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 (https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.merge.html) 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/ (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

---

Assignment 6 - Charles Alders

Imports and Reading Data

In [71]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from scipy.spatial.distance import euclidean
from scipy.spatial.distance import cosine
from scipy.stats import pearsonr
from scipy.spatial.distance import pdist, squareform
```

In [72]:
```
movies = pd.read_csv("/Users/charliealders/Desktop/Charlie/GitHub/MSDS600/Week6/movies.csv", index_col=0)
ratings = pd.read_csv("/Users/charliealders/Desktop/Charlie/GitHub/MSDS600/Week6/ratings.csv")
```

Merging data and analyzing user 2

In [73]:
```
df = movies.merge(ratings, how="outer", on="movieId")
user_2 = df[df["userId"]==2]
user_2.set_index("movieId", inplace=True)
user_2.head()
```

Out[73]:

movieId	title	genres	userId	rating	timestamp
318	Shawshank Redemption, The (1994)	Crime|Drama	2.0	3.0	1.445715e+09
333	Tommy Boy (1995)	Comedy	2.0	4.0	1.445715e+09
1704	Good Will Hunting (1997)	Drama|Romance	2.0	4.5	1.445715e+09
3578	Gladiator (2000)	Action|Adventure|Drama	2.0	4.0	1.445715e+09
6874	Kill Bill: Vol. 1 (2003)	Action|Crime|Thriller	2.0	4.0	1.445715e+09

Number of movies user two has rated:

In [74]:
```
user_2.shape[0]
```

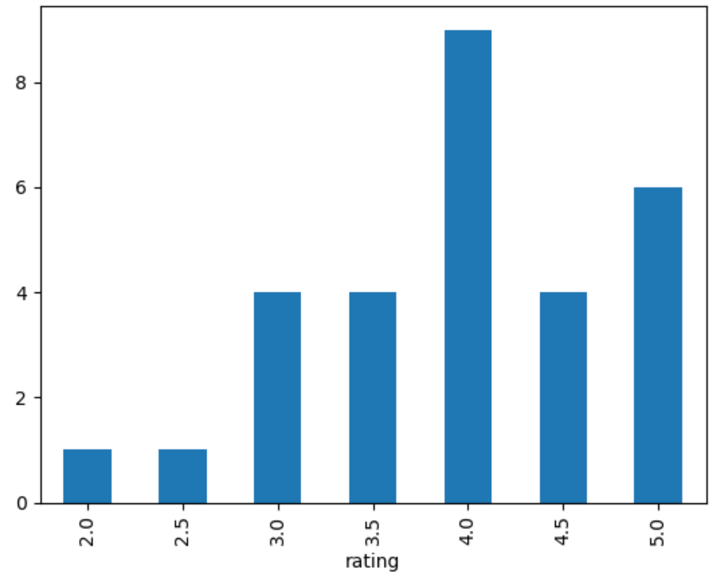
Out[74]: 29

In [75]:
```
user_2_ratings = user_2[["rating", "title"]].groupby('rating').count()
```

Distribution of ratings for user 2. Looks like the most common rating is 4.0, then 5.0.

In [76]:
```
user_2_ratings.plot(kind='bar', legend=None)
```

Out[76]:
```
<AxesSubplot:xlabel='rating'>
```



User 2's highest rated movies are Step Brothers, Inside Job, Warrior, The Wolf of Wall Street, etc.

In [77]:
```
user_2[user_2['rating']==5]
```

Out[77]:

movieId	title	genres	userId	rating	timestamp
60756	Step Brothers (2008)	Comedy	2.0	5.0	1.445715e+09
80906	Inside Job (2010)	Documentary	2.0	5.0	1.445715e+09
89774	Warrior (2011)	Drama	2.0	5.0	1.445715e+09
106782	Wolf of Wall Street, The (2013)	Comedy|Crime|Drama	2.0	5.0	1.445715e+09
122882	Mad Max: Fury Road (2015)	Action|Adventure|Sci-Fi|Thriller	2.0	5.0	1.445715e+09
131724	The Jinx: The Life and Deaths of Robert Durst ...	Documentary	2.0	5.0	1.445715e+09

Similarity Metrics

In [78]:
```
wide_df = ratings.pivot(index='userId', columns='movieId', values='rating')
wide_df.head()
```

Out[78]:

movieId / userId	1	2	3	4	5	6	7	8	9	10	...	193565	193567	193571	193573	193579	193581	193583	193585	193587	193609
1	4.0	NaN	4.0	NaN	NaN	4.0	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	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	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	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	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

5 rows × 9724 columns

In [79]:
```
cor = wide_df.T.corr()
cor.head()
```

Out[79]:

userId	1	2	3	4	5	6	7	8	9	10	...	601	602	603	604	
userId																
1	1.000000	NaN	0.079819	0.207983	0.268749	-0.291636	-0.118773	0.469668	0.918559	-0.037987	...	9.157371e-02	-1.597727e-16	-0.061503	-0.407556	-
2	NaN	1.0	NaN	NaN	NaN	NaN	-0.991241	NaN	NaN	0.037796	...	-3.873468e-01	NaN	-1.000000	NaN	
3	0.079819	NaN	1.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	0.433200	NaN	
4	0.207983	NaN	NaN	1.000000	-0.336525	0.148498	0.542861	0.117851	NaN	0.485794	...	-2.221127e-01	3.966413e-01	0.090090	-0.080296	
5	0.268749	NaN	NaN	-0.336525	1.000000	0.043166	0.158114	0.028347	NaN	-0.777714	...	2.719480e-16	1.533034e-01	0.234743	0.067791	-

5 rows × 610 columns

Pearson correlation indicates that user 2 is most similar (directly correlated) to user 341, 93, 143, 148, etc.

In [80]:
```
cor.loc[2].sort_values(ascending=False)
```

Out[80]:
```
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 [81]:
```
wide_df.fillna(-1, inplace=True)
```

In [82]:
```
euclidean_distances = squareform(pdist(wide_df, metric=euclidean))
```

In [83]:
```
euclidean_df = pd.DataFrame(data=euclidean_distances, columns=wide_df.index, index=wide_df.index)
```

In [84]:
```
euclidean_df.head()
```

Out[84]:

userId	1	2	3	4	5	6	7	8	9	10	...	601	602	603	
userId															
1	0.000000	86.239492	84.731930	96.979379	84.516271	108.083301	91.651514	84.380092	86.203248	96.969067	...	95.430603	90.288427	147.939177	9
2	86.239492	0.000000	36.806929	74.567084	41.039615	84.777650	60.172668	41.318882	40.450587	57.295288	...	55.859198	58.423026	145.090489	5
3	84.731930	36.806929	0.000000	73.908727	39.956226	84.584277	60.112395	40.441316	39.172695	58.150666	...	59.895743	57.701820	144.296570	5
4	96.979379	74.567084	73.908727	0.000000	72.608539	101.847926	83.330667	74.639132	75.591005	85.743804	...	84.604964	81.455509	137.952891	8
5	84.516271	41.039615	39.956226	72.608539	0.000000	77.479029	59.958319	33.837849	43.543082	60.274373	...	61.253571	48.383882	142.762040	4

5 rows × 610 columns

The euclidian distances show that the 4 most similar users to user 2 are users 442, 461, 189, and 508.

In [85]:
```
euclidean_df.loc[2].sort_values()
```

Out[85]:
```
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 [86]:
```
cosine_distances = squareform(pdist(wide_df, metric=cosine))
cosine_df = pd.DataFrame(cosine_distances, columns=wide_df.index, index=wide_df.index)
cosine_df.loc[2].sort_values()
```

Out[86]:
```
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
```

Euclidean and cosine distances show the same similar users, but Pearson correlation does not.

In [87]:
```
wide_df.replace(-1, np.NaN, inplace=True)
```

In [88]:
```
wide_df.loc[2].notna().equals(wide_df.loc[442].notna())
```

Out[88]:
```
False
```

Recommending movies

In [94]:
```
rated_5_by_442_not_seen_by_2 = (wide_df.loc[442] == 5) & (wide_df.loc[2].isna())

print(wide_df.loc[2][rated_5_by_442_not_seen_by_2])
(wide_df.loc[442][rated_5_by_442_not_seen_by_2])
```

```
Series([], Name: 2, dtype: float64)
```

Out[94]:
```
Series([], Name: 442, dtype: float64)
```

Even though I checked to see if user 2 and user 442 had rated the exact same movies, this doesn't check to see if user 2 has watched all of the same movies than user 442, and more. The above code returns an empty string because user 2 has seen all of the same movies that user 442 has rated.

In [95]:
```
rated_5_by_461_not_seen_by_2 = (wide_df.loc[461] == 5) & (wide_df.loc[2].isna())

print(wide_df.loc[2][rated_5_by_461_not_seen_by_2])
(wide_df.loc[461][rated_5_by_461_not_seen_by_2])
```

```
movieId
356   NaN
Name: 2, dtype: float64
```

Out[95]:
```
movieId
356    5.0
Name: 461, dtype: float64
```

In [98]:
```
movies.loc[356]
```

Out[98]:
```
title           Forrest Gump (1994)
genres     Comedy|Drama|Romance|War
Name: 356, dtype: object
```

User 2 and user 461 have very close cosine distance, and user 2 has not seen Forrest Gump, which user 461 rated 5 stars. It is likely that user 2 will enjoy this movie.

In [131]:
```
recommended_movie_ids = []
for key, value in cosine_df.loc[2].sort_values().items():
    if not wide_df.loc[2][(wide_df.loc[key]==5) & (wide_df.loc[2].isna())].empty:
        if value < 0.05:
            recommended_movie_ids.append(wide_df.loc[2][(wide_df.loc[key]==5) & (wide_df.loc[2].isna())].index.tolist(

from functools import reduce # had to look this part up: https://www.tutorialsteacher.com/articles/how-to-flatten-list
recommended_movie_ids = reduce(lambda a,b:a+b, recommended_movie_ids)
recommended_movies = [movies["title"].loc[x] for x in recommended_movie_ids]

print(recommended_movies)
```

```
['Forrest Gump (1994)', 'Usual Suspects, The (1995)', 'Pulp Fiction (1994)', 'My Big Fat Greek Wedding (2002)', 'Arr
ival (2016)', 'Léon: The Professional (a.k.a. The Professional) (Léon) (1994)', 'Saving Private Ryan (1998)', 'Matri
x, The (1999)', 'Fight Club (1999)', 'Memento (2000)', 'X-Men: Apocalypse (2016)']
```

The above list contains movies that user 2 has not seen, based on the top rated movies of users with a cosine distance of less than 0.05.

In [144]:
```
df[(df.userId==2) & (df.rating>=4.5)].sort_values("rating", ascending=False)
```

Out[144]:

	movieId	title	genres	userId	rating	timestamp
87792	60756	Step Brothers (2008)	Comedy	2.0	5.0	1.445715e+09
91890	80906	Inside Job (2010)	Documentary	2.0	5.0	1.445715e+09
93512	89774	Warrior (2011)	Drama	2.0	5.0	1.445715e+09
96387	106782	Wolf of Wall Street, The (2013)	Comedy|Crime|Drama	2.0	5.0	1.445715e+09
98110	122882	Mad Max: Fury Road (2015)	Action|Adventure|Sci-Fi|Thriller	2.0	5.0	1.445715e+09
98721	131724	The Jinx: The Life and Deaths of Robert Durst ...	Documentary	2.0	5.0	1.445715e+09
34763	1704	Good Will Hunting (1997)	Drama|Romance	2.0	4.5	1.445715e+09
86885	58559	Dark Knight, The (2008)	Action|Crime|Drama|IMAX	2.0	4.5	1.445715e+09
89054	68157	Inglourious Basterds (2009)	Action|Drama|War	2.0	4.5	1.445715e+09
91793	80489	Town, The (2010)	Crime|Drama|Thriller	2.0	4.5	1.445715e+09

Just by looking at user 2's top genres, it looks like they enjoy Drama, Comedy, and Crime movies, as well as some documentaries.

In [171]:
```
movies[["title", "genres"]][movies.index.isin(recommended_movie_ids)]
```

Out[171]:

movieId	title	genres
50	Usual Suspects, The (1995)	Crime|Mystery|Thriller
293	Léon: The Professional (a.k.a. The Professiona...	Action|Crime|Drama|Thriller
296	Pulp Fiction (1994)	Comedy|Crime|Drama|Thriller
356	Forrest Gump (1994)	Comedy|Drama|Romance|War
2028	Saving Private Ryan (1998)	Action|Drama|War
2571	Matrix, The (1999)	Action|Sci-Fi|Thriller
2959	Fight Club (1999)	Action|Crime|Drama|Thriller
4226	Memento (2000)	Mystery|Thriller
5299	My Big Fat Greek Wedding (2002)	Comedy|Romance
122924	X-Men: Apocalypse (2016)	Action|Adventure|Fantasy|Sci-Fi
164179	Arrival (2016)	Sci-Fi

As we can see from the recommended movies, most of them seem to be Drama, Comedy, or Crime, so it seems like user 2 would enjoy the recommended movies, just based on the genres. These recommendations are from the users with very similar interests to user 2, so I would say that the recommendations do make sense.

Summary

This recommender system utilized cosine distance to calculate and recommend new movies to user 2 (or any user). The reason I chose cosine distance was because it showed very similar results to euclidean distance, so I figured one of those two would have more accurate results. I took the movies that user 2 had not seen that other users who had a cosine distance of less than 0.05 had rated 5 stars. I am pretty confident in the results, as these are the most similar users based on the data, and the results were quite similar to those of euclidean distance. Looking at the recommendations themselves, the new movies were lots of crime, comedy, and drama genres, which were very similar to user 2's highest rated movies.