```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
pwd
```

```
'/content'
```

```
#import library
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import nltk
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')
nltk.download('omw-1.4')
from collections import Counter
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelBinarizer
# from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from wordcloud import WordCloud,STOPWORDS
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize,sent_tokenize
from bs4 import BeautifulSoup
import spacy
import re,string,unicodedata
from nltk.tokenize.toktok import ToktokTokenizer
from nltk.stem import LancasterStemmer,WordNetLemmatizer
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from textblob import TextBlob
from textblob import Word
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score

import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from sklearn.model_selection import train_test_split
import tensorflow.keras.layers as L
from tensorflow.keras.losses import MeanAbsoluteError
from tensorflow.keras.losses import SparseCategoricalCrossentropy
```

```
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.utils import plot_model
from tensorflow.keras.preprocessing.sequence import pad_sequences

import plotly.express as px

import os
import warnings
warnings.filterwarnings('ignore')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to /root/nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
/usr/local/lib/python3.8/dist-packages/torch/cuda/__init__.py:497: UserWarning: Can't initialize NVML
  warnings.warn("Can't initialize NVML")
```

```
# seed_value = 1337
# np.random.seed(seed_value)
# tf.random.set_seed(seed_value)
# rn.seed(seed_value)
```

```
data = pd.read_csv('/content/drive/MyDrive/projdata/tripadvisor_hotel_reviews.csv')
data.head(10)
```

	S.No.	Review	Rating
0	1	nice hotel expensive parking got good deal sta...	4
1	2	ok nothing special charge diamond member hilto...	2
2	3	nice rooms not 4* experience hotel monaco seat...	3
3	4	unique \tgreat stay \twonderful time hotel mon...	5
4	5	great stay great stay \twent seahawk game awes...	5
5	6	love monaco staff husband stayed hotel crazy w...	5
6	7	cozy stay rainy city \thusband spent 7 nights ...	5
7	8	excellent staff \thousekeeping quality hotel c...	4
8	9	hotel stayed hotel monaco cruise \trooms gener...	5
9	10	excellent stayed hotel monaco past w/e delight...	5

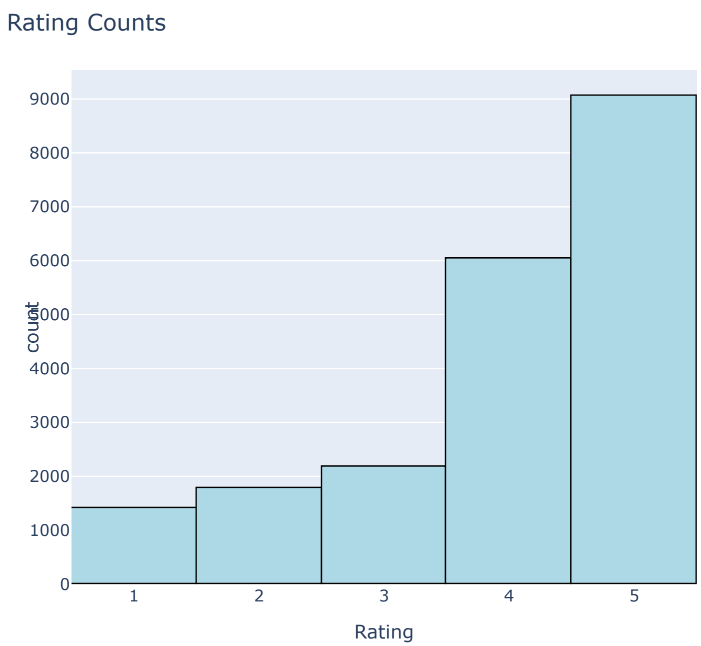
```
data.describe
```

```
<bound method NDFrame.describe of        S.No.                                             Review  Rating
0          1  nice hotel expensive parking got good deal sta...       4
1          2  ok nothing special charge diamond member hilto...       2
2          3  nice rooms not 4* experience hotel monaco seat...       3
3          4  unique \tgreat stay \twonderful time hotel mon...       5
4          5  great stay great stay \twent seahawk game awes...       5
...      ...                                                ...     ...
20486  20487  best kept secret 3rd time staying charm \tnot ...       5
```

```
20487  20488  great location price view hotel great quick pl...       4
20488  20489  ok just looks nice modern outside \tdesk staff...       2
20489  20490  hotel theft ruined vacation hotel opened sept ...       1
20490  20491  people talking \tca n't believe excellent rati...       2

[20491 rows x 3 columns]>
```

```
# #correct spelling
# def correct_spell(text):
#   text = TextBlob(text)
#   text = text.correct()
#   return text
# for i in range(2):
#   print(data['Review'][100+i])
#   data['Review'][100+i] = correct_spell(data['Review'][100+i])
#   print(data['Review'][100+i])
# # data["Review"] = pd.Series("auto corrrect this sentance")

# # t.apply(correct_spell)
# # data.head(10)
```

```
#analyze the data
plot = px.histogram(data, x="Rating")
plot.update_traces(marker_color="lightblue", marker_line_color="black", marker_line_width=1)
plot.update_layout(title="Rating Counts")
plot.show()
```



```
#change to all lower cases for review text
def lower_case(text):
  return text.lower()
# t = pd.Series(['HAHA', 'AAaa', 'HEllo'])
data["Review"] = data["Review"].apply(lower_case)


#remove special characters from review text
# print(data["Review"][20])
def remove_special(text):
  text = re.sub("[^A-Za-z0-9\s]", "", text)
  return text
# t = pd.Series("Hello%^*)123[.,")
data["Review"] = data["Review"].apply(remove_special)
# print(data["Review"][20])


#remove stop words
# print(data["Review"][20])
def remove_stopwords(text):
  stop_words = nltk.corpus.stopwords.words("english")
  word_token = word_tokenize(text)
  text = " ".join(w for w in word_token if not w in stop_words)
  return text
# t = pd.Series("This is the best tool in a while")
data["Review"] = data["Review"].apply(remove_stopwords)
# print(data["Review"][20])


for i in range(10):
  print(data['Review'][i])
```

```
nice hotel expensive parking got good deal stay hotel anniversary arrived late evening took advice previous reviews valet parking check quick easy little disappointed nonexistent view
ok nothing special charge diamond member hilton decided chain shot 20th anniversary seattle start booked suite paid extra website description suite bedroom bathroom standard hotel roo
nice rooms 4 experience hotel monaco seattle good hotel nt 4 levelpositives large bathroom mediterranean suite comfortable bed pillowsattentive housekeeping staffnegatives ac unit ma
unique great stay wonderful time hotel monaco location excellent short stroll main downtown shopping area pet friendly room showed signs animal hair smells monaco suite sleeping area
great stay great stay went seahawk game awesome downfall view building nt complain room huge staff helpful booked hotels website seahawk package charge parking got voucher taxi proble
love monaco staff husband stayed hotel crazy weekend attending memorial service best friend husband celebrating 12th wedding anniversary talk mixed emotions booked suite hotel monte c
cozy stay rainy city husband spent 7 nights monaco early january 2008 business trip chance come ridewe booked monte carlo suite proved comfortable longish stay room 905 located street
excellent staff housekeeping quality hotel chocked staff make feel home experienced exceptional service desk staff concierge door men maid service needs work maid failed tuck sheets t
hotel stayed hotel monaco cruise rooms generous decorated uniquely hotel remodeled pacific bell building charm sturdiness everytime walked bell men felt like coming home secure great
excellent stayed hotel monaco past delight reception staff friendly professional room smart comfortable bed particularly liked reception small dog received staff guests spoke loved m
```

```
# Stemming
def simple_stemmer(text):
  ps = nltk.porter.PorterStemmer()

  #text = ' '.join([ps.stem(word) for word in text.split()])
  words = word_tokenize(text)
  text = ' '.join([ps.stem(word) for word in words])
  return text

# No stemming
print(data["Review"][628])

# Apply stemming
print(simple_stemmer(data["Review"][628]))
```

```
#print(nltk.porter.PorterStemmer().stem("seattle"))
```

```
inconsistent arrived eliot spending wonderful night lenox eliot closer boston conservatory initially wanted stay room night stayed lenox small charming lobby eliot somewhat chaotic la
inconsist arriv eliot spend wonder night lenox eliot closer boston conservatori initi want stay room night stay lenox small charm lobbi eliot somewhat chaotic larg group check rain a
```

```
#Lemmatization
def lemmatize_word(text):
  lemmatizer = WordNetLemmatizer()
  word_token = word_tokenize(text)
  text = " ".join(lemmatizer.lemmatize(w) for w in word_token)
  return text
#no lemmatization
print(data["Review"][618])

# Apply lemmatization
print(lemmatize_word(data["Review"][618]))

# t = pd.Series("girls playing plays played studies caring cares cared")
# data["Review"] = data["Review"].apply(lemmatize_word)
# # data.head(20)
```

```
cold location atmosphere nice complimentary shuttle copley place helpful generally convenient suites comfortable spacious hotel dining extremely expensive overnight parking fee extren
cold location atmosphere nice complimentary shuttle copley place helpful generally convenient suite comfortable spacious hotel dining extremely expensive overnight parking fee extreme
```

```
#most frequent words for rating1
frequent_words1=pd.Series(" ".join(data["Review"][data["Rating"]==1]).split()).value_counts()[:20].index.tolist()


#most frequent words for rating2
frequent_words2=pd.Series(" ".join(data["Review"][data["Rating"]==2]).split()).value_counts()[:20].index.tolist()


#most frequent words for rating3
frequent_words3=pd.Series(" ".join(data["Review"][data["Rating"]==3]).split()).value_counts()[:20].index.tolist()


#most frequent words for rating4
frequent_words4=pd.Series(" ".join(data["Review"][data["Rating"]==4]).split()).value_counts()[:20].index.tolist()


#most frequent words for rating5
frequent_words5=pd.Series(" ".join(data["Review"][data["Rating"]==5]).split()).value_counts()[:20].index.tolist()
print(frequent_words5)
```

```
['hotel', 'room', 'great', 'staff', 'stay', 'nt', 'good', 'location', 'stayed', 'rooms', 'nice', 'breakfast', 'service', 'time', 'clean', 'excellent', 'day', 'beach', 'friendly', 'nig
```

```
#find the most common words among all 5 ratings
common_words = set(frequent_words1)&set(frequent_words2)&set(frequent_words3)&set(frequent_words4)&set(frequent_words5)
print(common_words)
```

```
{'good', 'service', 'day', 'room', 'stay', 'stayed', 'nt', 'hotel', 'night', 'time', 'staff', 'rooms'}
```

```
# Remove most frequent words?? Not sure if this is required
top5 = [" hotel ", " room ", " hotels ", " rooms ", " nt ", " s "," day ", " time ", " stay ", " night ", " stayed "]
for top in top5:
```

```
  for i in range(len(data["Review"])):
    data["Review"][i] = data["Review"][i].replace(top, " ")
print(data["Review"][9])
```

```
excellent monaco past delight reception staff friendly professional smart comfortable bed particularly liked reception small dog received staff guests spoke loved mild negative distar
```

```
data["Review"][10000]
```

```
'recommanded date 1 st december 2006we returned splendid nights thing realy pleas
antvery clean place nice staffbreakfast relatively expensive recommand outside ho
teltwo little problemes bit far metro station free connection internet'
```

```
#visualize the most common words for rating 1
rating1_words = " ".join([text for text in data["Review"][data["Rating"]==1]])
wordcloud = WordCloud(width = 900, height = 900).generate(rating1_words)
plt.figure(figsize = (10,10))
plt.imshow(wordcloud)
plt.axis("off")
plt.title("Most common Words in Rating 1")
```

```
Text(0.5, 1.0, 'Most common Words in Rating 1')
```

Most common Words in Rating 1


```
#visualize the most common words for rating 2
rating1_words = " ".join([text for text in data["Review"][data["Rating"]==2]])
wordcloud = WordCloud(width = 900, height = 900).generate(rating1_words)
plt.figure(figsize = (10,10))
```

```
plt.imshow(wordcloud)
plt.axis("off")
plt.title("Most common Words in Rating 2")
```

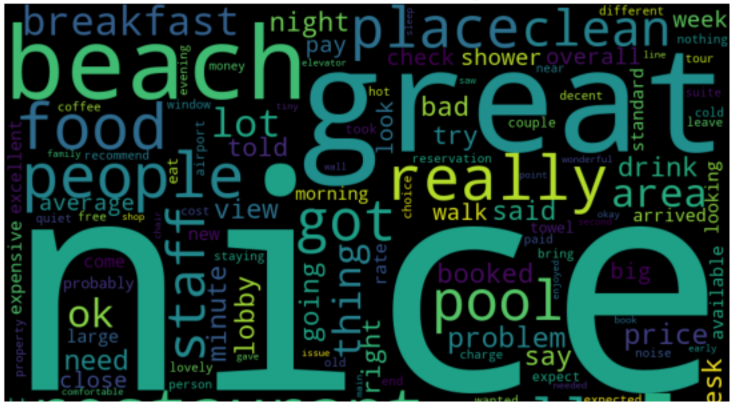
```
Text(0.5, 1.0, 'Most common Words in Rating 2')
```

Most common Words in Rating 2


```
#visualize the most common words for rating 3
rating1_words = " ".join([text for text in data["Review"][data["Rating"]==3]])
wordcloud = WordCloud(width = 900, height = 900).generate(rating1_words)
plt.figure(figsize = (10,10))
plt.imshow(wordcloud)
plt.axis("off")
plt.title("Most common Words in Rating 3")
```

```
Text(0.5, 1.0, 'Most common Words in Rating 3')
```

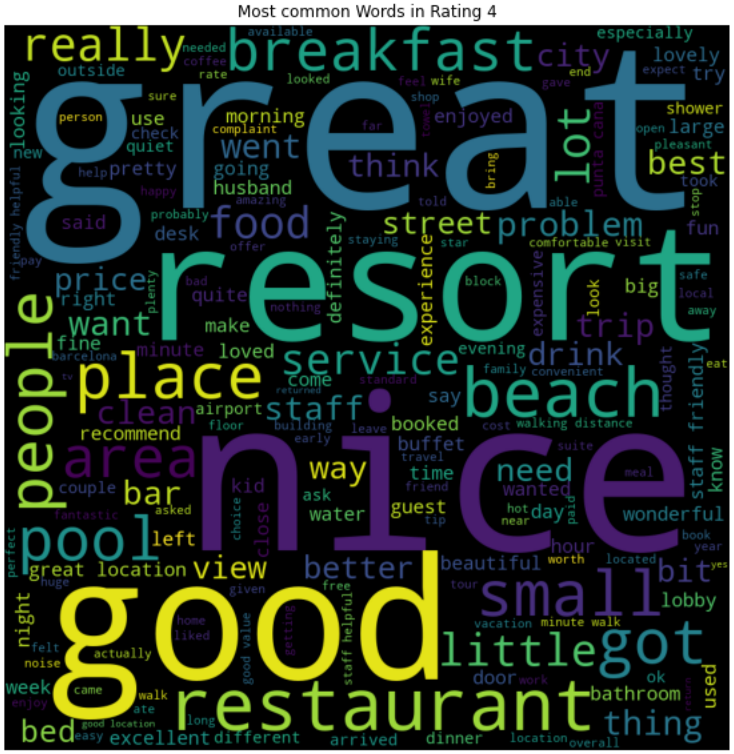
Most common Words in Rating 3




```
#visualize the most common words for rating 4
rating1_words = " ".join([text for text in data["Review"][data["Rating"]==4]])
wordcloud = WordCloud(width = 900, height = 900).generate(rating1_words)
plt.figure(figsize = (10,10))
plt.imshow(wordcloud)
plt.axis("off")
plt.title("Most common Words in Rating 4")
```

```
Text(0.5, 1.0, 'Most common Words in Rating 4')
```

Most common Words in Rating 4



```
#visualize the most common words for rating 5
rating1_words = " ".join([text for text in data["Review"][data["Rating"]==5]])
wordcloud = WordCloud(width = 900, height = 900).generate(rating1_words)
plt.figure(figsize = (10,10))
plt.imshow(wordcloud)
plt.axis("off")
plt.title("Most common Words in Rating 5")
```

```
Text(0.5, 1.0, 'Most common Words in Rating 5')
```

Most common Words in Rating 5


```
# Save data_copy into a csv file, so that read the data directly in the future
data.to_csv("/content/drive/MyDrive/projdata/tripadvisor_hotel_reviews_copy.csv", index = False)
```

```
# Read data from file for sentimental polarity analysis and overall rating prediction
data_copy = pd.read_csv("/content/drive/MyDrive/projdata/tripadvisor_hotel_reviews_copy.csv")
```

```
# Valence Aware Dictionary and Sentiment Reasoner (VADER) sentiment analysis
# Reference: https://deepnote.com/@abid/Trip-Advisor-Data-AnalysisML-f6060b39-d76c-4579-9648-a54bc8b5ffb5
!pip install vaderSentiment
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

# Create sentimental polarity
# This function will score a review in scale [-1,1], where "1" means most positive
# "-1" means most negative
```

```
sentiment_analyzer = SentimentIntensityAnalyzer()

def compound_score(text):
  return sentiment_analyzer.polarity_scores(text)["compound"]

# Define "postive, negative, neutral" sentiments
def sentiment(score):
  emotion = ""
  if (score >= 0.5):
    emotion = "Positive"
  elif (score <= -0.5):
    emotion = "Negative"
  else:
    emotion = "Neutral"
  return emotion
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: vaderSentiment in /usr/local/lib/python3.8/dist-packages (3.3.2)
Requirement already satisfied: requests in /usr/local/lib/python3.8/dist-packages (from vaderSentiment) (2.23.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.8/dist-packages (from requests->vaderSentiment) (2022.9.24)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.8/dist-packages (from requests->vaderSentiment) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.8/dist-packages (from requests->vaderSentiment) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.8/dist-packages (from requests->vaderSentiment) (1.24.3)
```

```
## Create sentiment score
polarity_scores = data_copy["Review"].astype("str").apply(compound_score)
data_copy["Sentiment_Score"] = polarity_scores

data_copy["Sentiment"] = data_copy["Sentiment_Score"].apply(sentiment)
```

```
## Visualize sentiment score
print(data_copy["Sentiment"][100:102])
print(data_copy["Sentiment_Score"][100:102])
print(data_copy["Review"][101])

# plot the count of "positive", "negative", and "neutral"
sns.countplot (data = data_copy, x = "Sentiment", palette = "tab10")

# plot the count of sentiment for each overall rating
viz = data_copy[['Rating', 'Sentiment']].value_counts().rename_axis(['Rating', 'Sentiment']).reset_index(name='counts')
figure = px.bar(x = viz.Rating, y = viz.counts, color = viz.Sentiment, color_discrete_sequence=px.colors.qualitative.Pastel,
                title = "Sentiment for Ratings", labels = {'x': 'Ratings', 'y': 'Total Number'})
figure.show()
```

```
0    Positive
1     Neutral
me: Sentiment, dtype: object
0    0.9753
1    0.3134
me: Sentiment_Score, dtype: float64
mp weekend expected charming 1929 property based website reviews expedia expect charming mean incompetent staff showers
```


```
## Overall rating prediction
# Possible models:
# Long Short Term Memory(LSTM):https://deepnote.com/@abid/Trip-Advisor-Data-AnalysisML-f6060b39-d76c-4579-9648-a54bc8b5ffb5
# Support Vector Machine (SVM)
# Ordinal logistic Regression: Coursera Week 11 Video 11.7 Last page
# Categorical Naive Bayes
```

```
# Subject to memory limitation
N = 5000

# data_copy = data[0:N]
data_copy = data.copy()
print(data_copy["Review"].shape)
#it_train = itoken(train$review, preprocessor = tolower, tokenizer = word_tokenizer)

from sklearn.feature_extraction.text import CountVectorizer
from scipy.sparse  import csr_matrix

## establish a document-term matrix
# Parameters require tunning
```

```
count_vect = CountVectorizer(ngram_range = (1,4),
                             max_features = 10000,
                             min_df = 0.001,
                             max_df = 0.5,
                             analyzer = "word")
X_train_counts = count_vect.fit_transform(data_copy["Review"])

# fit_transform returns one-dimensional array
X_train_counts.shape

# reshape into two-dimensional array
#X_train_counts = X_train_counts.reshape(N, -1)

# MUST convert csr_parse matrix to np.array!
X_train_counts = X_train_counts.toarray()
print(X_train_counts.shape)
```

```
(20491,)
(20491, 10000)
```

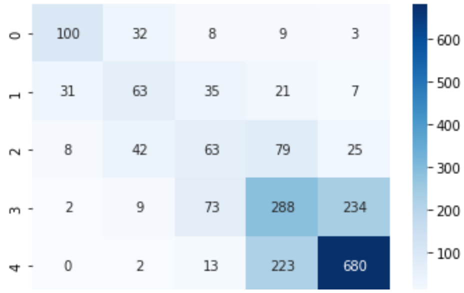
```
# combine X_train_counts and label

Y_train = np.array(data_copy["Rating"])
# Y_train = Y_train.reshape(,1)
print(X_train_counts.shape)

print(Y_train.shape)


print(type(X_train_counts))

# when two np.arrays have difference shape, must use np.concatenate(), instead of np.hstack()
#X_train = np.concatenate((X_train_counts, Y_train), axis = 1)
#print(X_train.shape) # should have one more column
#print(X_train[2,-1])
```

```
(20491, 10000)
(20491,)
<class 'numpy.ndarray'>
```

```
# Split training and test data
# Split 10% of total dataset as test data
# Split the remain 90% of total dataset into N folds. Use N-1 folds as training and the last 1 fold as test


# split training and test dataset using sklearn function train_test_split()
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_train_counts, Y_train, test_size=0.1, random_state=0)


#xpeng added session:
#from sklearn.feature_extraction.text import TfidfVectorizer
#from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score
# Models
#from sklearn.tree import DecisionTreeClassifier
#from sklearn.ensemble import RandomForestClassifier
```

```
#from sklearn.svm import SVC
#from sklearn.neighbors import KNeighborsClassifier
#from sklearn.naive_bayes import BernoulliNB

#tfid = TfidfVectorizer()
#train_tfid_matrix = tfid.fit_transform(X_train)
#test_tfid_matrix = tfid.transform(X_test)

#new_models = [DecisionTreeClassifier(),
#              RandomForestClassifier(),
#              SVC(),
#              KNeighborsClassifier(),
#              BernoulliNB()]

#accuracy = []

#for model in new_models:
#    cross_val = cross_val_score(model, train_tfid_matrix, y_train, scoring='accuracy',cv=StratifiedKFold(10)).mean()
#    accuracy.append(cross_val)

#models_name = ['DecisionTreeClassifier', 'RandomForestClassifier', 'SVC',
#        'KNeighborsClassifier', 'BernoulliNB']

#acc = pd.DataFrame({'Model': models_name, 'Accuracy': accuracy})
#acc

from sklearn.linear_model import LogisticRegression
# perform training
#lg = LogisticRegression(multi_class='ovr')
#lg = LogisticRegression(multi_class='multinomial')
lg = LogisticRegression(multi_class='auto')

lg_model = lg.fit(X_train, y_train)

# perform prediction
y_pred = lg_model.predict(X_test)



## evaluate prediction results
# return the mean accuracy
print("The mean accuracy on the test set is: ",lg_model.score(X_test,y_test))

from sklearn.metrics import confusion_matrix
print("Below is confusion matrix. Entry at (i,j) denotes that the true value is i, but predicted as j.")
print("Number on diagonal are the ones correctly predicted.")

sns.color_palette("Blues", as_cmap=True)
sns.heatmap(confusion_matrix(y_test, y_pred), annot = True, cmap="Blues", fmt='g')
plt.show()



# 2-star is the most difficult to predict, followed by 3-star and 4-star
```

```
The mean accuracy on the test set is:  0.58243902439024 39
Below is confusion matrix. Entry at (i,j) denotes that the true value is i, but pr
Number on diagonal are the ones correctly predicted.
```




```
coefficients = pd.DataFrame(lg.coef_)
coefficients.to_csv("lg_coefficients.csv", index = True)

ngrams = pd.DataFrame(count_vect.get_feature_names_out())
ngrams.to_csv("lg_ngrams.csv", index= True)


# Try different lambda (regularization coefficient)


#lambda_set = [0.001, 0.01, 0.1, 1, 10, 100]
#lambda_set = [0.0001]
#for lambda_temp in lambda_set:
#  lg = LogisticRegression(multi_class='auto', C = 1/lambda_temp)
#  lg_model = lg.fit(X_train, y_train)

#  # perform prediction
#  y_pred = lg_model.predict(X_test)

#  print(confusion_matrix(y_test, y_pred))



# Let's change the rating to be more general and easier to understand
def rating(score):
    if score > 3:
        return 'Good'
    elif score == 3:
        return 'Netral'
    else:
        return 'Bad'


df = data_copy.copy()
df['Rating'] = df['Rating'].apply(rating)
X_train, X_test, y_train, y_test = train_test_split(df['Review'], df['Rating'], test_size=0.2)


X_train, X_test, y_train, y_test = train_test_split(data_copy['Review'], data_copy['Rating'], test_size=0.2)


import pickle
from tensorflow.keras.regularizers import l1, l2
```

```
#Tokenize the data
# tokenizer = Tokenizer()
# tokenizer.fit_on_texts(data["Review"].values)
# X=tokenizer.texts_to_sequences(data["Review"].values)
# X=pad_sequences(X, padding='post', maxlen=350)

# encoding = {1: 0,
#             2: 1,
#             3: 2,
#             4: 3,
#             5: 4
#            }

# labels = ['1', '2', '3', '4', '5']

# y = data['Rating'].copy()
# y.replace(encoding, inplace=True)

# #parameters for LSTM
# vocab_size = 49536
# print(vocab_size)
# embedding_dim = 16
# num_epochs=3
# batch_size=100
# units = 76

tokenizer = Tokenizer(num_words=10000, oov_token='<OOV>')

tokenizer.fit_on_texts(X_train)
# print(tokenizer.word_index)
total_word = len(tokenizer.word_index)
print('Total distinct words: {}'.format(total_word))

train_seq = tokenizer.texts_to_sequences(X_train)
train_padded = pad_sequences(train_seq)

test_seq = tokenizer.texts_to_sequences(X_test)
test_padded = pad_sequences(test_seq)

# One hot encoding the label
lb = LabelBinarizer()
train_labels = lb.fit_transform(y_train)
test_labels = lb.transform(y_test)
```

```
Total distinct words: 69907
```

```
pickle.dump(tokenizer, open('tokenizer.pkl', 'wb'))
pickle.dump(lb, open('label.pkl', 'wb'))
```

```
model3 = tf.keras.models.Sequential([tf.keras.layers.Embedding(total_word, 8),
                                    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(16)),
                                    tf.keras.layers.Dropout(0.5),
                                    tf.keras.layers.Dense(8, kernel_regularizer=l2(0.001),
                                                          bias_regularizer=l2(0.001), activation='relu'),
                                    tf.keras.layers.Dropout(0.5),
                                    tf.keras.layers.Dense(3, activation='softmax')])
```

```
model3.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding (Embedding)       (None, None, 8)           559256    
                                                                 
 bidirectional (Bidirectiona  (None, 32)               3200      
 l)                                                              
                                                                 
 dropout (Dropout)           (None, 32)                0         
                                                                 
 dense (Dense)               (None, 8)                 264       
                                                                 
 dropout_1 (Dropout)         (None, 8)                 0         
                                                                 
 dense_1 (Dense)             (None, 3)                 27        
                                                                 
=================================================================
Total params: 562,747
Trainable params: 562,747
Non-trainable params: 0
_________________________________________________________________
```

```
#model3.compile(optimizer=tf.optimizers.Adam(learning_rate=0.05), loss='categorical_crossentropy', metrics=['accuracy'])

#model3.fit(train_padded, train_labels, epochs=3, validation_data=(test_padded, test_labels))
```

```
model1 = tf.keras.models.Sequential([tf.keras.layers.Embedding(total_word, 8),
                                    tf.keras.layers.LSTM(16),
                                    tf.keras.layers.Dense(3, activation='softmax')])

model1.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_1 (Embedding)     (None, None, 8)           559256    
                                                                 
 lstm_1 (LSTM)               (None, 16)                1600      
                                                                 
 dense_2 (Dense)             (None, 3)                 51        
                                                                 
=================================================================
Total params: 560,907
Trainable params: 560,907
Non-trainable params: 0
_________________________________________________________________
```

```
#model1.compile(optimizer=tf.optimizers.Adam(learning_rate=0.05), loss='categorical_crossentropy', metrics=['accuracy'])

#model1.fit(train_padded, train_labels, epochs=3, validation_data=(test_padded, test_labels))
```

```
model2 = tf.keras.models.Sequential([tf.keras.layers.Embedding(total_word, 8),
                                    tf.keras.layers.LSTM(16),
                                    tf.keras.layers.Dropout(0.5),
                                    tf.keras.layers.Dense(3, activation='softmax')])

model2.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (Embedding)     (None, None, 8)           559256

 lstm_2 (LSTM)               (None, 16)                1600

 dropout_2 (Dropout)         (None, 16)                0

 dense_3 (Dense)             (None, 3)                 51

=================================================================
Total params: 560,907
Trainable params: 560,907
Non-trainable params: 0
_________________________________________________________________
```

```
#model2.compile(optimizer=tf.optimizers.Adam(learning_rate=0.05), loss='categorical_crossentropy', metrics=['accuracy'])

#model2.fit(train_padded, train_labels, epochs=3, validation_data=(test_padded, test_labels))


pred2 = model3.predict(test_padded)
true_labels = np.argmax(test_labels, axis=-1)
pred_labels = np.argmax(pred2, axis=-1)
print(confusion_matrix(true_labels, pred_labels))
print(classification_report(true_labels, pred_labels))
```

```
129/129 [==============================] - 22s 165ms/step
[[143 137   0   0   0]
 [191 162   0   0   0]
 [254 186   0   0   0]
 [723 491   1   0   0]
 [992 818   1   0   0]]
              precision    recall  f1-score   support

           0       0.06      0.51      0.11       280
           1       0.09      0.46      0.15       353
           2       0.00      0.00      0.00       440
           3       0.00      0.00      0.00      1215
           4       0.00      0.00      0.00      1811

    accuracy                           0.07      4099
   macro avg       0.03      0.19      0.05      4099
weighted avg       0.01      0.07      0.02      4099
```

```
pred2 = model1.predict(test_padded)
true_labels = np.argmax(test_labels, axis=-1)
pred_labels = np.argmax(pred2, axis=-1)
print(confusion_matrix(true_labels, pred_labels))
print(classification_report(true_labels, pred_labels))
```

```
129/129 [==============================] - 14s 105ms/step
[[104  75 101   0   0]
 [125  98 130   0   0]
 [163 130 147   0   0]
 [532 272 411   0   0]
 [738 437 636   0   0]]
              precision    recall  f1-score   support

           0       0.06      0.37      0.11       280
           1       0.10      0.28      0.14       353
           2       0.10      0.33      0.16       440
           3       0.00      0.00      0.00      1215
           4       0.00      0.00      0.00      1811

    accuracy                           0.09      4099
   macro avg       0.05      0.20      0.08      4099
weighted avg       0.02      0.09      0.04      4099
```

```
pred2 = model2.predict(test_padded)
true_labels = np.argmax(test_labels, axis=-1)
pred_labels = np.argmax(pred2, axis=-1)
print(confusion_matrix(true_labels, pred_labels))
print(classification_report(true_labels, pred_labels))
```

```
129/129 [==============================] - 17s 110ms/step
[[ 91  66 123   0   0]
 [127  88 138   0   0]
 [141 126 173   0   0]
 [434 356 425   0   0]
 [571 520 720   0   0]]
              precision    recall  f1-score   support

           0       0.07      0.33      0.11       280
           1       0.08      0.25      0.12       353
           2       0.11      0.39      0.17       440
           3       0.00      0.00      0.00      1215
           4       0.00      0.00      0.00      1811

    accuracy                           0.09      4099
   macro avg       0.05      0.19      0.08      4099
weighted avg       0.02      0.09      0.04      4099
```

✓ 0s completed at 11:37 PM