```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import time
from collections import Counter
import re, nltk
from nltk import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
import folium
from matplotlib.colors import LinearSegmentedColormap
import missingno as msno
```

2 Exploratory Data Analysis

This dataset contains 515,738 customer reviews and scoring of 1493 Luxury Hotels across Europe. The csv file contains 17 fields. The description of each field is as below:

```
#loading the dataset from the Hotel_reviews dataset
df = pd.read_csv("Hotel_Reviews.csv")
```

```
#printing the columns names of the datset
df.columns
```

```
Index(['Hotel_Address', 'Additional_Number_of_Scoring', 'Review_Date',
       'Average_Score', 'Hotel_Name', 'Reviewer_Nationality',
       'Negative_Review', 'Review_Total_Negative_Word_Counts',
       'Total_Number_of_Reviews', 'Positive_Review',
       'Review_Total_Positive_Word_Counts',
       'Total_Number_of_Reviews_Reviewer_Has_Given', 'Reviewer_Score', 'Tags',
       'days_since_review', 'lat', 'lng'],
      dtype='object')
```

```
#printing the shape of the dataset
df.shape
```

```
(183145, 17)
```

```
print ('Number of data points : ', df.shape[0], \
       '\nNumber of features:', df.shape[1])
df.head()
```

```
Number of data points :  183145
Number of features: 17
```

Hotel_Address Additional_Number_of_Scoring Review_Date Average_Score Hotel_Name Reviewer_Nationality Negative_Review Rev

2.2 Data Cleaning

I am so angry that

```
#Removing duplicates from the dataset
print(sum(df.duplicated()))
df = df.drop_duplicates()
print('After removing Duplicates: {}'.format(df.shape))
```

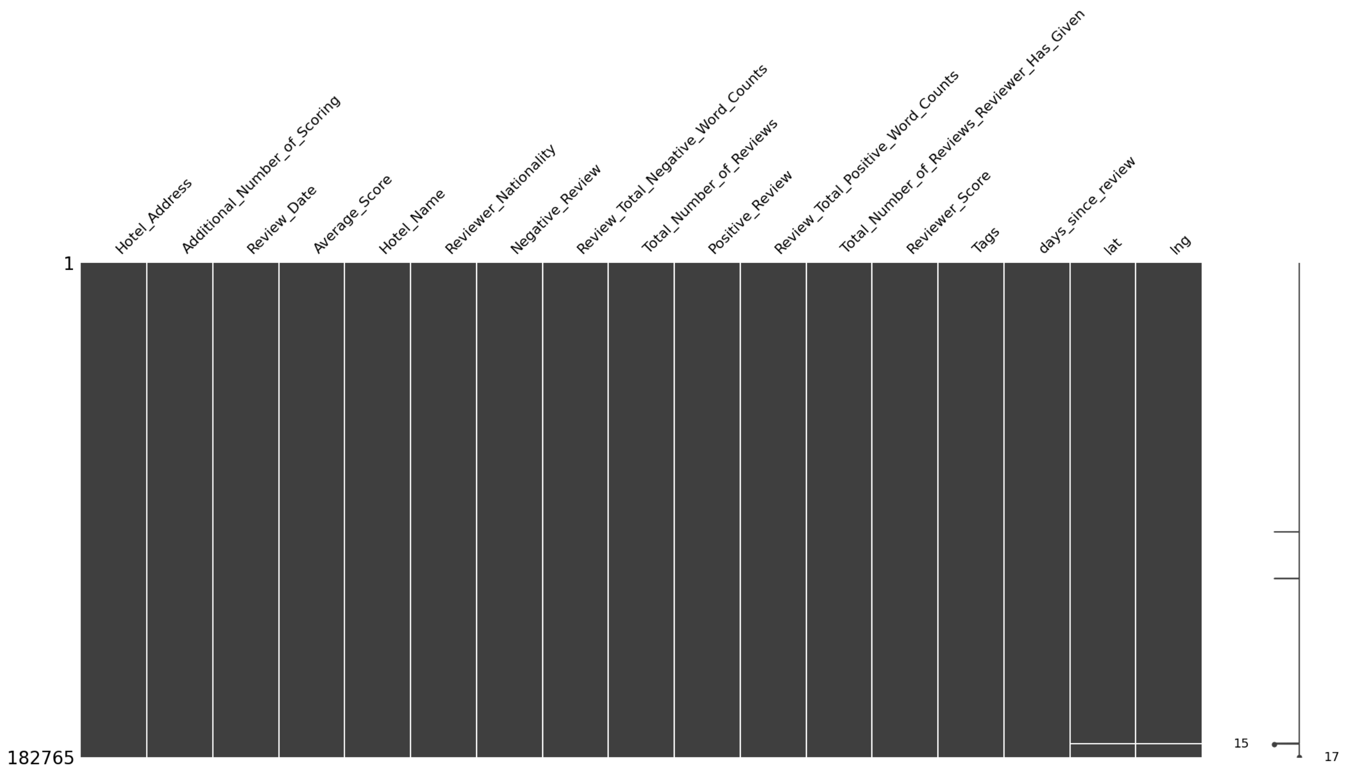
```
380
After removing Duplicates: (182765, 17)
```

Amsterdam ...

Checking for the missing values in the dataset.

```
msno.matrix(df)
```

```
<Axes: >
```




```
nans = lambda df: df[df.isnull().any(axis=1)]
nans_df = nans(df)
nans_df = nans_df[['Hotel_Name','lat','lng']]
print('No of missing values in the dataset: {}'.format(len(nans_df)))
```

```
No of missing values in the dataset: 382
```

```
nans_df.Hotel_Name.describe()
```

```
count                                      382
unique                                       3
top       Maison Albar Hotel Paris Op ra Diamond
freq                                       290
Name: Hotel_Name, dtype: object
```

```
# let's look at the reviews frequency of the missing Hotels.
nans_df.Hotel_Name.value_counts()
```

```
Maison Albar Hotel Paris Op ra Diamond    290
Holiday Inn Paris Montmartre               55
Mercure Paris Gare Montparnasse            37
Name: Hotel_Name, dtype: int64
```

Instead of removing the Nan values from the dataset, Try to fill the Nan values with the similar Hotel_Addresses lat, lng values in the dataset. If the Hotel_Address is matched with the other rows(i.e Nan valued rows) in the dataset, Fill the Nan values in the dataset with the matched values(i.e., lat,lng).

```
print('No of reviews in the dataset to that Hotel:')
print('Fleming s Selection Hotel Wien City: {}'.format(len(df.loc[df.Hotel_Name == 'Fleming s Selection Hotel Wien City'])))
print('Hotel City Central: {}'.format(len(df.loc[df.Hotel_Name == 'Hotel City Central'])))
print('Hotel Atlanta: {}'.format(len(df.loc[df.Hotel_Name == 'Hotel Atlanta'])))
print('Maison Albar Hotel Paris Op ra Diamond: {}'.format(len(df.loc[df.Hotel_Name == 'Maison Albar Hotel Paris Op ra Diamond'])))
print('Hotel Daniel Vienna: {}'.format(len(df.loc[df.Hotel_Name == 'Hotel Daniel Vienna'])))
print('Hotel Pension Baron am Schottentor: {}'.format(len(df.loc[df.Hotel_Name == 'Hotel Pension Baron am Schottentor'])))
print('Austria Trend Hotel Schloss Wilhelminenberg Wien: {}'.format(len(df.loc[df.Hotel_Name == 'Austria Trend Hotel Schloss Wilhelminenb
print('Derag Livinghotel Kaiser Franz Joseph Vienna: {}'.format(len(df.loc[df.Hotel_Name == 'Derag Livinghotel Kaiser Franz Joseph Vienna
print('NH Collection Barcelona Podium: {}'.format(len(df.loc[df.Hotel_Name == 'NH Collection Barcelona Podium'])))
print('City Hotel Deutschmeister: {}'.format(len(df.loc[df.Hotel_Name == 'City Hotel Deutschmeister'])))
print('Hotel Park Villa: {}'.format(len(df.loc[df.Hotel_Name == 'Hotel Park Villa'])))
print('Cordial Theaterhotel Wien: {}'.format(len(df.loc[df.Hotel_Name == 'Cordial Theaterhotel Wien'])))
print('Holiday Inn Paris Montmartre: {}'.format(len(df.loc[df.Hotel_Name == 'Holiday Inn Paris Montmartre'])))
print('Roomz Vienna: {}'.format(len(df.loc[df.Hotel_Name == 'Roomz Vienna'])))
print('Mercure Paris Gare Montparnasse: {}'.format(len(df.loc[df.Hotel_Name == 'Mercure Paris Gare Montparnasse'])))
print('Renaissance Barcelona Hotel: {}'.format(len(df.loc[df.Hotel_Name == 'Renaissance Barcelona Hotel'])))
print('Hotel Advance: {}'.format(len(df.loc[df.Hotel_Name == 'Hotel Advance'])))
```

```
No of reviews in the dataset to that Hotel:
Fleming s Selection Hotel Wien City: 0
Hotel City Central: 0
Hotel Atlanta: 0
Maison Albar Hotel Paris Op ra Diamond: 290
Hotel Daniel Vienna: 0
Hotel Pension Baron am Schottentor: 0
Austria Trend Hotel Schloss Wilhelminenberg Wien: 0
Derag Livinghotel Kaiser Franz Joseph Vienna: 0
NH Collection Barcelona Podium: 0
City Hotel Deutschmeister: 0
Hotel Park Villa: 0
Cordial Theaterhotel Wien: 0
Holiday Inn Paris Montmartre: 55
Roomz Vienna: 0
Mercure Paris Gare Montparnasse: 37
Renaissance Barcelona Hotel: 0
Hotel Advance: 0
```

From the above figures we see that the missing values and available values in the dataset are same.(i.e the inflat,lng values are not available in the entire dataset).

So, Now we can fill the NaN values in the dataset manually. (Simply we can ignore those rows in the dataset by removing them. But i decided not to delete the information and fill the lat,lng values manually just because when it comes to Business problem if i try to remove the data i am losing information of 17 Hotel's. It seems like losing our 17 clients.)

```
loc_lat = {'Fleming s Selection Hotel Wien City':48.209270,
       'Hotel City Central':48.2136,
       'Hotel Atlanta':48.210033,
       'Maison Albar Hotel Paris Op ra Diamond':48.875343,
       'Hotel Daniel Vienna':48.1888,
       'Hotel Pension Baron am Schottentor':48.216701,
      'Austria Trend Hotel Schloss Wilhelminenberg Wien':48.2195,
      'Derag Livinghotel Kaiser Franz Joseph Vienna':48.245998,
      'NH Collection Barcelona Podium':41.3916,
      'City Hotel Deutschmeister':48.22088,
      'Hotel Park Villa':48.233577,
      'Cordial Theaterhotel Wien':48.209488,
      'Holiday Inn Paris Montmartre':48.888920,
      'Roomz Vienna':48.186605,
      'Mercure Paris Gare Montparnasse':48.840012,
      'Renaissance Barcelona Hotel':41.392673,
      'Hotel Advance':41.383308}
```

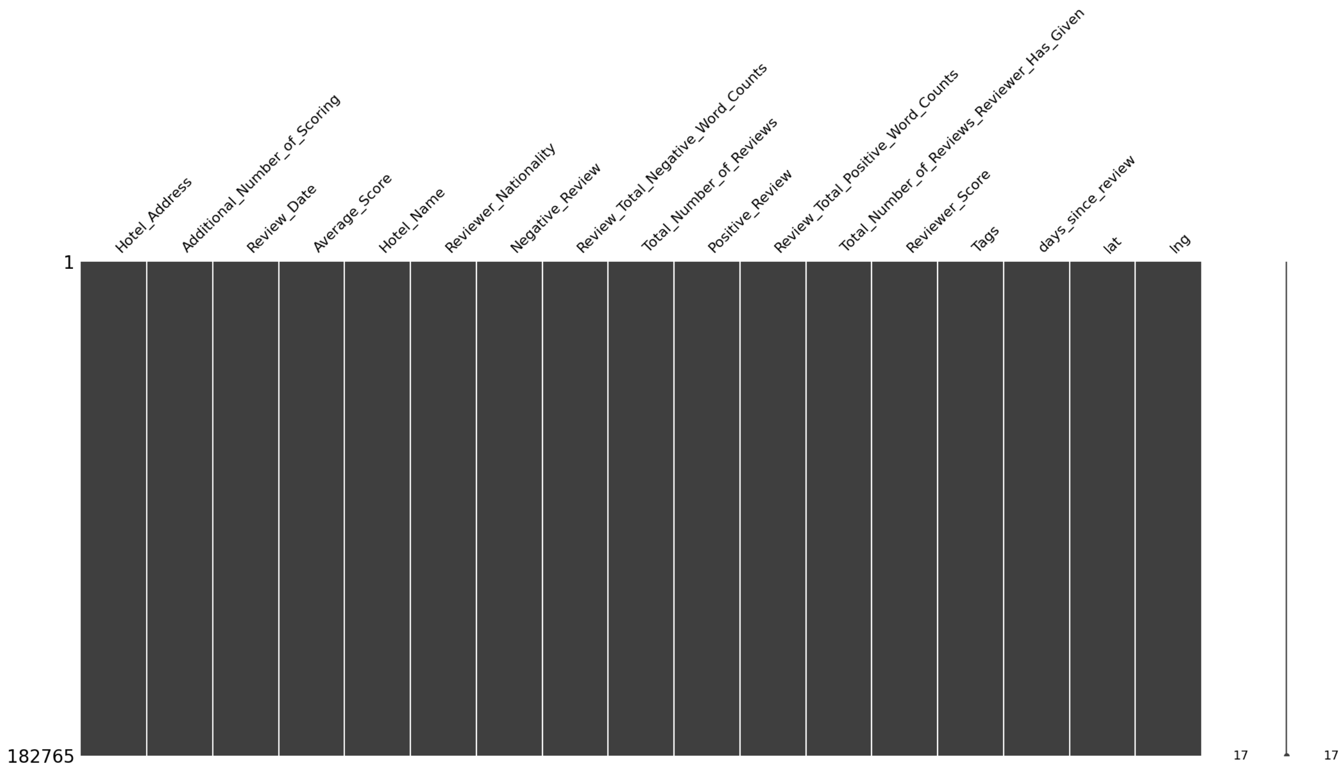
```
#longitude information of Hotels
loc_lng ={'Fleming s Selection Hotel Wien City':16.353479,
       'Hotel City Central':16.3799,
       'Hotel Atlanta':16.363449,
       'Maison Albar Hotel Paris Op ra Diamond':2.323358,
       'Hotel Daniel Vienna':16.3840,
       'Hotel Pension Baron am Schottentor':16.359819,
      'Austria Trend Hotel Schloss Wilhelminenberg Wien':16.2856,
      'Derag Livinghotel Kaiser Franz Joseph Vienna':16.341080,
```

```
      'NH Collection Barcelona Podium':2.1779,
      'City Hotel Deutschmeister':16.36663,
      'Hotel Park Villa':16.345682,
      'Cordial Theaterhotel Wien':16.351585,
      'Holiday Inn Paris Montmartre':2.333087,
      'Roomz Vienna':16.420643,
      'Mercure Paris Gare Montparnasse':2.323595,
      'Renaissance Barcelona Hotel':2.167494,
      'Hotel Advance':2.162828}
```

```
#filling the latitude information
df['lat'] = df['lat'].fillna(df['Hotel_Name'].apply(lambda x: loc_lat.get(x)))
#filling longitude information
df['lng'] = df['lng'].fillna(df['Hotel_Name'].apply(lambda x: loc_lng.get(x)))
```

```
#looking whether information is correctly filled or not.
msno.matrix(df)
```

```
<Axes: >
```




```
#saving the data to pickle files
df.to_pickle('After_filling_Nans')
```

```
#loading the data from the pickle file
df = pd.read_pickle('After_filling_Nans')
df
```

	Hotel_Address	Additional_Number_of_Scoring	Review_Date	Average_Score	Hotel_Name	Reviewer_Nationality	Negative_Revi
0	s Gravesandestraat 55 Oost 1092 AA Amsterdam Netherlands	194	8/3/2017	7.7	Hotel Arena	Russia	I am so angry t i made this p available via possible site use when plan my trips so no c will make mistake booking this pla I made booking booking com stayed for 6 nig in this hotel fr 11 to 17 J Upon arrival were placed i small room on 2nd floor of hotel It turned that this was the room booked I h specially reserv the 2 level dup room so that would have a windows and h ceilings The ro itself was ok if y don t mind broken wind that can not closed hello r and a mini fric that contair some sort of a weapon at lea guessed so by smell of intimately ask to change room and a explaining 2 tim that i booke duplex btw it co the same a simple double got way m volume due to high ceiling v offered a room only the next c SO i had to che out the next c before 11 o clo in order to get room i wanec Not the best v to begin y holiday So we h to wait till 13 00 order to checl my new ro what a wonde waist of my ti The room 02 got was just a wanted peaceful inter garden view window We w tired from wait the room so placed belongings a rushed to the In the evenin turned out t there wa constant noise the room i gues was made vibrating v tubes something it w constant a annoying as I

								annoying as AND it did stop even at 2 making it hard fall asleep for and my wi have an au recording th can not atta here but if y want i can sen via e mail T next day technician ca but was not a to determine cause of disturbing sou so i was offered change the ro once again hotel was fu booked and th had only 1 ro left the one t was smaller seems new
1	s Gravesandestraat 55 Oost 1092 AA Amsterdam Netherlands	194	8/3/2017	7.7	Hotel Arena		Ireland	No Negat
2	s Gravesandestraat 55 Oost 1092 AA Amsterdam Netherlands	194	7/31/2017	7.7	Hotel Arena		Australia	Rooms are n but for elderly a difficult as m rooms are t story with narr steps So ask single level Ins the rooms very very ba just tea coffee a boiler and no empty frid
								My room was d and I was afraid walk barefoot the floor wh looked as if it w not cleaned weeks Wh

3	s Gravesandestraat 55 Oost 1092 AA Amsterdam Netherlands	194	7/31/2017	7.7	Hotel Arena	United Kingdom	weeks Wh furniture wh looked nice pictures was d too and the d looked like it v attacked by angry dog shower drain v clogged and staff did respond to request to clea On a day v heavy rainfa pretty comm occurrence Amsterdam roof in my ro was leaking luc not on the b you could a see signs earlier wa damage I a saw inse running on floor Overall second floor of property look dirty and ba kept On top of of thi repairman w came to something i room next doo midnight was v noisy as w many of gues understand challenges running a hote an old building this negligence inconsistent w prices demand by the hotel the last night a I complair about wa damage the ni shift mana offered to mo me to a differ room but that o came pretty l around midni when I w already in bed a ready to sle
4	s Gravesandestraat 55 Oost 1092 AA Amsterdam Netherlands	194	7/24/2017	7.7	Hotel Arena	New Zealand	You Whe booked with y company on l you showed pictures of a ro I thought I w getting and pay for and then wh we arrived tha room was book and the staff t me we could c book the villa su theough th directly Wh was complet false advertis After being th we realised t you have grou lots of rooms the pho together leav me the consur confused a extrea disgrunt especially as

							my my wife s 4 birthday pres Please make y website m clear throu pricing and pho as again I dic really know wh was paying and how muc had wnded being Your pho told me I v getting someth I wasn t h happy and wo be using y ag
...	...	...	...	...	...	...	
183140	41 54 Buckingham Gate Westminster Borough London SW1E 6AF United Kingdom	1299	4/11/2017	8.7	St James Court A Taj Hotel London	United States of America	Room servic extremely pric and limi
183141	41 54 Buckingham Gate Westminster Borough London SW1E 6AF United Kingdom	1299	4/11/2017	8.7	St James Court A Taj Hotel London	United Kingdom	Only little critici was the tea a coffee facilities the room Only minimum was offer although sure if we h asked for m would have be offe
183142	41 54 Buckingham Gate Westminster Borough London SW1E 6AF United Kingdom	1299	4/10/2017	8.7	St James Court A Taj Hotel London	Austria	got a ro somewhere at end loud engi most proba from air conditio audibly in night through closed windo you do not hav good sleep i not comforta small bathro
183143	41 54 Buckingham Gate Westminster Borough London SW1E 6AF United Kingdom	1299	4/10/2017	8.7	St James Court A Taj Hotel London	Netherlands	I had one of older roo Especially bathroom need refurbishmer was clean outdated a when takin shower positior the showerhe too l
							Although this v my fifth time this nice ho nothing was do to welcome back No note fr the manager gift nada I notif several of

front desk cle

Basic stats for the feature: Hotel_Name

183144 Borough London 1299 4/7/2017 8.7 Hotel America some of th

```
df.Hotel_Name.describe()
```

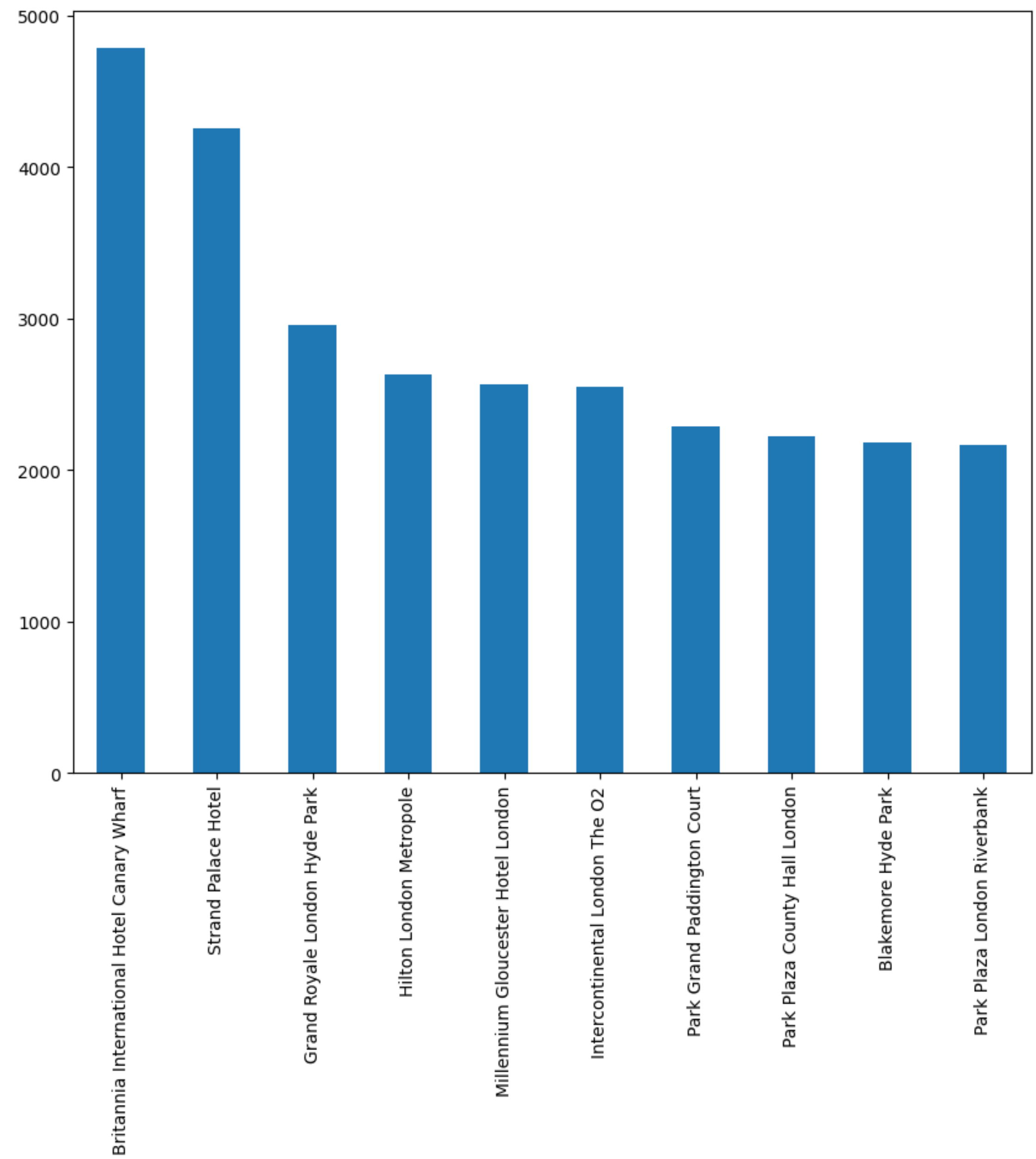
```
count                                       182765
unique                                         529
top       Britannia International Hotel Canary Wharf
freq                                          4789
Name: Hotel_Name, dtype: object
```

There are 1492 Hotel Names and the most reviewed Hotel is Britannia International Hotel Canary Wharf with 4789 reviews.

on vacat

```
# Let's look at the top 10 reviewed Hotels
Hotel_Name_count = df.Hotel_Name.value_counts()
Hotel_Name_count[:10].plot(kind='bar',figsize=(10,8))
```

```
<Axes: >
```

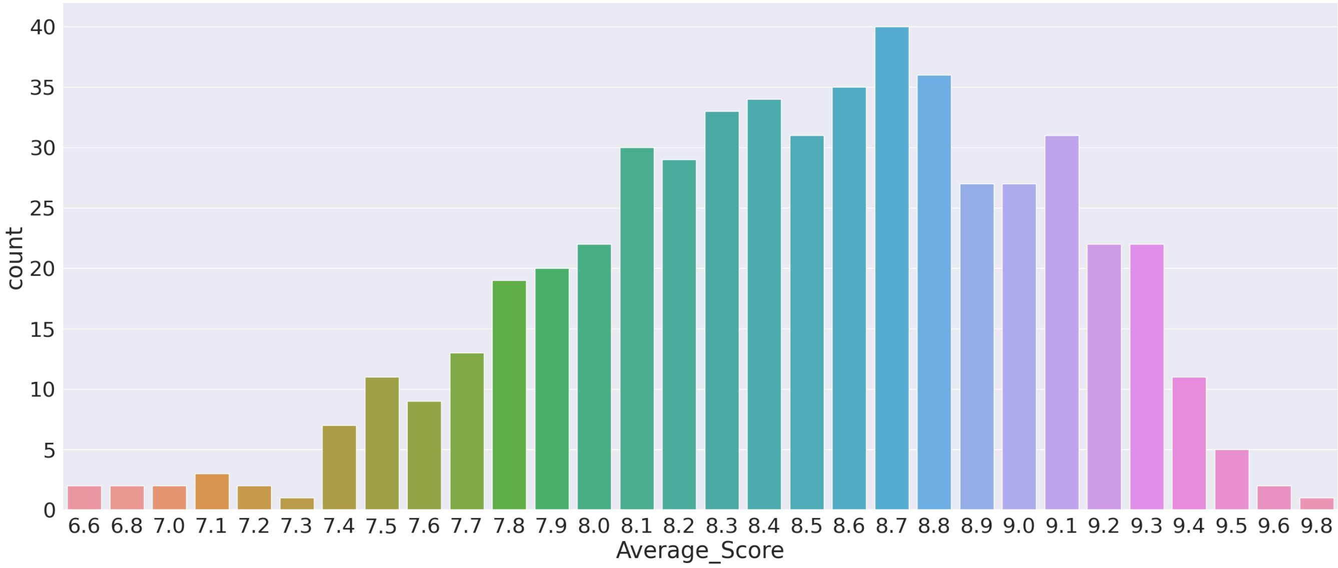


Basic stats for the feature: Average_Score ¶

```
import matplotlib.pylab as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 50, 18
rcParams["axes.labelsize"] = 16
from matplotlib import pyplot
import seaborn as sns
```

```
data_plot = df[["Hotel_Name","Average_Score"]].drop_duplicates()
sns.set(font_scale = 2.5)
a4_dims = (30, 12)
fig, ax = pyplot.subplots(figsize=a4_dims)
sns.countplot(ax = ax,x = "Average_Score",data=data_plot)
```

```
<Axes: xlabel='Average_Score', ylabel='count'>
```



we see that most of the Hotels average_score lie in the range of 8.0 and 9.1 range

Basic stats for the feature: Review_Nationality

```
text = ""
for i in range(df.shape[0]):
    text = " ".join([text,df["Reviewer_Nationality"].values[i]])
```

```
from wordcloud import WordCloud
wordcloud = WordCloud(background_color='black', width = 600,\
                      height=200, max_font_size=50, max_words=40).generate(text)
wordcloud.recolor(random_state=312)
plt.imshow(wordcloud)
plt.title("Wordcloud for countries ")
plt.axis("off")
plt.show()
```

Wordcloud for countries

```
df.Reviewer_Nationality.describe()
```

```
count                182765
unique                  206
top          United Kingdom
freq                 100922
Name: Reviewer_Nationality, dtype: object
```

```
# Let's look at the Top 10 Reviewer's Nationalities
Reviewer_Nat_Count = df.Reviewer_Nationality.value_counts()
print(Reviewer_Nat_Count[:10])
```

```
 United Kingdom              100922
 United States of America     11683
 Australia                     7810
 Ireland                       4665
 United Arab Emirates          3272
 Saudi Arabia                  3006
 France                        2630
 Switzerland                   2552
 Canada                        2546
 Netherlands                   2524
Name: Reviewer_Nationality, dtype: int64
```

The Reviewers belongs to 227 different countries and almost 47.57%(245110/515212) of Reviewers are from United Kingdom

Basic stats for the feature: Review_Date

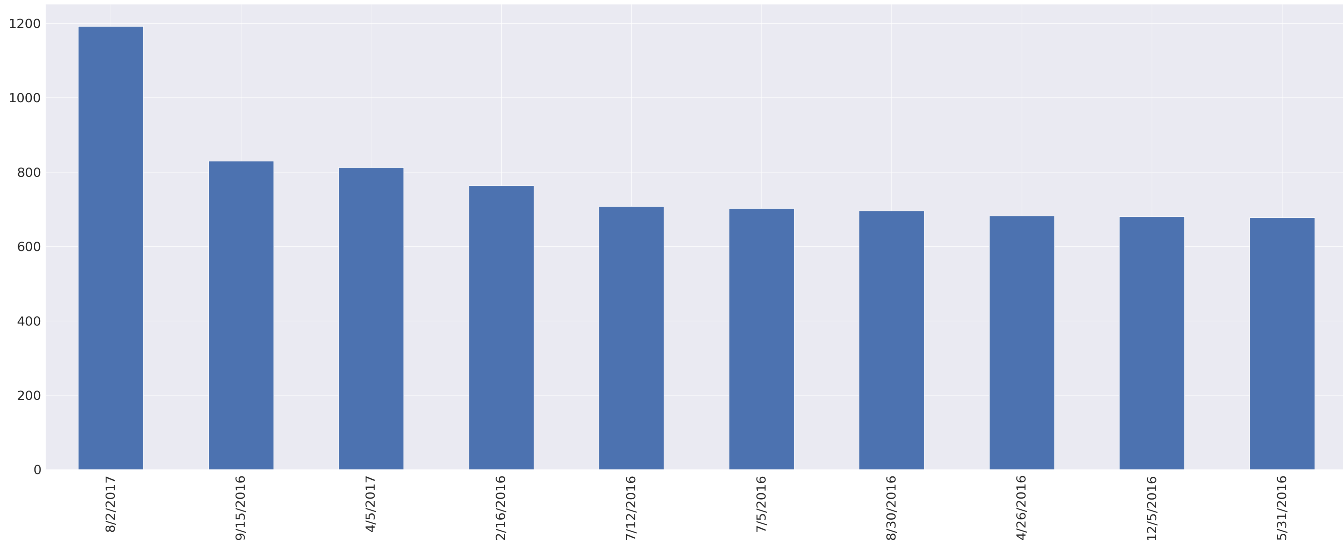
```
df.Review_Date.describe()
```

```
count        182765
unique          731
top        8/2/2017
freq           1192
Name: Review_Date, dtype: object
```

There Reviews are given on 731 dates and the most Reviews are given on 8/2/2017

```
# Let's look at the top 10 Reviews given dates
Review_Date_count = df.Review_Date.value_counts()
Review_Date_count[:10].plot(kind='bar')
```

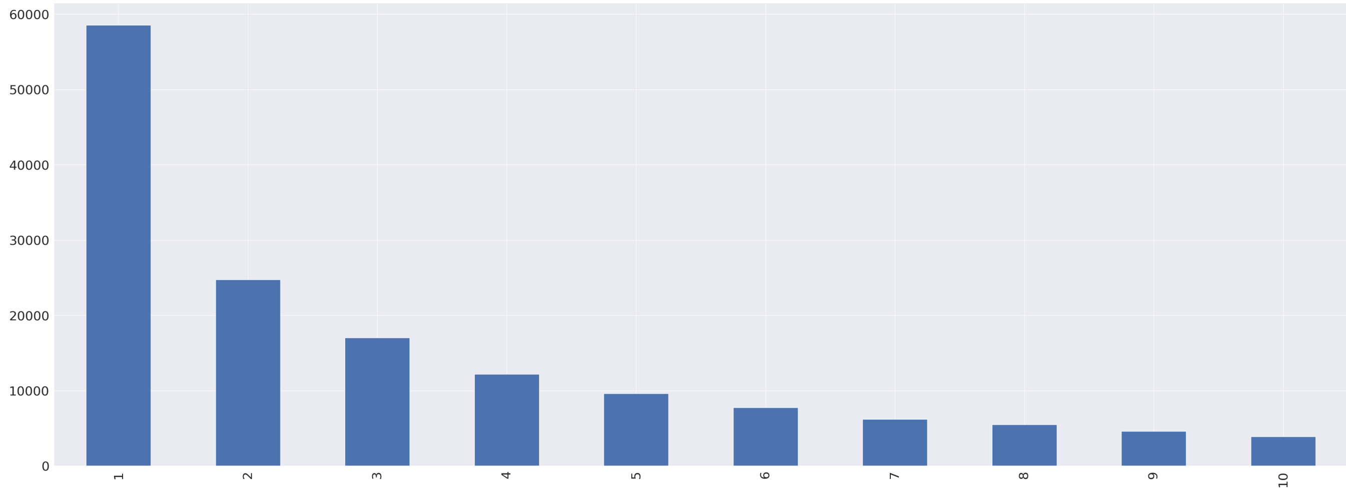
```
<Axes: >
```



Basic stats for the feature: Total_Number_of_Reviews_Reviewer_Has_Given

```
Reviewers_freq = df.Total_Number_of_Reviews_Reviewer_Has_Given.value_counts()
Reviewers_freq[:10].plot(kind='bar')
```

```
<Axes: >
```




```
Reviewers_freq[:10]
```

```
1     58546
2     24744
3     17058
4     12203
5      9644
6      7784
7      6217
8      5518
9      4614
10     3893
Name: Total_Number_of_Reviews_Reviewer_Has_Given, dtype: int64
```

We see that almost 29.99% (154506 / 515212) of user's reviewed for the first_time.

Basic stats for the feature: Review_Total_Positive_Word_Counts

```
pos_words = df.Review_Total_Positive_Word_Counts.value_counts()
pos_words[:10]
```

we see that 0 words are more in number it means they are completely Negative reviews. Lets have a look at them.

```
a = df.loc[df.Review_Total_Positive_Word_Counts == 0]
print('No of completely Negative reviews in the dataset:',len(a))
b = a[['Positive_Review','Negative_Review']]
b[:10]
```

```
No of completely Negative reviews in the dataset: 13145
```

	Positive_Review	Negative_Review
8	No Positive	Even though the pictures show very clean room...
32	No Positive	Our bathroom had an urine order Shower was ve...
98	No Positive	Got charged 50 for a birthday package when it...
121	No Positive	The first room had steep steps to a loft bed ...
134	No Positive	Foyer was a mess Only place to relax was the ...
146	No Positive	We booked a 3 night stay in a suite On arriva...
169	No Positive	Nothing One Of The Receptionist she did a rac...
172	No Positive	Hotel under sonstruction which we weren t awa...
202	No Positive	Renovation around the hotel sometimes can sta...
209	No Positive	Not given the room type we had booked and pre...

Basic stats for the feature: Review_Total_Negative_Word_Counts

```
neg_words = df.Review_Total_Negative_Word_Counts.value_counts()
neg_words[:10]
```

```
0     43846
2      8540
3      6592
6      6327
5      6150
7      5765
4      5433
8      5245
9      4838
10     4477
Name: Review_Total_Negative_Word_Counts, dtype: int64
```

```
a = df.loc[df.Review_Total_Negative_Word_Counts == 0 ]
print('No of completely positive reviews in the dataset:',len(a))
b = a[['Positive_Review','Negative_Review']]
b[:10]
```

```
No of completely positive reviews in the dataset: 43846
```

	Positive_Review	Negative_Review
1	No real complaints the hotel was great great ...	No Negative
13	This hotel is being renovated with great care...	No Negative
15	This hotel is awesome I took it sincirely bec...	No Negative
18	Public areas are lovely and the room was nice...	No Negative
48	The quality of the hotel was brilliant and ev...	No Negative
53	Beautiful setting in a lovely park room very ...	No Negative
55	The hotel is lovely and the staff were amazin...	No Negative
59	Basically everything The style of the hotel i...	No Negative
75	The whole hotel was very clean the staff were...	No Negative
78	Hotel was really nice staff were very friendl...	No Negative

Calculating no of positve and negative reviews

```
# For classifying positive and negative reviews
df['pos_count']=0
df['neg_count']=0
```

```
# since we found the words are in mixed case letters and with trailing whitespace
#we remove those white spaces and converting the reviews to lowercases
df['Negative_Review']=[x.lower().strip() for x in df['Negative_Review']]
df['Positive_Review']=[x.lower().strip() for x in df['Positive_Review']]
```

```
#if the Positive_Review contains the words 'no positive' and 'nothing' are considered as a Negative_Review.
# if the Negative_Review contains the word 'everything' it is also considered as Negative_Review.
# we are maiking those reveiews as 1 in neg_count(attribute).
df["neg_count"] = df.apply(lambda x: 1 if x["Positive_Review"] == 'no positive' or \
                           x['Positive_Review']=='nothing' or \
                           x['Negative_Review']=='everything' \
                           else x['pos_count'],axis = 1)
```

```
#if the Negative_Review contains the words 'no negative' and 'nothing' are considered as a Positive_Review.
#if the Positive_Review contains the word 'Everything' it is also considered as positive_Review.
#we are making those reviews as 1 in the pos_count(attribute).
df["pos_count"] = df.apply(lambda x: 1 if x["Negative_Review"] == 'no negative' or \
                           x['Negative_Review']=='nothing' or \
                           x['Positive_Review']=='everything' \
                           else x['pos_count'],axis = 1)
```

```
#seeing how many reviews are classified as positive one's
df.pos_count.value_counts()
```

```
0    131044
1     51721
Name: pos_count, dtype: int64
```

```
#seeing how many reviews are classified as negative one's
df.neg_count.value_counts()
```

```
0    168860
1     13905
Name: neg_count, dtype: int64
```

By adding those words we classified (1,49,981 + 37,854) i.e., 1,87,835 reviews.

```
# Calculating no of positive and negative reviews for each Hotel and storing them into reviews dataset.
reviews = pd.DataFrame(df.groupby(["Hotel_Name"])["pos_count","neg_count"].sum())
```

```
<ipython-input-41-b0cbee7ebc92>:2: FutureWarning: Indexing with multiple keys (implicitly converted to a tuple of keys) will be dep
  reviews = pd.DataFrame(df.groupby(["Hotel_Name"])["pos_count","neg_count"].sum())
```

```
reviews.head()
```

Hotel_Name	pos_count	neg_count
11 Cadogan Gardens	55	10
1K Hotel	26	12
Acad mie H tel Saint Germain	89	7
Ace Hotel London Shoreditch	163	25
Amarante Champs Elys es	18	10

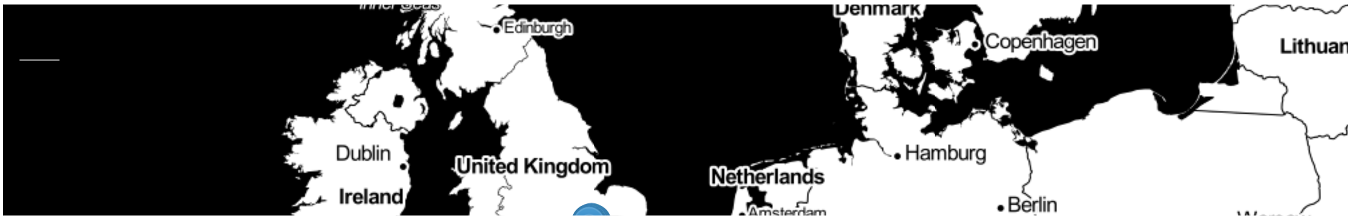
```
# Adding index to the reviews dataframe
reviews["HoteL_Name"] = reviews.index
reviews.index = range(reviews.shape[0])
reviews.head()
```

```
#calculating total number of reviews for each hotel
reviews["total"] = reviews["pos_count"] + reviews["neg_count"]
#calculating the positive ratio for each Hotel.
reviews["pos_ratio"] = reviews["pos_count"].astype("float")/reviews["total"].astype("float")
```

Finding the top 20 famous Hotels

```
#looking at the famous 20 hotels location in the map. Famous Hotels are calculated based on the total
#no of reviews the Hotel has.
famous_hotels = reviews.sort_values(by = "total",ascending=False).head(100)
pd.set_option('display.max_colwidth', 2000)
popular = famous_hotels["HoteL_Name"].values[:20]
popular_hotels =df.loc[df['Hotel_Name'].isin(popular)][["Hotel_Name",\
                                "Hotel_Address",'Average_Score','lat','lng']].drop_duplicates()
maps_osm = folium.Map(location=[47, 6], zoom_start=5, tiles = 'Stamen Toner' )
popular_hotels.apply(lambda row:folium.Marker(location=[row["lat"], row["lng"]])
                                             .add_to(maps_osm), axis=1)
```

```
maps_osm
```




```
#look at the Hotel_Name and Hotel_Address of those Hotels
popular_hotels
```

	Hotel_Name	Hotel_Address	Average_Score	lat	lng
2008	The Park Grand London Paddington	1 3 Queens Garden Westminster Borough London W2 3BA United Kingdom	7.7	51.514218	-0.180903
5257	Park Plaza County Hall London	1 Addington Street Lambeth London SE1 7RY United Kingdom	8.4	51.501400	-0.116009
8301	Grand Royale London Hyde Park	1 Inverness Terrace Westminster Borough London W2 3JP United Kingdom	7.7	51.510995	-0.186342
14829	Intercontinental London The O2	1 Waterview Drive Greenwich London SE10 0TW United Kingdom	9.4	51.502435	-0.000250
57597	M by Montcalm Shoreditch London Tech City	151 157 City Road Shoreditch Islington London EC1V 1JS United Kingdom	9.1	51.527847	-0.088947
63942	Britannia International Hotel Canary Wharf	163 Marsh Wall Docklands Tower Hamlets London E14 9SJ United Kingdom	7.1	51.501910	-0.023221
74223	Park Plaza London Riverbank	18 Albert Embankment Lambeth London SE1 7TJ United Kingdom	8.3	51.491374	-0.121419
96177	citizenM London Bankside	20 Lavington Street Southwark London SE1 0NZ United Kingdom	9.1	51.505151	-0.100472
100530	Mondrian London	20 Upper Ground Southwark London SE1 9PD United Kingdom	9.1	51.508404	-0.106799
108317	London Marriott Hotel West India Quay	22 Hertsmere Road Tower Hamlets London E14 4ED United Kingdom	8.9	51.507271	-0.021121
111930	Hilton London Metropole	225 Edgware Road Westminster Borough London W2 1JU United Kingdom	7.5	51.519569	-0.170521
117485	Park Plaza Victoria London	239 Vauxhall Bridge Road Westminster Borough London SW1V 1EQ United Kingdom	8.6	51.494254	-0.141476
119277	Club Quarters Hotel St Paul s	24 Ludgate Hill City of London London EC4M 7DR United Kingdom	8.4	51.513930	-0.101126
124658	DoubleTree by Hilton London Docklands Riverside	265 Rotherhithe Street Southwark London SE16 5HW United Kingdom	8.1	51.504348	-0.033444
127024	Park Grand Paddington Court	27 Devonshire Terrace Westminster Borough London W2 3DP United Kingdom	8.1	51.513556	-0.180002

Among the famous 20 Hotel's 19 Hotels are located in London and one more is located in Amsterdam

Finding the top 20 positive rated Hotels

```
#Looking at top 20 famous hotels with positive reviews.
pos = famous_hotels.sort_values(by = "pos_ratio",ascending=False)["HoteL_Name"].head(20).values
famous_pos = df.loc[df['Hotel_Name'].isin(pos)][["Hotel_Name","Hotel_Address",'lat','lng','Average_Score']].drop_duplicates()
positive_map = folium.Map(location=[47, 6], zoom_start=5, tiles = 'Stamen Toner' )
famous_pos.apply(lambda row:folium.Marker(location=[row["lat"], row["lng"]])
                                             .add_to(positive_map), axis=1)

positive_map
```


```
#look at the Hotel_Name and Hotel_Address of those Hotels
famous_pos
```

	Hotel_Name	Hotel_Address	lat	lng	Average_Score
971	Apex Temple Court Hotel	1 2 Serjeant s Inn Fleet Street City of London London EC4Y 1LL United Kingdom	51.513734	-0.108751	9.2
18445	The Nadler Soho	10 Carlisle Street Westminster Borough London W1D 3BR United Kingdom	51.514739	-0.134111	9.0
20546	The Nadler Victoria	10 Palace Place Westminster Borough London SW1E 5BW United Kingdom	51.499026	-0.142745	9.3
31647	Staybridge Suites London Stratford	10b Chestnut Plaza Westfield Stratford City Olympic Park Newham London E20 1GL United Kingdom	51.542635	-0.007327	9.2
44652	The Chamberlain	130 135 Minories City of London London EC3N 1NU United Kingdom	51.512246	-0.075733	8.9
54303	The Montague On The Gardens	15 Montague St Bloomsbury Camden London WC1B 5BJ United Kingdom	51.520181	-0.125696	9.3
57191	The Ritz London	150 Piccadilly Westminster Borough London W1J 9BR United Kingdom	51.506945	-0.141578	9.3
83097	The Hoxton Holborn	199 206 High Holborn Camden London WC1V 7BD United Kingdom	51.517240	-0.122032	9.2
85479	Hilton London Bankside	2 8 Great Suffolk Street Southwark London SE1 0UG United Kingdom	51.505696	-0.101525	9.3
96177	citizenM London Bankside	20 Lavington Street Southwark London SE1 0NZ United Kingdom	51.505151	-0.100472	9.1
107032	Montcalm Royal London House City of London	22 25 Finsbury Square City Islington London EC2A 1DX United Kingdom	51.521807	-0.085608	9.2
121850	The Nadler Kensington	25 Courtfield Gardens Kensington and Chelsea London SW5 0PG United Kingdom	51.493109	-0.190208	9.0
122627	Rosewood London	252 High Holborn Holborn Camden London WC1V 7EN United Kingdom	51.517330	-0.118097	9.4
147504	Shangri La Hotel at The Shard London	31 St Thomas Street Southwark London SE1 9QU United Kingdom	51.504497	-0.085556	9.4
158465	The Chesterfield Mayfair	35 Charles Street Mayfair Westminster Borough London W1J 5EB United Kingdom	51.507690	-0.147136	9.1
170437	Rubens At The Palace	39 Buckingham Palace Road Westminster Borough London SW1W 0PS United Kingdom	51.498147	-0.143649	8.7

Among the top 20 Hotels with positive reviews 11 Hotels are located in London, 4 in Netherlands, 2 in Milan, 2 in Spain and 1 in Vienna

```
#saving the dataframe to pickle file
reviews.to_pickle('reviews')
```

Preprocessing:

since the dataset has already removed the unicode and punctuation in the text data and transformed text into lower case.... Half of the work of preprocessing is done. Let's do the remaining preprocessing tasks like removing stopwords, stemming.

```
#loading the positive reviews and negative reviews to a single column as text
pos_reviews = df['Positive_Review'].values
```

```
pos_reviews = pos_reviews.tolist()
neg_reviews = df['Negative_Review'].values
neg_reviews = neg_reviews.tolist()
text = pos_reviews+neg_reviews


#providing score attribute to the review
score = ['positive' for i in range(len(pos_reviews))]
score += ['negative' for i in range(len(neg_reviews))]
#performing one-hot encoding to the score attrubute.(1- positive and 0- negative)
for i in range(0,len(score)):
    if score[i] == 'positive':
        score[i] = 1
    else:
        score[i] = 0


#loading required data to dataframe.
text_df = pd.DataFrame()
text_df['reviews'] = text
text_df['score'] = score
text_df.head(20)
```

	reviews	score
0	only the park outside of the hotel was beautiful	1
1	no real complaints the hotel was great great location surroundings rooms amenities and service two recommendations however firstly the staff upon check in are very confusing regarding deposit payments and the staff offer you upon checkout to refund your original payment and you can make a new one bit confusing secondly the on site restaurant is a bit lacking very well thought out and excellent quality food for anyone of a vegetarian or vegan background but even a wrap or toasted sandwich option would be great aside from those minor minor things fantastic spot and will be back when i return to amsterdam	1
2	location was good and staff were ok it is cute hotel the breakfast range is nice will go back	1
3	great location in nice surroundings the bar and restaurant are nice and have a lovely outdoor area the building also has quite some character	1
4	amazing location and building romantic setting	1
5	good restaurant with modern design great chill out place great park nearby the hotel and awesome main stairs	1
6	the room is spacious and bright the hotel is located in a quiet and beautiful park	1
7	good location set in a lovely park friendly staff food high quality we oth enjoyed the breakfast	1
8	no positive	1
9	the room was big enough and the bed is good the breakfast food and service on the hotel is good outside the hotel there is a big park which is very good for walk in the morning and evening many people are having picnics and do some bicycling	1
10	rooms were stunningly decorated and really spacious in the top of the building pictures are of room 300 the true beauty of the building has been kept but modernised brilliantly also the bath was lovely and big and inviting great more for couples restaurant menu was a bit pricey but there were loads of little eatery places nearby within walking distance and the tram stop into the centre was about a 6 minute walk away and only about 3 or 4 stops from the centre of amsterdam would recommend this hotel to anyone it s unbelievably well priced too	1
11	style location rooms	1
12	comfy bed good location	1
13	this hotel is being renovated with great care and with an appreciation for its unique structure and location my spacious and comfortable room had a large double paned glass window onto the lush greenery of the park the breakfast selection was spectacular all considered this was a great hotel for the price and i plan to return	1
14	it was very good very historic building that s why i chose it	1
15	this hotel is awesome i took it sincirely because a bit cheaper but the structure seem in an hold church close to one awesome park arrive in the city are like 10 minutes by tram and is super easy the hotel inside is awesome and really cool and the room is incredible nice with two floor and up one super big comfortable room i ll come back for sure there the staff very gentle one spanish man really really good	1
16	great onsite cafe amazing building park location amazing bobby gin and tonic	1
17	we loved the location of this hotel the fact that it is set in a park away from the busy centre of dam square was great the tram system was brilliant and easy to handle the hotel is lovely and the bed was comfy staff were very friendly and helpful and familiarized themselves with us when they realized we travelled from ireland	1
18	public areas are lovely and the room was nice but the window was broken and the drains in the bathroom smelt its an old building and clearly has old building issues	1

```
import nltk
nltk.download('stopwords')
```

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

```
# Perfoming preprocessing
start_time = time.time()
text = text_df['reviews'].values
print("Removing stop words...........................")
```

```
stop = set(stopwords.words('english'))
words = []
summary = []
all_pos_words = []
all_neg_words = []
for i in range(0,len(text)):
    if type(text[i]) == type('') :
        sentence = text[i]
        sentence = re.sub("[^a-zA-Z]"," ", sentence)
        buffer_sentence = [i for i in sentence.split() if i not in stop]
        word = ''
        for j in buffer_sentence:
            if len(j) >= 2:
                if i<=(len(text)/2):
                    all_pos_words.append(j)
                else:
                    all_neg_words.append(j)
                word +=' '+j
                summary.append(word)
print("performing stemming..........................")
porter = PorterStemmer()
for i in range(0,len(summary)):
    summary[i] = porter.stem(summary[i])
print("--- %s seconds ---" % (time.time() - start_time))
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
/usr/local/lib/python3.10/dist-packages/pandas/core/indexes/base.py in get_loc(self, key, method, tolerance)
   3801             try:
-> 3802                 return self._engine.get_loc(casted_key)
   3803             except KeyError as err:

4 frames
pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get_item()

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get_item()

KeyError: 'reviews'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call last)
/usr/local/lib/python3.10/dist-packages/pandas/core/indexes/base.py in get_loc(self, key, method, tolerance)
   3802                 return self._engine.get_loc(casted_key)
   3803             except KeyError as err:
-> 3804                 raise KeyError(key) from err
   3805             except TypeError:
   3806                 # If we have a listlike key, _check_indexing_error will raise

KeyError: 'reviews'
```

SEARCH STACK OVERFLOW

```
# no of words in positive and negative reviews
len(all_pos_words),len(all_neg_words)
summary
```

```
wash alongside hair dryer towels saf',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrob',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrobe hang',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrobe hangers cloth',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrobe hangers clothes hold',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrobe hangers clothes holders desk',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrobe hangers clothes holders desk chair',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrobe hangers clothes holders desk chair room',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrobe hangers clothes holders desk chair room servic',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body wash alongside hair dryer towels safe wardrobe hangers clothes holders desk chair room service hair',
 ' hotel lovely location min tram ride center train right outside hotel easy access everywhere staff super friendly always hand help advice wonderful bright comfortable clean rooms beds amazing felt sleeping clouds bathroom clean spacious airy shampoo body
wash alongside hair dryer towels safe wardrobe hangers clothes holders desk chair room service hair dry'
```

```
# displaying the frequency of words in positive and negative reviews
freq_dist_pos = Counter(all_pos_words)
freq_dist_neg = Counter(all_neg_words)
print('Most common positive words : ',freq_dist_pos.most_common(20))
print('Most common negative words : ',freq_dist_neg.most_common(20))
```

```
Most common positive words :  [('staff', 69793), ('location', 68955), ('room', 51361), ('hotel', 39937), ('good', 37011), ('great',
Most common negative words :  [('room', 68461), ('negative', 44399), ('hotel', 24243), ('small', 21652), ('breakfast', 21495), ('st
```

```
# no of positive and negative words
len(freq_dist_neg),len(freq_dist_pos)
```

```
(29661, 26064)
```

```
#converting the summary numpy array
score = text_df['score'].values
score
```

```
array([1, 1, 1, ..., 0, 0, 0])
```

```
# loading the data to dataframe and saving it into pickle file
text_df = pd.DataFrame()
text_df['Summary'] = summary
#text_df['score'] = score
text_df.to_pickle('text_df')
text_df
```

Summary

Sentiment Analysis for these reviews can be seen in this kernal:

https://colab.research.google.com/drive/1mHFIz_fDxDdUcBQdWP5nbydK6GsrJu4g?usp=sharing

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import time
import re, nltk
from nltk import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
from collections import Counter
import pickle
```

annoyed last times always received courteous note manager waiting room hotels must recognize loyal customers maybe manag

Loading the Data¶

```
data = pd.read_pickle('After preprocessing')
data
```

	Summary	score
0	park outside hotel beauti	1
1	real complaints hotel great great location su...	1
2	location good staff ok cute hotel breakfast r...	1
3	great location nice surroundings bar restaura...	1
4	amazing location building romantic set	1
...	...	...
1030419	trolly staff help take luggage room	0
1030420	hotel looks like sur	0
1030421	ac useless hot week vienna gave hot air	0
1030422	neg	0
1030423	rd floor work free wif	0

1030424 rows × 2 columns

```
df = pd.read_pickle('After_filling_Nans')
df
```

	Hotel_Address	Additional_Number_of_Scoring	Review_Date	Average_Score	Hotel_Name	Reviewer_Nationality	Negative_Review
0	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Russia	I am so angry that i made this post available..
1	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	8/3/2017	7.7	Hotel Arena	Ireland	No Negative
2	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	Australia	Rooms are nice but for elderly a bit difficul..
3	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/31/2017	7.7	Hotel Arena	United Kingdom	My room was dirty and I was afraid to walk ba..
4	s Gravesandestraat 55 Oost 1092 AA Amsterdam ...	194	7/24/2017	7.7	Hotel Arena	New Zealand	You When booked with your company on line y..
...	...	...	...	...	...	...	..
515733	Wurzbachgasse 21 15 Rudolfsheim F nfhaus 1150 ...	168	8/30/2015	8.1	Atlantis Hotel Vienna	Kuwait	no trolly or staff to help you take the lugga..

```
# loading the positive reviews and negative reviews into text.
pos_reviews = df['Positive_Review'].values
pos_reviews = pos_reviews.tolist()
neg_reviews = df['Negative_Review'].values
neg_reviews = neg_reviews.tolist()
text = pos_reviews+neg_reviews
```

```
#converting the data into numpy arrays
summary = np.array(data.Summary)
score = data['score'].values
```

Featurizer - Bag of words (Unigram)¶

1. Multinomial Naive Bayes:

```
import time
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
start_time = time.time()
best_params = [] #store best parameters for MultinomialNB
parameters = {'alpha':[i for i in range(1,100,10)]}
acc = []
score = list(score)
for i in range(2000,14000,1000):
  vec = CountVectorizer(max_features = i)
  data = vec.fit_transform(summary)
  nb = MultinomialNB()
  clf = GridSearchCV(nb, parameters,cv=5)
  x_train, x_test, y_train, y_test = train_test_split(data, score, test_size=0.3, random_state=42)
  clf.fit(x_train, y_train)
  acc.append(100.0*sum(clf.predict(x_test))/len((clf.predict(x_test))))
  best_params.append(clf.best_params_)
  vec = 0
  data = 0

print("--- %s seconds ---" % (time.time() - start_time))
```

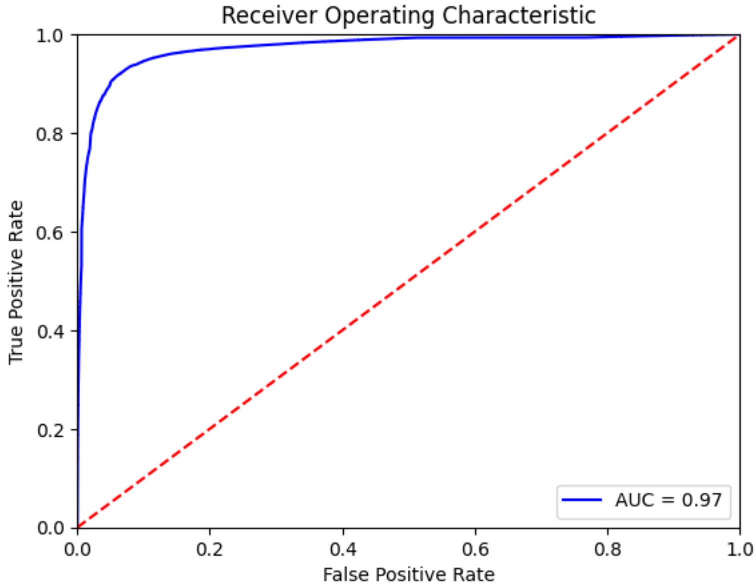
```
--- 541.3127810955048 seconds ---
```

```
##Confusion matrix
def show_confusion_matrix(C,class_labels=['0','1']):
    """
    C: ndarray, shape (2,2) as given by scikit-learn confusion_matrix function
    class_labels: list of strings, default simply labels 0 and 1.

    Draws confusion matrix with associated metrics.
    """
    import matplotlib.pyplot as plt
    import numpy as np
    assert C.shape == (2,2), "Confusion matrix should be from binary classification only."

    # true negative, false positive, false negative, true positive
    tn = C[0,0]; fp = C[0,1]; fn = C[1,0]; tp = C[1,1];

    NP = fn+tp # Num positive examples
    NN = tn+fp # Num negative examples
    N  = NP+NN # Total num of examples
    fig = plt.figure(figsize=(8,8))
    ax  = fig.add_subplot(111)
    ax.imshow(C, interpolation='nearest', cmap=plt.cm.gray)

    # Draw the grid boxes
    ax.set_xlim(-0.5,2.5)
    ax.set_ylim(2.5,-0.5)
    ax.plot([-0.5,2.5],[0.5,0.5], '-k', lw=2)
    ax.plot([-0.5,2.5],[1.5,1.5], '-k', lw=2)
    ax.plot([0.5,0.5],[-0.5,2.5], '-k', lw=2)
    ax.plot([1.5,1.5],[-0.5,2.5], '-k', lw=2)
    # Set xlabels
    ax.set_xlabel('Predicted Label', fontsize=16)
    ax.set_xticks([0,1,2])
    ax.set_xticklabels(class_labels + [''])
    ax.xaxis.set_label_position('top')
    ax.xaxis.tick_top()
    # These coordinate might require some tinkering. Ditto for y, below.
    ax.xaxis.set_label_coords(0.34,1.06)
     # Set ylabels
    ax.set_ylabel('True Label', fontsize=16, rotation=90)
    ax.set_yticklabels(class_labels + [''],rotation=90)
    ax.set_yticks([0,1,2])
    ax.yaxis.set_label_coords(-0.09,0.65)
    # Fill in initial metrics: tp, tn, etc...
    ax.text(0,0,
            'True Neg: %d\n(Num Neg: %d)'%(tn,NN),
            va='center',
            ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))
    ax.text(0,1,
            'False Neg: %d'%fn,
            va='center',
            ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))
    ax.text(1,0,
            'False Pos: %d'%fp,
            va='center',
            ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))
    ax.text(1,1,
            'True Pos: %d\n(Num Pos: %d)'%(tp,NP),
            va='center',
            ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))

    # Fill in secondary metrics: accuracy, true pos rate, etc...
    ax.text(2,0,
            'False Pos Rate: %.2f'%(fp / (fp+tn+0.)),
            va='center',
            ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))
    ax.text(2,1,
            'True Pos Rate: %.2f'%(tp / (tp+fn+0.)),
            va='center',
            ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))

    ax.text(2,2,
            'Accuracy: %.2f'%((tp+tn+0.)/N),
            va='center',
            ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))
    ax.text(0,2,
```

```
            'Neg Pre Val: %.2f'%(1-fn/(fn+tn+0.)),
            va='center',
            ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))

    ax.text(1,2,
            'Pos Pred Val: %.2f'%(tp/(tp+fp+0.)),
            va='center',
    ha='center',
            bbox=dict(fc='w',boxstyle='round,pad=1'))
    plt.tight_layout()
    plt.show()
```

```
start_time = time.time()
from sklearn.metrics import confusion_matrix
from sklearn.metrics import log_loss

score_Log_reg = []
y_pred = clf.predict(x_test)
conf_NB = confusion_matrix(y_test, y_pred)

print("Confusion matrix:\n",conf_NB)

#ROC for a given alpha for NB
from sklearn.metrics import roc_curve, auc
# Compute ROC curve and ROC area for each class
probs = clf.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
#Plot ROC
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
#print the log loss
a = log_loss(y_test, probs)
print("The log loss for the Naive bayes is:",a)
#print confusion matrix
show_confusion_matrix(conf_NB,['Negative','Positive'])

#Precision and recall
tn = conf_NB[0,0]; fp = conf_NB[0,1]; fn = conf_NB[1,0]; tp = conf_NB[1,1];

precision = 100*float(tp)/(tp+fp)
recall = 100*float(tp)/(tp+fn)

print("Precision :",precision)
print("Recall :",recall)
tp = conf_NB[0][0]
tn = conf_NB[1][1]
print("The accuracy is {} %".format(round(100.0*(tp+tn)/len(y_test),2)))
print('------------ %s seconds ------------'%(time.time()-start_time))
```

```
Confusion matrix:
 [[140915  13778]
 [  9455 144980]]
```




```
The log loss for the Naive bayes is: 0.2663865943835242
<ipython-input-35-ae1f0d567b1c>:40: UserWarning: FixedFormatter should only be used together with Fixec
  ax.set_yticklabels(class_labels + [''],rotation=90)
```

Predicted Label

2. Logistic Regression:

```
#Logistic regression hyperparameter tuning
import warnings
from sklearn.linear_model import SGDClassifier
warnings.filterwarnings('ignore')
start_time = time.time()
best_params_logreg = []
parameters = {'loss' :['log'],'penalty':['l1','l2','elasticnet'],'alpha':[float(i)/10 for i in range(1,10,1)],'n_jobs':[-1]}
warnings.filterwarnings('ignore')
clf = SGDClassifier()
clf = GridSearchCV(clf, parameters,cv=5)
clf.fit(x_train, y_train)
best_params_logreg.append(clf.best_params_)
print('Best parameters for Logistic Regression are:',best_params_logreg)
print("--- %s seconds ---" % (time.time() - start_time))
```

```
Best parameters for Logistic Regression are: [{'alpha': 0.1, 'loss': 'log', 'n_jobs': -1, 'penalty': 'l2'}]
--- 296.7039270401001 seconds ---
```

```
clf = SGDClassifier(loss = 'log',penalty = 'l2',alpha = 0.1, n_jobs = -1)
#choose acc to best parameters
clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)
conf_log_ref = confusion_matrix(y_test, y_pred)

print("Confusion matrix:\n",conf_log_ref)
#ROC for a given hyperparameters for logistic regression
from sklearn.metrics import roc_curve, auc
# Compute ROC curve and ROC area for each class
probs = clf.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
#Plot ROC
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

#print the log loss
a = log_loss(y_test, probs)
```

```
print("The log loss for the Logistic regression is:",a)
#print confusion matrix
show_confusion_matrix(conf_log_ref,['Negative','Positive'])

#Precision and recall
tn = conf_log_ref[0,0]; fp = conf_log_ref[0,1]; fn = conf_log_ref[1,0]; tp = conf_log_ref[1,1];

precision = 100*float(tp)/(tp+fp)
recall = 100*float(tp)/(tp+fn)
print("Precision :",precision)
print("Recall :",recall)

tp = conf_log_ref[0][0]
tn = conf_log_ref[1][1]
print("The accuracy is {} %".format(round(100.0*(tp+tn)/len(y_test),2)))
```

3. Support Vector Machine:

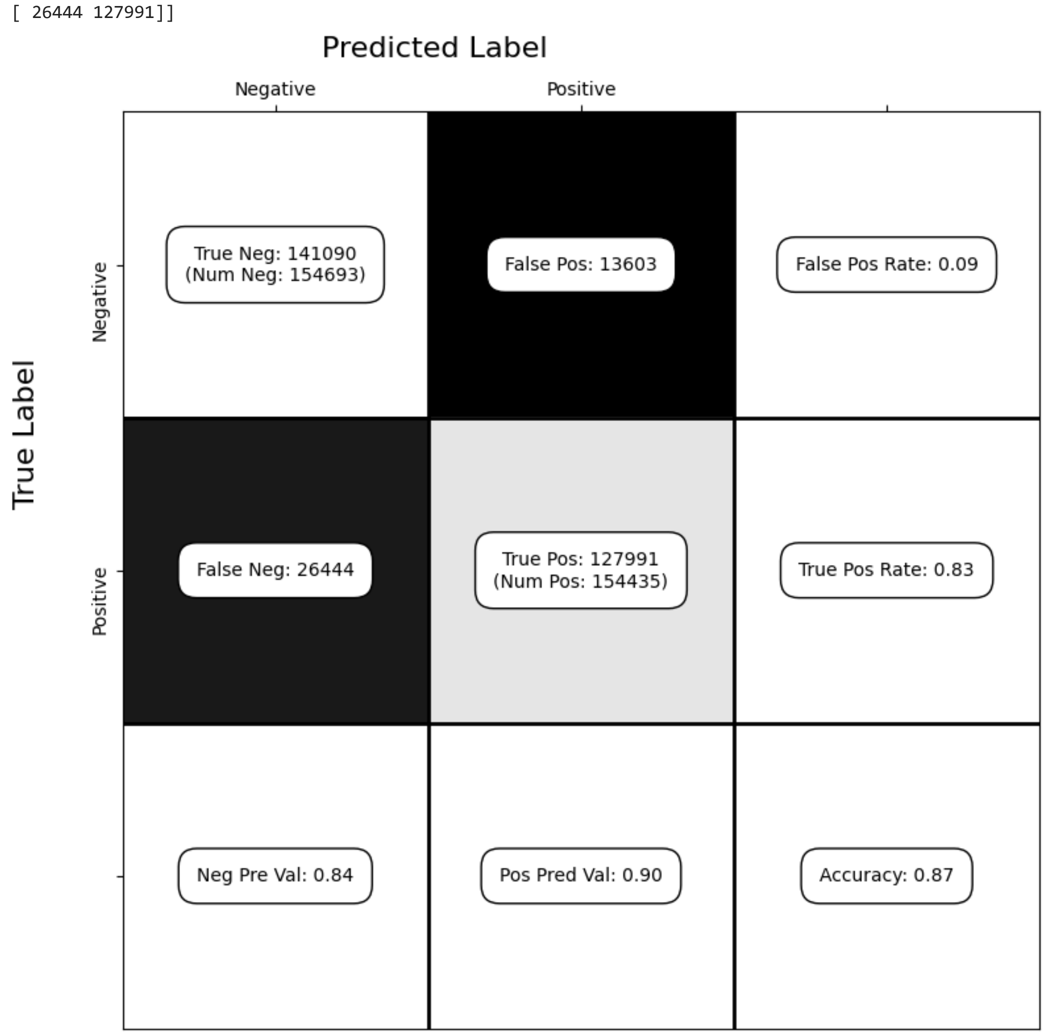
```
#SVM hyperparameter tuning
start_time = time.time()
best_params_SVM = []
parameters = {'loss' :['hinge'],'penalty':['l1','l2','elasticnet'],'alpha':[float(i)/10 for i in range(1,10,1)],'n_jobs':[-1]}

clf = SGDClassifier()
clf = GridSearchCV(clf, parameters,cv=5)
clf.fit(x_train, y_train)
best_params_SVM = clf.best_params_
```

```
print("Best hyperparameters for linear SVM:",best_params_SVM)
print('------{} seconds-------'.format(time.time()-start_time))
```

```
Best hyperparameters for linear SVM: {'alpha': 0.1, 'loss': 'hinge', 'n_jobs': -1, 'penalty': 'l2'}
------247.24474549293518 seconds-------
```

```
#Linear SVM
clf = SGDClassifier(penalty = 'l2', alpha = 0.1, n_jobs =  -1, loss = 'hinge')
#choose acc to best parameters
clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)
conf_SVM_ref = confusion_matrix(y_test, y_pred)
print("Confusion matrix:\n",conf_SVM_ref)
#print confusion matrix
show_confusion_matrix(conf_SVM_ref,['Negative','Positive'])
#Precision and recall
tn = conf_SVM_ref[0,0]; fp = conf_SVM_ref[0,1]; fn = conf_SVM_ref[1,0]; tp = conf_SVM_ref[1,1];
precision = 100*float(tp)/(tp+fp)
recall = 100*float(tp)/(tp+fn)
print("Precision :",precision)
print("Recall :",recall)
tp = conf_SVM_ref[0][0]
tn = conf_SVM_ref[1][1]
print("The accuracy is {} %".format(round(100.0*(tp+tn)/len(y_test),2)))
```

```
Confusion matrix:
 [[141090  13603]
 [ 26444 127991]]
```




```
Precision : 90.39295450372191
Recall : 82.87693851782304
The accuracy is 87.05 %
```

BOW Bi-gram :MultinomialNB

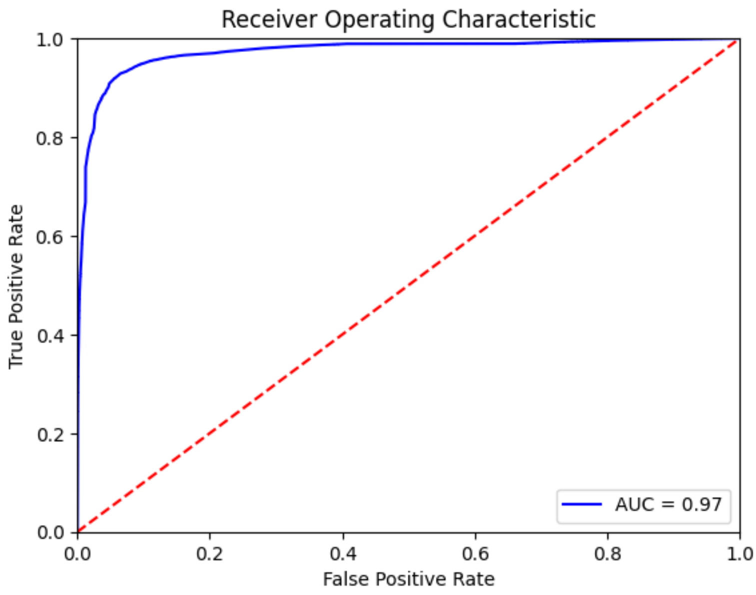
```
# Hyperparameter tuning for MultinomialNB with Bigrams
start_time = time.time()
best_params = []
parameters = {'alpha':[i for i in range(1,100,10)]}
features = [i for i in range(10000,130000,10000)]
acc = []
```

```
score = list(score)
for i in range(2000,14000,1000):
    vec = CountVectorizer(ngram_range=(1,2),max_features = i)
    data = vec.fit_transform(summary)
    nb = MultinomialNB()
    clf = GridSearchCV(nb, parameters,cv=5)
    x_train, x_test, y_train, y_test = train_test_split(data, score, test_size=0.3, random_state=42)
    clf.fit(x_train, y_train)
    acc.append(100.0*sum(clf.predict(x_test))/len((clf.predict(x_test))))
    best_params.append(clf.best_params_)
    vec = 0
    data = 0
print('-------- %s seconds -------'%(time.time()-start_time))
```

```
-------- 824.7739119529724 seconds -------
```

```
# MultinomialNb with Bigrams
score_Log_reg = []
y_pred = clf.predict(x_test)
conf_NB = confusion_matrix(y_test, y_pred)

print("Confusion matrix:\n",conf_NB)

#ROC for a given alpha for NB
from sklearn.metrics import roc_curve, auc
# Compute ROC curve and ROC area for each class
probs = clf.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
#Plot ROC
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
#print the log loss
a = log_loss(y_test, probs)
print("The log loss for the Naive bayes is:",a)

#print confusion matrix
show_confusion_matrix(conf_NB,['Negative','Positive'])
#Precision and recall
tn = conf_NB[0,0]; fp = conf_NB[0,1]; fn = conf_NB[1,0]; tp = conf_NB[1,1];

precision = 100*float(tp)/(tp+fp)
recall = 100*float(tp)/(tp+fn)

print("Precision :",precision)
print("Recall :",recall)
tp = conf_NB[0][0]
tn = conf_NB[1][1]
print("The accuracy is {} %".format(round(100.0*(tp+tn)/len(y_test),2)))
```

```
Confusion matrix:
 [[143243  11450]
 [ 10369 144066]]
```




```
The log loss for the Naive bayes is: 0.3279700928655696
```

Predicted Label

**TF-IDF: Multinomial Naive Bayes

```
# Hyperparameter tuning for MultinomialNB with Bigrams
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
start_time = time.time()
best_params = []
parameters = {'alpha':[i for i in range(1,100,10)]}
acc = []
score = list(score)
for i in range(2000,14000,1000):
    vec = TfidfVectorizer(max_features = i)
    data = vec.fit_transform(summary)
    nb = MultinomialNB()
    clf = GridSearchCV(nb, parameters,cv=5)
    x_train, x_test, y_train, y_test = train_test_split(data, score, test_size=0.3, random_state=42)
    clf.fit(x_train, y_train)
    acc.append(100.0*sum(clf.predict(x_test))/len((clf.predict(x_test))))
    best_params.append(clf.best_params_)
    vec = 0
    data = 0
print('-------- %s seconds -------'%(time.time()-start_time))
```

```
-------- 541.4709167480469 seconds -------
```

```
# MultinomialNb with TF-IDF
from sklearn.metrics import confusion_matrix
from sklearn.metrics import log_loss

score_Log_reg = []
y_pred = clf.predict(x_test)
conf_NB = confusion_matrix(y_test, y_pred)

print("Confusion matrix:\n",conf_NB)
#ROC for a given alpha for NB
from sklearn.metrics import roc_curve, auc
# Compute ROC curve and ROC area for each class
probs = clf.predict_proba(x_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)
#Plot ROC
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
```

```
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

#print the log loss
a = log_loss(y_test, probs)
print("The log loss for the Naive bayes is:",a)
#print confusion matrix
show_confusion_matrix(conf_NB,['Negative','Positive'])

#Precision and recall
tn = conf_NB[0,0]; fp = conf_NB[0,1]; fn = conf_NB[1,0]; tp = conf_NB[1,1];

precision = 100*float(tp)/(tp+fp)
recall = 100*float(tp)/(tp+fn)
print("Precision :",precision)
print("Recall :",recall)

tp = conf_NB[0][0]
tn = conf_NB[1][1]
print("The accuracy is {} %".format(round(100.0*(tp+tn)/len(y_test),2)))
```

Conclusion :

1. Accuracy of different models:

BOW - unigram : MultinomialNB : 92.48% Logistic Regression: 86.98%

SVM : 87.51

BOW - bigram : MultinomialNB : 92.94% TF_IDF:MultinomialNB : 92.44%

Word2Vec:Logistic Regression : 78.52%

Among all the models Multinomial Naive Bayes with bigrams is giving the best accuracy with 92.94%