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]:

```
#Perform some movie recommendations and analysis for user 2:
##How many movies has this user watched?
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:

```
#Perform some movie recommendations and analysis for user 2:
##How many movies has this user watched?
df_ratings = pd.read_csv('ratings.csv')
df_ratings
```

Out[2]:

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703

	userId	movieId	rating	timestamp
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931
...	...	...	...	...
100831	610	166534	4.0	1493848402
100832	610	168248	5.0	1493850091
100833	610	168250	5.0	1494273047
100834	610	168252	5.0	1493846352
100835	610	170875	3.0	1493846415

100836 rows × 4 columns

In [3]:

```
#Perform some movie recommendations and analysis for user 2:
##How many movies has this user watched?
df_movies = pd.read_csv('movies.csv', index_col='movieId')
df_movies
```

Out[3]:

	title	genres
movieId		
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

	title	genres
movieId		
193609	Andrew Dice Clay: Dice Rules (1991)	Comedy

9742 rows × 2 columns

In [4]:

```
#Perform some movie recommendations and analysis for user 2:
##How many movies has this user watched?

#df_ratings['userId'].value_counts()
df_ratings.groupby('userId').size()
```

Out[4]:

```
userId
1       232
2        29
3        39
4       216
5        44
       ...
606    1115
607     187
608     831
609      37
610    1302
Length: 610, dtype: int64
```

In [5]:

```
#according to the previous line, user #2 has watched 29 movies

##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.

df_merged = df_ratings.merge(df_movies, left_on='movieId', right_on='movieId')
df_merged
```

Out[5]:

	userId	movieId	rating	timestamp	title	genres
0	1	1	4.0	964982703	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	5	1	4.0	847434962	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
2	7	1	4.5	1106635946	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
3	15	1	2.5	1510577970	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
4	17	1	4.5	1305696483	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy

	userId	movieId	rating	timestamp	title	genres
...	...	...	...	...	...	...
100831	610	160341	2.5	1479545749	Bloodmoon (1997)	Action|Thriller
100832	610	160527	4.5	1479544998	Sympathy for the Underdog (1971)	Action|Crime|Drama
100833	610	160836	3.0	1493844794	Hazard (2005)	Action|Drama|Thriller
100834	610	163937	3.5	1493848789	Blair Witch (2016)	Horror|Thriller
100835	610	163981	3.5	1493850155	31 (2016)	Horror

100836 rows × 6 columns

In [6]:

```
unique_movie_counts = df_merged.groupby('title').size()
```

In [7]:

```
unique_movie_counts
#ax1 = df_userid2_sorted.plot.bar(x='title', y='rating', rot=90)
```

Out[7]:

```
title
'71 (2014)                                    1
'Hellboy': The Seeds of Creation (2004)       1
'Round Midnight (1986)                        2
'Salem's Lot (2004)                           1
'Til There Was You (1997)                     2
                                             ..
eXistenZ (1999)                              22
xXx (2002)                                   24
xXx: State of the Union (2005)                5
¡Three Amigos! (1986)                        26
À nous la liberté (Freedom for Us) (1931)     1
Length: 9719, dtype: int64
```

In [8]:

```
df_merged['title'].value_counts()
```

Out[8]:

```
Forrest Gump (1994)                    329
Shawshank Redemption, The (1994)       317
Pulp Fiction (1994)                    307
Silence of the Lambs, The (1991)       279
Matrix, The (1999)                     278
                                      ...
Sex, Drugs & Taxation (2013)             1
Extraordinary Tales (2015)               1
Tomorrow (2015)                          1
Embrace of the Serpent (2016)            1
```

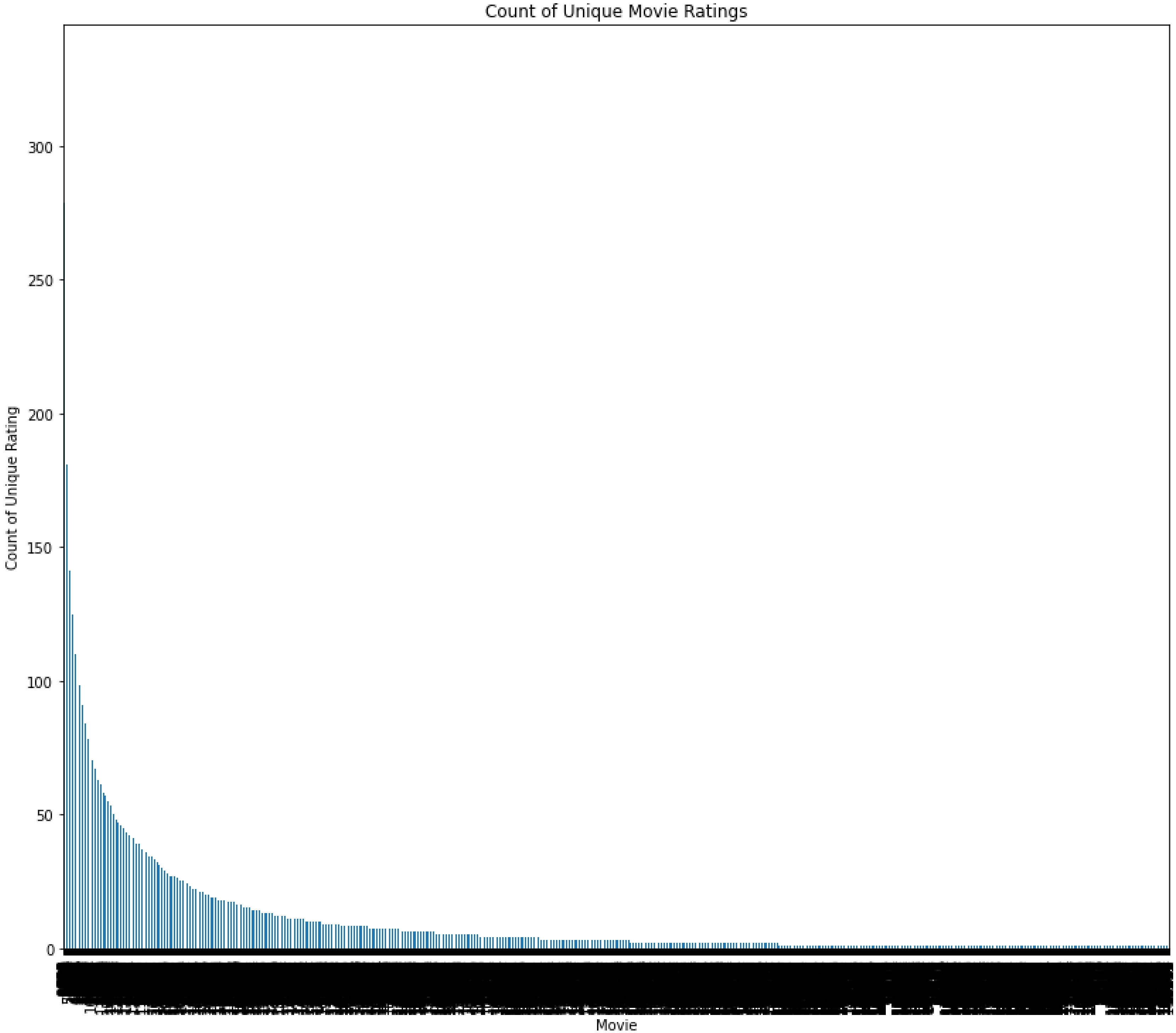
```
31 (2016)                                  1
Name: title, Length: 9719, dtype: int64
```

In [9]:

```python
df_merged['movieId'].value_counts().plot(kind='bar', figsize=(14, 12), rot=90)
plt.xlabel("Movie")
plt.ylabel("Count of Unique Rating")
plt.title("Count of Unique Movie Ratings")
```

Out[9]:

```
Text(0.5, 1.0, 'Count of Unique Movie Ratings')
```



In [10]:

```
##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.
```

```python
#the x-axis above is not readable, there are too many movies in this dataset
#just for fun, I will plot the movie ratings from user 2
df_userid2=df_merged[df_merged["userId"] == 2]
df_userid2
```

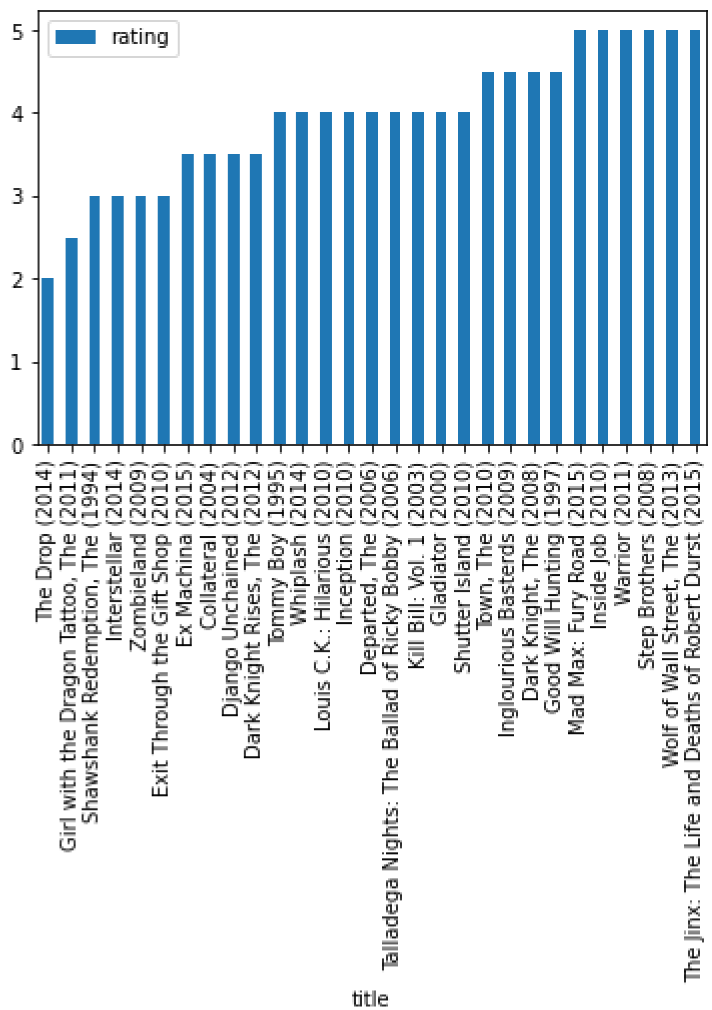
Out[10]:

	userId	movieId	rating	timestamp	title	genres
2267	2	333	4.0	1445715029	Tommy Boy (1995)	Comedy
15657	2	3578	4.0	1445714885	Gladiator (2000)	Action|Adventure|Drama
16296	2	318	3.0	1445714835	Shawshank Redemption, The (1994)	Crime|Drama
16613	2	1704	4.5	1445715228	Good Will Hunting (1997)	Drama|Romance
16754	2	6874	4.0	1445714952	Kill Bill: Vol. 1 (2003)	Action|Crime|Thriller
16885	2	8798	3.5	1445714960	Collateral (2004)	Action|Crime|Drama|Thriller
16929	2	46970	4.0	1445715013	Talladega Nights: The Ballad of Ricky Bobby (2...	Action|Comedy
16957	2	48516	4.0	1445715064	Departed, The (2006)	Crime|Drama|Thriller
17064	2	58559	4.5	1445715141	Dark Knight, The (2008)	Action|Crime|Drama|IMAX
17213	2	60756	5.0	1445714980	Step Brothers (2008)	Comedy
17241	2	68157	4.5	1445715154	Inglourious Basterds (2009)	Action|Drama|War
17329	2	71535	3.0	1445714974	Zombieland (2009)	Action|Comedy|Horror
17382	2	74458	4.0	1445714926	Shutter Island (2010)	Drama|Mystery|Thriller
17449	2	77455	3.0	1445714941	Exit Through the Gift Shop (2010)	Comedy|Documentary
17462	2	79132	4.0	1445714841	Inception (2010)	Action|Crime|Drama|Mystery|Sci-Fi|Thriller|IMAX
17605	2	80489	4.5	1445715340	Town, The (2010)	Crime|Drama|Thriller
17627	2	80906	5.0	1445715172	Inside Job (2010)	Documentary
17639	2	86345	4.0	1445715166	Louis C.K.: Hilarious (2010)	Comedy
17648	2	89774	5.0	1445715189	Warrior (2011)	Drama
17659	2	91529	3.5	1445714891	Dark Knight Rises, The (2012)	Action|Adventure|Crime|IMAX
17735	2	91658	2.5	1445714938	Girl with the Dragon Tattoo, The (2011)	Drama|Thriller
17777	2	99114	3.5	1445714874	Django Unchained (2012)	Action|Drama|Western
17848	2	106782	5.0	1445714966	Wolf of Wall Street, The (2013)	Comedy|Crime|Drama
17902	2	109487	3.0	1445715145	Interstellar (2014)	Sci-Fi|IMAX

	userId	movieId	rating	timestamp	title	genres
17975	2	112552	4.0	1445714882	Whiplash (2014)	Drama
18013	2	114060	2.0	1445715276	The Drop (2014)	Crime|Drama|Thriller
18016	2	115713	3.5	1445714854	Ex Machina (2015)	Drama|Sci-Fi|Thriller
18044	2	122882	5.0	1445715272	Mad Max: Fury Road (2015)	Action|Adventure|Sci-Fi|Thriller
18091	2	131724	5.0	1445714851	The Jinx: The Life and Deaths of Robert Durst ...	Documentary

In [11]:

```
##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.
df_userid2_sorted = df_userid2.sort_values('rating')
ax = df_userid2_sorted.plot.bar(x='title', y='rating', rot=90)
```



In [12]:

```python
##What are some of user 2's top movies?
df_userid2_topmovies = df_userid2[df_userid2["rating"] == 5.0]
df_userid2_topmovies
```

Out[12]:

	userId	movieId	rating	timestamp	title	genres
17213	2	60756	5.0	1445714980	Step Brothers (2008)	Comedy
17627	2	80906	5.0	1445715172	Inside Job (2010)	Documentary
17648	2	89774	5.0	1445715189	Warrior (2011)	Drama
17848	2	106782	5.0	1445714966	Wolf of Wall Street, The (2013)	Comedy|Crime|Drama
18044	2	122882	5.0	1445715272	Mad Max: Fury Road (2015)	Action|Adventure|Sci-Fi|Thriller
18091	2	131724	5.0	1445714851	The Jinx: The Life and Deaths of Robert Durst ...	Documentary

In [13]:

```python
##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
df_merged_ratings = df_merged.drop(columns=['timestamp', 'genres'])
#df_merged_ratings
wide = df_merged_ratings.pivot(index='userId', columns='movieId', values='rating')
wide.head()
```

Out[13]:

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

5 rows × 9724 columns

In [14]:

```python
##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
cor = wide.T.corr()
cor.head()
```

Out[14]:

userId	1	2	3	4	5	6	7	8	9	10	...	601	602	603	604

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

In [15]:

```
##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
cor.loc[2].sort_values(ascending=False)
```

Out[15]:

```
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 [16]:

```
# so, users 341, 93, 143, and 148 are most similar to user 2

##Recommend a few movies for user 2 using similarity metrics.
##Do the recommendations from this method make sense?
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 [17]:

```
##Recommend a few movies for user 2 using similarity metrics.
##Do the recommendations from this method make sense?
df_merged[df_merged["movieId"] == 1].head()
```

Out[17]:

	userId	movieId	rating	timestamp	title	genres
0	1	1	4.0	964982703	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	5	1	4.0	847434962	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
2	7	1	4.5	1106635946	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
3	15	1	2.5	1510577970	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
4	17	1	4.5	1305696483	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy

In [18]:

```
##Recommend a few movies for user 2 using similarity metrics.
##Do the recommendations from this method make sense?
df_merged[df_merged["movieId"] == 59900].head()
```

Out[18]:

	userId	movieId	rating	timestamp	title	genres
67575	21	59900	3.0	1427558545	You Don't Mess with the Zohan (2008)	Comedy
67576	41	59900	2.5	1458995086	You Don't Mess with the Zohan (2008)	Comedy
67577	51	59900	3.0	1230932750	You Don't Mess with the Zohan (2008)	Comedy
67578	52	59900	3.0	1468052115	You Don't Mess with the Zohan (2008)	Comedy
67579	68	59900	1.0	1269123306	You Don't Mess with the Zohan (2008)	Comedy

In [19]:

```
from scipy.spatial.distance import pdist, squareform
```

In [20]:

```
#So, we can recommend "Toy Story (1995)"
# and "You Don't Mess with the Zohan (2008)" as movies for User with userId 2
# this was using the Pearson coefficient as the metric
```

```
#let's try using cosine distance as the metric

##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
wide.fillna(-1, inplace=True)
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[20]:

```
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 [21]:

```
# we don't see user 341 at the top of the list using cosine distance, let's compared
cosine_df.loc[2].sort_values().loc[341]
```

Out[21]:

```
0.0892952689103661
```

In [22]:

```
##Recommend a few movies for user 2 using similarity metrics.
##Do the recommendations from this method make sense?

rated_5_by_442_not_watched_by_2 = (wide.loc[442] >= 4.5) & (wide.loc[2] == -1)
print(wide.loc[2][rated_5_by_442_not_watched_by_2])
print(wide.loc[442][rated_5_by_442_not_watched_by_2])
```

```
Series([], Name: 2, dtype: float64)
Series([], Name: 442, dtype: float64)
```

In [23]:

```
##Recommend a few movies for user 2 using similarity metrics.
##Do the recommendations from this method make sense?

rated_5_by_461_not_watched_by_2 = (wide.loc[461] >= 4.5) & (wide.loc[2] == -1)
print(wide.loc[2][rated_5_by_461_not_watched_by_2])
print(wide.loc[461][rated_5_by_461_not_watched_by_2])
```

```
movieId
356    -1.0
1246   -1.0
```

```
1784    -1.0
Name: 2, dtype: float64
movieId
356     5.0
1246    4.5
1784    4.5
Name: 461, dtype: float64
```

In [24]:

```
##Recommend a few movies for user 2 using similarity metrics.
##Do the recommendations from this method make sense?
df_merged[df_merged["movieId"] == 356].head()
```

Out[24]:

	userId	movieId	rating	timestamp	title	genres
2426	1	356	4.0	964980962	Forrest Gump (1994)	Comedy|Drama|Romance|War
2427	6	356	5.0	845553200	Forrest Gump (1994)	Comedy|Drama|Romance|War
2428	7	356	5.0	1106635915	Forrest Gump (1994)	Comedy|Drama|Romance|War
2429	8	356	3.0	839463527	Forrest Gump (1994)	Comedy|Drama|Romance|War
2430	10	356	3.5	1455301685	Forrest Gump (1994)	Comedy|Drama|Romance|War

In [25]:

```
##Recommend a few movies for user 2 using similarity metrics.
##Do the recommendations from this method make sense?
df_merged[df_merged["movieId"] == 1246].head()
```

Out[25]:

	userId	movieId	rating	timestamp	title	genres
34051	7	1246	1.5	1106635678	Dead Poets Society (1989)	Drama
34052	18	1246	4.0	1455618445	Dead Poets Society (1989)	Drama
34053	24	1246	4.0	1458942000	Dead Poets Society (1989)	Drama
34054	31	1246	3.0	850467468	Dead Poets Society (1989)	Drama
34055	42	1246	5.0	996214893	Dead Poets Society (1989)	Drama

In [26]:

```
##Recommend a few movies for user 2 using similarity metrics.
##Do the recommendations from this method make sense?
df_merged[df_merged["movieId"] == 1784].head()
```

Out[26]:

	userId	movieId	rating	timestamp	title	genres
34434	7	1784	0.5	1106635416	As Good as It Gets (1997)	Comedy|Drama|Romance

	userId	movieId	rating	timestamp	title	genres
34435	10	1784	3.5	1455301699	As Good as It Gets (1997)	Comedy|Drama|Romance
34436	11	1784	5.0	902155043	As Good as It Gets (1997)	Comedy|Drama|Romance
34437	18	1784	3.5	1456672335	As Good as It Gets (1997)	Comedy|Drama|Romance
34438	19	1784	2.0	965706163	As Good as It Gets (1997)	Comedy|Drama|Romance

In [27]:

```
from scipy.spatial.distance import euclidean
```

In [28]:

```
##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

#now let's compare users using the euclidean distance
euclidean(wide.iloc[2], wide.iloc[341])
```

Out[28]: 41.212862069989754

In [29]:

```
##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
euclidean_distances = squareform(pdist(wide, metric=euclidean))
euclidean_df = pd.DataFrame(data=euclidean_distances, columns=wide.index, index=wide.index)
euclidean_df.head()
```

Out[29]:

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
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
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
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
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

5 rows × 610 columns

In [30]:

```
##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
euclidean_df.loc[2].sort_values()
```

Out[30]:

```
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 [31]:

```
# so cosine distance and euclidean distance give similar users for user 2
# let's see how user 341 (from Pearson coefficient) compares
euclidean_df.loc[2].sort_values().loc[341]
```

Out[31]:

```
42.91852746774987
```

In [32]:

```
#since the euclidean distance gives the same users for user 2, we
#can recommend the same movies: Forrest Gump, Dead Poets Society, and As Good as it Gets
```

In [ ]:

Analysis/Summary

For both parts of the assignment, write a short analysis and summary of what you did, the results, and the significance. Do this in a markdown cell here at the bottom, like this one.

Write a short analysis of the results, and justify which similarity metric(s) you used.

To begin this assignment, I answered the question "how many movies has user 2 watched?". I did this by using the groupby function, counting the # of rows from each user. I saw that user 2 has watched 29 movies. Or, user 2 has rated 29 movies at least.

I then plotted a bar chart of user 2's movies. I began the plotting by merging the movies and ratings dataset so I could access the movie titles. I sorted the movies user 2 has watched based on rating, and used plot.bar to create the bar chart.

Filtering the movies to only see user 2's movies with 5.0 ratings, I saw that user 2's top movies were Step Brothers, Inside Job, Warrior, Wolf of Wall Street, Mad Max: Fury Road, and The Jinx.

Next, I found the most similar users to user 2 and recommended a few movies to user 2 using the following 3 separate metrics: Pearson coefficient, cosine distance, and euclidean distance.

Using the Pearson coefficient, I found user 341 to be most similar to user 2. To find the movies to recommend, I filtered the movies by movies which user 2 hadn't seen, and user 341 rated as 5.0. These movies turned out to be "Toy Story" and "You Don't Mess with the Zohan". To see if these make sense, I didn't see any animated movies in user 2's top-rated movies. I saw mostly popular drama/action movies in user 2's top movies. This was slightly peculiar to me.

Using the cosine distance, I found user 442 to be most similar to user 2. However, user 442 had very low ratings on all their movie ratings, so I moved to the next similar user. This was user 461. Using user 461's top movies, I found "Forrest Gump", "Dead Poets Society", and "As Good as It Gets" to be the top recommendations for user 2. These seemed to be much better recommendations for user 2 as they are all popular dramas.

Using the euclidean distance as a metric, I found the same exact results as the cosine distance. The same users were the most similar (442, 461) and the same three movies were recommended.

This assignment was interesting! And there were a lot of real-world applications for it.

Please let me know if you have any questions.

Thank you, Jeremy

```
In [ ]:
```