title(f'confusion_matrix_Train {model_name}')

    plt.subplot(1,2,2)
```

```
sns.heatmap(cm_test, annot = True, cmap= 'Blues')
plt.title(f'confusion_matrix_Test {model_name}')
plt.tight_layout()
plt.show()
```

Training Models: 100% 3/3 [02:53<00:00, 57.15s/it]

```
=============================
MultinomialNB
=============================
▬ Training Accuracy(CrossValidation), 75.0 %
Test confusion matrix :
 [[864 229 107]
 [ 30 965 205]
 [ 14 327 859]]

Test ROC-AUC : 0.53
<Figure size 800x350 with 0 Axes>
```

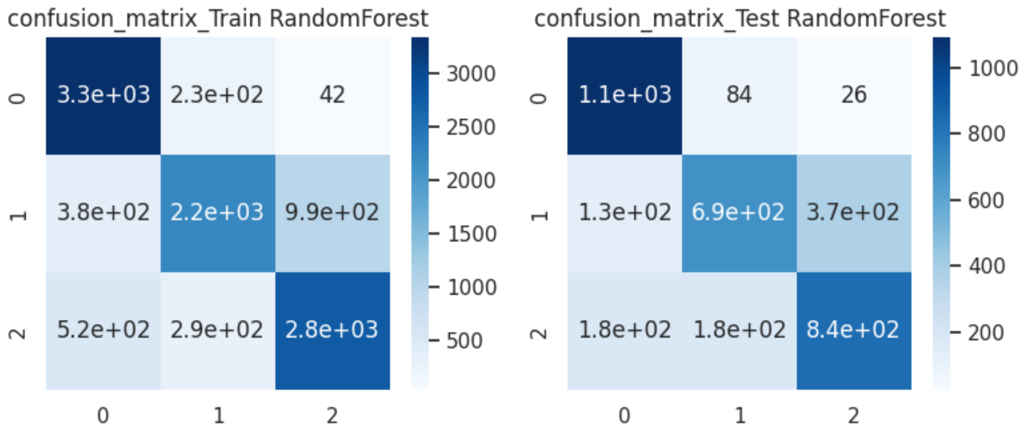



```
=============================
GaussianNB
=============================
▬ Training Accuracy(CrossValidation), 70.0 %
Test confusion matrix :
```

```
from sklearn.ensemble import RandomForestClassifier

model_name='RandomForest'
print('==='*10)
print('model_name : ', model_name)
print('==='*10)
#=====================================================
rfc = RandomForestClassifier(criterion='entropy')
rfc.fit(x_train,y_train)
y_pred_train = model.predict(x_train)
y_pred_test = model.predict(x_test)

#=====================================================
#            Cross Validation
#-------------------------------------------------------
CV_train_acc =(cross_val_score(model, x_train, y_train, cv =10).mean()).round(2)*100
CV_test_acc =(cross_val_score(model, x_test, y_test, cv =10).mean()).round(2)*100

print(f'▬ Training Accuracy(CrossValidation), {CV_train_acc} %' )

cm_test = confusion_matrix(y_test, y_pred_test)
cm_train = confusion_matrix(y_train, y_pred_train)
```

```
fpr, tpr, _ = roc_curve(y_test, y_pred_test, pos_label=1)
roc_auc = auc(fpr, tpr)
print(f'Train confusion matrix :\n {cm_train}')
print()
print(f'Test confusion matrix :\n {cm_test}')
print()
print(f'Test ROC-AUC : {roc_auc:.2f}')

plt.figure(figsize = (8,3.5))
plt.subplot(1,2,1)
sns.heatmap(cm_train, annot = True, cmap= 'Blues')
plt.title(f'confusion_matrix_Train {model_name}')

plt.subplot(1,2,2)
sns.heatmap(cm_test, annot = True, cmap= 'Blues')
plt.title(f'confusion_matrix_Test {model_name}')
plt.tight_layout()
# Show the plot
plt.show()
```

```
==============================
model_name :  RandomForest
==============================
- Training Accuracy(CrossValidation), 73.0 %
Train confusion matrix :
 [[3332  226   42]
 [ 375 2238  987]
 [ 521  287 2792]]

Test confusion matrix :
 [[1090   84   26]
 [ 132  694  374]
 [ 180  180  840]]

Test ROC-AUC : 0.62
```



## Conclusion :

- To manage runtime efficiently, I carefully selected a smaller subset of 10,000 records for analysis. This allowed me to work with a manageable dataset while still gaining valuable insights.
- Text Preprocessing with NLTK: Leveraging the power of NLTK, I performed essential text preprocessing tasks to ensure data quality and consistency. This step lays a solid foundation for accurate sentiment analysis.
- Vader Sentiment Analysis: I adopted the Vader sentiment analysis model to generate sentiment labels (the dependent variable). Vader is a robust choice for this task, providing quick and reliable sentiment categorization.
- Machine Learning Models: To predict sentiment labels, I employed both Naive Bayes and ensemble models. Through the use of 10-fold cross-validation, I achieved a commendable level of accuracy, showcasing the potential of these models in sentiment analysis tasks.
- Room for Improvement: While the project has delivered promising results, there is significant room for enhancement. Hyperparameter tuning, a valuable technique for fine-tuning models, remains unexplored in this project. This presents an exciting opportunity to further boost accuracy and refine the models.