# Name: Arul kumar ARK

Roll No.: 225229103

# Lab: 10: Build a recommender system based on amazon reviews

```
In [1]:

#importing the packages
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

In [27]:

df = pd.read_csv("ratings_Beauty.csv")
df.head()
```

### Out[27]:

	Userld	ProductId	Rating	Timestamp
0	A39HTATAQ9V7YF	0205616461	5.0	1369699200
1	A3JM6GV9MNOF9X	0558925278	3.0	1355443200
2	A1Z513UWSAAO0F	0558925278	5.0	1404691200
3	A1WMRR494NWEWV	0733001998	4.0	1382572800
4	A3IAAVS479H7M7	0737104473	1.0	1274227200

```
In [3]:
```

```
#shape of the dataset
print("There are",df.shape[0], "rows and", df.shape[1],"columns.")
```

There are 2023070 rows and 4 columns.

```
In [4]: ▶
```

```
#info method
df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2023070 entries, 0 to 2023069

Data columns (total 4 columns):

# Column Dtype
-----0 UserId object
1 ProductId object
2 Rating float64
3 Timestamp int64

dtypes: float64(1), int64(1), object(2)

memory usage: 61.7+ MB

# In [5]: ▶

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

## Out[5]:

	Userld	ProductId	Rating	Timestamp
count	2023070	2023070	2.023070e+06	2.023070e+06
unique	1210271	249274	NaN	NaN
top	A3KEZLJ59C1JVH	B001MA0QY2	NaN	NaN
freq	389	7533	NaN	NaN
mean	NaN	NaN	4.149036e+00	1.360389e+09
std	NaN	NaN	1.311505e+00	4.611860e+07
min	NaN	NaN	1.000000e+00	9.087552e+08
25%	NaN	NaN	4.000000e+00	1.350259e+09
50%	NaN	NaN	5.000000e+00	1.372810e+09
75%	NaN	NaN	5.000000e+00	1.391472e+09
max	NaN	NaN	5.000000e+00	1.406074e+09

```
In [6]: ▶
```

```
# Mean rating for each Product
product_rating = df.groupby('ProductId')['Rating'].mean()
product_rating.head()
```

# Out[6]:

ProductId 0205616461 5.0 0558925278 4.0 0733001998 4.0 0737104473 1.0 0762451459 5.0

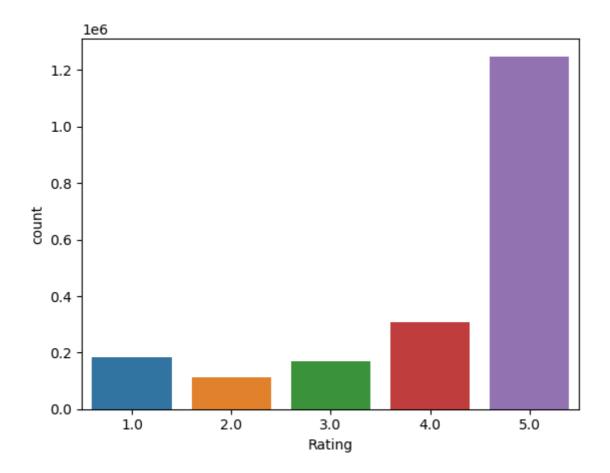
Name: Rating, dtype: float64

```
In [7]:
                                                                                       M
# Count of the number of ratings per Product
product_rating_count = df.groupby('ProductId')['Rating'].count()
product_rating_count.head()
Out[7]:
ProductId
0205616461
              1
0558925278
0733001998
              1
0737104473
0762451459
              1
Name: Rating, dtype: int64
In [8]:
                                                                                       M
# Un-Reliability factor
unreliability = df.groupby('ProductId')['Rating'].std(ddof = -1)
unreliability.head()
Out[8]:
ProductId
0205616461
              0.000000
              0.816497
0558925278
0733001998
              0.000000
0737104473
              0.000000
              0.000000
0762451459
Name: Rating, dtype: float64
Step 3: Check for missing values and outliers
In [9]:
                                                                                       H
df.isnull().sum()
Out[9]:
UserId
             0
ProductId
Rating
             0
```

Timestamp dtype: int64

```
In [10]: ▶
```

```
import seaborn as sns
sns.countplot(x='Rating',data=df)
plt.show()
```



```
In [11]: ▶
```

```
def find_outliers_IQR(df):
    q1=df.quantile(0.25)
    q3=df.quantile(0.75)
    IQR=q3-q1
    outliers = df[((df<(q1-1.5*IQR)) | (df>(q3+1.5*IQR)))]
    return outliers
```

```
In [12]:
```

```
#outlier for rating feature in the dataset
outliers = find_outliers_IQR(df['Rating'])
print("number of outliers: "+ str(len(outliers)))
print("max outlier value: "+ str(outliers.max()))
print("min outlier value: "+ str(outliers.min()))
```

number of outliers: 296818
max outlier value: 2.0
min outlier value: 1.0

```
H
In [13]:
#outlier for timestamp feature in dataset
outliers = find_outliers_IQR(df['Timestamp'])
print("number of outliers: "+ str(len(outliers)))
print("max outlier value: "+ str(outliers.max()))
print("min outlier value: "+ str(outliers.min()))
number of outliers: 154846
max outlier value: 1288396800
min outlier value: 908755200
In [14]:
                                                                                          M
# Data frame with calculated fields and measures
unique_products_list = df.ProductId.unique()
data_model = pd.DataFrame({'Rating': product_rating[unique_products_list],\
 'Count': product_rating_count[unique_products_list], \
 'Unreliability': unreliability[unique_products_list]})
data_model.head()
Out[14]:
           Rating Count Unreliability
  ProductId
                           0.000000
0205616461
              5.0
                      1
0558925278
              4.0
                      2
                           0.816497
0733001998
                           0.000000
              4.0
                      1
0737104473
                           0.000000
              1.0
                      1
0762451459
              5.0
                      1
                           0.000000
In [15]:
                                                                                          H
# Removing outliers and improbable data points
data_model = data_model[data_model.Count > 50][data_model.Count < 1001].copy()</pre>
print(data_model.shape)
(6763, 3)
In [16]:
                                                                                          M
# Normalization function to range 0 - 10
def normalize(values):
    mn = values.min()
```

return(10.0/(mx - mn) \* (values - mx)+10)

mx = values.max()

```
In [17]: ▶
```

```
data_model_norm = normalize(data_model)
data_model_norm.head()
```

#### Out[17]:

	Rating	Count	Unreliability
ProductId			
9790790961	7.991506	0.201913	6.557281
B00004TMFE	5.713948	0.913921	7.953812
B00004TUBL	8.992153	5.387885	4.449336
B00004TUBV	7.984827	1.275239	6.268773
B00004U9UY	9.244724	1.009564	4.066169

# Step 4: Apply Recommendations algorithms to the dataset

```
In [18]:

# Setting up the model
```

```
# Setting up the model
# Recommend 20 similar items
from sklearn.neighbors import KNeighborsClassifier
engine = KNeighborsClassifier(n_neighbors=20)
# Training data points
data_points = data_model_norm[['Count', 'Rating', 'Unreliability']].values
#Training labels
labels = data_model_norm.index.values
print("Data points: ", data_points)
print('\n')
print('\n')
print("Labels: ",labels)
```

```
Data points: [[0.20191286 7.99150579 6.55728119]
  [0.91392136 5.71394752 7.95381168]
  [5.38788523 8.99215344 4.44933587]
...
  [0.21253985 9.6117244 2.18485285]
  [3.04994687 9.33120102 2.47548276]
  [4.64399575 8.69505981 5.78555039]]

Labels: ['9790790961' 'B00004TMFE' 'B00004TUBL' ... 'B00KWE08Q0' 'B00KWFDBKE'
  'B00L5JHZJO']
```

```
In [19]: ▶
```

```
engine.fit(data_points, labels)
```

# Out[19]:

KNeighborsClassifier(n\_neighbors=20)

# Step 5: Give recommendations and interpret your result

```
# User entered value
product_id = 'B00004TUBL'
product_data = data_model_norm.loc[product_id][['Count', 'Rating', 'Unreliability']].val
# Find recommended products
recommended_products = engine.kneighbors(X=[product_data], n_neighbors=20, return_distar
# List of product IDs from the indexes
products_list = data_model_norm.iloc[recommended_products[0]].index.tolist()
print("Recommended products:")
print(products_list)
```

#### Recommended products:

['B00004TUBL', 'B0000AFUTL', 'B00CNOUZE2', 'B008TBTA6C', 'B009GIOVKC', 'B
0000DNSR0', 'B000NWGCZ2', 'B00D6EDGYE', 'B002TPQPEE', 'B0013TM9UQ', 'B004
XA81ZE', 'B009GEUPDS', 'B00132ZG3U', 'B00H93NJLS', 'B0000Q2DL4', 'B000F35
R00', 'B0018DAUKI', 'B001DKQ308', 'B001ET77NY', 'B00178TVXG']

In [24]: ▶

```
# Showing recommended products
ax = data_model_norm.plot(kind='scatter', x='Rating', y='Count', color='grey', alpha=0.2
data_model_norm.iloc[recommended_products[0]].plot(kind='scatter', x='Rating', y='Count'
    color='orange', alpha=0.5, ax=ax)
ax2 = data_model_norm.plot(kind='scatter', x='Rating', y='Unreliability', color='grey')
data_model_norm.iloc[recommended_products[0]].plot(kind='scatter', x='Rating', y='Unreli
    color='orange', alpha=0.5, ax=ax2)
plt.show()
```

