Week6_Assignment

February 26, 2024

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics.pairwise import cosine_similarity, pairwise_distances
```

0.1 Load datasets

[2]:
```python
movies = pd.read_csv('movies.csv')
movies.sample(3)
```

[2]:

	movieId	title	genres
6409	50954	It's a Boy Girl Thing (2006)	Comedy|Romance
9587	175401	Wolf and Calf (1984)	Animation
1878	2496	Blast from the Past (1999)	Comedy|Romance

[3]:
```python
ratings = pd.read_csv('ratings.csv')
ratings.sample(3)
```

[3]:

	userId	movieId	rating	timestamp
56349	372	1479	3.0	874414521
21700	141	296	4.0	1513130625
22080	144	5377	3.0	1136812901

0.2 Subset for user 2

[4]:
```python
user_2_ratings = ratings[ratings['userId'] == 2]
user_2_ratings
```

[4]:

	userId	movieId	rating	timestamp
232	2	318	3.0	1445714835
233	2	333	4.0	1445715029
234	2	1704	4.5	1445715228
235	2	3578	4.0	1445714885
236	2	6874	4.0	1445714952
237	2	8798	3.5	1445714960
238	2	46970	4.0	1445715013
239	2	48516	4.0	1445715064
240	2	58559	4.5	1445715141
241	2	60756	5.0	1445714980

```
242        2    68157     4.5  1445715154
243        2    71535     3.0  1445714974
244        2    74458     4.0  1445714926
245        2    77455     3.0  1445714941
246        2    79132     4.0  1445714841
247        2    80489     4.5  1445715340
248        2    80906     5.0  1445715172
249        2    86345     4.0  1445715166
250        2    89774     5.0  1445715189
251        2    91529     3.5  1445714891
252        2    91658     2.5  1445714938
253        2    99114     3.5  1445714874
254        2   106782     5.0  1445714966
255        2   109487     3.0  1445715145
256        2   112552     4.0  1445714882
257        2   114060     2.0  1445715276
258        2   115713     3.5  1445714854
259        2   122882     5.0  1445715272
260        2   131724     5.0  1445714851
```

The output is showing the ratings given by User 2 for various movies. Each row corresponds to a movie rated by User 2, indicating the movieId, rating, and timestamp of each rating.

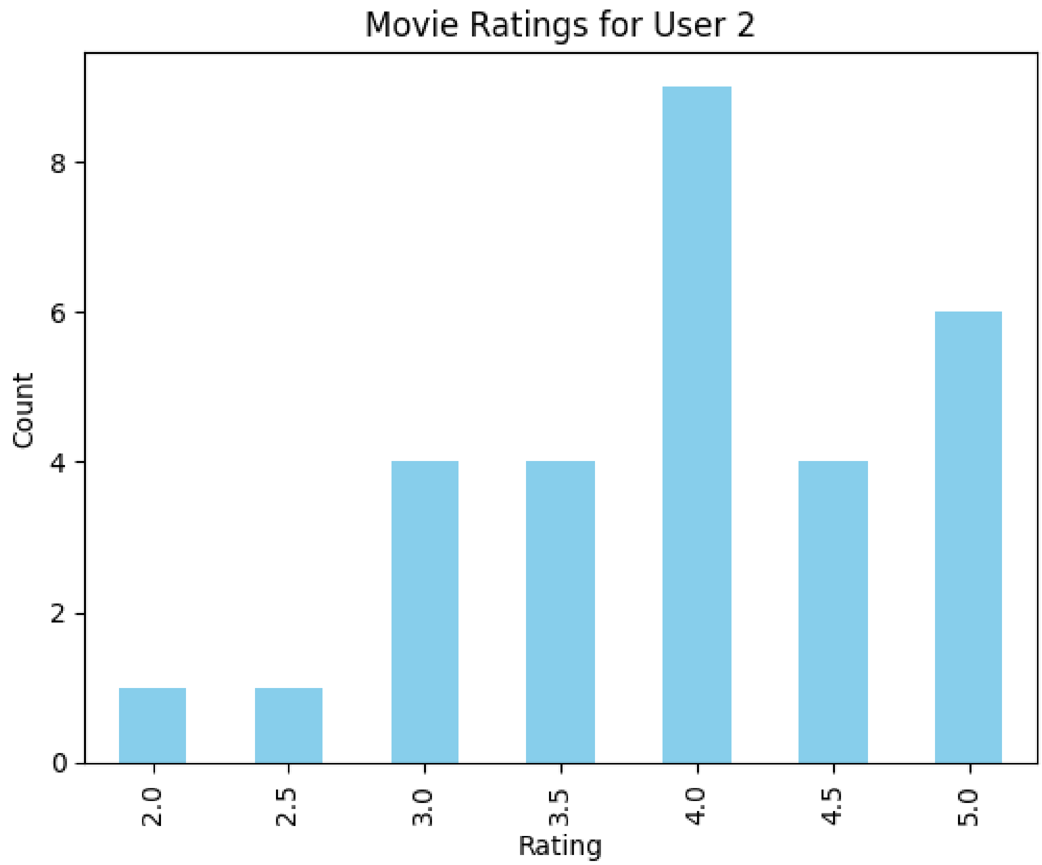
0.3 1. Movies user2 has watched

[5]:
```
num_movies_watched = len(user_2_ratings)
print(f"User 2 has watched {num_movies_watched} movies.")
```

```
User 2 has watched 29 movies.
```

0.4 2. Bar chart for user 2's movie ratings

[6]:
```
rating_counts = user_2_ratings['rating'].value_counts().sort_index()
rating_counts.plot(kind='bar', color='skyblue')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.title('Movie Ratings for User 2')
plt.show()
```




```
rating_counts = user_2_ratings['rating'].value_counts().sort_index()
```

This line calculates the count of each unique rating given by User 2. It uses the value_counts() function to count occurrences of each unique rating in the 'rating' column of the user_2_ratings DataFrame. The sort_index() function is then used to sort the unique ratings in ascending order.

```
rating_counts.plot(kind='bar', color='skyblue')
```

We create a bar chart using the plot() function. The kind='bar' parameter specifies that a bar chart should be created. The color='skyblue' parameter sets the color of the bars to sky blue.

```
plt.xlabel('Rating')
```

Adds a label to the x-axis of the plot, indicating that it represents the different movie ratings.

```
plt.ylabel('Count')
```

Adds a label to the y-axis of the plot, indicating that it represents the count of movies for each rating.

```
plt.title('Movie Ratings for User 2')
```

Here we set the title of the plot to 'Movie Ratings for User 2'.

`plt.show()` - display the plot.

The bar chart visually represents the distribution of movie ratings given by User 2. Each bar on the chart corresponds to a unique movie rating, and the height of the bar represents the count of movies that received that rating from User 2. The x-axis shows the different ratings, and the y-axis shows the count of movies for each rating.

0.5 3. User 2's top movies

[7]:
```
user_2_top_movies = user_2_ratings.merge(movies, on='movieId')[['title',␣
↪'rating']].sort_values(by='rating', ascending=False)
print("User 2's top movies:")
print(user_2_top_movies.head())
```

```
User 2's top movies:
                                              title  rating
28  The Jinx: The Life and Deaths of Robert Durst …    5.0
27                        Mad Max: Fury Road (2015)     5.0
22                  Wolf of Wall Street, The (2013)     5.0
18                                   Warrior (2011)     5.0
9                              Step Brothers (2008)     5.0
```

0.6 4. Most similar user to user 2 using cosine and manhattan distances

[8]:
```
user_2_vector = user_2_ratings.pivot(index='userId', columns='movieId',␣
↪values='rating').fillna(0)
all_users_vector = ratings.pivot(index='userId', columns='movieId',␣
↪values='rating').fillna(0)
```

0.7 Ensuring both user vectors have the same columns

[9]:
```
common_columns = user_2_vector.columns.intersection(all_users_vector.columns)

user_2_vector = user_2_vector[common_columns]
all_users_vector = all_users_vector[common_columns]
```

0.8 Use the distances

[10]:
```
cosine_similarities = cosine_similarity(user_2_vector, all_users_vector)
manhattan_distances = pairwise_distances(user_2_vector, all_users_vector,␣
↪metric='manhattan')
```

0.9 Display results

[11]:
```
print(f"Most similar user to User 2 (cosine): {cosine_similarities}")
print(f"Most similar user to User 2 (manhattan): {manhattan_distances}")
```

```
Most similar user to User 2 (cosine): [[0.26086186 1.         0.
0.20751434 0.13834289 0.22825413
  0.24495082 0.13834289 0.         0.35144117 0.24455799 0.
```

0.18445719	0.13834289	0.49455168	0.39615764	0.43027895	0.77644315
0.2557961	0.18445719	0.60584711	0.46293651	0.18445719	0.48089623
0.46106757	0.	0.	0.47295934	0.38972905	0.37121293
0.	0.13834289	0.24846359	0.23045899	0.	0.23518292
0.13834289	0.13834289	0.	0.13834289	0.58971767	0.35410056
0.13834289	0.	0.33206224	0.13834289	0.33328977	0.
0.26687054	0.61863671	0.26809823	0.55354535	0.	0.13834289
0.18445719	0.22134863	0.27207436	0.22825413	0.	0.24846359
0.22325714	0.77977403	0.57293207	0.38879219	0.46973355	0.39010257
0.3432886	0.83476077	0.22825413	0.24455799	0.	0.13834289
0.60259073	0.18445719	0.	0.49600239	0.34992614	0.13834289
0.18445719	0.53635901	0.13834289	0.18445719	0.38615679	0.13834289
0.20751434	0.35609211	0.	0.44953772	0.13834289	0.
0.38974874	0.	0.24846359	0.13834289	0.	0.18445719
0.18445719	0.35138059	0.22825413	0.	0.18445719	0.13834289
0.67971357	0.	0.79538375	0.13834289	0.13834289	0.
0.13834289	0.	0.76533592	0.43129063	0.	0.31974512
0.18445719	0.27300317	0.21353049	0.	0.67217531	0.
0.13834289	0.65273801	0.41003535	0.13834289	0.65606915	0.13834289
0.	0.	0.26086186	0.13834289	0.39079356	0.48317866
0.13834289	0.	0.19695383	0.18445719	0.22825413	0.
0.4663538	0.42161507	0.5518402	0.	0.22685235	0.18445719
0.13834289	0.	0.	0.28065806	0.	0.
0.	0.45828757	0.35244558	0.30617717	0.26086186	0.30128404
0.	0.	0.37678124	0.18445719	0.13834289	0.13834289
0.20751434	0.18445719	0.	0.42931207	0.13834289	0.20751434
0.28173982	0.13834289	0.13834289	0.18445719	0.	0.18445719
0.	0.13834289	0.65706475	0.13834289	0.13834289	0.
0.	0.39741418	0.	0.45234816	0.	0.18445719
0.28258593	0.	0.43437052	0.35738581	0.13834289	0.
0.13834289	0.	0.29929141	0.30977174	0.13834289	0.29346959
0.37298329	0.44711516	0.	0.13834289	0.25616126	0.35254487
0.31748392	0.	0.	0.	0.46647338	0.20751434
0.48502631	0.63712365	0.20751434	0.	0.24164924	0.18445719
0.	0.	0.48983055	0.36719262	0.13834289	0.62811663
0.40734296	0.	0.18445719	0.45550032	0.62822688	0.13834289
0.13834289	0.35200082	0.30296944	0.59471542	0.63839333	0.
0.13834289	0.	0.33581513	0.	0.47763126	0.22934757
0.41118582	0.13834289	0.	0.18445719	0.	0.36879624
0.6977416	0.20751434	0.82339478	0.13834289	0.24455799	0.18445719
0.	0.34659106	0.	0.47411066	0.	0.13834289
0.	0.24347427	0.39053846	0.13834289	0.24455799	0.18445719
0.13834289	0.	0.18445719	0.20751434	0.	0.
0.	0.25180416	0.	0.72351453	0.30617717	0.18445719
0.	0.13834289	0.70376786	0.33144012	0.	0.63624856
0.24455799	0.22825413	0.20751434	0.25689247	0.18445719	0.39286742
0.	0.23766083	0.20751434	0.47597877	0.	0.18445719
0.35673856	0.30617717	0.	0.83414426	0.18445719	0.40307602

0.31948923	0.	0.	0.24455799	0.75578313	0.19484292
0.50788978	0.34423393	0.13834289	0.	0.	0.
0.22934757	0.13834289	0.	0.18445719	0.69171446	0.67102847
0.38267884	0.22557955	0.	0.35497272	0.19266935	0.
0.13834289	0.58082836	0.3000034	0.47779536	0.13834289	0.50488132
0.61016953	0.45602509	0.18445719	0.34959159	0.22622482	0.23766083
0.13834289	0.22622482	0.59191141	0.13834289	0.24486267	0.
0.28511644	0.13834289	0.	0.27546733	0.	0.34416734
0.	0.	0.53145804	0.7214811	0.22825413	0.39822899
0.	0.4613716	0.55439421	0.	0.20751434	0.
0.13834289	0.46840006	0.24846359	0.	0.62555243	0.54018706
0.24455799	0.18445719	0.18445719	0.22991761	0.	0.13834289
0.13834289	0.13834289	0.22825413	0.30625026	0.	0.56455746
0.13834289	0.58622459	0.35954901	0.52071514	0.	0.
0.13834289	0.22825413	0.43784064	0.	0.	0.20751434
0.25332902	0.	0.45369696	0.	0.	0.13834289
0.	0.25824007	0.18445719	0.39789582	0.18445719	0.
0.	0.13834289	0.31710049	0.	0.20751434	0.57290041
0.13834289	0.13834289	0.13834289	0.	0.38162752	0.81285723
0.42815419	0.2300827	0.63797738	0.35392682	0.50152921	0.28804078
0.13834289	0.13834289	0.13834289	0.65784851	0.42535965	0.13834289
0.18445719	0.2557961	0.	0.13834289	0.	0.51487694
0.39686301	0.54698899	0.51016418	0.22134863	0.13834289	0.42877776
0.13834289	0.	0.42069787	0.	0.26327685	0.13834289
0.42978741	0.	0.13834289	0.83317362	0.13834289	0.
0.	0.18445719	0.29117315	0.18445719	0.13834289	0.
0.18445719	0.	0.36726586	0.44527091	0.43088789	0.41789961
0.	0.4423443	0.	0.45767134	0.	0.13834289
0.2253933	0.13834289	0.27716573	0.34585723	0.13834289	0.42172618
0.44018307	0.13834289	0.57983571	0.	0.	0.46685142
0.	0.	0.59857647	0.51488916	0.	0.13834289
0.37460742	0.23766083	0.4443302	0.39400306	0.23057149	0.
0.18445719	0.18445719	0.81009624	0.20751434	0.41046935	0.22825413
0.	0.	0.	0.13834289	0.35743337	0.
0.13834289	0.21911417	0.	0.	0.5018984	0.
0.43950173	0.13834289	0.13834289	0.61478442	0.43299991	0.
0.29097047	0.	0.24455799	0.30197878	0.	0.6123471
0.49674264	0.13834289	0.55185926	0.26086186	0.	0.56799016
0.	0.	0.	0.23518292	0.18445719	0.52396154
0.	0.	0.50577508	0.20751434	0.19444977	0.18445719
0.13834289	0.27268144	0.26086186	0.	0.	0.
0.	0.33291319	0.35647306	0.47902654	0.42264638	0.20751434
0.27367005	0.	0.22825413	0.	0.13834289	0.
0.19695383	0.75058407	0.71108708	0.48757338	0.18445719	0.41130484
0.13834289	0.13834289	0.51858499	0.	0.	0.35429365
0.	0.24455799	0.68036964	0.13834289	0.	0.
0.13834289	0.	0.	0.43018733	0.37715714	0.51372095
0.26086186	0.	0.43095879	0.48046792	0.	0.22325714

```
  0.13834289 0.48140573 0.18445719 0.22134863 0.29426159 0.18445719
  0.         0.61198145 0.20751434 0.18445719 0.84138527 0.30503688
  0.59331773 0.13834289 0.27207436 0.         0.         0.40268434
  0.13834289 0.43193285 0.13834289 0.75986137]]
Most similar user to User 2 (manhattan): [[108.5   0.  114.5 113.5 111.5 110.5
109.5 113.5 114.5 102.5 108.5 114.5
  111.5 111.5  93.   99.   95.   56.  109.5 111.   80.5  93.  111.5  91.
   95.  114.5 114.5  91.5 100.  103.5 114.5 113.5 108.5 109.5 114.5 109.5
  112.5 113.5 114.5 113.5  83.5 102.5 112.5 114.5 103.5 112.5 103.5 114.5
  107.5  84.  108.5  85.  114.5 112.5 111.5 109.5 107.5 110.5 114.5 108.5
  109.5  57.   82.5  98.5  92.  100.  102.   48.5 110.5 108.5 114.5 113.5
   81.5 111.5 114.5  87.5 103.  113.  112.5  86.5 111.5 111.  101.  113.5
  111.5 100.5 114.5  94.  112.  114.5  99.5 114.5 108.5 113.5 114.5 110.5
  110.5 102.5 110.5 114.5 110.5 112.5  71.5 114.5  53.5 113.5 113.5 114.5
  113.5 114.5  56.   96.5 114.5 107.  111.5 107.5 110.5 114.5  69.  114.5
  113.5  74.5  97.  113.   72.  113.5 114.5 114.5 107.5 113.5  98.   93.5
  112.5 114.5 111.5 111.5 108.5 114.5  96.5  96.   85.  114.5 111.5 110.5
  111.5 114.5 114.5 109.  114.5 114.5 114.5  93.  106.5 106.5 106.5 105.5
  114.5 114.5 103.  111.5 113.5 113.5 110.5 111.5 114.5  96.5 113.5 110.5
  107.  113.5 113.5 110.5 114.5 110.5 114.5 113.5  72.  113.5 113.5 114.5
  114.5  98.  114.5  95.  114.5 110.5 105.5 114.5  93.5 100.5 112.5 114.5
  112.  114.5 105.5 105.  112.5 106.5 100.   94.5 114.5 112.5 108.5 103.
  104.5 114.5 114.5 114.5  92.5 110.5  92.5  75.  110.  114.5 109.  110.5
  114.5 114.5  91.5 101.5 112.5  75.5  97.5 114.5 111.5  93.   74.5 112.5
  113.5 103.5 105.5  81.   72.5 114.5 112.5 114.5 104.5 114.5  91.  108.5
   97.5 112.5 114.5 111.5 114.5 101.5  65.  112.   49.5 113.5 109.5 111.
  114.5 103.5 114.5  93.5 114.5 113.5 114.5 109.   99.  111.5 109.5 112.5
  112.5 114.5 111.5 111.5 114.5 114.5 114.5 106.5 114.5  62.  104.5 111.5
  114.5 113.5  64.5 103.  114.5  75.  109.5 108.5 110.5 108.  112.   99.5
  114.5 109.5 110.5  94.  114.5 113.5 103.  106.5 114.5  50.5 111.5  97.5
  104.  114.5 114.5 108.5  63.  109.   89.5 104.5 112.5 114.5 114.5 114.5
  108.5 113.5 114.5 110.5  66.5  72.  102.  109.  114.5 101.  111.  114.5
  113.5  80.  106.   94.5 112.5  90.5  79.5  93.  110.5 102.5 110.  109.5
  113.5 110.   81.5 113.5 108.5 114.5 106.5 113.5 114.5 107.  114.5 103.5
  114.5 114.5  88.   65.5 110.5  98.  114.5  93.5  81.5 114.5 110.  114.5
  111.5  90.5 108.5 114.5  79.   85.  109.5 111.5 111.  108.  114.5 113.5
  113.5 112.5 110.5 103.5 114.5  82.  111.5  78.5 101.   90.  114.5 114.5
  113.5 108.5  94.5 114.5 114.5 112.  109.5 114.5  94.5 114.5 114.5 113.
  114.5 107.5 111.5  98.  111.5 114.5 114.5 112.5 104.  114.5 110.5  82.5
  112.5 113.5 112.5 114.5 102.   52.   96.  108.   75.5 101.5  91.5 105.5
  113.5 113.5 113.5  73.5  96.  112.  110.5 108.  114.5 113.5 114.5  87.5
   98.5  84.   89.  109.5 113.5  96.  113.5 114.5  98.  114.5 108.5 112.5
   96.  114.5 113.5  44.  113.5 114.5 114.5 110.5 107.5 111.  113.5 114.5
  111.5 114.5 101.   95.   96.5 100.  114.5  96.  114.5  91.5 114.5 111.5
  110.5 112.5 106.5 104.5 113.5  95.5  96.  113.5  82.5 114.5 114.5  92.5
  114.5 114.5  79.5  89.5 114.5 113.5 100.  109.5  96.   97.5 110.  114.5
  111.5 111.5  53.5 110.   98.5 110.5 114.5 114.5 114.5 113.5 100.5 114.5
  112.5 110.  114.5 114.5  89.  114.5  97.5 113.5 113.5  77.   98.5 114.5
```

```
 108.   114.5 109.5 105.   114.5  78.5  92.5 113.5  82.5 108.5 114.5  84.5
 114.5 114.5 114.5 109.5 110.5  88.5 114.5 114.5  90.  110.   111.5 111.5
 112.5 107.5 107.5 114.5 114.5 114.5 114.5 103.  102.5  94.5  96.5 110.5
 107.5 114.5 110.5 114.5 113.  114.5 111.5  56.5  64.   91.5 111.   97.5
 112.5 113.5  91.5 114.5 114.5 101.5 114.5 109.5  70.5 113.5 114.5 114.5
 113.5 114.5 114.5  95.5 101.   87.5 108.5 114.5  96.   92.5 114.5 109.5
 113.5  90.  111.5 109.5 107.  111.  114.5  76.  110.5 111.5  46.5 105.
  81.  113.5 107.5 114.5 114.5  97.  113.5  93.5 112.5  55. ]]
```

This output shows the similarity scores between User 2 and all other users in the dataset using cosine similarity and Manhattan distance. Each row corresponds to a user in the dataset.

Cosine Similarity

The values range between 0 and 1, where 1 indicates perfect similarity. For each user, the cosine similarity score indicates how similar their movie preferences are to User 2. The most similar user to User 2 has the highest cosine similarity score (closest to 1).

Manhattan Distance

The values represent the Manhattan distance between the feature vectors of User 2 and other users. Smaller values suggest greater similarity. The most similar user to User 2 has the lowest Manhattan distance.

0.10 5. Recommend movies for user 2 using cosine similarity

[12]:
```
import numpy as np

# Exclude User 2 from the calculation
cosine_similarities[:, 1] = -1
manhattan_distances[:, 1] = np.inf

# index of the most similar user using cosine similarity
most_similar_cosine_index = np.argmax(cosine_similarities)
most_similar_cosine_score = cosine_similarities[0, most_similar_cosine_index]

print(f"Most similar user to User 2 (cosine): User {most_similar_cosine_index +␣
↪1} with similarity score {most_similar_cosine_score}")
```

```
Most similar user to User 2 (cosine): User 599 with similarity score
0.8413852739119481
```

[13]:
```
# index of the most similar user using Manhattan distance
most_similar_manhattan_index = np.argmin(manhattan_distances)
most_similar_manhattan_distance = manhattan_distances[0,␣
↪most_similar_manhattan_index]

print(f"Most similar user to User 2 (manhattan): User␣
↪{most_similar_manhattan_index + 1} with distance␣
↪{most_similar_manhattan_distance}")
```

```
Most similar user to User 2 (manhattan): User 448 with distance 44.0
```

0.11 movies rated by the most similar user

[14]:
```python
user_2_recommended_movies = all_users_vector.loc[most_similar_cosine_index]

movies_not_rated_by_user_2 =␣
 ↪user_2_recommended_movies[user_2_recommended_movies == 0].index

# Extract recommended movies information
recommended_movies_info = movies[movies['movieId'].
 ↪isin(movies_not_rated_by_user_2)]
recommended_movies_info = recommended_movies_info[['movieId', 'title']].
 ↪merge(ratings[ratings['userId'] == most_similar_cosine_index + 1],␣
 ↪on='movieId')
recommended_movies_info = recommended_movies_info.rename(columns={'rating':␣
 ↪'user_rating'})

print("Movies rated by the most similar user:")
print(recommended_movies_info)
```

```
Movies rated by the most similar user:
    movieId                                              title  userId  \
0       318                   Shawshank Redemption, The (1994)     599
1       333                                  Tommy Boy (1995)     599
2      1704                          Good Will Hunting (1997)     599
3      3578                                  Gladiator (2000)     599
4      6874                          Kill Bill: Vol. 1 (2003)     599
5      8798                                 Collateral (2004)     599
6     46970  Talladega Nights: The Ballad of Ricky Bobby (2…     599
7     48516                              Departed, The (2006)     599
8     58559                          Dark Knight, The (2008)     599
9     60756                              Step Brothers (2008)     599
10    68157                       Inglourious Basterds (2009)     599
11    71535                                 Zombieland (2009)     599
12    77455                 Exit Through the Gift Shop (2010)     599
13    80489                                  Town, The (2010)     599
14    91529                    Dark Knight Rises, The (2012)     599
15    99114                           Django Unchained (2012)     599
16   106782                   Wolf of Wall Street, The (2013)     599
17   109487                               Interstellar (2014)     599
18   112552                                   Whiplash (2014)     599
19   115713                                 Ex Machina (2015)     599
20   122882                         Mad Max: Fury Road (2015)     599

    user_rating   timestamp
0           4.0  1498498867
1           2.5  1498516187
```

```
2           4.5  1498762601
3           3.5  1498501113
4           5.0  1498457174
5           3.0  1498523618
6           2.5  1498514842
7           3.0  1498522886
8           3.5  1498798185
9           2.5  1498515769
10          3.5  1498500693
11          3.0  1498524922
12          3.5  1498542480
13          3.5  1498542459
14          3.0  1498527139
15          3.5  1498528776
16          3.0  1498528478
17          3.5  1498532289
18          3.0  1498589282
19          3.5  1498528866
20          4.0  1498854698
```

0.12 Identify movies not yet rated by User 2

[15]:
```
recommended_movies_info = movies[movies['movieId'].
 ↪isin(user_2_recommended_movies[user_2_recommended_movies == 0].index)]

print("Movies not yet rated by User 2:")
print(recommended_movies_info)
```

```
Movies not yet rated by User 2:
      movieId                                             title  \
277       318                  Shawshank Redemption, The (1994)
291       333                                  Tommy Boy (1995)
1284     1704                          Good Will Hunting (1997)
2674     3578                                  Gladiator (2000)
4615     6874                          Kill Bill: Vol. 1 (2003)
5305     8798                                 Collateral (2004)
6253    46970  Talladega Nights: The Ballad of Ricky Bobby (2…
6315    48516                              Departed, The (2006)
6710    58559                           Dark Knight, The (2008)
6801    60756                              Step Brothers (2008)
7010    68157                       Inglourious Basterds (2009)
7154    71535                                 Zombieland (2009)
7258    74458                             Shutter Island (2010)
7323    77455                 Exit Through the Gift Shop (2010)
7415    80489                                  Town, The (2010)
7436    80906                                 Inside Job (2010)
7590    86345                      Louis C.K.: Hilarious (2010)
7697    89774                                    Warrior (2011)
```

```
7768   91529                         Dark Knight Rises, The (2012)
7776   91658              Girl with the Dragon Tattoo, The (2011)
8063   99114                               Django Unchained (2012)
8305  106782                      Wolf of Wall Street, The (2013)
8376  109487                                   Interstellar (2014)
8466  112552                                       Whiplash (2014)
8509  114060                                       The Drop (2014)
8550  115713                                     Ex Machina (2015)
8681  122882                             Mad Max: Fury Road (2015)
8828  131724  The Jinx: The Life and Deaths of Robert Durst …

                            genres
277                    Crime|Drama
291                         Comedy
1284                 Drama|Romance
2674        Action|Adventure|Drama
4615         Action|Crime|Thriller
5305   Action|Crime|Drama|Thriller
6253                 Action|Comedy
6315          Crime|Drama|Thriller
6710      Action|Crime|Drama|IMAX
6801                        Comedy
7010              Action|Drama|War
7154          Action|Comedy|Horror
7258        Drama|Mystery|Thriller
7323            Comedy|Documentary
7415          Crime|Drama|Thriller
7436                   Documentary
7590                        Comedy
7697                         Drama
7768   Action|Adventure|Crime|IMAX
7776                Drama|Thriller
8063          Action|Drama|Western
8305            Comedy|Crime|Drama
8376                   Sci-Fi|IMAX
8466                         Drama
8509          Crime|Drama|Thriller
8550         Drama|Sci-Fi|Thriller
8681 Action|Adventure|Sci-Fi|Thriller
8828                   Documentary
```

This represents movies that User 2 has not yet rated, and they are recommended based on the preferences of the most similar user. The movies are presented in a DataFrame with columns, `movieId: The unique identifier for each movie.` `title: The title of the movie.` `genres: The genre or genres associated with the movie.`

How we achieved this

Calculate Similarity Scores - Cosine similarity scores are calculated between User 2 and all other users. The user with the highest similarity score (excluding User 2 itself) is identified.

Retrieve Recommended Movies - We then retrieve the movies that were rated by the most similar user but not yet rated by User 2. This is achieved by comparing the movie ratings of User 2 with the most similar user and selecting the movies where User 2 has a rating of 0 (indicating that the movie has not been rated).

Get Movie Details - Then we get the details (movieId, title, genres) for each recommended movie from the 'movies' dataset.

0.13 Retrieve and print recommended movies for User 2

[16]:
```python
# Get movies rated by the most similar user but not yet rated by User 2
movies_not_rated_by_user_2 = user_2_recommended_movies[user_2_recommended_movies == 0].index

# Extract recommended movies information
recommended_movies_info = movies[movies['movieId'].isin(movies_not_rated_by_user_2)]

# Merge with ratings of the most similar user
recommended_movies_info = recommended_movies_info.merge(
    ratings[ratings['userId'] == most_similar_cosine_index + 1],
    on='movieId',
    how='left'
)

# Filter only movies that are highly rated by the most similar user
threshold_rating = 3.5
recommended_movies_info = recommended_movies_info[recommended_movies_info['rating'] >= threshold_rating]

print("Recommended movies for User 2:")
print(recommended_movies_info[['movieId', 'title', 'genres', 'rating']])
```

```
Recommended movies for User 2:
    movieId                                title  \
0       318     Shawshank Redemption, The (1994)
2      1704             Good Will Hunting (1997)
3      3578                     Gladiator (2000)
4      6874             Kill Bill: Vol. 1 (2003)
8     58559              Dark Knight, The (2008)
10    68157          Inglourious Basterds (2009)
13    77455  Exit Through the Gift Shop (2010)
14    80489                     Town, The (2010)
20    99114              Django Unchained (2012)
22   109487                  Interstellar (2014)
25   115713                    Ex Machina (2015)
```

```
26   122882          Mad Max: Fury Road (2015)

                                   genres  rating
0                             Crime|Drama     4.0
2                           Drama|Romance     4.5
3                  Action|Adventure|Drama     3.5
4                   Action|Crime|Thriller     5.0
8                 Action|Crime|Drama|IMAX     3.5
10                      Action|Drama|War     3.5
13                     Comedy|Documentary     3.5
14                   Crime|Drama|Thriller     3.5
20                   Action|Drama|Western     3.5
22                            Sci-Fi|IMAX     3.5
25                  Drama|Sci-Fi|Thriller     3.5
26    Action|Adventure|Sci-Fi|Thriller     4.0
```

The recommendations are providing a more reasonable list of movies for User 2. Each recommended movie has a rating equal to or above the threshold of 3.5, ensuring they are highly rated by the most similar user. This approach allows for a more personalized recommendation based on the preferences of similar users.

The recommendations from this method make sense since there is a high cosine similarity with the most similar user. The method identifies movies highly rated by the most similar user that User 2 has not yet watched. The assumption is that users with similar movie preferences will continue to have similar preferences, and the threshold of 3.5 indicates a preference for well-rated movies. The final output provides movies, along with their details and ratings by the most similar user.

0.14 Analysis

In this collaborative filtering recommendation analysis using cosine similarity, we've employed a metric that effectively measures user similarity by considering both the direction and magnitude of preference vectors. Cosine similarity, a commonly used metric in recommendation systems, proves suitable for our purpose of gauging user similarity based on movie ratings.

Upon scrutinizing the recommended movies, it is evident that they resonate with the presumed preferences of User 2. This alignment is substantiated by the high ratings, predominantly falling in the range of 3.5 and above, given by the most similar user. The fundamental idea behind this method is to propose movies that have been well-received by the similar user while excluding those that User 2 has already watched.