# Assignment:

1. Perform some movie recommendations and analysis for user 2:

- How many movies has this user watched?
- Plot a bar chart of their movie ratings. The bar chart should be the counts of the number of unique ratings.
  - Hint: the `sort_index()` function from pandas might be helpful to make the bar plot look nicer.
- What are some of user 2's top movies?
  - Hint: to get the actual movie titles, you can use pandas merge function, although using the movie IDs is OK too.
- Find the most similar user in the movielens dataset to user 2 using at least 2 distance metrics. Be sure to use cosine distance as one of your choices.
- Recommend a few movies for user 2 using similarity metrics.
- Do the recommendations from this method make sense?
- Write a short analysis of the results, and justify which similarity metric(s) you used.

Optional challenges:

- Perform other analyses (e.g. EDA, visualizations) of the movies watched from this dataset, or from a bigger part of the dataset for the movielens dataset: https://grouplens.org/datasets/movielens/
- Add yourself as a user in the data with ratings for movies you've watched, and find recommendations for next movies to watch.
- Use a more advanced collaborative or content-based recommender to make recommendations (e.g. using the surprise package in Python)
  - Try making predictions for user 2. How do they compare with our basic model?
  - Add your own movie ratings, or use another recommender dataset and add your own preferences, then get recommendations for yourself

In [1]:
```
#import numpy as np
#import pandas as pd
#import matplotlib.pyplot as plt
```

## Import ratings data

In [15]:
```
df = pd.read_csv('ratings.csv', index_col='movieId')
df
```

Out[15]:

| | userId | rating | timestamp |
|---|---|---|---|
| **movieId** | | | |
| **1** | 1 | 4.0 | 964982703 |
| **3** | 1 | 4.0 | 964981247 |
| **6** | 1 | 4.0 | 964982224 |
| **47** | 1 | 5.0 | 964983815 |
| **50** | 1 | 5.0 | 964982931 |
| **...** | ... | ... | ... |
| **166534** | 610 | 4.0 | 1493848402 |
| **168248** | 610 | 5.0 | 1493850091 |
| **168250** | 610 | 5.0 | 1494273047 |
| **168252** | 610 | 5.0 | 1493846352 |
| **170875** | 610 | 3.0 | 1493846415 |

100836 rows × 3 columns

In [16]:

```
col = df.columns
col
```

Out[16]:

```
Index(['userId', 'rating', 'timestamp'], dtype='object')
```

## Look at movies watched by user 2

User 2 has watched and rated 58 movies

In [19]:

```
two_df = df[df['userId'] == 2]
two_df
```

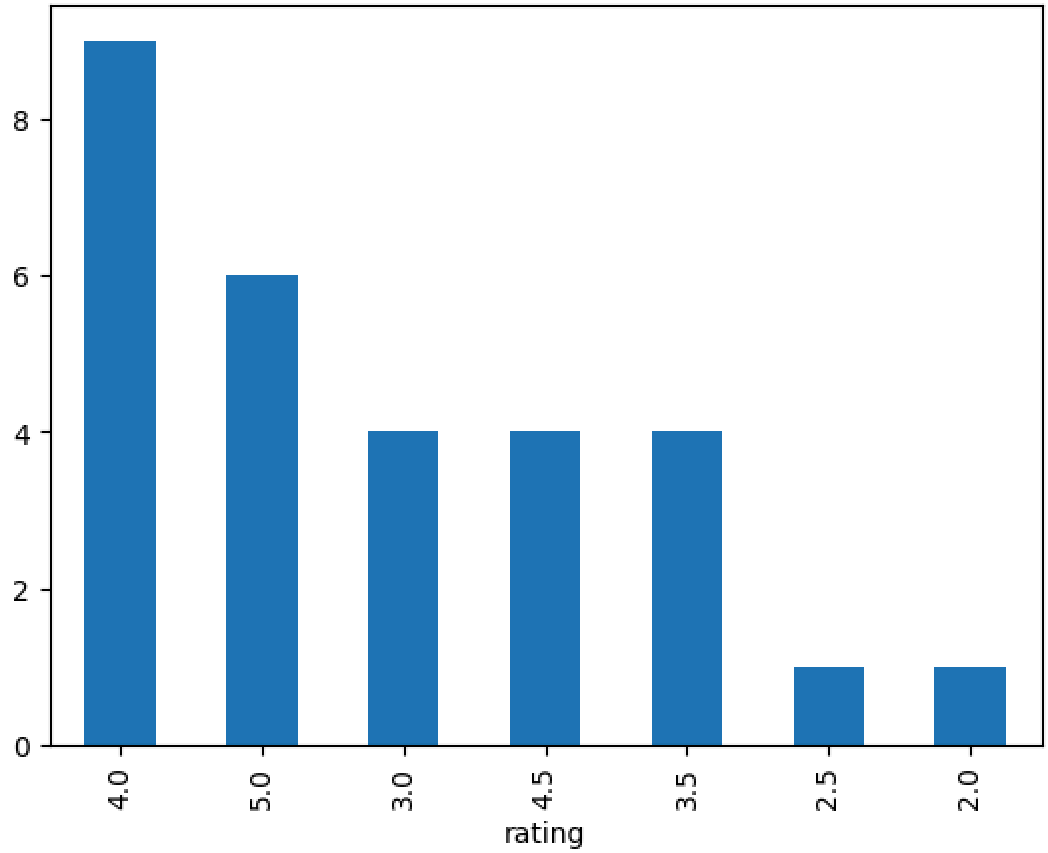
Out[19]:

| movieId | userId | rating | timestamp |
|---|---|---|---|
| 318 | 2 | 3.0 | 1445714835 |
| 333 | 2 | 4.0 | 1445715029 |
| 1704 | 2 | 4.5 | 1445715228 |
| 3578 | 2 | 4.0 | 1445714885 |
| 6874 | 2 | 4.0 | 1445714952 |
| 8798 | 2 | 3.5 | 1445714960 |
| 46970 | 2 | 4.0 | 1445715013 |
| 48516 | 2 | 4.0 | 1445715064 |
| 58559 | 2 | 4.5 | 1445715141 |
| 60756 | 2 | 5.0 | 1445714980 |
| 68157 | 2 | 4.5 | 1445715154 |
| 71535 | 2 | 3.0 | 1445714974 |
| 74458 | 2 | 4.0 | 1445714926 |
| 77455 | 2 | 3.0 | 1445714941 |
| 79132 | 2 | 4.0 | 1445714841 |
| 80489 | 2 | 4.5 | 1445715340 |
| 80906 | 2 | 5.0 | 1445715172 |
| 86345 | 2 | 4.0 | 1445715166 |
| 89774 | 2 | 5.0 | 1445715189 |
| 91529 | 2 | 3.5 | 1445714891 |
| 91658 | 2 | 2.5 | 1445714938 |
| 99114 | 2 | 3.5 | 1445714874 |
| 106782 | 2 | 5.0 | 1445714966 |
| 109487 | 2 | 3.0 | 1445715145 |
| 112552 | 2 | 4.0 | 1445714882 |
| 114060 | 2 | 2.0 | 1445715276 |
| 115713 | 2 | 3.5 | 1445714854 |
| 122882 | 2 | 5.0 | 1445715272 |
| 131724 | 2 | 5.0 | 1445714851 |

## Plot

In [20]:
```
two_df['rating'].value_counts().plot.bar()
```

Out[20]: <Axes: xlabel='rating'>




## User 2 top movies

### Importing movies file

In [21]:
```
df2 = pd.read_csv('movies.csv', index_col='movieId')
df2
```

Out[21]:

| movieId | title | genres |
|---|---|---|
| 1 | Toy Story (1995) | Adventure\|Animation\|Children\|Comedy\|Fantasy |
| 2 | Jumanji (1995) | Adventure\|Children\|Fantasy |
| 3 | Grumpier Old Men (1995) | Comedy\|Romance |
| 4 | Waiting to Exhale (1995) | Comedy\|Drama\|Romance |
| 5 | Father of the Bride Part II (1995) | Comedy |
| ... | ... | ... |
| 193581 | Black Butler: Book of the Atlantic (2017) | Action\|Animation\|Comedy\|Fantasy |
| 193583 | No Game No Life: Zero (2017) | Animation\|Comedy\|Fantasy |
| 193585 | Flint (2017) | Drama |
| 193587 | Bungo Stray Dogs: Dead Apple (2018) | Action\|Animation |
| 193609 | Andrew Dice Clay: Dice Rules (1991) | Comedy |

9742 rows × 2 columns

## Merging the two datasets and sorting by rating descending.

We can see some of user 2's top movies include The Jinx: The Life and Deaths of Robert Durst, Mad Max: Fury Road, and The Wolf of Wall Street

In [35]:

```
two_df.merge(df2, how='inner', on='movieId', sort='True').sort_values(by='rating',
```

Out[35]:

| movieId | userId | rating | timestamp | title | genres |
|---|---|---|---|---|---|
| **131724** | 2 | 5.0 | 1445714851 | The Jinx: The Life and Deaths of Robert Durst ... | Documentary |
| **122882** | 2 | 5.0 | 1445715272 | Mad Max: Fury Road (2015) | Action\|Adventure\|Sci-Fi\|Thriller |
| **106782** | 2 | 5.0 | 1445714966 | Wolf of Wall Street, The (2013) | Comedy\|Crime\|Drama |
| **89774** | 2 | 5.0 | 1445715189 | Warrior (2011) | Drama |
| **60756** | 2 | 5.0 | 1445714980 | Step Brothers (2008) | Comedy |
| **80906** | 2 | 5.0 | 1445715172 | Inside Job (2010) | Documentary |
| **1704** | 2 | 4.5 | 1445715228 | Good Will Hunting (1997) | Drama\|Romance |
| **58559** | 2 | 4.5 | 1445715141 | Dark Knight, The (2008) | Action\|Crime\|Drama\|IMAX |
| **68157** | 2 | 4.5 | 1445715154 | Inglourious Basterds (2009) | Action\|Drama\|War |
| **80489** | 2 | 4.5 | 1445715340 | Town, The (2010) | Crime\|Drama\|Thriller |
| **333** | 2 | 4.0 | 1445715029 | Tommy Boy (1995) | Comedy |
| **112552** | 2 | 4.0 | 1445714882 | Whiplash (2014) | Drama |
| **86345** | 2 | 4.0 | 1445715166 | Louis C.K.: Hilarious (2010) | Comedy |
| **79132** | 2 | 4.0 | 1445714841 | Inception (2010) | Action\|Crime\|Drama\|Mystery\|Sci-Fi\|Thriller\|IMAX |
| **74458** | 2 | 4.0 | 1445714926 | Shutter Island (2010) | Drama\|Mystery\|Thriller |
| **48516** | 2 | 4.0 | 1445715064 | Departed, The (2006) | Crime\|Drama\|Thriller |
| **46970** | 2 | 4.0 | 1445715013 | Talladega Nights: The Ballad of Ricky Bobby (2... | Action\|Comedy |
| **6874** | 2 | 4.0 | 1445714952 | Kill Bill: Vol. 1 (2003) | Action\|Crime\|Thriller |
| **3578** | 2 | 4.0 | 1445714885 | Gladiator (2000) | Action\|Adventure\|Drama |
| **91529** | 2 | 3.5 | 1445714891 | Dark Knight Rises, The (2012) | Action\|Adventure\|Crime\|IMAX |

| movieId | userId | rating | timestamp | title | genres |
|---|---|---|---|---|---|
| 99114 | 2 | 3.5 | 1445714874 | Django Unchained (2012) | Action\|Drama\|Western |
| 8798 | 2 | 3.5 | 1445714960 | Collateral (2004) | Action\|Crime\|Drama\|Thriller |
| 115713 | 2 | 3.5 | 1445714854 | Ex Machina (2015) | Drama\|Sci-Fi\|Thriller |
| 77455 | 2 | 3.0 | 1445714941 | Exit Through the Gift Shop (2010) | Comedy\|Documentary |
| 71535 | 2 | 3.0 | 1445714974 | Zombieland (2009) | Action\|Comedy\|Horror |
| 109487 | 2 | 3.0 | 1445715145 | Interstellar (2014) | Sci-Fi\|IMAX |
| 318 | 2 | 3.0 | 1445714835 | Shawshank Redemption, The (1994) | Crime\|Drama |
| 91658 | 2 | 2.5 | 1445714938 | Girl with the Dragon Tattoo, The (2011) | Drama\|Thriller |
| 114060 | 2 | 2.0 | 1445715276 | The Drop (2014) | Crime\|Drama\|Thriller |

## Most similar user in the movielens dataset to user 2

In [47]:
```
wide = ratings.pivot(index='userId', columns='movieId', values='rating')
wide.head()
```

Out[47]:

| movieId<br>userId | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | ... | 193565 | 193567 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4.0 | NaN | 4.0 | NaN | NaN | 4.0 | NaN | NaN | NaN | NaN | ... | NaN | NaN |
| 2 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN |
| 3 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN |
| 4 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN |
| 5 | 4.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN |

5 rows × 9724 columns

In [48]:
```
cor = wide.T.corr()
```

In [49]:
```
cor.head()
```

Out[49]:

| userId | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | |
|---|---|---|---|---|---|---|---|---|---|
| userId | | | | | | | | | |
| 1 | 1.000000 | NaN | 0.079819 | 0.207983 | 0.268749 | -0.291636 | -0.118773 | 0.469668 | 0.91 |
| 2 | NaN | 1.0 | NaN | NaN | NaN | NaN | -0.991241 | NaN | |
| 3 | 0.079819 | NaN | 1.000000 | NaN | NaN | NaN | NaN | NaN | |
| 4 | 0.207983 | NaN | NaN | 1.000000 | -0.336525 | 0.148498 | 0.542861 | 0.117851 | |
| 5 | 0.268749 | NaN | NaN | -0.336525 | 1.000000 | 0.043166 | 0.158114 | 0.028347 | |

5 rows × 610 columns

## Using Pearson, user 341 is one of the most like user 2

In [51]:
```
cor.loc[2].sort_values(ascending=False)
```

Out[51]:
```
userId
2      1.0
341    1.0
93     1.0
143    1.0
148    1.0
      ...
602    NaN
604    NaN
605    NaN
607    NaN
609    NaN
Name: 2, Length: 610, dtype: float64
```

In [52]:
```
wide.loc[2].notna().equals(wide.loc[341].notna())
```

Out[52]:
```
False
```

In [53]:
```
rated_5_by_341_not_watched_by_2 = (wide.loc[341] == 5) & (wide.loc[2].isna())
print(wide.loc[2][rated_5_by_341_not_watched_by_2])
print(wide.loc[341][rated_5_by_341_not_watched_by_2])
```

```
movieId
1        NaN
59900    NaN
Name: 2, dtype: float64
movieId
1         5.0
59900     5.0
Name: 341, dtype: float64
```

In [54]:
```
wide.fillna(-1, inplace=True)
```

In [56]:
```
from scipy.spatial.distance import euclidean
```

In [57]:
```
euclidean(wide.iloc[2], wide.iloc[341])
```

Out[57]:
```
41.212862069989754
```

In [58]:
```
from scipy.spatial.distance import pdist, squareform
```

In [59]:
```
euclidean_distances = squareform(pdist(wide, metric=euclidean)) # or metric='euclid
```

In [60]:
```
euclidean_df = pd.DataFrame(data=euclidean_distances, columns=wide.index, index=wid
```

In [61]:
```
euclidean_df.head()
```

Out[61]:

| userId | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| **userId** | | | | | | | | |
| **1** | 0.000000 | 86.239492 | 84.731930 | 96.979379 | 84.516271 | 108.083301 | 91.651514 | 84.38 |
| **2** | 86.239492 | 0.000000 | 36.806929 | 74.567084 | 41.039615 | 84.777650 | 60.172668 | 41.31 |
| **3** | 84.731930 | 36.806929 | 0.000000 | 73.908727 | 39.956226 | 84.584277 | 60.112395 | 40.44 |
| **4** | 96.979379 | 74.567084 | 73.908727 | 0.000000 | 72.608539 | 101.847926 | 83.330667 | 74.63 |
| **5** | 84.516271 | 41.039615 | 39.956226 | 72.608539 | 0.000000 | 77.479029 | 59.958319 | 33.83 |

5 rows × 610 columns

### Using Euclidean, user 442 is more like user 2

In [63]:
```
euclidean_df.loc[2].sort_values()
```

Out[63]:
```
userId
2        0.000000
442     29.000000
461     30.495901
189     30.809901
508     31.488093
          ...
448    171.200175
610    171.373860
599    185.184368
474    206.630709
414    232.408046
Name: 2, Length: 610, dtype: float64
```

In [64]:
```
euclidean_df.loc[2].sort_values().loc[341]
```

Out[64]: 42.91852746774987

### Cosine has the same user, 442, as the closest to user 2

In [67]:
```
cosine_distances = squareform(pdist(wide, metric='cosine'))
cosine_df = pd.DataFrame(cosine_distances, columns=wide.index, index=wide.index)
cosine_df.loc[2].sort_values()
```

Out[67]:
```
userId
2      0.000000
442    0.042025
461    0.046059
189    0.046957
508    0.049443
         ...
610    0.762312
448    0.817785
599    0.936812
474    0.975777
414    1.084648
Name: 2, Length: 610, dtype: float64
```

In [66]:
```
cosine_df.loc[2].sort_values().loc[341]
```

Out[66]: 0.0892952689103661

## Create Recommendations

In [38]:
```
ratings = pd.read_csv('ratings.csv')
movies = pd.read_csv('movies.csv')
```

In [39]:
```
movies.head()
```

Out[39]:

| | movieId | title | genres |
|---|---|---|---|
| **0** | 1 | Toy Story (1995) | Adventure\|Animation\|Children\|Comedy\|Fantasy |
| **1** | 2 | Jumanji (1995) | Adventure\|Children\|Fantasy |
| **2** | 3 | Grumpier Old Men (1995) | Comedy\|Romance |
| **3** | 4 | Waiting to Exhale (1995) | Comedy\|Drama\|Romance |
| **4** | 5 | Father of the Bride Part II (1995) | Comedy |

In [40]:
```
ratings.head()
```

Out[40]:

| | userId | movieId | rating | timestamp |
|---|---|---|---|---|
| **0** | 1 | 1 | 4.0 | 964982703 |
| **1** | 1 | 3 | 4.0 | 964981247 |
| **2** | 1 | 6 | 4.0 | 964982224 |
| **3** | 1 | 47 | 5.0 | 964983815 |
| **4** | 1 | 50 | 5.0 | 964982931 |

In [41]:
```
pd.to_datetime(ratings['timestamp'], unit='s')
```

Out[41]:
```
0         2000-07-30 18:45:03
1         2000-07-30 18:20:47
2         2000-07-30 18:37:04
3         2000-07-30 19:03:35
4         2000-07-30 18:48:51
                  ...
100831    2017-05-03 21:53:22
100832    2017-05-03 22:21:31
100833    2017-05-08 19:50:47
100834    2017-05-03 21:19:12
100835    2017-05-03 21:20:15
Name: timestamp, Length: 100836, dtype: datetime64[ns]
```

In [42]:
```
ratings.groupby('movieId').sum()
```

Out[42]:

| movieId | userId | rating | timestamp |
|---|---|---|---|
| **1** | 65904 | 843.0 | 242914455479 |
| **2** | 36251 | 377.5 | 124938583322 |
| **3** | 14747 | 169.5 | 52265734386 |
| **4** | 1539 | 16.5 | 6290052048 |
| **5** | 14679 | 150.5 | 48640552594 |
| **...** | ... | ... | ... |
| **193581** | 184 | 4.0 | 1537109082 |
| **193583** | 184 | 3.5 | 1537109545 |
| **193585** | 184 | 3.5 | 1537109805 |
| **193587** | 184 | 3.5 | 1537110021 |
| **193609** | 331 | 4.0 | 1537157606 |

9724 rows × 3 columns

In [43]:
```
ratings.groupby('movieId').sum().sort_values(by='rating', ascending=False)
```

Out[43]:

| movieId | userId | rating | timestamp |
|---|---|---|---|
| 318 | 95829 | 1404.0 | 376924839127 |
| 356 | 101385 | 1370.0 | 386165236681 |
| 296 | 90621 | 1288.5 | 349204311001 |
| 2571 | 85236 | 1165.5 | 350270041779 |
| 593 | 85535 | 1161.0 | 320035674330 |
| ... | ... | ... | ... |
| 160872 | 21 | 0.5 | 1468113939 |
| 8236 | 580 | 0.5 | 1167791433 |
| 57326 | 232 | 0.5 | 1241823595 |
| 82684 | 567 | 0.5 | 1525289916 |
| 138798 | 298 | 0.5 | 1450453125 |

9724 rows × 3 columns

In [44]:
```
movies.set_index('movieId', inplace=True)
```

In [45]:
```
top_idx = ratings.groupby('movieId').sum().sort_values(by='rating', ascending=False
movies.loc[top_idx]
```

Out[45]:

| | title | genres |
|---|---|---|
| **movieId** | | |
| **318** | Shawshank Redemption, The (1994) | Crime\|Drama |
| **356** | Forrest Gump (1994) | Comedy\|Drama\|Romance\|War |
| **296** | Pulp Fiction (1994) | Comedy\|Crime\|Drama\|Thriller |
| **2571** | Matrix, The (1999) | Action\|Sci-Fi\|Thriller |
| **593** | Silence of the Lambs, The (1991) | Crime\|Horror\|Thriller |
| **...** | ... | ... |
| **160872** | Satanic (2016) | Horror |
| **8236** | While the City Sleeps (1956) | Drama\|Film-Noir |
| **57326** | In the Name of the King: A Dungeon Siege Tale ... | Action\|Adventure\|Fantasy |
| **82684** | Trash Humpers (2009) | Drama |
| **138798** | Joe Dirt 2: Beautiful Loser (2015) | Comedy |

9724 rows × 2 columns

### Pulp Fiction, The Matrix, and Shawshank Redemption make sense to as recommendations

In [46]:

```
pd.concat([movies, ratings.groupby('movieId').sum()], axis=1).sort_values(by='ratin
```

Out[46]:

| movieId | title | genres | userId | rating | timestamp |
|---|---|---|---|---|---|
| 318 | Shawshank Redemption, The (1994) | Crime\|Drama | 95829.0 | 1404.0 | 3.769248e+11 |
| 356 | Forrest Gump (1994) | Comedy\|Drama\|Romance\|War | 101385.0 | 1370.0 | 3.861652e+11 |
| 296 | Pulp Fiction (1994) | Comedy\|Crime\|Drama\|Thriller | 90621.0 | 1288.5 | 3.492043e+11 |
| 2571 | Matrix, The (1999) | Action\|Sci-Fi\|Thriller | 85236.0 | 1165.5 | 3.502700e+11 |
| 593 | Silence of the Lambs, The (1991) | Crime\|Horror\|Thriller | 85535.0 | 1161.0 | 3.200357e+11 |
| ... | ... | ... | ... | ... | ... |
| 30892 | In the Realms of the Unreal (2004) | Animation\|Documentary | NaN | NaN | NaN |
| 32160 | Twentieth Century (1934) | Comedy | NaN | NaN | NaN |
| 32371 | Call Northside 777 (1948) | Crime\|Drama\|Film-Noir | NaN | NaN | NaN |
| 34482 | Browning Version, The (1951) | Drama | NaN | NaN | NaN |
| 85565 | Chalet Girl (2011) | Comedy\|Romance | NaN | NaN | NaN |

9742 rows × 5 columns

# Analysis/Summary

### What We Did

We analyzed the movies user 2 has watched and rated to recommend some new ones they might like. User 2 rated 58 movies, and we made a chart showing how often they gave each rating. Their top picks include "The Jinx: The Life and Deaths of Robert Durst," "Mad Max: Fury Road," and "The Wolf of Wall Street."

### Finding a Similar User

To find someone with similar taste, we checked other users' ratings using Pearson correlation, Euclidean distance, and cosine distance. User 341 matched best with Pearson, but users 442 matched better with both Euclidean and cosine distance.

### Our Recommendations

Looking at what user 442 loved that user 2 hasn’t seen yet, we recommended movies like "The Matrix" and "Pulp Fiction" These picks fit well with user 2’s preferences.

### Why It Matters

Using different methods to find similar users gave us a solid way to make personalized recommendations. This approach can help improve recommendation systems for other users too.