User-Based Collaborative Filtering Recommender System

In [1]:

```
import pickle
import numpy as np                 # Python library for numerical computation (tha
import pandas as pd                # Python library for easy to use data structure
import scipy as sp                 # Python library for numerical algorithms
from matplotlib import pyplot      # Python library for plotting data
import matplotlib.pyplot as plt    # Python library to plot data
import seaborn as sns              # Python library based on matplotlib
import missingno as msno           # Python library to detect missing numbers
from scipy.sparse import csr_matrix
from sklearn.neighbors import NearestNeighbors
```

In [2]:

```
pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

In [3]:

```
pd.set_option('display.max_colwidth',100)

# This data is available on open online source. the original data contains arou

# To read data from CSV file which is used for this Hotel recommendation system
data = pd.read_csv('Hotel_Reviews.csv')

# To show the data of CSV file
data.head()
```

Out[3]:

	Hotel_Id	Property_Name	Review_Title	Review_Text	Location_of _The _Reviewer	Date_Of_Review
0	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012
1	2.000	Corinthia Hotel London	By far, my best hotel in the world	I had a pleasure of staying in this hotel for 7 nights recently. This hotel was perfect in every...	Savannah, Georgia	3/23/2016
2	3.000	The Savoy	First visit to the American Bar at the Savoy	A very lovely first visit to this iconic hotel bar! | Wonderful service, without being intrusive...	London	7/30/2013
3	4.000	Rhodes Hotel	Nice stay	3 of us stayed at the Rhodes Hotel for 4 nights, its a great location for taking the Paddington ...	Maui, Hawaii	06/02/2012
4	5.000	The Savoy	Perfection	Form the moment we arrived until we left we experienced absolute perfection in service excellanc...	London, United Kingdom	11/24/2017

In [4]:

```
# This command will indicate list of all columns used in CSV
data.columns
```

Out[4]:

```
Index(['Hotel_Id', 'Property_Name', 'Review_Title', 'Review_Text',
       'Location_of _The _Reviewer', 'Date_Of_Review'],
      dtype='object')
```

In [5]:

```
# This command provides total descriptions of CSV
data.describe()
```

Out[5]:

	Hotel_Id
count	9999.000
mean	5000.000
std	2886.607
min	1.000
25%	2500.500
50%	5000.000
75%	7499.500
max	9999.000

In [6]:

```
data.describe(include='all')
```

Out[6]:

	Hotel_Id	Property_Name	Review_Title	Review_Text	Location_of_The_Reviewer	Date_Of_Review
count	9999.000	9997	9997	9997	8575	9996
unique	NaN	20	8674	9997	3297	3045
top	NaN	The Savoy	Excellent	excellent and elegant experience, very freindly staff. nice location quiet. very clean and relat...	London, United Kingdom	10/03/2018
freq	NaN	1995	42	1	722	19
mean	5000.000	NaN	NaN	NaN	NaN	NaN
std	2886.607	NaN	NaN	NaN	NaN	NaN
min	1.000	NaN	NaN	NaN	NaN	NaN
25%	2500.500	NaN	NaN	NaN	NaN	NaN
50%	5000.000	NaN	NaN	NaN	NaN	NaN
75%	7499.500	NaN	NaN	NaN	NaN	NaN
max	9999.000	NaN	NaN	NaN	NaN	NaN

In [7]:

```
# Any dataset contains duplicate data. To calculate the aggregation of duplicate

print(sum(data.duplicated()))
```

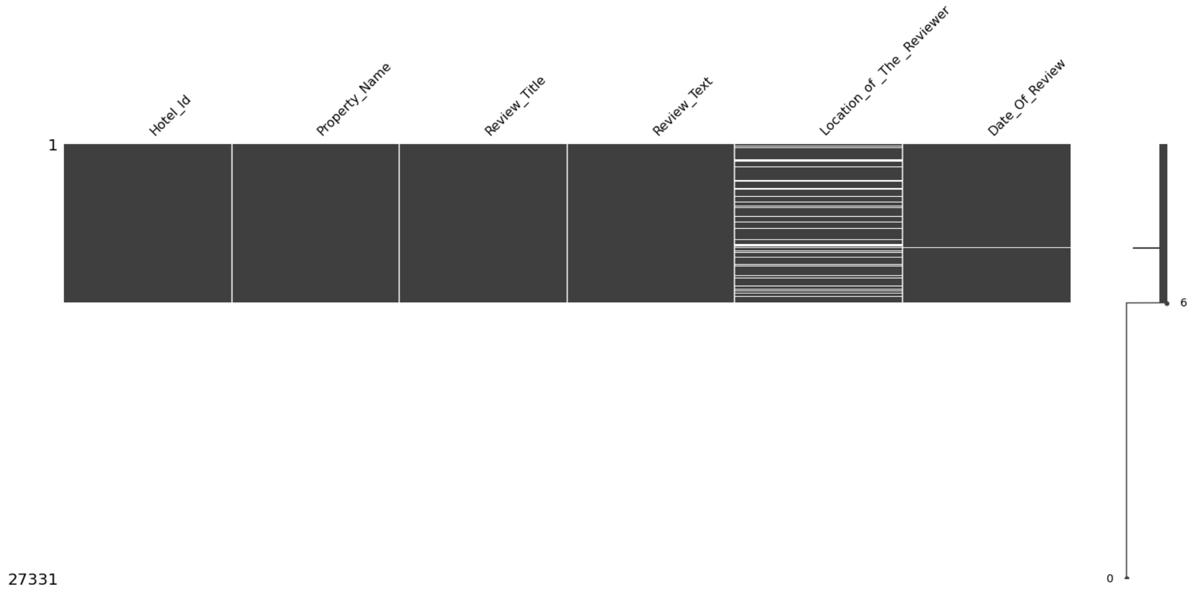
```
17331
```

In [8]:

```
# Any data obtained is not pure. some of the features have missing values.
#To check the missing data from the dataset

msno.matrix(data)
```

Out[8]:

```
<AxesSubplot:>
```



In [9]:

```
# We do not need duplicates of the data. This command gets rid the duplicate dat
data = data.drop_duplicates()
```

In [10]:

```
# After dropping the duplicate values we need to check the sum of the duplicates
print(sum(data.duplicated()))
```

```
0
```

In [11]:

```
# Easiest way to handle the missing value is by skipping/Dropping that missing v
# below command will drop the missing values and will provide the pure data

data = data.dropna()
```

In [12]:

```
data.describe()
```

Out[12]:

	Hotel_Id
count	8575.000
mean	4992.283
std	2887.016
min	1.000
25%	2491.500
50%	4984.000
75%	7501.500
max	9999.000

Data Visualisation

In [13]:

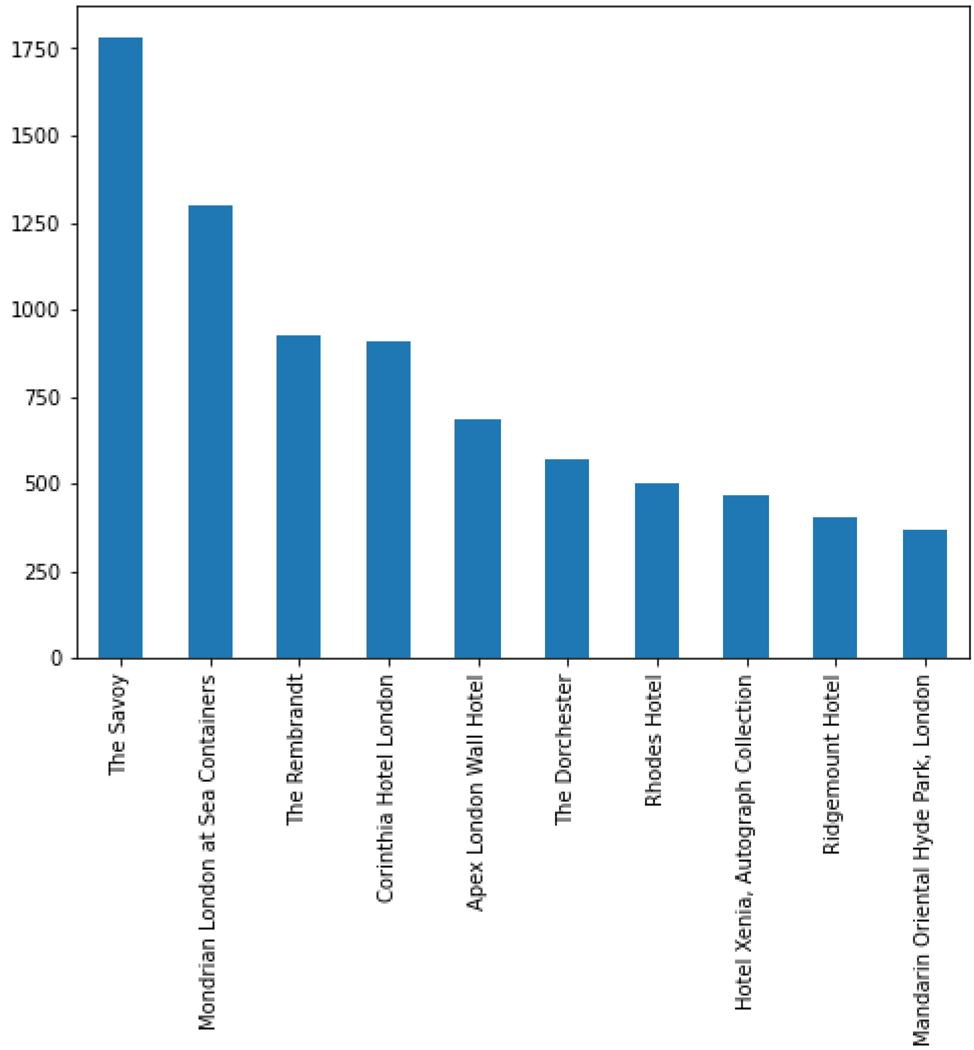
```
#sns.distplot(data['Review_Rating']);
```

In [14]:

```
# The below graph provides visualization about which hotel has got maximum numbe
# This provides top ten best hotels

Hotel_counts = data.Property_Name.value_counts()
Hotel_counts[:10].plot(kind='bar',figsize=(8,6))
```

Out[14]:

<AxesSubplot:>

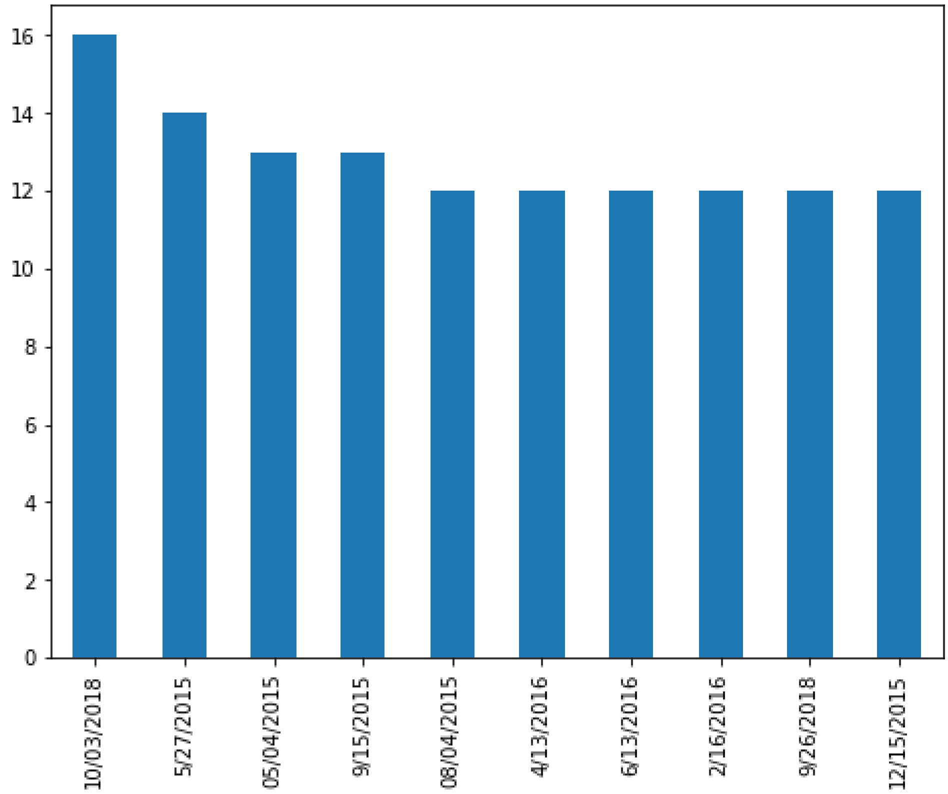


In [15]:

```
# The below bar graph provides analysis of data according to the date

Review_Date_count = data.Date_Of_Review.value_counts()
Review_Date_count[:10].plot(kind='bar', figsize = ( 8, 6))
```

Out[15]:

```
<AxesSubplot:>
```



In [16]:

```
# Another CSV file that provides only ratings according to the User_Id, and Hote

ratings = pd.read_csv('Ratings.csv')
ratings.head()
```

Out[16]:

	User_Id	Hotel_Id	rating	timestamp
0	1	31	2.500	1260759144
1	1	1029	3.000	1260759179
2	1	1061	3.000	1260759182
3	1	1129	2.000	1260759185
4	1	1172	4.000	1260759205

In [17]:

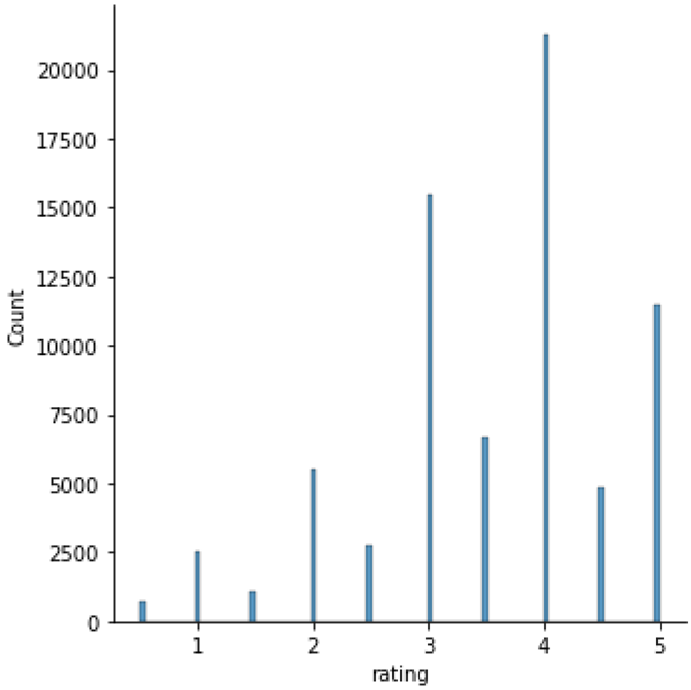
```
# For collaborative filtering, we are required to merge two datasets in single c

df = pd.merge(data, ratings, on='Hotel_Id') # From both of the data sets it merg
df.head()
```

Out[17]:

	Hotel_Id	Property_Name	Review_Title	Review_Text	Location_of _The _Reviewer	Date_Of_Review	User_Id	r
0	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	7	
1	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	9	
2	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	13	
3	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	15	
4	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	19	

In [18]:

```
# sns plot of ratings
sns.displot(df['rating']);
```



In [19]:

```
# Calculate the average rating of hotels

mean_rating  = df
mean_rating = mean_rating.groupby ('Property_Name') ['rating'].mean()
```

In [20]:

```
# Create new dataset for average (mean) rating
new = pd.DataFrame()
new ['mean_rating'] = mean_rating
```

In [21]:

```
new.columns
```

Out[21]:

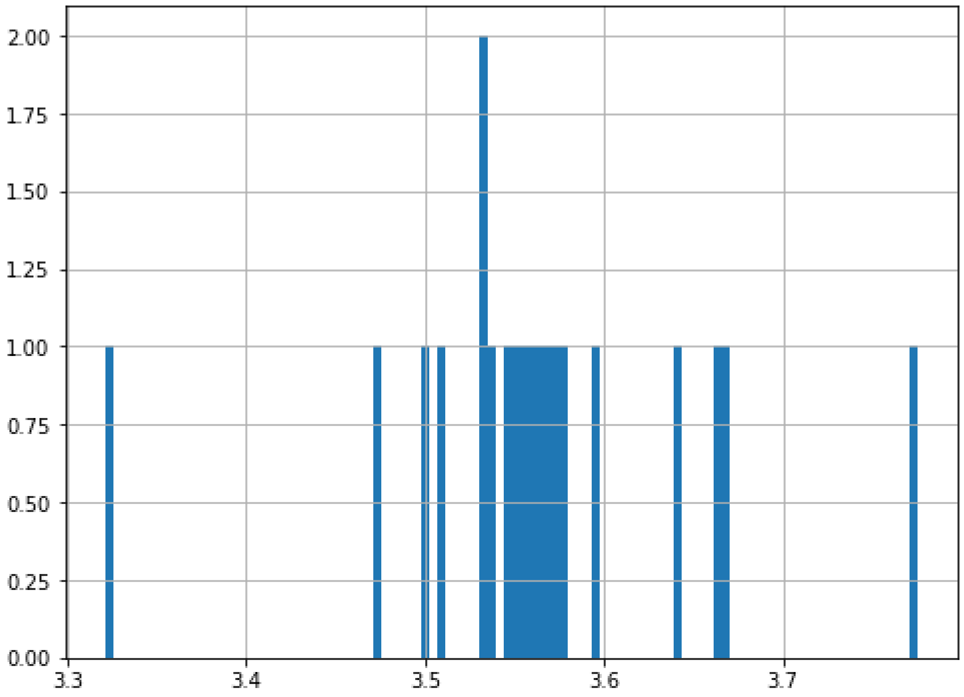
```
Index(['mean_rating'], dtype='object')
```

In [22]:

```
# Plot mean_rating (Average rating) graph

plt.figure (figsize = (8,6))
new['mean_rating'].hist(bins = 100)
```

Out[22]:

<AxesSubplot:>

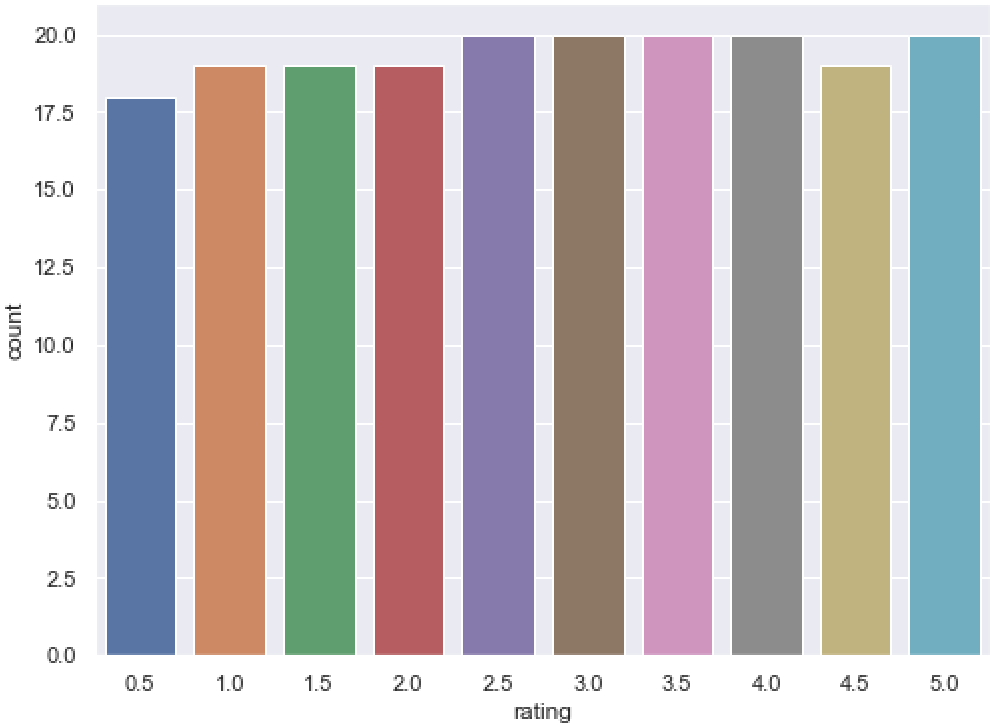


In [23]:

```
# This graph provides all the ratings

Review_plot = df[["Property_Name","rating"]].drop_duplicates()
sns.set(font_scale = 1)
a4_dims = (8, 6)
fig, ax = pyplot.subplots(figsize=a4_dims)
sns.countplot(ax = ax,x = "rating",data=Review_plot)
```

Out[23]:

```
<AxesSubplot:xlabel='rating', ylabel='count'>
```



Collaborative Filtering using KNN Algorithm

In [24]:

```
# This code provides total number of counts

combine_hotel_rating = df.dropna(axis = 0, subset = ['Property_Name'])
hotel_ratingCount = (combine_hotel_rating.
     groupby(by = ['Property_Name'])['rating'].
     count().
     reset_index().
     rename(columns = {'rating': 'totalRatingCount'})
     [['Property_Name', 'totalRatingCount']]
    )
hotel_ratingCount.head()
```

Out[24]:

	Property_Name	totalRatingCount
0	45 Park Lane - Dorchester Collection	394
1	A To Z Hotel	873
2	Apex London Wall Hotel	6354
3	Bulgari Hotel, London	1362
4	City View Hotel	17

In [25]:

```
rating_with_totalRatingCount = combine_hotel_rating.merge(hotel_ratingCount, lef
rating_with_totalRatingCount.head()
```

Out[25]:

	Hotel_Id	Property_Name	Review_Title	Review_Text	Location_of_The_Reviewer	Date_Of_Review	User_Id	r
0	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	7	
1	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	9	
2	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	13	
3	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	15	
4	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	19	

In [26]:

```
print(hotel_ratingCount['totalRatingCount'].describe())
```

```
count       20.000
mean      3620.950
std       3944.127
min         17.000
25%        545.000
50%       2066.500
75%       5924.250
max      13968.000
Name: totalRatingCount, dtype: float64
```

In [27]:

```
# The recommendation system works on the basis of popularity of ratings.
# For sake of simplicity I used popularity threshold.
# If the rating count of the hotel increases more than the popularity,
# it will simply count that hotel as most popular hotel.

popularity_threshold = 50
rating_popular_hotels= rating_with_totalRatingCount.query('totalRatingCount >= @
rating_popular_hotels.head()
```

Out[27]:

	Hotel_Id	Property_Name	Review_Title	Review_Text	Location_of_The_Reviewer	Date_Of_Review	User_Id	r
0	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	7	
1	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	9	
2	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	13	
3	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	15	
4	1.000	Apex London Wall Hotel	Ottima qualit‡ prezzo	Siamo stati a Londra per un week end ed abbiamo alloggiato in questo ottimo Hotel prenotato da a...	Casale Monferrato, Italy	10/20/2012	19	

In [28]:

```
rating_popular_hotels.shape
```

Out[28]:

```
(72402, 10)
```

In [29]:

```
# For the varification of raw echelon form, create pivot table

hotel_features_df = rating_popular_hotels.pivot_table(index='Property_Name',colu
```

In [30]:

```
# KNN is non paramatric lazy learning method.
# For User Based filtering purpose, KNN is best approch in collaborative filteri

hotel_features_df_matrix = csr_matrix(hotel_features_df.values)
hotel_features_df = hotel_features_df.reset_index()
```

In [31]:

```
vector = hotel_features_df.drop('Property_Name', axis = 1).to_numpy()
```

In [32]:

```
from sklearn.metrics.pairwise import cosine_similarity
```

In [33]:

```
similarity = cosine_similarity(vector)
```

In [34]:

```
similarity
```

Out[34]:

```
array([[1.        , 0.56595318, 0.50432343, 0.54272422, 0.50743982,
        0.51977847, 0.52174183, 0.54597278, 0.54348176, 0.51864527,
        0.51517965, 0.49268252, 0.53851346, 0.52948112, 0.5036353 ,
        0.52120908, 0.51188191, 0.5054735 , 0.54875409],
       [0.56595318, 1.        , 0.70231895, 0.64446472, 0.71810599,
        0.43662364, 0.70635322, 0.61390396, 0.68217227, 0.50301141,
        0.7006789 , 0.59594845, 0.67860231, 0.70555761, 0.70405301,
        0.63343959, 0.70033186, 0.71382956, 0.68754752],
       [0.50432343, 0.70231895, 1.        , 0.80108029, 0.94881371,
        0.39292063, 0.92141452, 0.62578879, 0.85689739, 0.49418591,
        0.95183595, 0.61286715, 0.90515781, 0.88022063, 0.9323327 ,
        0.75204193, 0.94380458, 0.95773499, 0.74007246],
       [0.54272422, 0.64446472, 0.80108029, 1.        , 0.79744774,
        0.41815661, 0.78223729, 0.6532407 , 0.77271422, 0.51373043,
        0.80414686, 0.65137193, 0.76747667, 0.75921486, 0.78530672,
        0.69953065, 0.79300766, 0.80376194, 0.69489198],
       [0.50743982, 0.71810599, 0.94881371, 0.79744774, 1.        ,
        0.38592446, 0.91163862, 0.63029354, 0.86198729, 0.5037174 ,
        0.95673316, 0.61303934, 0.90522601, 0.88154819, 0.93934203,
        0.75392687, 0.94404763, 0.97010719, 0.74814138],
       [0.51977847, 0.43662364, 0.39292063, 0.41815661, 0.38592446,
        1.        , 0.40362529, 0.45551423, 0.42776079, 0.4662878 ,
        0.39961724, 0.39732504, 0.41066384, 0.41287078, 0.3962811 ,
        0.4308166 , 0.40202595, 0.3851753 , 0.46330005],
       [0.52174183, 0.70635322, 0.92141452, 0.78223729, 0.91163862,
        0.40362529, 1.        , 0.6284481 , 0.84670097, 0.50694558,
        0.92417231, 0.60509167, 0.87985817, 0.87046428, 0.91169052,
        0.73907649, 0.9100324 , 0.92694345, 0.74533829],
       [0.54597278, 0.61390396, 0.62578879, 0.6532407 , 0.63029354,
        0.45551423, 0.6284481 , 1.        , 0.66255192, 0.49085228,
        0.62997218, 0.54097063, 0.62778119, 0.63092296, 0.61681511,
        0.60916043, 0.64160879, 0.62565775, 0.64439638],
       [0.54348176, 0.68217227, 0.85689739, 0.77271422, 0.86198729,
        0.42776079, 0.84670097, 0.66255192, 1.        , 0.52999143,
        0.8685351 , 0.61551162, 0.85652159, 0.81246996, 0.85761389,
        0.70970132, 0.86662067, 0.86817054, 0.71799811],
       [0.51864527, 0.50301141, 0.49418591, 0.51373043, 0.5037174 ,
        0.4662878 , 0.50694558, 0.49085228, 0.52999143, 1.        ,
        0.50655366, 0.47073753, 0.51691285, 0.52104278, 0.50140851,
        0.52931054, 0.50731404, 0.49963166, 0.50301548],
       [0.51517965, 0.7006789 , 0.95183595, 0.80414686, 0.95673316,
        0.39961724, 0.92417231, 0.62997218, 0.8685351 , 0.50655366,
        1.        , 0.61555099, 0.91716986, 0.89150059, 0.94443159,
        0.7588113 , 0.95255065, 0.97427614, 0.74889978],
       [0.49268252, 0.59594845, 0.61286715, 0.65137193, 0.61303934,
        0.39732504, 0.60509167, 0.54097063, 0.61551162, 0.47073753,
        0.61555099, 1.        , 0.58499399, 0.58978667, 0.60032915,
        0.55676439, 0.61219904, 0.60845936, 0.5670131 ],
       [0.53851346, 0.67860231, 0.90515781, 0.76747667, 0.90522601,
        0.41066384, 0.87985817, 0.62778119, 0.85652159, 0.51691285,
        0.91716986, 0.58499399, 1.        , 0.87359035, 0.89362789,
        0.75976531, 0.9050082 , 0.91745203, 0.75604008],
       [0.52948112, 0.70555761, 0.88022063, 0.75921486, 0.88154819,
        0.41287078, 0.87046428, 0.63092296, 0.81246996, 0.52104278,
        0.89150059, 0.58978667, 0.87359035, 1.        , 0.88010297,
```

```
        0.74675626, 0.87342603, 0.89383146, 0.74932066],
       [0.5036353 , 0.70405301, 0.9323327 , 0.78530672, 0.93934203,
        0.3962811 , 0.91169052, 0.61681511, 0.85761389, 0.50140851,
        0.94443159, 0.60032915, 0.89362789, 0.88010297, 1.        ,
        0.75487485, 0.93330027, 0.95502602, 0.74716402],
       [0.52120908, 0.63343959, 0.75204193, 0.69953065, 0.75392687,
        0.4308166 , 0.73907649, 0.60916043, 0.70970132, 0.52931054,
        0.7588113 , 0.55676439, 0.75976531, 0.74675626, 0.75487485,
        1.        , 0.76470827, 0.75631707, 0.69474119],
       [0.51188191, 0.70033186, 0.94380458, 0.79300766, 0.94404763,
        0.40202595, 0.9100324 , 0.64160879, 0.86662067, 0.50731404,
        0.95255065, 0.61219904, 0.9050082 , 0.87342603, 0.93330027,
        0.76470827, 1.        , 0.95880825, 0.75194925],
       [0.5054735 , 0.71382956, 0.95773499, 0.80376194, 0.97010719,
        0.3851753 , 0.92694345, 0.62565775, 0.86817054, 0.49963166,
        0.97427614, 0.60845936, 0.91745203, 0.89383146, 0.95502602,
        0.75631707, 0.95880825, 1.        , 0.73845098],
       [0.54875409, 0.68754752, 0.74007246, 0.69489198, 0.74814138,
        0.46330005, 0.74533829, 0.64439638, 0.71799811, 0.50301548,
        0.74889978, 0.5670131 , 0.75604008, 0.74932066, 0.74716402,
        0.69474119, 0.75194925, 0.73845098, 1.        ]])
```

In [35]:

```python
def recommend(hotel):
    index = hotel_features_df[hotel_features_df['Property_Name'] == hotel].index
    distances = sorted(list(enumerate(similarity[index])),reverse=True,key = lam

    recommended_list = []

    for i in distances[1:6]:
        recommended_list.append(hotel_features_df.iloc[i[0]]['Property_Name'])


    recommended_df = pd.DataFrame(recommended_list)
    recommended_df.columns = ['Top 5 Recommended Hotels']
    return recommended_df
```

In [36]:

```
index = hotel_features_df[hotel_features_df['Property_Name'] == 'Apex London Wal
distances = sorted(list(enumerate(similarity[index])),reverse=True,key = lambda

recommended_list = []

for i in distances[1:6]:
    recommended_list.append(hotel_features_df.iloc[i[0]].Property_Name)

recommended_df = pd.DataFrame(recommended_list)
recommended_df.columns = ['Top 5 Recommended Hotels']
recommended_df
```

Out[36]:

	Top 5 Recommended Hotels
0	The Savoy
1	Mondrian London at Sea Containers
2	Corinthia Hotel London
3	The Rembrandt
4	The Dorchester

In [37]:

```
recommend('Apex London Wall Hotel')
```

Out[37]:

	Top 5 Recommended Hotels
0	The Savoy
1	Mondrian London at Sea Containers
2	Corinthia Hotel London
3	The Rembrandt
4	The Dorchester

In [38]:

```
pickle.dump(hotel_features_df,open('hotels.pkl','wb'))
```

In [39]:

```
hotel_features_df['Property_Name'].values
```

Out[39]:

```
array(['45 Park Lane - Dorchester Collection', 'A To Z Hotel',
       'Apex London Wall Hotel', 'Bulgari Hotel, London',
       'Corinthia Hotel London', 'Hartley Hotel',
       'Hotel Xenia, Autograph Collection', 'London Guest House',
       'Mandarin Oriental Hyde Park, London', 'Marble Arch Hotel',
       'Mondrian London at Sea Containers', 'Newham Hotel',
       'Rhodes Hotel', 'Ridgemount Hotel', 'The Dorchester',
       'The Lanesborough', 'The Rembrandt', 'The Savoy',
       'The Wellesley Knightsbridge, a Luxury Collection Hotel, Londo
n'],
      dtype=object)
```

In [40]:

```
pickle.dump(hotel_features_df.to_dict(),open('hotel_dict.pkl','wb'))
```

In [41]:

```
pickle.dump(similarity,open('similarity.pkl','wb'))
```

In [ ]:

```

```