RE - Amazon Product Recommendation

Problem Statement

Online E-commerce websites like Amazon, Filpkart uses different recommendation models to provide different suggestions to different users. Build your own recommendation system for products on an e-commerce website like Amazon.com.

Amazon currently uses item-to-item collaborative filtering, which scales to massive data sets and produces high-quality recommendations in real time. This type of filtering matches each of the user's purchases and rated items to similar items, then combines those similar items into a recommendation list for the user.

In this project we are going to build recommendation model for the electronics products of Amazon.

Dataset

The source of the dataset - Amazon Reviews data (http://jmcauley.ucsd.edu/data/amazon/). The repository has several datasets. For this case study, we are using the Electronics dataset. The columns in this dataset are:

- **userId**
- **productId**
- **ratings**
- **timestamp**

Imports and Configurations

In [1]:
```
# Utilities
import math, random, warnings
from time import time
from datetime import datetime
from collections import defaultdict
from IPython.core.interactiveshell import InteractiveShell

# Mathematical calculation
import numpy as np
from scipy.sparse.linalg import svds
from sklearn import model_selection
from sklearn.metrics.pairwise import cosine_similarity

# Data handling
import pandas as pd

# Data Visualization
```

```
import matplotlib.pyplot as plt
import seaborn as sns

# scikit-surprise recommender package
from surprise import SVD, KNNWithMeans
from surprise import Dataset, Reader, accuracy
from surprise.model_selection import train_test_split, GridSearchCV
from surprise.prediction_algorithms.baseline_only import BaselineOnly
```

In [2]:
```
# Configure for any default setting of any library
InteractiveShell.ast_node_interactivity = "all"
warnings.filterwarnings('ignore')
%matplotlib inline
# sns.set(style='whitegrid', palette='deep', font='sans-serif', font_scale=1.2, col
pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

Comments

- **InteractiveShell** setting displays the full output for a cell, not just the latest one.
- Ignore all warnings in the notebook for an user friendly view
- **%matplotlib inline** sets the backend of matplotlib to the 'inline' backend: With this backend, the output of plotting commands is displayed inline without needing to call plt.show() every time a data is plotted.
- **sns.set()** sets few of the Seaborn's asthetic parameters
- Pandas **display.float_format** supress the scintific notation in pandas dataframe for easy readbability

---

Q1. Read and explore the given dataset. (Rename column/add headers, plot histograms, find data characteristics)

Load the Dataset

In [3]:
```
# Load the dataset into a Pandas dataframe called ratingsand skip any lines that re
ratings = pd.read_csv('ratings_Electronics.csv',
                      names=['userId', 'productId', 'rating', 'timestamp'],
                      error_bad_lines=False,
                      warn_bad_lines=False)

# Save an original copy of the dataframe
ratings_original = ratings.copy(deep=True)
```

In [4]:
```
# Check the head of the dataset
ratings.head()
# Check the tail of the dataset
ratings.tail()
```

Out[4]:

	userId	productId	rating	timestamp
0	AKM1MP6P0OYPR	0132793040	5.000	1365811200
1	A2CX7LUOHB2NDG	0321732944	5.000	1341100800
2	A2NWSAGRHCP8N5	0439886341	1.000	1367193600
3	A2WNBOD3WNDNKT	0439886341	3.000	1374451200
4	A1GI0U4ZRJA8WN	0439886341	1.000	1334707200

Out[4]:

	userId	productId	rating	timestamp
7824477	A2YZI3C9MOHC0L	BT008UKTMW	5.000	1396569600
7824478	A322MDK0M89RHN	BT008UKTMW	5.000	1313366400
7824479	A1MH90R0ADMIK0	BT008UKTMW	4.000	1404172800
7824480	A10M2KEFPEQDHN	BT008UKTMW	4.000	1297555200
7824481	A2G81TMIOIDEQQ	BT008V9J9U	5.000	1312675200

Comments

- To take a closer look at the data, pandas library provides **".head()"** function which returns first five observations and **".tail()"** function which returns last five observations of the data set.

Inspect the Dataset

In [5]:
```
# Get the shape and size of the dataset
print("Number of rows    :",ratings.shape[0])
print("Number of columns :",ratings.shape[1])
```

```
Number of rows    : 7824482
Number of columns : 4
```

In [6]:
```
# Get more info on it
# 1. Name of the columns
# 2. Find the data types of each columns
# 3. Look for any null/missing values
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7824482 entries, 0 to 7824481
Data columns (total 4 columns):
userId       object
productId    object
rating       float64
timestamp    int64
dtypes: float64(1), int64(1), object(2)
memory usage: 238.8+ MB
```

In [7]:
```
# Check for any Null values in the dataset
ratings.isnull().sum()
```

```
Out[7]: userId       0
        productId    0
        rating       0
        timestamp    0
        dtype: int64
```

Observations

- The dataset comprises of **7824482 rows** and **4 columns**.
- There are **NO null/missing** present in the dataset.
- int64 datatype of timestamp column indicates that it is in **Unix timestamp** format where each number is the number of seconds passed after **January 1, 1970 at UTC**.

Drop Duplicates

It's not certain how this data was collected or if it processed before it was published; there could be some duplicated ratings in here. To check, we'll see if there are any duplicated userId and productId combination.

```
In [8]: # Get a dataframe consisting only of ratings that are duplicated
rating_combination = ['userId', 'productId']
ratings[ratings.duplicated(subset=rating_combination, keep=False)].sort_values(rati

# ratings.drop_duplicates(subset=['userId','productId','rating'],inplace=True)
```

Out[8]:

userId	productId	rating	timestamp

There are **NO Duplicate** rows present.

Readable Timestamp

As observed, the timestamp is in Unix timestamp format where each number is the number of seconds passed after January 1, 1970 at UTC. Convert the timestamp column to a readable date time format and change the datatype to datetime.

```
In [9]: # Convert the timestamp column to a readable date time format
ratings['timestamp'] = ratings.timestamp.apply(lambda ts: datetime.utcfromtimestamp
# Convert the datatype to datetime
ratings['timestamp'] = pd.to_datetime(ratings['timestamp'])
ratings.head()
ratings.info()
```

Out[9]:

	userId	productId	rating	timestamp
0	AKM1MP6P0OYPR	0132793040	5.000	2013-04-13
1	A2CX7LUOHB2NDG	0321732944	5.000	2012-07-01
2	A2NWSAGRHCP8N5	0439886341	1.000	2013-04-29
3	A2WNBOD3WNDNKT	0439886341	3.000	2013-07-22
4	A1GI0U4ZRJA8WN	0439886341	1.000	2012-04-18

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7824482 entries, 0 to 7824481
Data columns (total 4 columns):
userId       object
productId    object
rating       float64
timestamp    datetime64[ns]
dtypes: datetime64[ns](1), float64(1), object(2)
memory usage: 238.8+ MB
```

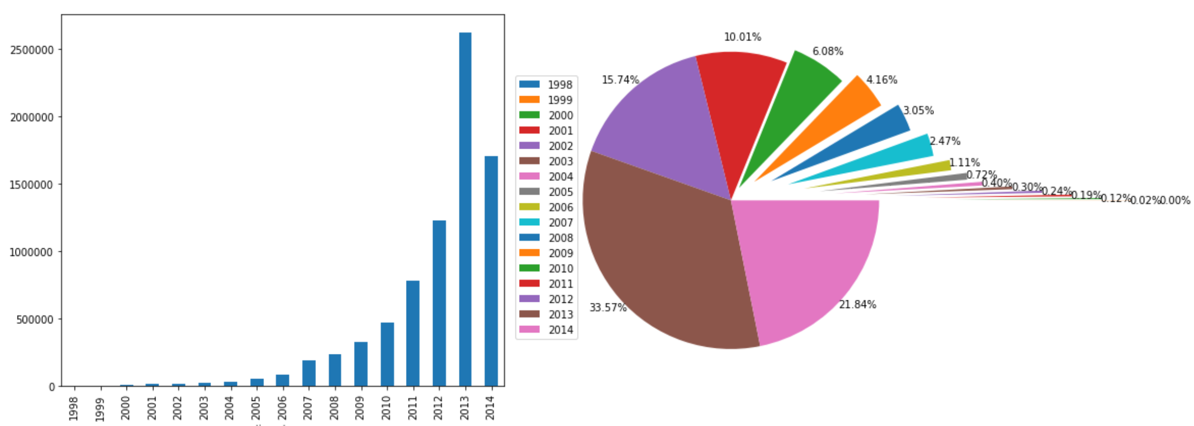
In [10]:

```python
# Get the timespan of data
print("Minimum recorded ts:",ratings.timestamp.min())
print("Maximum recorded ts:",ratings.timestamp.max())
```

```
Minimum recorded ts: 1998-12-04 00:00:00
Maximum recorded ts: 2014-07-23 00:00:00
```

In [11]:

```python
# Visualize the year wise ratings distribution
fig, ax = plt.subplots(1, 2, figsize=(16,6))
year_wise_count = ratings.timestamp.groupby(ratings['timestamp'].dt.year).count()
_ = year_wise_count.plot(kind='bar', ax=ax[0])
explode = (1.9,1.7,1.5,1.3,1.1,0.9,0.7,0.6,0.5,0.4,0.3,0.2,0.1,0,0,0,0)
_ = ax[1].pie(year_wise_count, explode=explode, autopct='%1.2f%%', pctdistance=1.1)
_ = ax[1].legend(labels=year_wise_count.index,bbox_to_anchor=(0.1,0.85))
plt.tight_layout()
```



Observaton:

- The data is collected from 1998 till 2014. And we can see every year the ratings for electronics products are increasing continuously except for an unusual hike in the year 2013 for some unknown reasons.

- After converting to readable format of datatime, it is noticed that this column doesn't contain any time component, just the date component is there.

As there is no time (HHMMSS) component present, it is **not feasible** to somehow make a concept of transaction out of it. Provided the exact hour minute and seconds components are given for each record, grouping them into simillar timestamps and userIds, we could've considered some products to be purchased in a single transaction. Besided this is a product review dataset. Hence we can't apply **Market Basket** analysis. So dropping the timestamp column, which is of no use now.

In [12]:
```
# Drop the timestamp column
ratings.drop(labels='timestamp', axis=1, inplace=True)
ratings.head()
```

Out[12]:

	userId	productId	rating
0	AKM1MP6P0OYPR	0132793040	5.000
1	A2CX7LUOHB2NDG	0321732944	5.000
2	A2NWSAGRHCP8N5	0439886341	1.000
3	A2WNBOD3WNDNKT	0439886341	3.000
4	A1GI0U4ZRJA8WN	0439886341	1.000

In [13]:
```
# Check the count of unique user and product data
unique_original = (ratings.userId.nunique(), ratings.productId.nunique())
print('Count of unique Users    :', unique_original[0])
print('Count of unique Products :', unique_original[1])
```

```
Count of unique Users    : 4201696
Count of unique Products : 476002
```

In [14]:
```
# Find the minimum and maximum ratings
print("The Minimum rating is:",ratings.rating.min())
print("The Maximum rating is:",ratings.rating.max())
```

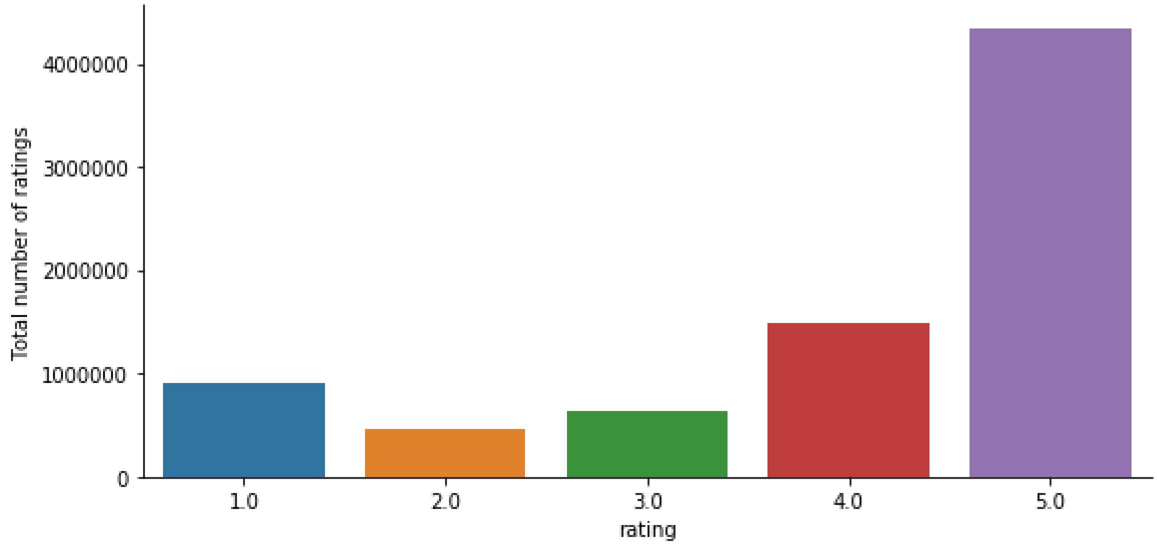
```
The Minimum rating is: 1.0
The Maximum rating is: 5.0
```

In [15]:
```
# Check the distribution of ratings
print('Count of observations in each ratings:')
ratings.rating.value_counts()
g = sns.factorplot("rating", data=ratings, aspect=2.0, kind='count')
g.set_ylabels("Total number of ratings")
```

```
Count of observations in each ratings:
```

Out[15]:
```
5.000    4347541
4.000    1485781
1.000     901765
3.000     633073
2.000     456322
Name: rating, dtype: int64
```

Out[15]: <seaborn.axisgrid.FacetGrid at 0x1950933dfd0>



In [16]:
```
# Find the unique products under each ratings
ratings.groupby('rating')['productId'].nunique()
```

Out[16]:
```
rating
1.000    176283
2.000    123419
3.000    152827
4.000    223845
5.000    358458
Name: productId, dtype: int64
```

Observations:

- Extreme high count in rating 5 indicates Amazon delivers good quality products in electronics department.
- Count plot and number of unique product under each rating category shows that there is more frequency under rating 5 followed by rating 4 and rating 1.
- This means ideally people are more sensitive towards extreme experiences. In other words more ratings can be observed when users are extremely satisfied or extremely unsatisfied.
- Users do not bother to rate usually for the average experience with any product, so is the reason rating 2 and 3 are having lesser frequency compared to others.

Q2. Take subset of dataset to make it less sparse/more dense. (For example, keep the users only who has given 50 or more number of ratings)

Data Sparsity

Many recommender systems run into a problem called the **Cold-Start problem**. Essentially, a user can't be recommended anything because they haven't rated anything! Additionally, if you introduce a new product, nobody has rated it and it can't be recommended. Since we have rating data, we're going to run into either of these problems. Because of this problem, also the mathematical space becomes very much sparse.

If a user has rated one or very few items, how well could a recommender system work? If we have one point of a line, we have no idea which direction the line is going. In the same vein, if we have a user with only one or very few ratings, though we might be able to rule out some items, but it would be very difficult to be confident in our recommendations for that user.

For this reason, I'm going to explore how many ratings have been submitted per user.

In [17]:
```
# Find the top 10 users based on ratings
most_rated = ratings.userId.value_counts().rename_axis('UserId').reset_index(name='
# most_rated = ratings.groupby('userId').size().sort_values(ascending=False)
most_rated.head(10)
```

Out[17]:

	UserId	# ratings
0	A5JLAU2ARJ0BO	520
1	ADLVFFE4VBT8	501
2	A3OXHLG6DIBRW8	498
3	A6FIAB28IS79	431
4	A680RUE1FDO8B	406
5	A1ODOGXEYECQQ8	380
6	A36K2N527TXXJN	314
7	A2AY4YUOX2N1BQ	311
8	AWPODHOB4GFWL	308
9	ARBKYIVNYWK3C	296

Density of the matrix

Density of a matrix can be described as the measure of closeness of datapoints to each other when the matrix is projected into a mathematical space with the no of dimensions equal to the column of the matrix and each row representing a point in that dimensional space. More the density of the matrix more close the data points are in the mathematical space forming a cloud or any other shape. When the data points are scattered far apart in the vector space, such matrix is called as a sparse matrix.

In [18]:
```
# Find the density of the rating matrix
print('Total observed ratings in the dataset  :', len(ratings))
possible_num_of_ratings = ratings.userId.nunique() * ratings.productId.nunique()
```

```
print('Total ratings possible for the dataset :', possible_num_of_ratings)
density = len(ratings) / possible_num_of_ratings * 100
print('Density of the dataset                 : {:4.5f}%'.format(density))
```

```
Total observed ratings in the dataset  : 7824482
Total ratings possible for the dataset : 2000015699392
Density of the dataset                 : 0.00039%
```

Getting rid of users who have rated less than 50 products, as we can see the **density of the user-item matrix is 0.00039%**

In [19]:
```
# Drop the users who have rated less than 50 products
ratings = ratings[ratings.userId.isin(most_rated[most_rated['# ratings'] >= 50].Use
print('# unique USERS who have rated 50 or more products :', ratings.userId.nunique
print('# unique USERS dropped      :', unique_original[0] - ratings.userId.nunique(
print('# unique ITEMS remaining    :', ratings.productId.nunique())
print('# unique ITEMS dropped      :', unique_original[1] - ratings.productId.nuniq
print('\nFinal length of the dataset :', len(ratings))
```

```
# unique USERS who have rated 50 or more products : 1540
# unique USERS dropped      : 4200156
# unique ITEMS remaining    : 48190
# unique ITEMS dropped      : 427812

Final length of the dataset : 125871
```

Observations:

- There was a huge no of users (4200156) who haven't rated atleast 50 products. These records would not have drawn a proper intuation about user similarity considering the total no. of records in the dataset. Hence we dropped all such users and are now left with **1540 unique users** with 50 or more ratings under each one's umbrella. Which is almost **0.04%** of total no of users in the original dataset.
- In the process of getting rid of such users, we ended up dropping 427812 unique products and their ratings. Now we are left with only **48190 unique products** which is almost **10%** of the original list of products.
- As a whole we **dropped** 7824482-125871=**7698611 records** which is almost **98.4%** of the original dataset.

In [20]:
```
# Find the density of the final matrix
final_ratings_matrix = ratings.pivot(index='userId', columns='productId', values='r
print('Shape of final_ratings_matrix          :', final_ratings_matrix.shape)
print('Total observed ratings in the dataset  :', len(ratings))
possible_num_of_ratings = final_ratings_matrix.shape[0] * final_ratings_matrix.shap
print('Total ratings possible for the dataset :', possible_num_of_ratings)
density = len(ratings) / possible_num_of_ratings * 100
print('Density of the dataset                 : {:4.2f}%'.format(density))
```

```
Shape of final_ratings_matrix          : (1540, 48190)
Total observed ratings in the dataset  : 125871
Total ratings possible for the dataset : 74212600
Density of the dataset                 : 0.17%
```

In [21]:
```
# Calculate the increase in density
```

```
print('The density of the user-item matrix increased by {:4.2f}%'.format((0.17-0.00
```

```
The density of the user-item matrix increased by 434.90%
```

Observations:

- After dropping about 98.4% of the data with very less ratings per user, the **density of the resultant matrix increased by 434.9%**.
- A **density of 0.17%** shows that the data set is still highly sparse such that it is not feasible to visualize with matplotlib spy.

Q3. Split the data randomly into train and test dataset. (For example split it in 70:30 ratio)

In [22]:
```
# Divide the dataset in 70:30 ratio
trainset, testset = model_selection.train_test_split(ratings, test_size=0.3, random
trainset.head()
testset.head()
```

Out[22]:

	userId	productId	rating
5815696	A197T2N6RU7K56	B007N6OED8	5.000
412740	A3HR0ZZOFKQ97N	B0001Y7UAI	5.000
444340	AGHZXQL9F94T9	B0002A6YVC	2.000
3481712	A2XJMQ2COPGWJH	B003NSBF32	2.000
4580022	A2D1LPEUCTNT8X	B004YKKT26	4.000

Out[22]:

	userId	productId	rating
4930282	A2UOHALGF2X77Q	B005G81E9M	3.000
3333831	A27M75LRSJ788H	B003FG6IV6	5.000
7490425	A35W3JQYP0M655	B00E3FHXYO	5.000
679608	A1FR68QH6Z4YZM	B0009R3N9E	5.000
583942	A25FL6VLD7S23S	B00079Q5DK	2.000

In [23]:
```
print('Shape of the training set  :', trainset.shape)
print('Shape of the test set      :', testset.shape)
```

```
Shape of the training set  : (88109, 3)
Shape of the test set      : (37762, 3)
```

In [24]:
```
# Check the ratings distribution in both train and test set
fig, axes = plt.subplots(1, 2, figsize=(15,5))
axes[0].set_title('Training Set')
sns.countplot('rating', data=trainset, ax=axes[0])
axes[1].set_title('Testing Set')
```

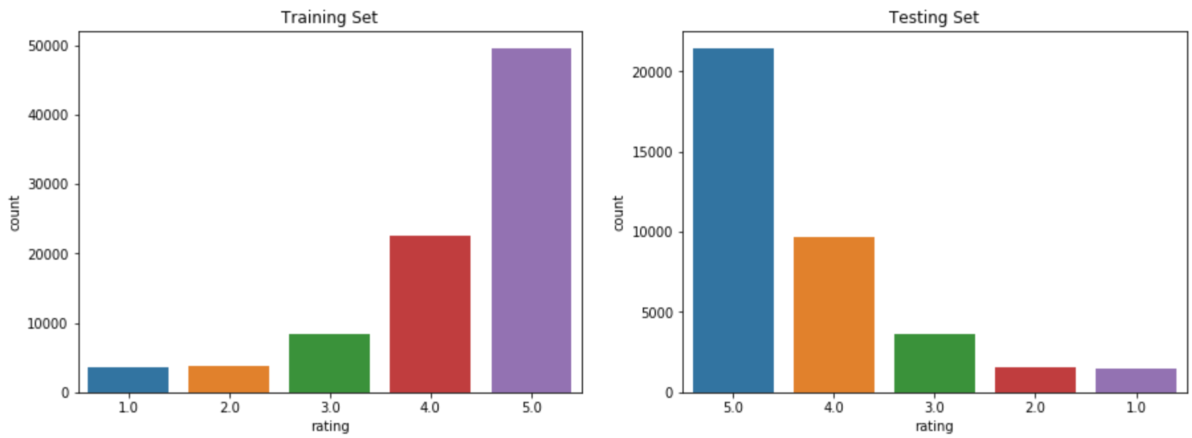
```
sns.countplot('rating', data=testset, ax=axes[1],
              order=testset.rating.value_counts().index)
```

Out[24]: Text(0.5, 1.0, 'Training Set')

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x17da7ebe240>

Out[24]: Text(0.5, 1.0, 'Testing Set')

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x17d868a09e8>



Observations:

- Train Test set split resulted into 88109 training data and 37762 testing dataset.
- Both the datasets are having almost equal no of data points under each rating.

Q4. Build Popularity Recommender model. (Non-personalised)

Popularity Based

Easiest way to build a recommendation system is popularity based, simply over all the products that are popular, So how to identify popular products, which could be identified by which are all the products that are bought most.

Let's group the products to find the count of reatings each one of them has recieved. this could be considered as their individual scores.

In [25]:
```
# Create a method to recommend products based on popularity
def recommend_popular(df, top_n, userId=None):
    # Generate a recommendation rank based upon score
    df['Rank'] = df['score'].rank(ascending=0, method='first')
    recommendations = df.sort_values(['score', 'productId'], ascending=[0,1])

    # Add UserId column for which the recommendations are being generated
    if userId:
        recommendations.insert(0,'userId',userId)
```

```
    # Get the top N recommendations
    return recommendations.head(top_n)
```

Method 1: UserId count for each unique product as recommended score
The score for each product in this method is calculated as the sum of the number of users rated. Ratings can be of good and bad. This method doesn't bother about the quality of the ratings recieved, rather just counts how many ratings are present for each product.

In [26]:
```
#Count of user_id for each unique product as recommendation score
product_grp = ratings.groupby(['productId']).agg({'userId': 'count'}).reset_index()
product_grp.rename(columns={'userId': 'score'}, inplace=True)
product_grp.head()
```

Out[26]:

	productId	score
0	0594451647	1
1	0594481813	1
2	0970407998	2
3	0972683275	4
4	1400501466	6

In [27]:
```
# Find recommendation for top 5 products
recommend_popular(product_grp, 5)
```

Out[27]:

	productId	score	Rank
39003	B0088CJT4U	206	1.000
24827	B003ES5ZUU	184	2.000
11078	B000N99BBC	167	3.000
38250	B007WTAJTO	164	4.000
38615	B00829TIEK	149	5.000

Method 2: Average of ratings for each unique product as recommended score
The score for each product in this method is calculated as the average of the ratings recieved. This method is better than method 1.

In [28]:
```
#Count of user_id for each unique product as recommendation score
product_grp = ratings.groupby(['productId']).agg({'rating': 'mean'}).reset_index()
product_grp.rename(columns={'rating': 'score'}, inplace=True)
product_grp.head()
```

Out[28]:

	productId	score
0	0594451647	5.000
1	0594481813	3.000
2	0970407998	2.500
3	0972683275	4.750
4	1400501466	3.333

In [29]:

```
# Find recommendation for top 5 products
recommend_popular(product_grp, 5)
```

Out[29]:

	productId	score	Rank
0	0594451647	5.000	1.000
5	1400501520	5.000	2.000
12	1400699169	5.000	3.000
13	1685560148	5.000	4.000
14	3744295508	5.000	5.000

Method 3: Sum of ratings for each unique product as recommended score
The score for each product in this method is calculated as the sum of all ratings recieved. This is practically the best approach to determine the popularity of an item considering only the users ratings are given. This is also preferred over avg (method 2) as average of one 5 star rating is exactly same as the average of more than one 5 star ratings, but the product with more 5 star ratings would be considered as the most popular.

In [30]:

```
#Count of user_id for each unique product as recommendation score
product_grp = ratings.groupby(['productId']).agg({'rating': 'sum'}).reset_index()
product_grp.rename(columns={'rating': 'score'}, inplace=True)
product_grp.head()
```

Out[30]:

	productId	score
0	0594451647	5.000
1	0594481813	3.000
2	0970407998	5.000
3	0972683275	19.000
4	1400501466	20.000

In [31]:

```
# Find recommendation for top 5 products
recommend_popular(product_grp, 5)
```

Out[31]:

	productId	score	Rank
24827	B003ES5ZUU	895.000	1.000
39003	B0088CJT4U	869.000	2.000
11078	B000N99BBC	797.000	3.000
38250	B007WTAJTO	771.000	4.000
38615	B00829TIEK	661.000	5.000

In [32]:

```
# Find recommendation for couple of users
find_recom = {'A197T2N6RU7K56': 6,
              'A1FR68QH6Z4YZM': 3,
              'A10AFVU66A79Y1': 8}   # This list is user, top_n recommendation dict
for user in find_recom:
    print("Top %d recommendations for the userId: %s" %(find_recom[user],user))
    recommend_popular(product_grp,find_recom[user],user)
    print("\n")
```

```
Top 6 recommendations for the userId: A197T2N6RU7K56
```

Out[32]:

	userId	productId	score	Rank
24827	A197T2N6RU7K56	B003ES5ZUU	895.000	1.000
39003	A197T2N6RU7K56	B0088CJT4U	869.000	2.000
11078	A197T2N6RU7K56	B000N99BBC	797.000	3.000
38250	A197T2N6RU7K56	B007WTAJTO	771.000	4.000
38615	A197T2N6RU7K56	B00829TIEK	661.000	5.000
38611	A197T2N6RU7K56	B00829THK0	605.000	6.000

```
Top 3 recommendations for the userId: A1FR68QH6Z4YZM
```

Out[32]:

	userId	productId	score	Rank
24827	A1FR68QH6Z4YZM	B003ES5ZUU	895.000	1.000
39003	A1FR68QH6Z4YZM	B0088CJT4U	869.000	2.000
11078	A1FR68QH6Z4YZM	B000N99BBC	797.000	3.000

```
Top 8 recommendations for the userId: A10AFVU66A79Y1
```

Out[32]:

	userId	productId	score	Rank
24827	A10AFVU66A79Y1	B003ES5ZUU	895.000	1.000
39003	A10AFVU66A79Y1	B0088CJT4U	869.000	2.000
11078	A10AFVU66A79Y1	B000N99BBC	797.000	3.000
38250	A10AFVU66A79Y1	B007WTAJTO	771.000	4.000
38615	A10AFVU66A79Y1	B00829TIEK	661.000	5.000
38611	A10AFVU66A79Y1	B00829THK0	605.000	6.000
39338	A10AFVU66A79Y1	B008DWCRQW	561.000	7.000
28761	A10AFVU66A79Y1	B004CLYEDC	551.000	8.000

Observations:

- Popularity recommender models works based on the popularity of products.
- The products with highest number of ratings gets recommended irrespective of user's interest. This is the model used as a basic recommendation even when the user is not even logged into Amazon.
- So is observed above that all the 3 users recieved the same recommendations i.e the top n rated products under Electronics category.

Q5. Build Collaborative Filtering model

Collaborative Filtering

Collaborative filtering is the process of filtering out information or patterns using techniques involving collaboration among multiple agents, viewpoints, data sources, etc.This is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (collaborating). The underlying assumption of the collaborative filtering approach is that if a person A has the same opinion as a person B on a matter, A is more likely to have B's opinion on a different matter than that of a randomly chosen person.

This technique doesn’t need anything else except users’ historical preference on a set of items. Because it’s based on historical data. In terms of user preference, it usually expressed by two categories.

- **Explicit Rating**: It is a rate given by a user to an item on a sliding scale, like 5 stars for any movie or an item. This is the most direct feedback from users to show how much they like an item.
- **Implicit Rating**: This suggests users' preference indirectly, such as page views, clicks, purchase records, whether or not listen to a music track, and so on.

Nearest Neighborhood - The standard method of Collaborative Filtering is known as Nearest Neighborhood algorithm.

Types of Collaborative Filtering (CF)

- Item Based Collaborative Filtering (IBCF)
    - Compute similarity between Items
- User Based Collaborative Filtering (UBCF)
    - Compute similarity between Users

IBCF vs. UBCF

- IBCF is more efficient than UBCF
- Typical applications involve far more Users than Items. Hence Similarity matrix for IBCF is more compact than UBCF
- Similarity estimates between items is also more likely to converge over time than similarity between users. Hence the similarities can be pre computed and cached unlike similarity between users that need to be dynamically computed at every certain interval.
- However, the IBCF recommendations tend to be more conservative than UBCF

Similarity Metrics: The following are the two popular similarity metrics used in recommender systems. **Jaccard Similarity** is useful when the User/Item Matrix contain binary values

- **Cosine Similarity**: Similarity is the cosine of the angle between the 2 item vectors represented by:

$$Cosine\ Similarity : CosSim(x, y) = \frac{\sum_i x_i y_i}{\sqrt{\sum (x_i)^2}\sqrt{\sum (y_i)^2}} = \frac{\langle x, y \rangle}{\|x\|\|y\|}$$

- **Pearson Correlation**: Similarity is the Pearson correlation between two vectors represented by:

$$Pearson\ Correlation : Corr(x, y) = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2}\sqrt{\sum (y_i - \bar{y})^2}} = \frac{\langle x - \bar{x}, y - \bar{y} \rangle}{\|x - \bar{x}\|\|y - \bar{y}\|}$$
$$= CosSim(x - \bar{x},\ y - \bar{y})$$

User Based Collaborative Filtering (UBCF)

This algorithm first finds the similarity score between users. Based on this similarity score, it then picks out the most similar users and recommends products which these similar users have liked or bought previously.

$$\hat{r}_{ui} = \frac{\sum_{v \in N_i^k(u)} similarity(u, v).\, r_{vi}}{\sum_{v \in N_i^k(u)} similarity(u, v)}$$

Item Based Collaborative Filtering (IBCF)

This algorithm first finds the similarity score between items. Based on this similarity score, it then picks out the most similar items and recommends that to the user which these similar items have been liked or bought previously.

$$\hat{r}_{ui} = \frac{\sum_{j \in N_u^k(i)} similarity(i,j).\, r_{uj}}{\sum_{j \in N_u^k(j)} similarity(i,j)}$$

First step is to create the sparse matrix. Let's attempt both UBCF and IBCF consecutively.

In [33]:

```
# Create the User-Item sparse matrix
user_item = ratings.pivot(index='userId', columns='productId', values='rating').fil
print('Shape of User-Item sparse matrix:', user_item.shape)
user_item.head()
```

```
Shape of User-Item sparse matrix: (1540, 48190)
```

Out[33]:

productId	0594451647	0594481813	0970407998	0972683275	1400501466	14005015
userId						
A100UD67AHFODS	0.000	0.000	0.000	0.000	0.000	0.0
A100WO06OQR8BQ	0.000	0.000	0.000	0.000	0.000	0.0
A105S56ODHGJEK	0.000	0.000	0.000	0.000	0.000	0.0
A105TOJ6LTVMBG	0.000	0.000	0.000	0.000	0.000	0.0
A10AFVU66A79Y1	0.000	0.000	0.000	0.000	0.000	0.0

5 rows × 48190 columns

In [34]:

```
# Create the Item-User sparse matrix
item_user = ratings.pivot(index='productId', columns='userId', values='rating').fil
print('Shape of Item-User sparse matrix:', item_user.shape)
item_user.head()
```

```
Shape of Item-User sparse matrix: (48190, 1540)
```

Out[34]:

userId	A100UD67AHFODS	A100WO06OQR8BQ	A105S56ODHGJEK	A105TOJ6LTVMBG	A10A
productId					
0594451647	0.000	0.000	0.000	0.000	
0594481813	0.000	0.000	0.000	0.000	
0970407998	0.000	0.000	0.000	0.000	
0972683275	0.000	0.000	0.000	0.000	
1400501466	0.000	0.000	0.000	0.000	

5 rows × 1540 columns

Now, we will calculate the similarity. We can use the cosine_similarity function from sklearn to calculate the cosine similarity.

In [35]:
```
# Calculate the user-user similarity
user_similarity = cosine_similarity(user_item)
np.fill_diagonal(user_similarity, 0)
user_similarity_df = pd.DataFrame(user_similarity,index=user_item.index, columns=us
user_similarity_df.head()
```

Out[35]:

userId	A100UD67AHFODS	A100WO06OQR8BQ	A105S56ODHGJEK	A105TOJ6LTVMB(
userId				
A100UD67AHFODS	0.000	0.011	0.000	0.01!
A100WO06OQR8BQ	0.011	0.000	0.013	0.01(
A105S56ODHGJEK	0.000	0.013	0.000	0.00(
A105TOJ6LTVMBG	0.015	0.016	0.000	0.00(
A10AFVU66A79Y1	0.026	0.009	0.022	0.00(

5 rows × 1540 columns

In [36]:
```
# Calculate the item-item similarity
item_similarity = cosine_similarity(item_user)
np.fill_diagonal(item_similarity, 0)
item_similarity_df = pd.DataFrame(item_similarity, index=item_user.index, columns=i
item_similarity_df.head()
```

Out[36]:

productId	0594451647	0594481813	0970407998	0972683275	1400501466	1400501520	14(
productId							
0594451647	0.000	0.000	0.000	0.000	0.000	0.000	
0594481813	0.000	0.000	0.000	0.000	0.000	0.000	
0970407998	0.000	0.000	0.000	0.000	0.000	0.000	
0972683275	0.000	0.000	0.000	0.000	0.000	0.000	
1400501466	0.000	0.000	0.000	0.000	0.000	0.539	

5 rows × 48190 columns

Now that we have both the smiliarity matrices in our hand, let's see the n-Neighborhood.

In [37]:
```
# Method to find top N neighbors
def find_n_neighbors(df,n):
    order = np.argsort(df.values, axis=1)[:, :n]
    df = df.apply(axis=1, func=lambda x: pd.Series(x.sort_values(ascending=False).i
                                                   index=['top{}'.format(i) for i i
    return df
```

In [38]:
```
# Find 10 neighbors of each user
user_10_neighbors = find_n_neighbors(user_similarity_df, 10)
```

```python
user_10_neighbors.head(10)
```

Out[38]:

userId	top1	top2	top3	top4
A100UD67AHFODS	A2FZQF0MH29VYN	A11FX8HL2ANK6T	A3CG93783LP0FO	A2NOW4U7W3F7RI
A100WO06OQR8BQ	A3963R7EPE3A7E	A30UP2KKD5IQEP	A2Y3WWPUKIJ59I	A298GL2D0BHGKZ
A105S56ODHGJEK	A17UNMURMLX0ZE	ABMNX856X89CS	ANTN61S4L7WG9	A2LF16F0KX9L7P
A105TOJ6LTVMBG	A1TQBAHI3M4ZBQ	A10ZFE6YE0UHW8	A2XXBZPQT5EXHV	A1NZLRAZJGD99W
A10AFVU66A79Y1	ACQYIC13JXAOI	A25QJBK33C4O0R	A2PMR2PIGWKCQ9	A4H4KYSM2KQ85
A10H24TDLK2VDP	ANTN61S4L7WG9	A2QRXQPHDMFCQV	A3V2EZ6MA32FF6	A3SP7T2PZ3HSDE
A10NMELR4KX0J6	ARC5ASW9CUAGP	A1PS4OYWUB0VX	A3F7USIDJBR8WU	A3GX0FAMEXV6FB
A10O7THJ2O20AG	AWSK1ZAEU1KFL	A365PBEOWM7EI7	AZ8XSDMIX04VJ	AN9CP6J4JF91X
A10PEXB6XAQ5XF	A267FU71Z01CIH	A1TR1R2QKWRSRA	A2MJ8OL2FYN7CW	A1CMD08Z49PGKQ
A10X9ME6R66JDX	A206CGM6J75UJY	A1R19YYR5OR26T	A1TQBAHI3M4ZBQ	A87N6UTYA6NOB

In [39]:

```python
# Find 10 neighbors of each item
item_10_neighbors = find_n_neighbors(item_similarity_df, 10)
item_10_neighbors.head(10)
```

Out[39]:

productId	top1	top2	top3	top4	top5	top6
0594451647	B005B47AIU	B005OIB714	B0076AUCKU	B0058FN6V2	B0073V1NP0	B000MYOJMY
0594481813	B00D30UX8I	B0009YFS4A	B00BSE79KQ	B00C80UFJQ	B00CBDUD60	B009WESJEY
0970407998	B00009R8D3	B00078Y24K	B001E9BIU2	B001EYU6Q4	B0015IOUK2	B000XALL8W
0972683275	B007J4BOWI	B008U25LI6	B003ICXCZM	B004HW67MW	B003GZDB1Q	B0002ZPIXM
1400501466	B0049QV65O	B00BC4J5O0	B0098JS19G	B002LITT3S	B000GT6HAM	B000J46TFW
1400501520	B0030LKGAU	B0053EVW1Y	B004HO58NO	B002YIG8BQ	B004P1ITV2	B00462RU60
1400501776	B00462RU60	B003D2BS4E	B0053EVVTW	B004P1ITV2	B004P1ITU8	B002YIG8BQ
1400532620	B00BGTN06A	B006K59QRC	B002NFZSL6	B007AHQMTO	B00004WHFL	B00BJ91VEA
1400532655	B005JHF5RM	B004NTO2I0	B0034XDTF8	B000E39V9E	B0003009E4	B002V92X9Y
140053271X	B000EXWJ66	B000GT6HAM	B008I6672I	B0044R1VY4	B002LITT3S	B005KHFF2Q

Let's verify the similarity in both item and user base to find out if our calculatios are correct

In [40]:

```python
def get_users_similar_products(user1, user2):
    common_products = ratings[ratings.userId == user1].merge(
    ratings[ratings.userId == user2],
    on = "productId",
```

```
    how = "inner" )
    return common_products[['rating_x', 'rating_y', 'productId']].head()
```

In [41]:
```
# Check the similarity of two users
get_users_similar_products('A100UD67AHFODS', 'A2FZQF0MH29VYN')
```

Out[41]:

	rating_x	rating_y	productId
0	5.000	5.000	B0002KVQBA
1	3.000	4.000	B002HWRJY4
2	4.000	5.000	B0071BTJPI
3	5.000	5.000	B0097BEFYA
4	5.000	5.000	B00A83I8G2

Observations:

- From the above step we can see that the similarity we generated is true since both the given users (**A100UD67AHFODS**, **A2FZQF0MH29VYN**) have almost same ratings and likings.

item_similarity and user_similarity are item-item and user-user similarity matrix in an array form respectively. The next step is to make predictions based on these similarities. Let's define a function to do just that.

In [42]:
```
# Method to predict the rating
def predict(ratings, similarity, type='user'):
    if type == 'user':
        mean_user_rating = ratings.mean(axis=1)
        #We use np.newaxis so that mean_user_rating has same format as ratings
        ratings_diff = (ratings - mean_user_rating[:, np.newaxis])
        pred = mean_user_rating[:, np.newaxis] + similarity.dot(ratings_diff) / np.
    elif type == 'item':
        pred = ratings.dot(similarity) / np.array([np.abs(similarity).sum(axis=1)])
    return pred
```

Finally, we will make predictions based on user similarity and item similarity and recommend product based on similarity.

In [43]:
```
# Predict the ratings for both UBCF and IBCF
st=time()
user_prediction = predict(user_item, user_similarity, type='user')
user_prediction = pd.DataFrame(user_prediction, index=user_item.index, columns=user
user_prediction.head()

item_prediction = predict(user_item, item_similarity, type='item')
# Commenting out following 2 lines as it throws MemoryError due to the high sparsit
# item_prediction = pd.DataFrame(item_prediction, index=item_user.index, columns=it
# item_prediction.head()
print('Time taken %.2fs to find out the user and item prediction' % (time()-st))
```

Out[43]:

productId	0594451647	0594481813	0970407998	0972683275	1400501466	14005015
userId						
A100UD67AHFODS	0.017	0.002	0.006	0.012	0.014	0.0
A100WO06OQR8BQ	0.006	0.002	0.004	0.021	0.009	0.0
A105S56ODHGJEK	-0.003	-0.003	-0.001	0.003	0.003	-0.0
A105TOJ6LTVMBG	-0.002	0.002	0.001	0.015	0.006	-0.0
A10AFVU66A79Y1	-0.003	-0.003	0.005	0.010	0.010	0.0

5 rows × 48190 columns

```
Time taken 1203.40s to find out the user and item prediction
```

In [44]:

```
# Method to Recommend the items with the highest predicted ratings
def recommend_items(userId, orig_df, preds_df, top_n):
    # Get and sort the user's ratings
    sorted_user_ratings = orig_df.loc[userId].sort_values(ascending=False) #sorted_
    sorted_user_predictions = preds_df.loc[userId].sort_values(ascending=False) #so

    # Prepare recommendations
    recommedations = pd.concat([sorted_user_ratings, sorted_user_predictions], axis
    recommedations.index.name = 'Recommended Items'
    recommedations.columns = ['user_ratings', 'user_predictions']

    # Take the products which user has NOT rated
    recommedations = recommedations.loc[recommedations.user_ratings == 0]
    recommedations = recommedations.sort_values('user_predictions', ascending=False
    return recommedations.head(top_n)
```

In [45]:

```
# Find recommendation for couple of users using UBCF
find_recom = {'A100UD67AHFODS': 6,
              'A100WO06OQR8BQ': 3,
              'A105S56ODHGJEK': 8}   # This list is user, top_n recommendation dict
for user in find_recom:
    print("Top %d recommendations for the userId: %s" %(find_recom[user],user))
    recommend_items(user, user_item, user_prediction, find_recom[user])
    print("\n")
```

```
Top 6 recommendations for the userId: A100UD67AHFODS
```

Out[45]:

	user_ratings	user_predictions
Recommended Items		
B003ES5ZUU	0.000	0.873
B007WTAJTO	0.000	0.684
B0088CJT4U	0.000	0.509
B00G4UQ6U8	0.000	0.485
B002V88HFE	0.000	0.463
B00829THK0	0.000	0.462

```
Top 3 recommendations for the userId: A100WO06OQR8BQ
```

Out[45]:

Recommended Items	user_ratings	user_predictions
B000N99BBC	0.000	0.883
B00829TIEK	0.000	0.749
B004CLYEDC	0.000	0.730

```
Top 8 recommendations for the userId: A105S56ODHGJEK
```

Out[45]:

Recommended Items	user_ratings	user_predictions
B0088CJT4U	0.000	1.343
B00829THK0	0.000	0.885
B002R5AM7C	0.000	0.844
B004CLYEDC	0.000	0.836
B004CLYEFK	0.000	0.792
B004T9RR6I	0.000	0.662
B003ES5ZUU	0.000	0.616
B00834SJNA	0.000	0.607

Observations:

- Unlike popularity model, the recommendations are personalized here as indicated by the different set of recommendations for different users based on their likings.
- It is taking too long to calculate the item-item similarity as the item base is pretty huge than the user base.

UBCF and IBCF are **Neighborhood approaches** of collaborative recommendation system. Based on certain similarity metrics, the nearest neighbors are calculated which are considered to be similar in terms of past history. Because of the high sparsity of the user-item matrix, it is computationally heavy to calculate the neighborhood for the user-user or item-item similarity resulting in non-reliable recommendations some time. To deal with this problem of huge sparsity, **Latent Factor approach** is used.

Matrix Factorization based Collaborative Filtering

Matrix Factorization based CF works on the principle of **Latent Factor approach**. It deals with the latent factors of item base resulting in reducing the dimensionality of the mathematical space in one hand, and improving the performance because of the less sparsity of the resultant user-item base on the other.

Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) can be used to decompose any given Matrix, M into a product of 3 matrices as follows:

$$M = U \times \sum \times V^T$$

Where:

- U: Left Singular Matrix
- V: Right Singular Matrix
- $\sum$: Diagonal Matrix of Latent Factors, and the values of the diagonal of $\sum$ are called the **singular values**

The matrix can be approximated to a lower rank by considering only the largest singular values.

In [46]:
```
# Trying out different latent factors
svd_list = [svds(user_item, k=k) for k in [100,250,500,750,1000]]
pred_list = [pd.DataFrame(np.dot(np.dot(svd[0], np.diag(svd[1])), svd[2]),
                          index=user_item.index,
                          columns=user_item.columns) for svd in svd_list]
RMSE_list = [round((((user_item.mean() - pred.mean()) ** 2).mean() ** 0.5), 5) for
RMSE_list
```

Out[46]:
```
[0.00236, 0.00181, 0.00133, 0.00096, 0.0007]
```

In [47]:
```
# Singular Value Decomposition
U, sigma, Vt = svds(user_item, k=50)
# Construct diagonal array in SVD
sigma = np.diag(sigma)
```

SVD is useful in many tasks, such as data compression, noise reduction similar to Principal Component Analysis and Latent Semantic Indexing (LSI), used in document retrieval and word similarity in Text mining

In [48]:
```
# Print the shape of the decomposed matrices
print('Shape of the Left Singular matrix          :', U.shape)
print('Shape of the Latent Factor Diagonal matrix :', sigma.shape)
print('Shape of the Right Singular matrix         :', Vt.shape)
U.shape, sigma.shape, Vt.shape
```

```
Shape of the Left Singular matrix          : (1540, 50)
Shape of the Latent Factor Diagonal matrix : (50, 50)
Shape of the Right Singular matrix         : (50, 48190)
```

Out[48]:
```
((1540, 50), (50, 50), (50, 48190))
```

In [49]:
```
# Predicted ratings
svd_prediction = pd.DataFrame(np.dot(np.dot(U, sigma), Vt), index=user_item.index,
svd_prediction.head()
```

Out[49]:

productId userId	0594451647	0594481813	0970407998	0972683275	1400501466	14005015
A100UD67AHFODS	0.005	0.002	0.004	-0.041	0.010	0.0
A100WO06OQR8BQ	0.002	-0.011	-0.001	0.130	0.008	-0.0
A105S56ODHGJEK	-0.002	-0.003	-0.007	0.007	0.005	-0.0
A105TOJ6LTVMBG	0.002	0.011	-0.006	-0.014	0.000	0.0
A10AFVU66A79Y1	0.001	-0.003	0.011	0.014	0.010	0.0

5 rows × 48190 columns

In [50]:
```
# Find recommendation for couple of users
find_recom = {'A100UD67AHFODS': 6,
              'A100WO06OQR8BQ': 3,
              'A105S56ODHGJEK': 8}   # This list is user, top_n recommendation dict
for user in find_recom:
    print("Top %d recommendations for the userId: %s" %(find_recom[user],user))
    recommend_items(user, user_item, svd_prediction, find_recom[user])
    print("\n")
```

```
Top 6 recommendations for the userId: A100UD67AHFODS
```

Out[50]:

Recommended Items	user_ratings	user_predictions
B0019EHU8G	0.000	1.407
B003ES5ZUU	0.000	1.097
B007OY5V68	0.000	0.987
B000JMJWV2	0.000	0.946
B009SYZ8OC	0.000	0.848
B00DTZYHX4	0.000	0.745

```
Top 3 recommendations for the userId: A100WO06OQR8BQ
```

Out[50]:

Recommended Items	user_ratings	user_predictions
B000N99BBC	0.000	1.825
B004CLYEDC	0.000	1.250
B001TH7GSW	0.000	1.006

```
Top 8 recommendations for the userId: A105S56ODHGJEK
```

Out[50]:

Recommended Items	user_ratings	user_predictions
B0088CJT4U	0.000	1.558
B004T9RR6I	0.000	1.195
B00BOHNYU6	0.000	1.033
B00ARB5FLQ	0.000	0.989
B00829THK0	0.000	0.912
B002R5AM7C	0.000	0.885
B009HQCAPQ	0.000	0.826
B0097CZHAU	0.000	0.807

Observations:

- Unlike popularity model, the recommendations are personalized here as indicated by the different set of recommendations for different users based on their likings.

Q6. Evaluate both the models. (Once the model is trained on the training data, it can be used to compute the error (RMSE) on predictions made on the test data)

Root Mean Square Error (RMSE)

In [51]:

```
# Method to calculate RMSE for different model
def calculate_rmse(orig_df, preds_df):
    rmse_df = pd.concat([orig_df.mean(), preds_df.mean()], axis=1)
    rmse_df.columns = ['Avg_actual_ratings', 'Avg_predicted_ratings']
    RMSE = round(np.sqrt(((rmse_df.Avg_actual_ratings - rmse_df.Avg_predicted_ratin
    print('\nRMSE for this recommender model = {}\n'.format(RMSE))
    return rmse_df.head()
```

Evaluation of User Based CF

In [52]:

```
calculate_rmse(user_item, user_prediction)
```

```
RMSE for this recommender model = 0.00516
```

Out[52]:

productId	Avg_actual_ratings	Avg_predicted_ratings
0594451647	0.003	0.002
0594481813	0.002	0.002
0970407998	0.003	0.003
0972683275	0.012	0.012
1400501466	0.013	0.009

Evaluation of Item Based CF

In [57]:
```
calculate_rmse(user_item, item_prediction)
```

```
RMSE for this recommender model = nan
```

Out[57]:

	Avg_actual_ratings	Avg_predicted_ratings
0594451647	0.003	nan
0594481813	0.002	nan
0970407998	0.003	nan
0972683275	0.012	nan
1400501466	0.013	nan

Evaluation of Matrix Factorization based CF

In [54]:
```
calculate_rmse(user_item, svd_prediction)
```

```
RMSE for this recommender model = 0.00275
```

Out[54]:

productId	Avg_actual_ratings	Avg_predicted_ratings
0594451647	0.003	0.002
0594481813	0.002	0.003
0970407998	0.003	0.003
0972683275	0.012	0.010
1400501466	0.013	0.005

Observations:

- RMSE for Matrix Factorization model based recommender system is the lowest among all.

- This is indicative that the model accuracy increases with decrease in no of dimensions as well as the sparsity.
- So is the reason this approach is most popular in recommendation systems.

Q7. Get top - K (K = 5) recommendations. Since our goal is to recommend new products to each user based on his/her habits, we will recommend 5 new products.

Let's recommend for 2 users for Top 5 products using all the 3 algorithms

In [59]:
```
# Create a list of users
users = ['A100UD67AHFODS','A100WO06OQR8BQ']
top_k = 5

# UBCF Recommendation
print('User Based Collaborative Filtering (UBCF)')
for user in users:
    print("Top %d recommendations for the userId: %s" %(top_k,user))
    recommend_items(user, user_item, user_prediction, top_k)
    print("\n")
```

```
User Based Collaborative Filtering (UBCF)
Top 5 recommendations for the userId: A100UD67AHFODS
```

Out[59]:

Recommended Items	user_ratings	user_predictions
B003ES5ZUU	0.000	0.873
B007WTAJTO	0.000	0.684
B0088CJT4U	0.000	0.509
B00G4UQ6U8	0.000	0.485
B002V88HFE	0.000	0.463

```
Top 5 recommendations for the userId: A100WO06OQR8BQ
```

Out[59]:

Recommended Items	user_ratings	user_predictions
B000N99BBC	0.000	0.883
B00829TIEK	0.000	0.749
B004CLYEDC	0.000	0.730
B00829THK0	0.000	0.653
B004CLYEFK	0.000	0.573

In [60]:
```python
# IBCF Recommendation
print('Item Based Collaborative Filtering (IBCF)')
for user in users:
    print("Top %d recommendations for the userId: %s" %(top_k,user))
    recommend_items(user, user_item, item_prediction, top_k)
    print("\n")
```

```
Item Based Collaborative Filtering (IBCF)
Top 5 recommendations for the userId: A100UD67AHFODS
```

Out[60]:

	user_ratings	user_predictions
Recommended Items		
0594451647	0.000	nan
0594481813	0.000	nan
0970407998	0.000	nan
0972683275	0.000	nan
1400501466	0.000	nan

```
Top 5 recommendations for the userId: A100WO06OQR8BQ
```

Out[60]:

	user_ratings	user_predictions
Recommended Items		
0594451647	0.000	nan
0594481813	0.000	nan
0970407998	0.000	nan
0972683275	0.000	nan
1400501466	0.000	nan

In [61]:
```python
# SVD Recommendation
print('Matrix Factorization based Collaborative Filtering (SVD)')
for user in users:
    print("Top %d recommendations for the userId: %s" %(top_k,user))
    recommend_items(user, user_item, svd_prediction, top_k)
    print("\n")
```

```
Matrix Factorization based Collaborative Filtering (SVD)
Top 5 recommendations for the userId: A100UD67AHFODS
```

Out[61]:

Recommended Items	user_ratings	user_predictions
B0019EHU8G	0.000	1.407
B003ES5ZUU	0.000	1.097
B007OY5V68	0.000	0.987
B000JMJWV2	0.000	0.946
B009SYZ8OC	0.000	0.848

```
Top 5 recommendations for the userId: A100WO06OQR8BQ
```

Out[61]:

Recommended Items	user_ratings	user_predictions
B000N99BBC	0.000	1.825
B004CLYEDC	0.000	1.250
B001TH7GSW	0.000	1.006
B00834SJSK	0.000	0.948
B00AQRUW4Q	0.000	0.757

Observations:

- Each approach has its own way of finding similarity among items and users. So is the reason top 5 recommendations are different for same users in different approaches.

Implementation using SURPRISE package

Surprise is an easy-to-use Python scikit for recommender systems. The name *SurPRISE* roughly stands for Simple Python Recommendataion System Engine.

Installation

- With pip (requirement: numpy and C compiler): `$ pip install scikit-surprise`
- With conda: `$ conda install -c conda-forge scikit-surprise`

It provides various ready-to-use prediction algorithms such as baseline algorithms, neiborhood methods and matrix factorization based algorithms. We will be using **BaselineOnly**, **KNNWithMeans** and **SVD** algorithms to build our recommender system.

Load the Dataset

In [26]:
```
# Set the rating scale
```

```
reader = Reader(rating_scale=(1, 5))

# Load data from the rattings data frame into surprise DataFolds
ratings_surp = Dataset.load_from_df(ratings, reader)

# Check the type of the loaded data
type(ratings_surp)
```

Out[26]: surprise.dataset.DatasetAutoFolds

Split the data randomly into train and test dataset

In [27]:
```
# Divide the dataset in 70:30 ratio
trainset, testset = train_test_split(ratings_surp, test_size=0.3, random_state=123)

# Check the datatype of train and test set
type(trainset)
```

Out[27]: surprise.trainset.Trainset

Baseline Estimate

Baseline estimates look at the average rating an item earned in the entire dataset, and the average rating a user usually gives. Sometimes, some items are rated higher on average than others. In a similar way, some users rate items more critically than others. These deviations are used in baseline estimates to predict a score.

Baseline estimates can be calculated using Stochastic Gradient Descent (SGD) or Alternating Least Squares (ALS). In this example, I'll be using ALS.

Hyperparameter Tuning

Let's run GridSearchCV provided in the SURPRISE package to find the best hyperparameter

In [47]:
```
st = time()
grid_param = {'bsl_options': {'method': ['als'],
                              'n_epochs': random.sample(range(10, 20), 3),
                              'reg_u': random.sample(range(10, 30), 3),
                              'reg_i': random.sample(range(10, 30), 3)}
             }

gs = GridSearchCV(algo_class=BaselineOnly, param_grid=grid_param, measures=['RMSE',
gs.fit(ratings_surp)
print(gs.best_score['rmse'], gs.best_params['rmse'])
print('Time taken %.2fs to tune the best hyper-parameter for Support Vector classif
```

```
0.9784276753334241 {'bsl_options': {'method': 'als', 'n_epochs': 16, 'reg_u': 11,
'reg_i': 11}}
Time taken 3615.86s to tune the best hyper-parameter for Support Vector classifier
```

Evaluate the Baseline Estimate model

In [64]:
```
algo = BaselineOnly(bsl_options=gs.best_params['rmse']['bsl_options'])
algo.fit(trainset)
predictions = algo.test(testset)
print('RMSE of Baseline Estimate is:', accuracy.rmse(predictions, verbose=False))
```

```
Estimating biases using als...
```

Out[64]:
```
<surprise.prediction_algorithms.baseline_only.BaselineOnly at 0x17d883b8d30>
```

```
RMSE of Baseline Estimate is: 0.9890872145160831
```

In [103...
```
# Convert the predictions into pandas dataframe
baseline_prediction = pd.DataFrame(predictions)
baseline_prediction.head()
```

Out[103]:

	uid	iid	r_ui	est	details
0	A34C9AFFZOI45T	B000KMU0NU	5.000	4.759	{'was_impossible': False}
1	AXYM52DNK6NDF	B004C5HM6Y	5.000	4.302	{'was_impossible': False}
2	A1TQBAHI3M4ZBQ	B000ENRQ3M	3.000	4.633	{'was_impossible': False}
3	A1TDR7Y90SVCHL	B0055OKHQS	5.000	4.296	{'was_impossible': False}
4	A2IFKH3TJ10387	B005YR1PV2	4.000	4.091	{'was_impossible': False}

In [104...
```
# Sort in descending order
baseline_prediction.sort_values(by=['uid','est'], ascending=False, inplace=True)
# Predict for a particular user
algo.predict(uid='A100UD67AHFODS', iid='B0019EHU8G')
```

Out[104]:
```
Prediction(uid='A100UD67AHFODS', iid='B0019EHU8G', r_ui=None, est=4.98421308341941
4, details={'was_impossible': False})
```

Recommendation using Baseline Estimate

In [81]:
```
# Extract all null ratings in the original trainset (was_impossible=True)
testset_new = trainset.build_anti_testset()
len(testset_new)
```

Out[81]:
```
58722951
```

In [106...
```
# Create a list of users
users = ['A1TQBAHI3M4ZBQ','A1TDR7Y90SVCHL']
top_k = 5

# Baseline Recommendation
print('Baseline Estimate - SURPRISE')
top_k_recoms = baseline_prediction.groupby('uid').head(top_k).reset_index(drop=True
for user in users:
    print("Top %d recommendations for the userId: %s" %(top_k,user))
    top_k_recoms[top_k_recoms.uid.isin([user])]
    print("\n")
```

```
Baseline Estimate - SURPRISE
Top 5 recommendations for the userId: A1TQBAHI3M4ZBQ
```

Out[106]:

	uid	iid	r_ui	est	details
6095	A1TQBAHI3M4ZBQ	B005K7192G	5.000	5.000	{'was_impossible': False}
6096	A1TQBAHI3M4ZBQ	B000CRFOMK	5.000	5.000	{'was_impossible': False}
6097	A1TQBAHI3M4ZBQ	B00006IW1X	5.000	4.908	{'was_impossible': False}
6098	A1TQBAHI3M4ZBQ	B00BWF5U0M	4.000	4.859	{'was_impossible': False}
6099	A1TQBAHI3M4ZBQ	B0011WCVPI	5.000	4.810	{'was_impossible': False}

```
Top 5 recommendations for the userId: A1TDR7Y90SVCHL
```

Out[106]:

	uid	iid	r_ui	est	details
6105	A1TDR7Y90SVCHL	B001TH7T2U	5.000	4.716	{'was_impossible': False}
6106	A1TDR7Y90SVCHL	B002JQNXZC	5.000	4.507	{'was_impossible': False}
6107	A1TDR7Y90SVCHL	B000HDJT4S	5.000	4.425	{'was_impossible': False}
6108	A1TDR7Y90SVCHL	B000JJSQ30	5.000	4.409	{'was_impossible': False}
6109	A1TDR7Y90SVCHL	B0064Z71T8	1.000	4.406	{'was_impossible': False}

User Based Collaborative Filtering (UBCF)

We will be using Pearson's correlation similarity with KNNWithMeans algorithm to achieve this recommendation.

In [28]:

```
# Instantiate and train the User based KNN algorithm
algo = KNNWithMeans(50, sim_options = { 'name':'pearson', 'user_based':True })
algo.fit(trainset)
```

```
Computing the pearson similarity matrix...
Done computing similarity matrix.
```

Out[28]:

```
<surprise.prediction_algorithms.knns.KNNWithMeans at 0x1950dc62978>
```

Evaluate the model

In [29]:

```
predictions = algo.test(testset)
print('RMSE of User Based approach is:', accuracy.rmse(predictions, verbose=False))
```

```
RMSE of User Based approach is: 1.0567664621980295
```

In [30]:

```
# Convert the predictions into pandas dataframe
ubcf_prediction = pd.DataFrame(predictions)
ubcf_prediction.head()
```

Out[30]:

	uid	iid	r_ui	est	details
0	A34C9AFFZOI45T	B000KMU0NU	5.000	4.265	{'was_impossible': True, 'reason': 'User and/o...
1	AXYM52DNK6NDF	B004C5HM6Y	5.000	4.265	{'was_impossible': True, 'reason': 'User and/o...
2	A1TQBAHI3M4ZBQ	B000ENRQ3M	3.000	4.907	{'actual_k': 0, 'was_impossible': False}
3	A1TDR7Y90SVCHL	B0055OKHQS	5.000	4.265	{'was_impossible': True, 'reason': 'User and/o...
4	A2IFKH3TJ10387	B005YR1PV2	4.000	4.373	{'actual_k': 0, 'was_impossible': False}

In [31]:

```
# Sort in descending order
ubcf_prediction.sort_values(by=['uid','est'], ascending=False, inplace=True)
# Predict for a particular user
algo.predict(uid='A100UD67AHFODS', iid='B0019EHU8G')
```

Out[31]:

```
Prediction(uid='A100UD67AHFODS', iid='B0019EHU8G', r_ui=None, est=5, details={'act
ual_k': 2, 'was_impossible': False})
```

Recommendation using User Based approach

In [32]:

```
# Create a list of users
users = ['A1TQBAHI3M4ZBQ','A1TDR7Y90SVCHL']
top_k = 5

# Baseline Recommendation
print('User Based - SURPRISE')
top_k_recoms = ubcf_prediction.groupby('uid').head(top_k).reset_index(drop=True)
for user in users:
    print("Top %d recommendations for the userId: %s" %(top_k,user))
    top_k_recoms[top_k_recoms.uid.isin([user])]
    print("\n")
```

```
User Based - SURPRISE
Top 5 recommendations for the userId: A1TQBAHI3M4ZBQ
```

Out[32]:

	uid	iid	r_ui	est	details
6095	A1TQBAHI3M4ZBQ	B000ENRQ3M	3.000	4.907	{'actual_k': 0, 'was_impossible': False}
6096	A1TQBAHI3M4ZBQ	B005K7192G	5.000	4.907	{'actual_k': 0, 'was_impossible': False}
6097	A1TQBAHI3M4ZBQ	B00006IW1X	5.000	4.907	{'actual_k': 0, 'was_impossible': False}
6098	A1TQBAHI3M4ZBQ	B000ETXOC8	5.000	4.907	{'actual_k': 0, 'was_impossible': False}
6099	A1TQBAHI3M4ZBQ	B0015ZIS8K	5.000	4.907	{'actual_k': 0, 'was_impossible': False}

```
Top 5 recommendations for the userId: A1TDR7Y90SVCHL
```

Out[32]:

	uid	iid	r_ui	est	details
6105	A1TDR7Y90SVCHL	B002ZCXJZE	5.000	5.000	{'actual_k': 1, 'was_impossible': False}
6106	A1TDR7Y90SVCHL	B000HDJT4S	5.000	4.366	{'actual_k': 0, 'was_impossible': False}
6107	A1TDR7Y90SVCHL	B003EO1H7E	4.000	4.366	{'actual_k': 0, 'was_impossible': False}
6108	A1TDR7Y90SVCHL	B0064Z71T8	1.000	4.366	{'actual_k': 0, 'was_impossible': False}
6109	A1TDR7Y90SVCHL	B000JJSQ30	5.000	4.366	{'actual_k': 0, 'was_impossible': False}

Item Based Collaborative Filtering (UBCF)

We will be using Pearson's correlation similarity with KNNWithMeans algorithm to achieve this recommendation.

In [23]:
```
# Use smaller ratings dataset to avoid MemoryError (Dropped 80% data)
ratings_surp_sm = Dataset.load_from_df(ratings.sample(frac=0.8, random_state=25), R
trainset_sm, testset_sm = train_test_split(ratings_surp_sm, test_size=0.3, random_s
```

In [24]:
```
# Instantiate and train the Item Based KNN algorithm
algo = KNNWithMeans(50, sim_options = { 'name':'pearson', 'user_based':False })
algo.fit(trainset_sm)
```

```
Computing the pearson similarity matrix...
KeyboardInterrupt

Done computing similarity matrix.
```

NOTE: As the Item base is large enough, even afetr re-sampling the dataset by dropping 80% of the data throws MemoryError. Hence re-fraining from attempting IBCF using SURPRISE package

Evaluate the model

In [ ]:
```
predictions = algo.test(testset_sm)
print('RMSE of Item Based approach is:', accuracy.rmse(predictions, verbose=False))
```

In [ ]:
```
# Convert the predictions into pandas dataframe
ibcf_prediction = pd.DataFrame(predictions)
ibcf_prediction.head()
```

In [ ]:
```
# Sort in descending order
ibcf_prediction.sort_values(by=['uid','est'], ascending=False, inplace=True)
# Predict for a particular user
algo.predict(uid='A100UD67AHFODS', iid='B0019EHU8G')
```

Recommendation using Item Based approach

In [ ]:
```
# Create a list of users
```

```python
users = ['A1TQBAHI3M4ZBQ','A1TDR7Y90SVCHL']
top_k = 5

# Baseline Recommendation
print('Item Based - SURPRISE')
top_k_recoms = ibcf_prediction.groupby('uid').head(top_k).reset_index(drop=True)
for user in users:
    print("Top %d recommendations for the userId: %s" %(top_k,user))
    top_k_recoms[top_k_recoms.uid.isin([user])]
    print("\n")
```

Matrix Factorization based Collaborative Filtering (SVD)

In [47]:
```python
# Instantiate and train the SVD algorithm
algo = SVD(n_factors=10, biased=False)
algo.fit(trainset)
```

Out[47]: `<surprise.prediction_algorithms.matrix_factorization.SVD at 0x1950dc60cc0>`

Evaluate the model

In [43]:
```python
predictions = algo.test(testset)
print('RMSE of SVD approach is:', accuracy.rmse(predictions, verbose=False))
```

```
RMSE of SVD approach is: 1.6730182576277408
```

In [44]:
```python
# Convert the predictions into pandas dataframe
svd_surp_prediction = pd.DataFrame(predictions)
svd_surp_prediction.head()
```

Out[44]:

	uid	iid	r_ui	est	details
0	A34C9AFFZOI45T	B000KMU0NU	5.000	4.265	{'was_impossible': True, 'reason': 'User and i...
1	AXYM52DNK6NDF	B004C5HM6Y	5.000	4.265	{'was_impossible': True, 'reason': 'User and i...
2	A1TQBAHI3M4ZBQ	B000ENRQ3M	3.000	4.141	{'was_impossible': False}
3	A1TDR7Y90SVCHL	B0055OKHQS	5.000	4.265	{'was_impossible': True, 'reason': 'User and i...
4	A2IFKH3TJ10387	B005YR1PV2	4.000	3.424	{'was_impossible': False}

In [45]:
```python
# Sort in descending order
svd_surp_prediction.sort_values(by=['uid','est'], ascending=False, inplace=True)
# Predict for a particular user
algo.predict(uid='A100UD67AHFODS', iid='B0019EHU8G')
```

Out[45]:
```
Prediction(uid='A100UD67AHFODS', iid='B0019EHU8G', r_ui=None, est=4.15824242677329
2, details={'was_impossible': False})
```

Recommendation using Matrix Factorization approach

In [46]:
```python
# Create a list of users
users = ['A1TQBAHI3M4ZBQ','A1TDR7Y90SVCHL']
top_k = 5
```

```python
# Baseline Recommendation
print('SVD - SURPRISE')
top_k_recoms = svd_surp_prediction.groupby('uid').head(top_k).reset_index(drop=True
for user in users:
    print("Top %d recommendations for the userId: %s" %(top_k,user))
    top_k_recoms[top_k_recoms.uid.isin([user])]
    print("\n")
```

```
SVD - SURPRISE
Top 5 recommendations for the userId: A1TQBAHI3M4ZBQ
```

Out[46]:

	uid	iid	r_ui	est	details
6095	A1TQBAHI3M4ZBQ	B000CRFOMK	5.000	5.000	{'was_impossible': False}
6096	A1TQBAHI3M4ZBQ	B000Q8UAWY	5.000	5.000	{'was_impossible': False}
6097	A1TQBAHI3M4ZBQ	B00006IW1X	5.000	4.870	{'was_impossible': False}
6098	A1TQBAHI3M4ZBQ	B005K7192G	5.000	4.584	{'was_impossible': False}
6099	A1TQBAHI3M4ZBQ	B0071OSXYS	1.000	4.265	{'was_impossible': True, 'reason': 'User and i...

```
Top 5 recommendations for the userId: A1TDR7Y90SVCHL
```

Out[46]:

	uid	iid	r_ui	est	details
6105	A1TDR7Y90SVCHL	B002ZCXJZE	5.000	4.631	{'was_impossible': False}
6106	A1TDR7Y90SVCHL	B002JQNXZC	5.000	4.441	{'was_impossible': False}
6107	A1TDR7Y90SVCHL	B001TH7T2U	5.000	4.276	{'was_impossible': False}
6108	A1TDR7Y90SVCHL	B0055OKHQS	5.000	4.265	{'was_impossible': True, 'reason': 'User and i...
6109	A1TDR7Y90SVCHL	B0001RM3WU	5.000	4.265	{'was_impossible': True, 'reason': 'User and i...

Q8. Summarise your insights.

Model-based Collaborative Filtering is a personalised recommender system, the recommendations are based on the past behavior of the user and it is not dependent on any additional information.

The Popularity-based recommender system is non-personalised and the recommendations are based on frequecy counts, which may be not suitable to the user.You can see the differance above for the user id **A100UD67AHFODS**, **A2FZQF0MH29VYN**, The Popularity based model has recommended the same set of 5 products to both but Collaborative Filtering based model has recommended entire different list based on the user past purchase history.