Netflix Movie Recommendation Engine

Netflix held the Netflix Prize open competition for the best algorithm to predict user ratings for films. The grand prize was $1,000,000. This is the dataset that was used in that competition and we're going to use it to built an effective recommendation engine.

There's a movie_titles.csv file containing the details of the movie and there are 4 other combined_data_(1,2,3,4).txt files containing the user ratings.

Loading the dependencies and the data

In [1]:
```
# importing basic dependencies
import numpy as np
import pandas as pd
import scipy as sp
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import os
warnings.filterwarnings('ignore')
```

In [2]:
```python
# Loading the movie_titles.csv
movies=pd.read_csv('movie_titles.csv', names=['id','year','title'])

# peek into the dataframe
movies.head()
```

Out[2]:

	id	year	title
0	1	2003.0	Dinosaur Planet
1	2	2004.0	Isle of Man TT 2004 Review
2	3	1997.0	Character
3	4	1994.0	Paula Abdul's Get Up & Dance
4	5	2004.0	The Rise and Fall of ECW

In [3]:
```python
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17770 entries, 0 to 17769
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   id      17770 non-null  int64  
 1   year    17763 non-null  float64
 2   title   17770 non-null  object 
dtypes: float64(1), int64(1), object(1)
memory usage: 416.6+ KB
```

In the following piece of code we're combining all the four text files containing the user ratings into one massive rating.csv file.

In [4]:
```python
# creating a new file if it doesn't exist already
if not os.path.isfile('rating.csv'):

    # opening the newly created file on the 'write' mode
    rating=open('rating.csv', mode='w')

    separated_data=['combined_data_1.txt','combined_data_2.txt',
                    'combined_data_3.txt','combined_data_4.txt']

    # iterating through the separate files containing the user ratings
    for file in separated_data:
        with open(file) as f:
            # processing each line of the currently open file
            for line in f:
                line=line.strip()
                if line[-1]==':':
                    movie_id=line[:-1]
                else:
                    combining_rows=[x for x in line.split(',')]
                    combining_rows=[movie_id]+combining_rows
                    rating.write(','.join(combining_rows))
                    rating.write('\n')
        f.close()
    rating.close()
```

In [5]:
```
# Loading the above new csv file into a dataframe
rating=pd.read_csv('rating.csv', sep=',',
                   names=['Movie_Id', 'Customer_Id','Rating','Date'])
```

In [6]:
```
# peek into the dataframe
rating.head()
```

Out[6]:

	Movie_Id	Customer_Id	Rating	Date
0	1	1488844	3	2005-09-06
1	1	822109	5	2005-05-13
2	1	885013	4	2005-10-19
3	1	30878	4	2005-12-26
4	1	823519	3	2004-05-03

In [7]:
```
# merging the movies dataframe with rating dataframe
df=pd.merge(movies, rating, left_on='id', right_on='Movie_Id', how='inner')
```

In [8]:
```
# peek into the dataframe
df.head()
```

Out[8]:

	id	year	title	Movie_Id	Customer_Id	Rating	Date
0	1	2003.0	Dinosaur Planet	1	1488844	3	2005-09-06
1	1	2003.0	Dinosaur Planet	1	822109	5	2005-05-13
2	1	2003.0	Dinosaur Planet	1	885013	4	2005-10-19
3	1	2003.0	Dinosaur Planet	1	30878	4	2005-12-26
4	1	2003.0	Dinosaur Planet	1	823519	3	2004-05-03

Clearly we can drop id as it is merely as copy of Movie_Id and the title, year and Date are also not relevant in the context of building a recommendation system.

We're going to work with the following three variables only Movie_Id, Customer_Id and Rating.

In [9]:
```
# dropping the unnecessary variables
df=df[['Movie_Id', 'Customer_Id', 'Rating']]
```

Exploratory Data Analysis

In [10]:
```
# checking the metadata
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100480507 entries, 0 to 100480506
Data columns (total 3 columns):
 #   Column       Dtype
---  ------       -----
 0   Movie_Id     int64
 1   Customer_Id  int64
 2   Rating       int64
dtypes: int64(3)
memory usage: 3.0 GB
```

In [11]:
```
print(f'There are {df.Movie_Id.unique().shape[0]} unique movies in the dataframe')
```

```
There are 17770 unique movies in the dataframe
```

In [12]:
```
print(f'There are {df.Customer_Id.unique().shape[0]} customers in the dataframe')
```

```
There are 480189 customers in the dataframe
```

In [13]:
```
print(f"The minimum Customer_Id and the maximum Customer_Id in the df are {df.Customer_Id.r
```

```
The minimum Customer_Id and the maximum Customer_Id in the df are 6 and 2649429 respectiv
ely and we
know that there are only 480189 unique customers in the df which will lead to confusion.
Hence we're going to map them as continuous integers
```

In [14]:
```
# creating a dict map to map old Customer_Id to new and continuous Customer_Id
mapping={old:new for old,new in
         list(zip(sorted(df.Customer_Id.unique()),
                  range(df.Customer_Id.unique().shape[0])))}
```

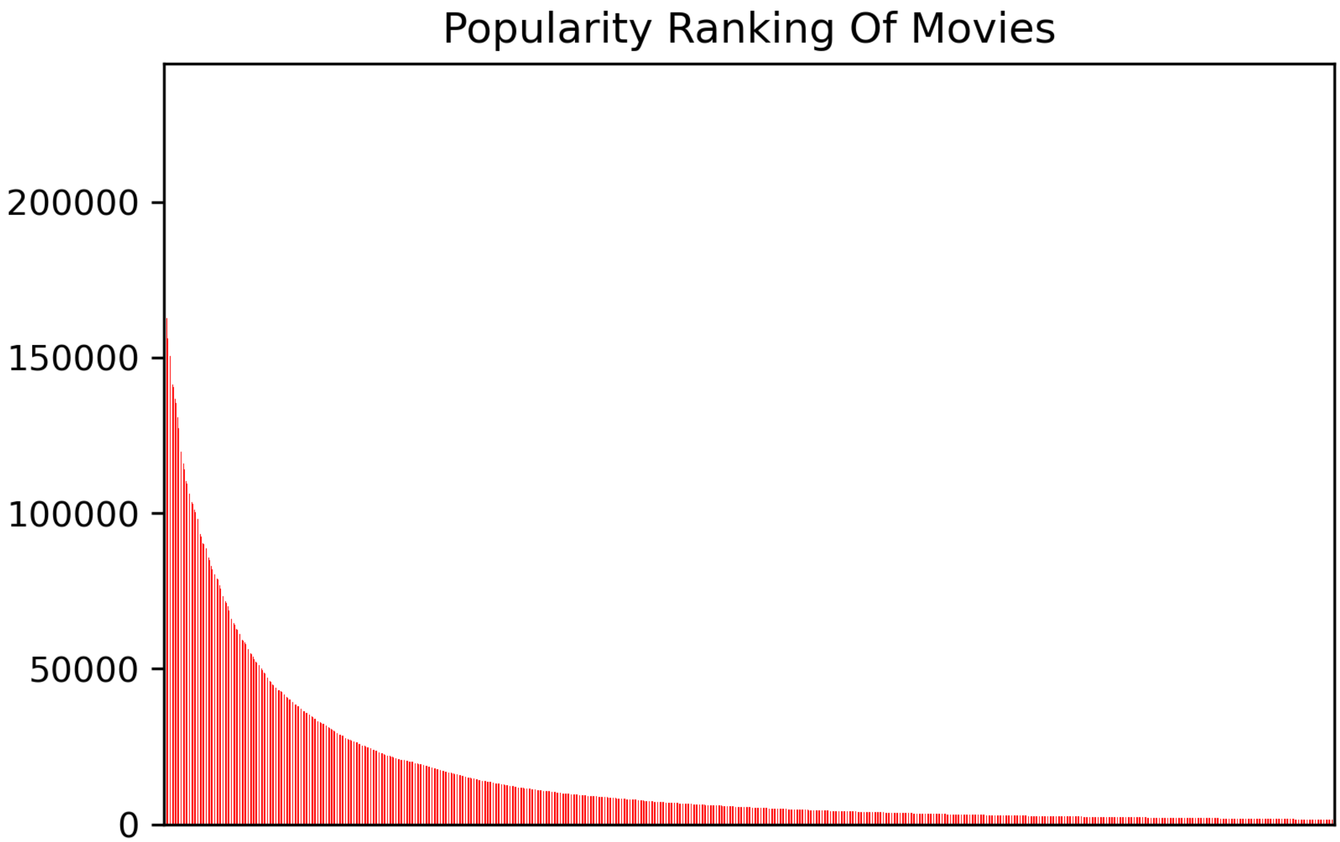
In [15]:
```
# applying the above mapping
df['Customer_Id']=df['Customer_Id'].map(mapping)
```

In [16]:
```
# checking if the new Customer_Id is continuous
print(df.Customer_Id.unique().shape[0])
print(df.Customer_Id.min())
print(df.Customer_Id.max())
```

```
480189
0
480188
```

Checking the distribution of popularity of the movies

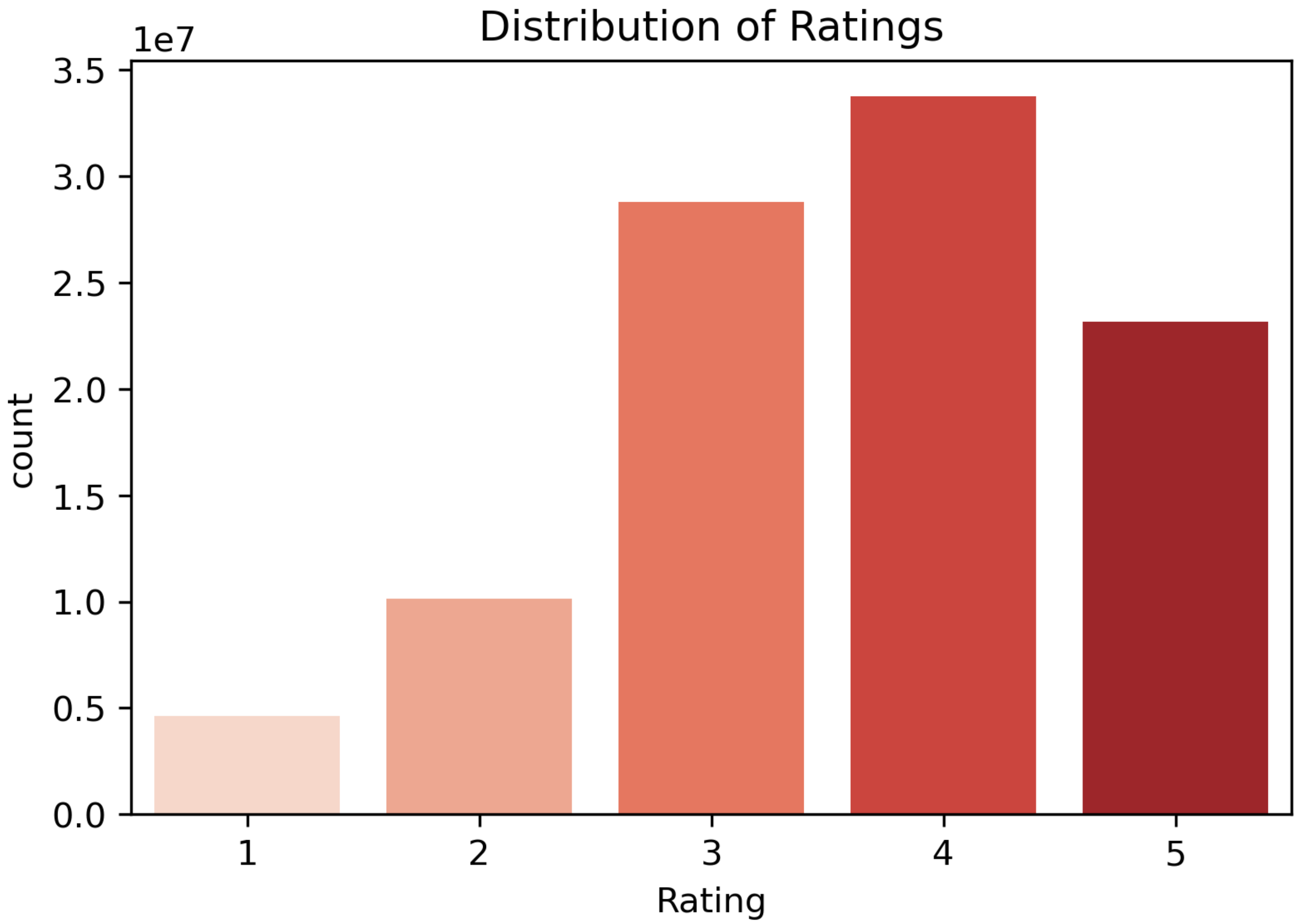
In [17]:
```
plt.figure(dpi=300)
plt.title('Popularity Ranking Of Movies')
df.Movie_Id.value_counts()[:6000].plot(kind='bar', color='red')
plt.xticks(ticks=[]);
```



The above plot shows the long tail distribution of the movies. The first few 100 movies or so have ratings steeply dropping from 230000 to 50000 and the rest of the movies have very low number of ratings. (Note that we've considered only the 6000 most popular movies).

Checking the distribution of ratings of the movies

In [18]:
```
plt.figure(dpi=300)
plt.title('Distribution of Ratings')
sns.countplot(df.Rating, palette='Reds');
```



As we can clearly see that 4 stars and 3 stars are the most and the second most frequent ratings given by users.

In [19]:
```
# there are no NaNs in any of the columns
df.isna().sum()
```

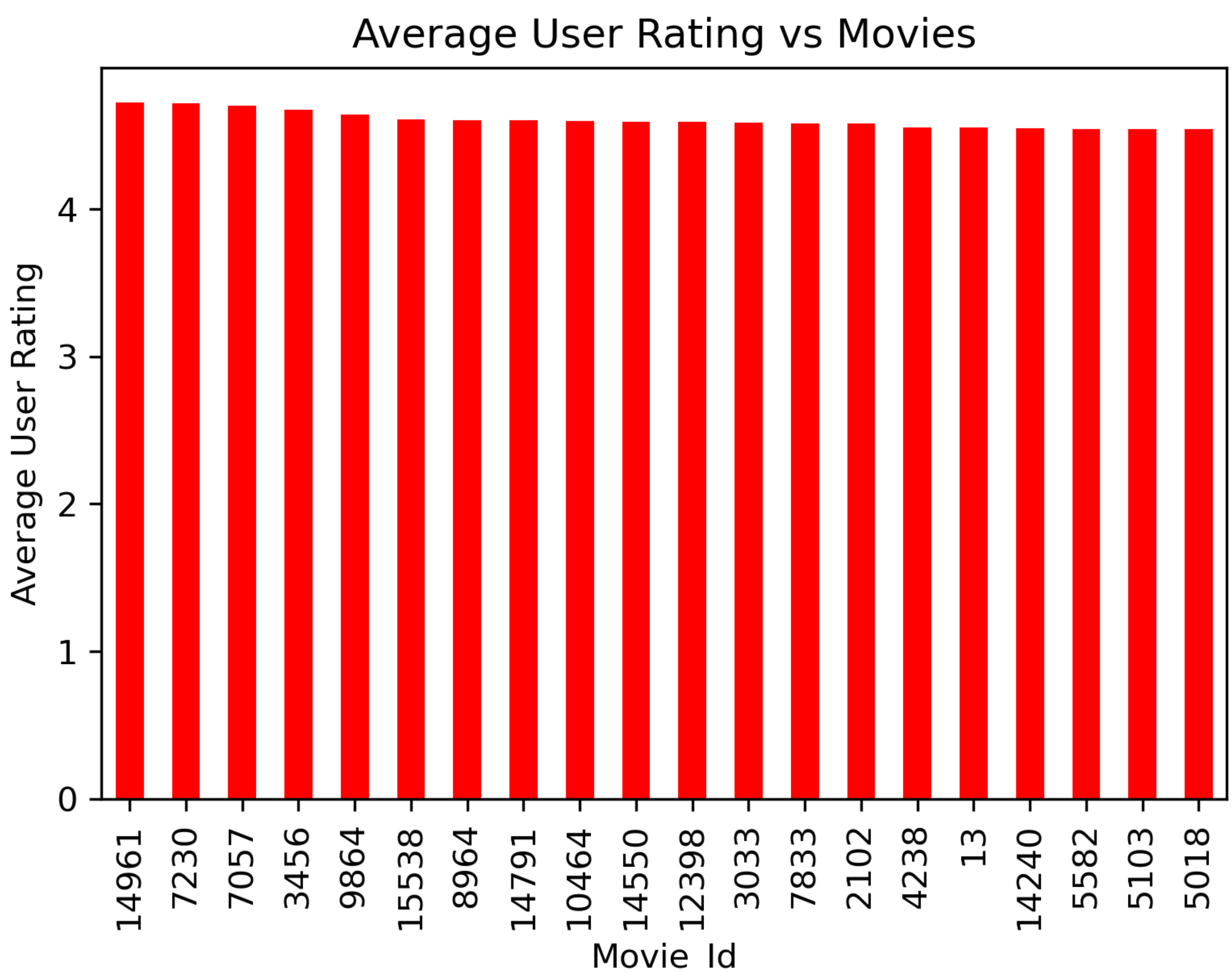
Out[19]:
```
Movie_Id       0
Customer_Id    0
Rating         0
dtype: int64
```

In [20]:
```
# there are no duplicated ratings
df.duplicated(['Movie_Id','Customer_Id']).sum()
```

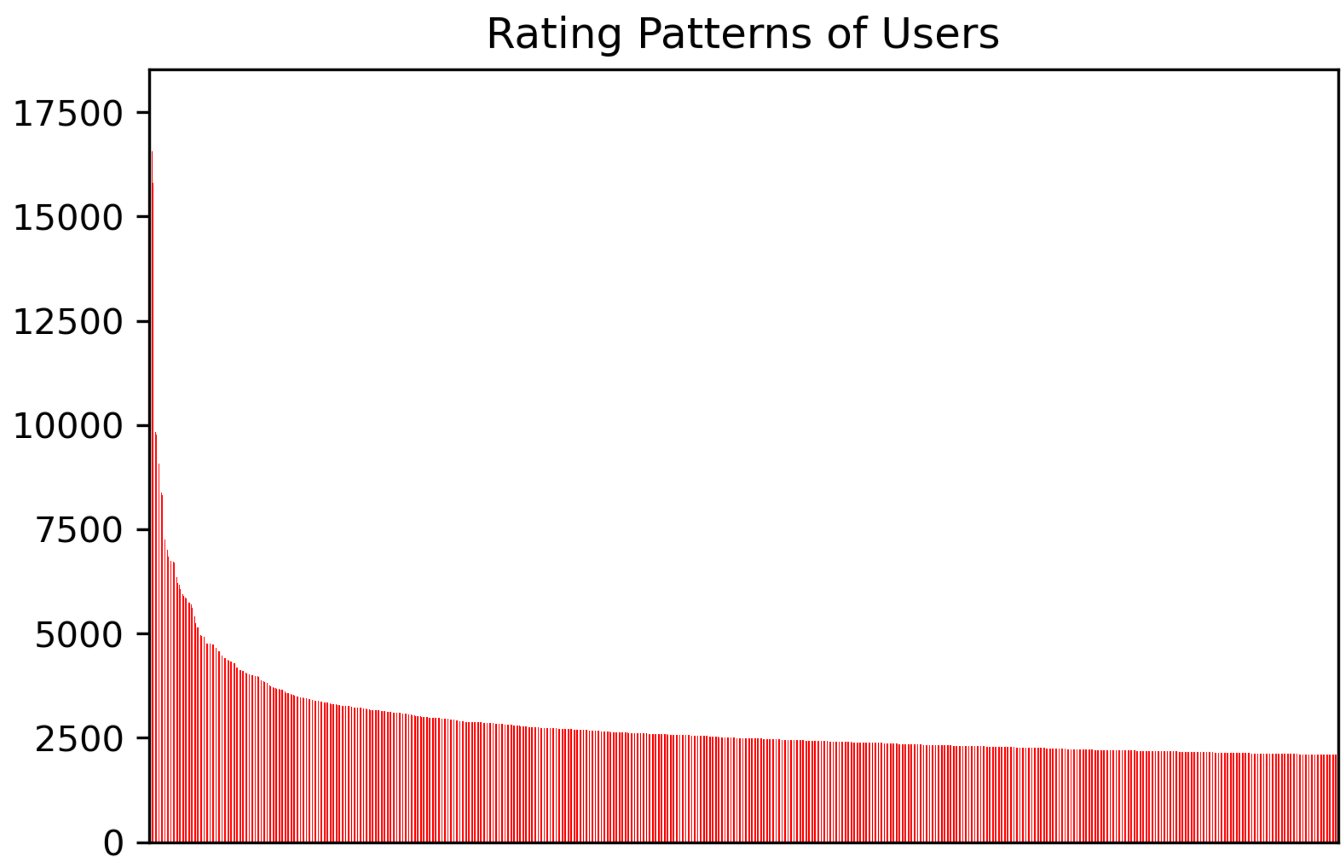
Out[20]:
```
0
```

List of top 20 best movies as per the average user rating.

In [21]:
```
# average user rating of top 20 movies
plt.figure(dpi=300)
plt.title('Average User Rating vs Movies')
plt.ylabel('Average User Rating')
(df.groupby(by='Movie_Id')['Rating']
 .mean().sort_values(ascending=False)[:20]).plot(kind='bar', color='red');
```



In [22]:
```
plt.figure(dpi=300)
plt.title('Rating Patterns of Users')
df.Customer_Id.value_counts()[:1000].plot(kind='bar', color='red')
plt.xticks(ticks=[]);
```



The above plot displays the rating patterns of the top 1000 frequent users and their rating behavior ranges from rating almost all movies to rating only handful of movies

In [23]:
```
# statistical description of ratings
df.Rating.describe()
```

Out[23]:
```
count    1.004805e+08
mean     3.604290e+00
std      1.085219e+00
min      1.000000e+00
25%      3.000000e+00
50%      4.000000e+00
75%      4.000000e+00
max      5.000000e+00
Name: Rating, dtype: float64
```

Utility Matrix

Here we're going to produce the utility matrix by pivoting the dataframe df with Movie_Id as rows, Customer_Id as columns and the Rating as the cell values. Also we're going to use item-item cosine similarity based collaborative filtering technique to build our recommendation system.

Let's centre the rating vectors of every movie by subtracting it by average rating of the movie. We're doing this in order to make better sense of the cosine similarity.

In [24]:
```
# finding the average rating for each movie
mean_rating=df.groupby(by='Movie_Id')[['Rating']].mean()
mean_rating.head()
```

Out[24]:

Movie_Id	Rating
1	3.749543
2	3.558621
3	3.641153
4	2.739437
5	3.919298

In [25]:
```
# merging the above df with the original df
tmp=pd.merge(df, mean_rating, left_on='Movie_Id',
             right_index=True, how='inner')
tmp.head()
```

Out[25]:

	Movie_Id	Customer_Id	Rating_x	Rating_y
0	1	270045	3	3.749543
1	1	149546	5	3.749543
2	1	160878	4	3.749543
3	1	5466	4	3.749543
4	1	149791	3	3.749543

In [26]:
```
# creating a df containing the movie-wise centred ratings
df=tmp[['Movie_Id','Customer_Id']]
df['Rating']=tmp['Rating_x']-tmp['Rating_y']
df.head()
```

Out[26]:

	Movie_Id	Customer_Id	Rating
0	1	270045	-0.749543
1	1	149546	1.250457
2	1	160878	0.250457
3	1	5466	0.250457
4	1	149791	-0.749543

Since utility matrix is going to be a massive, we're going to use csr_matrix to represent it.

In [27]:
```
rows=df.Movie_Id.values
cols=df.Customer_Id.values
data=df.Rating.values
utility=sp.sparse.csr_matrix((data, (rows, cols)),
shape=(1+df.Movie_Id.unique().shape[0],1+df.Customer_Id.unique().shape[0]))
utility
```

Out[27]:
```
<17771x480190 sparse matrix of type '<class 'numpy.float64'>'
	with 100480507 stored elements in Compressed Sparse Row format>
```

In [28]:
```
# unsupervised learning algo for recommendation system
from sklearn.neighbors import NearestNeighbors
```

In [29]:
```
# capturing the pair of movie index and user index who actually rated the movie
mov_idx,user_idx=utility.nonzero()
```

Recommender System Based On Collaborative Filtering Item-Item Cosine Similarity

In [30]:
```
def recommendations(user_id):
    # list of top 5 movies rated by the given user
    user_top_movies=utility[:,user_id].toarray().reshape(-1,)

    # finding the argmax for top 5 ratings
    user_top_movies=user_top_movies.argsort()[-5:][::-1]

    print(f'The list of top 5 rated movies by the Customer_Id {user_id} are')
    for film in movies.iloc[user_top_movies]['title'].values:
          print(film)

    # rating vectors of all the movies rated by this user
    # in otherwords utility submatrix
    sub_utility=utility[mov_idx[user_idx==user_id]]

    # instantiating KNN model with default 5 neigbors
    knn=NearestNeighbors(metric='cosine', n_jobs=-1, algorithm='brute')

    # training the above algorithm on the utility submatrix
    knn.fit(sub_utility)

    # collecting list of movies not watched by this user
    unwatched
    =list(set(range(1,17771)).difference(set(mov_idx[user_idx==user_id])))

    unwatched_rating=[-10]*17771
    # for every unwatched film by this user
    for newfilm in unwatched:

        # we're finding the rating vector of the movie
        rate_vector=utility[newfilm].toarray()

        # extracting the cosine distances and movie_id
        distance,movieid=knn.kneighbors(rate_vector, 5, return_distance=True)

        # reshape the distance and the ids
        distance,movieid=distance.reshape(-1,),movieid.reshape(-1,)

        # converting cosine distance to cosine similarity
        similarity=1-distance

        # ratings of the aforementioned 5 most similar movies by this user
        rates=utility[:,user_id][movieid].toarray().reshape(-1,)

        # finding the weighted mean of the 5 highly rated movies
        predicted_rating=np.dot(similarity,rates)/np.abs(similarity).sum()

        # assigning the predicted_rating at the respective index
        # corresponding to the movie index
        unwatched_rating[newfilm]=predicted_rating

    # converting it to numpy array
    unwatched_rating=np.array(unwatched_rating)

    # finding the argmax for top 5 ratings
    top_recommends=unwatched_rating.argsort()[-5:][::-1]

    print(f'\nThe list of top 5 recommended movies for the Customer_Id {user_id} are')
    for recommend in movies.iloc[top_recommends]['title'].values:
          print(recommend)
```

Making Recommendations

The recommender function will first display top 5 highly rated movies by a given Customer_ID and then it'll display top 5 recommended movies for this user. Do not expect these recommended movies to be similar to these top 5 highly rated movies by the user. Top 5 highly rated movies are displayed only to give you a gist of this particular user's taste however this meagre list of top 5 cannot capture the his taste completely (Imagine this user has given 5 star rating for 40 movies and the top 5 highly rated movies by this user will be just the first instance of the top 5). But the top 5 recommendations take into all the movies that the user has rated.

In [31]:
```
recommendations(160179)
```

```
The list of top 5 rated movies by the Customer_Id 160179 are
Proof Positive
The Bible Collection: Joseph
Dragon Ball: King Piccolo Saga: Part 2
Last Flight of Noah's Ark
Grind

The list of top 5 recommended movies for the Customer_Id 160179 are
Bonjour Monsieur Shlomi
Lois & Clark: The New Adventures of Superman: Season 1
Kojak: Season 1
It Was a Wonderful Life
Inner Senses
```

In [32]:
```
recommendations(82281)
```

```
The list of top 5 rated movies by the Customer_Id 82281 are
Beauty and the Beast: Special Edition
The Velocity of Gary
Love Me Tonight
Head On
Gladiator

The list of top 5 recommended movies for the Customer_Id 82281 are
Para Para Sakura
Disorganized Crime
High Times' Potluck
Worth Winning
Earth vs. The Flying Saucers
```

Recommending Similar Movies While Searching

In [33]:
```
# nearest_neighbor object to find the similar movies
similar_movies=NearestNeighbors(metric='cosine', n_jobs=-1, algorithm='brute')

# fitting the above learning algo on the utility matrix
similar_movies.fit(utility)

def search():
    # lower casing the searched title
    movie_name=input('Enter your search phrase here: ').lower()

    # finding the matches in the list of movie titles
    filtered=movies[movies.title.str.lower().str.contains(movie_name)]

    if len(filtered)==0:
        print("Couldn't find this movie. Please try again!")
        return
    if len(filtered)>10:
        print("Search phrase is too generic. Please try again!")
        return

    print(f'\nTop matches for your search phrase are:')
    for title in filtered.title.values:
        print(title)

    match_ids=filtered.id.values # list of search phrase matching movie ids
    similar_ids=[]
    seen=set() # to avoid repeatedly recommending same movie

    for ids in match_ids:
        # capturing cosine distance and similar movie id from kneighbors
        # for ids from every matching id
        dis,mov=similar_movies.kneighbors(utility[ids],
                                          n_neighbors=6,
                                          return_distance=True)
        for i in range(1,6):
            # adding the cosine distance and similar movie id as long as
            # the similar movie id is not already in the match_ids list
            if (mov[0][i] not in match_ids) and (mov[0][i] not in seen):
                seen.add(mov[0][i])
                similar_ids.append([dis[0][i],mov[0][i]])

    similar_ids.sort(key=lambda x:x[0]) # sorting based on the distance

    print(f'\nRecommended watch:')
    for dist, mov_id in similar_ids[:10]:
        # printing only the titles of the top 10 most similar movies
        print(movies.title.values[movies.id==mov_id][0])
```

In [34]:
```
search()
```

```
Enter your search phrase here: sdfhjk
Couldn't find this movie. Please try again!
```

In [35]:
```
search()
```

```
Enter your search phrase here: a
Search phrase is too generic. Please try again!
```

In [36]:
```
search()
```

```
Enter your search phrase here: the godfather

Top matches for your search phrase are:
The Godfather  Part II
The Godfather  Part III
The Godfather
The Godfather Trilogy: Bonus Material

Recommended watch:
GoodFellas: Special Edition
One Flew Over the Cuckoo's Nest
The Silence of the Lambs
Apocalypse Now
Star Wars: Episode I: The Phantom Menace
Hannibal
Scarface: 20th Anniversary Edition
The Devil's Advocate
Seven: Bonus Material
Scarface: 20th Anniversary Edition: Bonus Material
```

In [37]:
```
search()
```

```
Enter your search phrase here: finding nemo

Top matches for your search phrase are:
Finding Nemo (Widescreen)
Finding Nemo (Full-screen)

Recommended watch:
Monsters  Inc.
Shrek (Full-screen)
Shrek 2
A Bug's Life
The Incredibles
Toy Story 2
```

In [38]:
```
search()
```

```
Enter your search phrase here: Shaolin Soccer

Top matches for your search phrase are:
Shaolin Soccer

Recommended watch:
Kung Fu Hustle
The Legend of Drunken Master
Iron Monkey
The Blind Swordman: Zatoichi
Once Upon a Time in China 2
```

You can see from the above examples that
If we search for a gangster movie, then our model recommends similar gangster movies.
If we search for a animated movie, then our model recommends similar animated movies.
If we search for a chinese movie, then our model recommends similar chinese movies.

The highlight is that, all these recommendations are purely based on the similarity between the ratings of the movies, not based on the similarity between the content of the movies. Because our model is built using collaborative filtering approach and not using content based filtering approach.

Hope you found this notebook useful!
Lets connect
[https://www.linkedin.com/in/fazil-mohammed-4062711b2/ (https://www.linkedin.com/in/fazil-mohammed-4062711b2/)](https://www.linkedin.com/in/fazil-mohammed-4062711b2/)