1. Import the libraries

[ ] ↳ 6 cells hidden

2. Load the dataset and add headers

```
# Import the dataset and give the column names
columns=['userId', 'productId', 'ratings','timestamp']
electronics_df=pd.read_csv('/content/ratings_Electronics 3.csv',names=columns)
```

```
electronics_df.head()
```

	userId	productId	ratings	timestamp
0	AKM1MP6P0OYPR	0132793040	5.0	1365811200
1	A2CX7LUOHB2NDG	0321732944	5.0	1341100800
2	A2NWSAGRHCP8N5	0439886341	1.0	1367193600
3	A2WNBOD3WNDNKT	0439886341	3.0	1374451200
4	A1GI0U4ZRJA8WN	0439886341	1.0	1334707200

Dropping the timestamp column

```
electronics_df.drop('timestamp',axis=1,inplace=True)
```

```
electronics_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7824482 entries, 0 to 7824481
Data columns (total 3 columns):
 #   Column     Dtype
---  ------     -----
 0   userId     object
 1   productId  object
 2   ratings    float64
dtypes: float64(1), object(2)
memory usage: 179.1+ MB
```

```
#Check the number of rows and columns
rows,columns=electronics_df.shape
print('Number of rows: ',rows)
print('Number of columns: ',columns)
```

```
Number of rows:  7824482
Number of columns:  3
```

```
#Check the datatypes
electronics_df.dtypes
```

```
userId        object
productId     object
ratings      float64
dtype: object
```

```
#Taking subset of the dataset
electronics_df1=electronics_df.iloc[:50000,0:]
```

- Since the data is very big. Consider electronics_df1 named dataframe with first 50000 rows and all columns from 0 of dataset.

```
electronics_df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   userId     50000 non-null  object
 1   productId  50000 non-null  object
 2   ratings    50000 non-null  float64
```

```
dtypes: float64(1), object(2)
memory usage: 1.1+ MB
```

```
#Summary statistics of rating variable
electronics_df1['ratings'].describe().transpose()
```

```
count    50000.00000
mean         4.03524
std          1.35555
min          1.00000
25%          4.00000
50%          5.00000
75%          5.00000
max          5.00000
Name: ratings, dtype: float64
```

- Rating are on the scale 1 to 5.

Handling Missing values

```
#Check for missing values
print('Number of missing values across columns: \n',electronics_df.isnull().sum())
```

```
Number of missing values across columns:
 userId       0
productId    0
ratings      0
dtype: int64
```

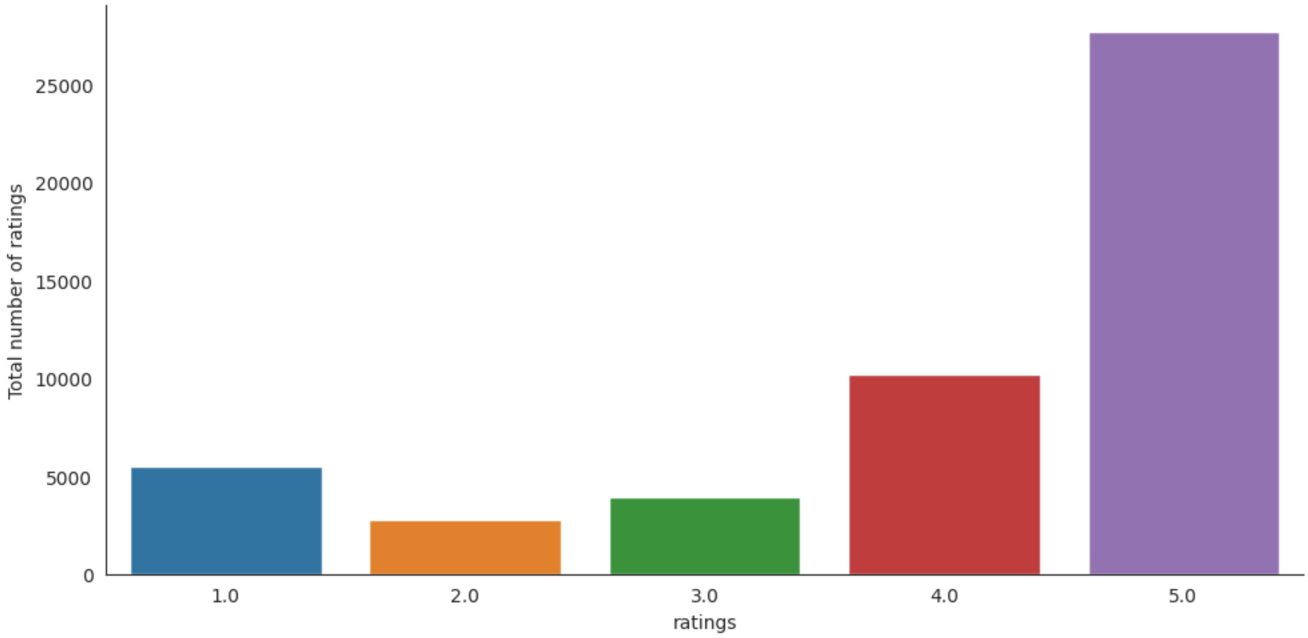
- There are no missing records in the dataset.

Ratings

```
import seaborn as sns

# Check the distribution of the rating
with sns.axes_style('white'):
    g = sns.catplot(x="ratings", data=electronics_df1, aspect=2.0, kind='count')
    g.set_ylabels("Total number of ratings")
```

```
<seaborn.axisgrid.FacetGrid at 0x7f30b41451e0>
```



- We can see that more number of users have given the rating of 5.

Users and products

```
# Number of unique user id  in the data
print('Number of unique users in Raw data = ', electronics_df1['userId'].nunique())
# Number of unique product id  in the data
print('Number of unique product in Raw data = ', electronics_df1['productId'].nunique())
```

```
Number of unique users in Raw data =  46554
Number of unique product in Raw data =  3446
```

3. Taking the subset of dataset to make it less sparse/ denser.

```
#Check the top 10 users based on ratings
most_rated=electronics_df1.groupby('userId').size().sort_values(ascending=False)[:10]
print('Top 10 users based on ratings: \n',most_rated)
```

```
Top 10 users based on ratings:
 userId
A231WM2Z2JL0U3    37
AY8Q1X7G96HV5     31
ALUNVOQRXOZIA     20
A1NVD0TKNS1GT5    19
A243HY69GIAHFI    18
A1RPTVW5VEOSI     17
A1ISUNUWG0K02V    16
A1MJMYLRTZ76ZX    16
A7Y6AVS576M03     15
A3MEIR72XKQY88    15
dtype: int64
```

```
counts=electronics_df1.userId.value_counts()
electronics_df1_final=electronics_df1[electronics_df1.userId.isin(counts[counts>=15].index)]
print('Number of users who have rated 15 or more items =', len(electronics_df1_final))
print('Number of unique users in the final data = ', electronics_df1_final['userId'].nunique())
print('Number of unique products in the final data = ', electronics_df1_final['userId'].nunique())
```

```
Number of users who have rated 15 or more items = 219
Number of unique users in the final data =  11
Number of unique products in the final data =  11
```

- electronics_df1_final has the users who have rated 25 or more items.

ratings analysis in final dataset

```
#constructing the pivot table
final_ratings_matrix = electronics_df1_final.pivot(index = 'userId', columns ='productId', values = 'ratings').fillna(0)
final_ratings_matrix.head()
```

productId	1400599997	B00000DM9M	B00000J061	B00000J08C	B00000J0A2	B00000J0E8	B00000J1QZ	B00000J1US	B00000J3H!
userId									
A1ISUNUWG0K02V	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	5.(
A1MJMYLRTZ76ZX	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
A1NVD0TKNS1GT5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
A1RPTVW5VEOSI	0.0	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.(
A231WM2Z2JL0U3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	0.(

5 rows × 186 columns

- It shows that it is a sparse matrix. So, many cells are filled with 0 values.

```
print('Shape of final_ratings_matrix: ', final_ratings_matrix.shape)
```

```
Shape of final_ratings_matrix:  (11, 186)
```

```
#Calucating the density of the rating marix
given_num_of_ratings = np.count_nonzero(final_ratings_matrix)
print('given_num_of_ratings = ', given_num_of_ratings)
possible_num_of_ratings = final_ratings_matrix.shape[0] * final_ratings_matrix.shape[1]
print('possible_num_of_ratings = ', possible_num_of_ratings)
density = (given_num_of_ratings/possible_num_of_ratings)
density *= 100
print ('density: {:4.2f}%'.format(density))
```

```
given_num_of_ratings =  219
possible_num_of_ratings =  2046
density: 10.70%
```

- The density value of the matrix also shows that it is a sparse matrix.

4. Splitting the data

```
#Split the data randomnly into train and test datasets into 70:30 ratio
train_data, test_data = train_test_split(electronics_df1_final, test_size = 0.3, random_state=0)
train_data.head()
```

	userId	productId	ratings
17509	AY8Q1X7G96HV5	B00000JSES	4.0
11968	A243HY69GIAHFI	B00000J3Q7	3.0
35533	A1RPTVW5VEOSI	B00003WGP5	5.0
31480	A1NVD0TKNS1GT5	B00002JXFH	4.0
13526	A23ZO1BVFFLGHO	B00000J570	5.0

```
print('Shape of training data: ',train_data.shape)
print('Shape of testing data: ',test_data.shape)
```

```
Shape of training data:  (153, 3)
Shape of testing data:  (66, 3)
```

5. Building Popularity Recommder model

```
#Count of user_id for each unique product as recommendation score
train_data_grouped = train_data.groupby('productId').agg({'userId': 'count'}).reset_index()
train_data_grouped.rename(columns = {'userId': 'score'},inplace=True)
train_data_grouped
```

	productId	score
0	1400599997	1
1	B00000DM9M	1
2	B00000J061	1
3	B00000J08C	1
4	B00000J1QZ	1
...	...	...
129	B00004TH2W	1
130	B00004TH2Y	1
131	B00004THCX	1
132	B00004THCZ	1
133	B00004THDE	1

134 rows × 2 columns

```
#Sort the products on recommendation score
train_data_sort = train_data_grouped.sort_values(['score', 'productId'], ascending = [0,1])

#Generate a recommendation rank based upon score
train_data_sort['rank'] = train_data_sort['score'].rank(ascending=0, method='first')

#Get the top 5 recommendations
```

```
popularity_recommendations = train_data_sort
popularity_recommendations
```

	productId	score	rank
87	B00004RC2D	4	1.0
57	B00002SWHH	3	2.0
99	B00004SC3Y	3	3.0
100	B00004SCKA	3	4.0
6	B00000J3II	2	5.0
...	...	...	...
129	B00004TH2W	1	130.0
130	B00004TH2Y	1	131.0
131	B00004THCX	1	132.0
132	B00004THCZ	1	133.0
133	B00004THDE	1	134.0

134 rows × 3 columns

```
# Use popularity based recommender model to make predictions
def recommend(user_id):
    user_recommendations = popularity_recommendations

    #Add user_id column for which the recommendations are being generated
    user_recommendations['userId'] = user_id

    #Bring user_id column to the front
    cols = user_recommendations.columns.tolist()
    cols = cols[-1:] + cols[:-1]
    user_recommendations = user_recommendations[cols]

    return user_recommendations
```

```
find_recom = [18,160,156]   # This list is user choice.
for i in find_recom:
    print("The list of recommendations for the userId: %d\n" %(i))
    print(recommend(i))
    print("\n")
```

```
The list of recommendations for the userId: 18

     userId   productId  score   rank
87       18  B00004RC2D      4    1.0
57       18  B00002SWHH      3    2.0
99       18  B00004SC3Y      3    3.0
100      18  B00004SCKA      3    4.0
6        18  B00000J3II      2    5.0
..      ...         ...    ...    ...
129      18  B00004TH2W      1  130.0
130      18  B00004TH2Y      1  131.0
131      18  B00004THCX      1  132.0
132      18  B00004THCZ      1  133.0
133      18  B00004THDE      1  134.0

[134 rows x 4 columns]


The list of recommendations for the userId: 160

     userId   productId  score   rank
87      160  B00004RC2D      4    1.0
57      160  B00002SWHH      3    2.0
99      160  B00004SC3Y      3    3.0
100     160  B00004SCKA      3    4.0
6       160  B00000J3II      2    5.0
..      ...         ...    ...    ...
129     160  B00004TH2W      1  130.0
130     160  B00004TH2Y      1  131.0
131     160  B00004THCX      1  132.0
132     160  B00004THCZ      1  133.0
133     160  B00004THDE      1  134.0

[134 rows x 4 columns]


The list of recommendations for the userId: 156

     userId   productId  score   rank
```

```
87      156  B00004RC2D      4    1.0
57      156  B00002SWHH      3    2.0
99      156  B00004SC3Y      3    3.0
100     156  B00004SCKA      3    4.0
6       156  B00000J3II      2    5.0
..      ...         ...    ...    ...
129     156  B00004TH2W      1  130.0
130     156  B00004TH2Y      1  131.0
131     156  B00004THCX      1  132.0
132     156  B00004THCZ      1  133.0
133     156  B00004THDE      1  134.0

[134 rows x 4 columns]
```

- Since, it is a Popularity recommender model, so, all the three users are given the same recommendations. Here, we predict the products based on the popularity. It is not personalized to particular user. It is a non-personalized recommender system.

6. Building Collaborative Filtering recommender model.

```
electronics_df_CF = pd.concat([train_data, test_data]).reset_index()
electronics_df_CF.head()
```

	index	userId	productId	ratings
0	17509	AY8Q1X7G96HV5	B00000JSES	4.0
1	11968	A243HY69GIAHFI	B00000J3Q7	3.0
2	35533	A1RPTVW5VEOSI	B00003WGP5	5.0
3	31480	A1NVD0TKNS1GT5	B00002JXFH	4.0
4	13526	A23ZO1BVFFLGHO	B00000J570	5.0

User Based Collaborative Filtering model

```
# Matrix with row per 'user' and column per 'item'
pivot_df = electronics_df_CF.pivot(index = 'userId', columns ='productId', values = 'ratings').fillna(0)
pivot_df.head()
```

productId	1400599997	B00000DM9M	B00000J061	B00000J08C	B00000J0A2	B00000J0E8	B00000J1QZ	B00000J1US	B00000J3H!
userId									
A1ISUNUWG0K02V	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	5.(
A1MJMYLRTZ76ZX	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
A1NVD0TKNS1GT5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
A1RPTVW5VEOSI	0.0	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.(
A231WM2Z2JL0U3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	0.(

5 rows × 186 columns

```
print('Shape of the pivot table: ', pivot_df.shape)
```

```
Shape of the pivot table:  (11, 186)
```

```
#define user index from 0 to 10
pivot_df['user_index'] = np.arange(0, pivot_df.shape[0], 1)
pivot_df.head()
```

productId	1400599997	B00000DM9M	B00000J061	B00000J08C	B00000J0A2	B00000J0E8	B00000J1QZ	B00000J1US	B00000J3H!
userId									
A1ISUNUWG0K02V	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	5.(
A1MJMYLRTZ76ZX	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(
A1NVD0TKNS1GT5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.(

```
pivot_df.set_index(['user_index'], inplace=True)
# Actual ratings given by users
pivot_df.head()
```

productId	1400599997	B00000DM9M	B00000J061	B00000J08C	B00000J0A2	B00000J0E8	B00000J1QZ	B00000J1US	B00000J3H5	B00
user_index										
0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	5.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	0.0	

5 rows × 186 columns

- As this is a sparse matrix we will use SVD.

Singular Value Decomposition

```
# Singular Value Decomposition

from scipy.sparse import csr_matrix
from scipy.sparse.linalg import svds

# Convert the pivot table to a sparse matrix
pivot_sparse = csr_matrix(pivot_df.values)

# Perform Singular Value Decomposition
U, sigma, Vt = svds(pivot_sparse, k=10)
```

```
print('Left singular matrix: \n',U)
```

```
Left singular matrix:
 [[ 2.65871898e-01 -8.28788249e-01  1.14160900e-01 -2.15685919e-01
   2.65928896e-04 -4.93636653e-02 -1.66297884e-01 -3.12732051e-01
   1.53122256e-01 -1.38465143e-01]
 [ 5.53711304e-02 -1.21204397e-01 -8.17836609e-02  3.29682359e-01
   1.47955175e-01 -8.18019500e-01  2.13209931e-01  2.76257471e-01
   2.09061119e-01 -1.01498819e-01]
 [ 5.46679471e-01  1.37512688e-01  2.79596983e-02  1.45212122e-01
   3.57798248e-02  1.89642626e-01  6.60636300e-01 -2.07100247e-01
  -3.59790632e-02 -1.23044532e-01]
 [ 4.63168744e-02 -5.39880164e-02 -8.32935752e-01  1.36292972e-01
  -1.12974956e-02  9.74799278e-02  5.43326589e-02 -2.99913518e-01
   1.00398248e-01 -1.16155900e-01]
 [-4.82857184e-02  5.06969281e-03  6.10478781e-02  7.63553438e-02
  -8.79528911e-02  1.33412578e-01 -9.24837886e-02  2.48586367e-01
  -1.79064339e-01 -9.26201600e-01]
 [-1.33072419e-01  3.30520700e-01 -8.58433108e-03 -6.82184355e-01
   3.10981905e-02 -4.06414738e-01  1.22417282e-01 -4.14339191e-01
  -4.04459226e-03 -2.33218097e-01]
 [-5.85058830e-01 -2.82858362e-01  2.67444902e-01  1.03926107e-01
   7.39796949e-02  1.25896947e-01  5.86529180e-01 -1.64067216e-01
  -9.37707797e-03 -1.79755959e-02]
 [-5.04793124e-01 -1.13702295e-01 -3.57486565e-01  6.92659013e-02
  -2.00732743e-02  4.29965080e-02 -5.56583151e-04 -2.51788542e-02
  -9.00894193e-04 -3.04631617e-02]
 [ 1.37401523e-02 -1.68164402e-03 -5.23514746e-02 -1.04867805e-01
   9.72327480e-01  1.54469490e-01 -6.89319218e-02  9.60100045e-02
  -2.28758644e-02 -4.64399549e-02]
 [-7.77524293e-02  2.36994718e-01  2.76662643e-01  5.39661989e-01
   1.21856053e-01 -7.39304558e-02 -3.36795340e-01 -6.29018917e-01
   1.54119324e-01 -1.21495612e-01]
 [-4.31106769e-02  1.34978010e-01  5.75166098e-02 -1.26848095e-01
```

```
 -4.30464817e-02  2.30094616e-01  4.18979575e-02  1.64726898e-01
  9.30068553e-01 -1.07164263e-01]]
```

```
print('Sigma: \n',sigma)
```

```
Sigma:
 [15.65710264 16.05091576 17.43121071 17.74252629 18.18622003 18.83061496
 19.14527912 19.94315139 22.99328895 28.83750492]
```

- As sigma is not a diagonal matrix we have to convert it into diagonal matrix.

```
# Construct diagonal array in SVD
sigma = np.diag(sigma)
print('Diagonal matrix: \n',sigma)
```

```
Diagonal matrix:
 [[15.65710264  0.          0.          0.          0.          0.
   0.          0.          0.          0.        ]
 [ 0.         16.05091576  0.          0.          0.          0.
   0.          0.          0.          0.        ]
 [ 0.          0.         17.43121071  0.          0.          0.
   0.          0.          0.          0.        ]
 [ 0.          0.          0.         17.74252629  0.          0.
   0.          0.          0.          0.        ]
 [ 0.          0.          0.          0.         18.18622003  0.
   0.          0.          0.          0.        ]
 [ 0.          0.          0.          0.          0.         18.83061496
   0.          0.          0.          0.        ]
 [ 0.          0.          0.          0.          0.          0.
  19.14527912  0.          0.          0.        ]
 [ 0.          0.          0.          0.          0.          0.
   0.         19.94315139  0.          0.        ]
 [ 0.          0.          0.          0.          0.          0.
   0.          0.         22.99328895  0.        ]
 [ 0.          0.          0.          0.          0.          0.
   0.          0.          0.         28.83750492]]
```

```
print('Right singular matrix: \n',Vt)
```

```
Right singular matrix:
 [[-0.00496595 -0.01376713  0.01479101 ... -0.0110137  -0.01541975
  -0.0110137 ]
 [ 0.01476518  0.04204683 -0.01681774 ...  0.03363746  0.00157925
   0.03363746]
 [ 0.01587168  0.01649817 -0.2389208  ...  0.01319853  0.01751108
   0.01319853]
 ...
 [-0.0315406   0.04129911 -0.07519211 ...  0.03303929  0.06232374
   0.03303929]
 [ 0.0067028   0.20224783  0.02183208 ...  0.16179826 -0.03893839
   0.16179826]
 [-0.00421311 -0.01858071 -0.02013973 ... -0.01486457 -0.16058976
  -0.01486457]]
```

```
#Predicted ratings
all_user_predicted_ratings = np.dot(np.dot(U, sigma), Vt)
# Convert predicted ratings to dataframe
preds_df = pd.DataFrame(all_user_predicted_ratings, columns = pivot_df.columns)
preds_df.head()
```

productId	1400599997	B00000DM9M	B00000J061	B00000J08C	B00000J0A2	B00000J0E8	B00000J1QZ	B00000J1US	B00000J3H5	B000
0	-0.005077	-0.010023	0.219864	-0.010023	-0.020310	-0.006562	2.962929	0.026594	4.938216	4
1	-0.000261	-0.000515	0.011300	-0.000515	-0.001044	-0.000337	-0.001905	0.001367	-0.003176	-0
2	-0.016300	-0.032177	0.705839	-0.032177	-0.065201	-0.021066	-0.119009	0.085374	-0.198349	-0
3	0.018068	0.035667	4.217599	0.035667	0.072274	0.023351	0.131918	-0.094635	0.219864	0
4	0.002185	0.004314	-0.094635	0.004314	0.008742	0.002824	0.015956	4.988553	0.026594	0

5 rows × 186 columns

```
# Recommend the items with the highest predicted ratings

def recommend_items(userID, pivot_df, preds_df, num_recommendations):
    # index starts at 0
    user_idx = userID-1
    # Get and sort the user's ratings
```

```
    sorted_user_ratings = pivot_df.iloc[user_idx].sort_values(ascending=False)
    #sorted_user_ratings
    sorted_user_predictions = preds_df.iloc[user_idx].sort_values(ascending=False)
    #sorted_user_predictions
    temp = pd.concat([sorted_user_ratings, sorted_user_predictions], axis=1)
    temp.index.name = 'Recommended Items'
    temp.columns = ['user_ratings', 'user_predictions']
    temp = temp.loc[temp.user_ratings == 0]
    temp = temp.sort_values('user_predictions', ascending=False)
    print('\nBelow are the recommended items for user(user_id = {}):\n'.format(userID))
    print(temp.head(num_recommendations))
```

```
userID = 4
num_recommendations = 5
recommend_items(userID, pivot_df, preds_df, num_recommendations)
```

```
Below are the recommended items for user(user_id = 4):

                   user_ratings  user_predictions
Recommended Items
B00004T1WZ                  0.0          1.526746
B00004T1WX                  0.0          1.526746
B00000J4ER                  0.0          1.526746
B00001P4XA                  0.0          1.526746
B00000JYLO                  0.0          1.526746
```

```
userID = 7
num_recommendations = 5
recommend_items(userID, pivot_df, preds_df, num_recommendations)
```

```
Below are the recommended items for user(user_id = 7):

                   user_ratings  user_predictions
Recommended Items
B00000JYLO                  0.0          1.236873
B00000J4ER                  0.0          1.236873
B00001P4XA                  0.0          1.236873
B00004T1WX                  0.0          1.236873
B00004T1WZ                  0.0          1.236873
```

```
userID = 8
num_recommendations = 5
recommend_items(userID, pivot_df, preds_df, num_recommendations)
```

```
Below are the recommended items for user(user_id = 8):

                   user_ratings  user_predictions
Recommended Items
B00000J061                  0.0          1.526746
B00004TH2W                  0.0          1.526746
B00004RIPE                  0.0          1.526746
B00003WGP5                  0.0          1.526746
B00001QHP5                  0.0          1.526746
```

- Since, it is a Collaborative recommender model, so, all the three users are given different recommendations based on users past behaviour.

7. Evaluation of Collabrative recommendation model

```
# Actual ratings given by the users
final_ratings_matrix.head()
```

productId	1400599997	B00000DM9M	B00000J061	B00000J08C	B00000J0A2	B00000J0E8	B00000J1QZ	B00000J1US	B00000J3H!
userId									

```
# Average ACTUAL rating for each item
final_ratings_matrix.mean().head()
```

```
productId
1400599997    0.090909
B00000DM9M    0.454545
B00000J061    0.454545
B00000J08C    0.454545
B00000J0A2    0.363636
dtype: float64
```

```
# Predicted ratings
preds_df.head()
```

productId	1400599997	B00000DM9M	B00000J061	B00000J08C	B00000J0A2	B00000J0E8	B00000J1QZ	B00000J1US	B00000J3H5	B000
0	-0.005077	-0.010023	0.219864	-0.010023	-0.020310	-0.006562	2.962929	0.026594	4.938216	4
1	-0.000261	-0.000515	0.011300	-0.000515	-0.001044	-0.000337	-0.001905	0.001367	-0.003176	-0
2	-0.016300	-0.032177	0.705839	-0.032177	-0.065201	-0.021066	-0.119009	0.085374	-0.198349	-0
3	0.018068	0.035667	4.217599	0.035667	0.072274	0.023351	0.131918	-0.094635	0.219864	0
4	0.002185	0.004314	-0.094635	0.004314	0.008742	0.002824	0.015956	4.988553	0.026594	0

5 rows × 186 columns

```
# Average PREDICTED rating for each item
preds_df.mean().head()
```

```
productId
1400599997    0.088513
B00000DM9M    0.449816
B00000J061    0.558292
B00000J08C    0.449816
B00000J0A2    0.354053
dtype: float64
```

```
rmse_df = pd.concat([final_ratings_matrix.mean(), preds_df.mean()], axis=1)
rmse_df.columns = ['Avg_actual_ratings', 'Avg_predicted_ratings']
print(rmse_df.shape)
rmse_df['item_index'] = np.arange(0, rmse_df.shape[0], 1)
rmse_df.head()
```

```
(186, 2)
```

productId	Avg_actual_ratings	Avg_predicted_ratings	item_index
1400599997	0.090909	0.088513	0
B00000DM9M	0.454545	0.449816	1
B00000J061	0.454545	0.558292	2
B00000J08C	0.454545	0.449816	3
B00000J0A2	0.363636	0.354053	4

```
RMSE = round((((rmse_df.Avg_actual_ratings - rmse_df.Avg_predicted_ratings) ** 2).mean() ** 0.5), 5)
print('\nRMSE SVD Model = {} \n'.format(RMSE))
```

```
RMSE SVD Model = 0.05854
```

8. Getting top - K (K = 5) recommendations.

```
# Enter 'userID' and 'num_recommendations' for the user #
userID = 5
num_recommendations = 12
recommend_items(userID, pivot_df, preds_df, num_recommendations)
```

```
Below are the recommended items for user(user_id = 5):

                   user_ratings  user_predictions
Recommended Items
B00000JYLO                  0.0          0.184667
B00004T1WX                  0.0          0.184667
B00004T1WZ                  0.0          0.184667
B00000J4ER                  0.0          0.184667
B00001P4XA                  0.0          0.184667
B00004SV25                  0.0          0.147733
B00004RFC4                  0.0          0.147733
B00004RFC6                  0.0          0.147733
B00004RFC5                  0.0          0.110800
B00004RFC0                  0.0          0.110800
B00004T1MB                  0.0          0.110800
B00004RF6K                  0.0          0.090032
```

Result Evaluation

✓ 0s completed at 16:58