Week 6-Assignment

MSDS 600 - Introduction to Data Science

Recommender Systems

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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

Load and explore data

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

In [2]:
```
ratings = pd.read_csv('ratings.csv')
movies = pd.read_csv('movies.csv')
```

In [3]:
```
movies.head()
```

Out[3]:

	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 [4]:
```
ratings.head()
```

Out[4]:

	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

Number of movies watched by User 2

In [5]:
```
movies_count_per_user = ratings.groupby('userId')['movieId'].count().reset_index(name='MovieIdCount')
movies_count_per_user
```

Out[5]:

	userId	MovieIdCount
0	1	232
1	2	29
2	3	39
3	4	216
4	5	44
...	...	...
605	606	1115
606	607	187
607	608	831
608	609	37
609	610	1302

610 rows × 2 columns

In [6]:
```
display(movies_count_per_user.loc[movies_count_per_user.userId == 2])
```

	userId	MovieIdCount
1	2	29

Below is another way to filter User 2 Number of movies count.

In [7]:
```
print(movies_count_per_user.loc[1])
```

```
userId           2
MovieIdCount    29
Name: 1, dtype: int64
```

Bar Chart of Movie Ratings

Bar Chart - User 2 Movie Ratings

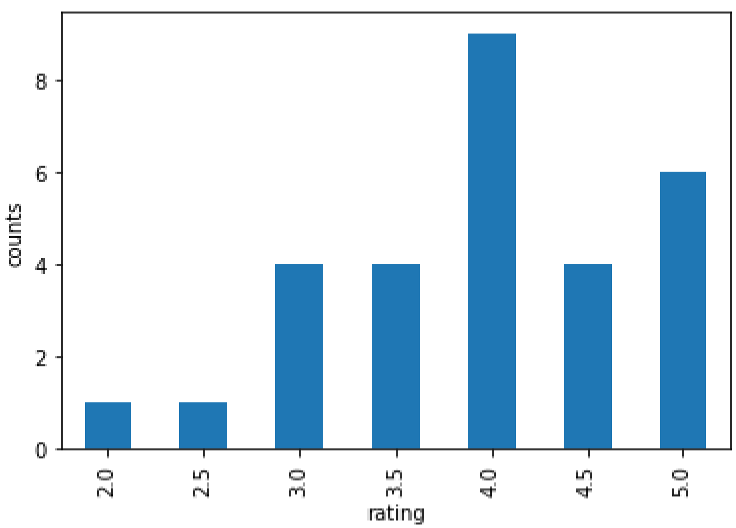
In [8]:
```
user_2_rating = ratings[ratings['userId'] == 2]
user_2_rating.head()
```

Out[8]:

	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

In [9]:
```
user_2_rating['rating'].value_counts().sort_index().plot.bar()
plt.xlabel('rating')
plt.ylabel('counts')
```

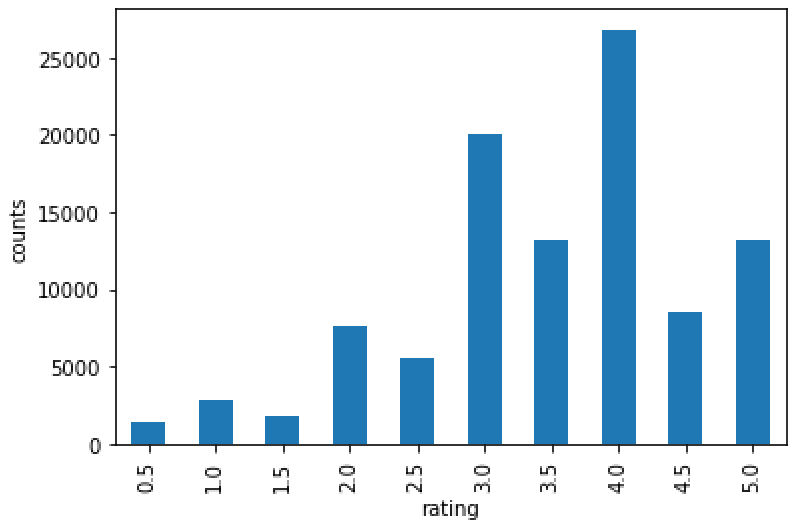
Out[9]: `Text(0, 0.5, 'counts')`



Bar Chart - All Users Movie Ratings

In [10]:
```
ratings['rating'].value_counts().sort_index().plot.bar()
plt.xlabel('rating')
plt.ylabel('counts')
```

Out[10]: Text(0, 0.5, 'counts')



User 2's Top Movies

In [11]:
```
user2_top_movies = pd.merge(user_2_rating, movies, on='movieId')
user2_top_movies.sort_values(by='rating', ascending=False).head()
```

Out[11]:

	userId	movieId	rating	timestamp	title	genres
28	2	131724	5.0	1445714851	The Jinx: The Life and Deaths of Robert Durst ...	Documentary
27	2	122882	5.0	1445715272	Mad Max: Fury Road (2015)	Action|Adventure|Sci-Fi|Thriller
22	2	106782	5.0	1445714966	Wolf of Wall Street, The (2013)	Comedy|Crime|Drama
18	2	89774	5.0	1445715189	Warrior (2011)	Drama
9	2	60756	5.0	1445714980	Step Brothers (2008)	Comedy

Collaborative Filtering Recommender

Transforming ratings DataFrame to "Wide" format for calculating similarities between users.

In [12]:
```
wide = ratings.pivot(index='userId', columns='movieId', values='rating')
wide.head()
```

Out[12]:

movieId	1	2	3	4	5	6	7	8	9	10	...	193565	193567	193571	193573	193579	193581	193583	19358
userId																			
1	4.0	NaN	4.0	NaN	NaN	4.0	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
5	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

5 rows × 9724 columns

Pearson Correlation

In [13]:
```
cor = wide.T.corr()
```

In [14]:
```
cor.head()
```

Out[14]:

userId	1	2	3	4	5	6	7	8	9	10	...	601	602	
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	-
2	NaN	1.0	NaN	NaN	NaN	NaN	-0.991241	NaN	NaN	0.037796	...	-3.873468e-01	NaN	-
3	0.079819	NaN	1.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	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	
5	0.268749	NaN	NaN	-0.336525	1.000000	0.043166	0.158114	0.028347	NaN	-0.777714	...	2.719480e-16	1.533034e-01	

5 rows × 610 columns

In [15]:
```
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]:
```
wide.loc[2].notna().equals(wide.loc[341].notna())
```

Out[16]:
```
False
```

Pearson Correlation- Recommending Movies to User 2 based on Top Movies rated by User

341

In [17]:
```
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
```

Euclidean Distance

In [18]:
```
wide.fillna(-1, inplace=True)
```

In [19]:
```
def euclidean_distance(vector1, vector2):
    return np.sqrt(np.sum((vector1 - vector2) ** 2))

def euclidean_distance(vector1, vector2):
    return np.linalg.norm(vector1 - vector2)

from scipy.spatial.distance import euclidean
```

In [20]:
```
euclidean(wide.iloc[2], wide.iloc[341])
```

Out[20]:
```
41.212862069989754
```

In [21]:
```
from scipy.spatial.distance import pdist, squareform
```

In [22]:
```
euclidean_distances = squareform(pdist(wide, metric=euclidean))
```

In [23]:
```
euclidean_df = pd.DataFrame(data=euclidean_distances, columns=wide.index, index=wide.index)
```

In [24]:
```
euclidean_df.head()
```

Out[24]:

userId	1	2	3	4	5	6	7	8	9	10	...	601	
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.
2	86.239492	0.000000	36.806929	74.567084	41.039615	84.777650	60.172668	41.318882	40.450587	57.295288	...	55.859198	58.
3	84.731930	36.806929	0.000000	73.908727	39.956226	84.584277	60.112395	40.441316	39.172695	58.150666	...	59.895743	57.
4	96.979379	74.567084	73.908727	0.000000	72.608539	101.847926	83.330667	74.639132	75.591005	85.743804	...	84.604964	81.
5	84.516271	41.039615	39.956226	72.608539	0.000000	77.479029	59.958319	33.837849	43.543082	60.274373	...	61.253571	48.

5 rows × 610 columns

In [25]:
```
euclidean_df.loc[2].sort_values()
```

Out[25]:
```
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
```

`User 341` which was next similar user to `User 2` using Pearson Correlation is not the closest user using Euclidean Distance.

In [26]:
```
euclidean_df.loc[2].sort_values().loc[341]
```

Out[26]:
```
42.91852746774987
```

Checking Top Movie ratings given by `User 442` for recommending movies to `User 2`

In [27]:
```
#  Getting Top Rating Given by User 442 and Index of it.
print(wide.loc[442].max())
print(wide.loc[442].argmax())
```

```
2.5
320
```

In [28]:
```
# Getting Top Movies by User 442
user_442_rating = ratings[ratings['userId'] == 442]
user442_top_movies = pd.merge(user_442_rating, movies, on='movieId')
user442_top_movies.sort_values(by='rating', ascending=False).head()
```

Out[28]:

	userId	movieId	rating	timestamp	title	genres
0	442	362	2.5	1331560498	Jungle Book, The (1994)	Adventure|Children|Romance
19	442	4361	2.5	1331560492	Tootsie (1982)	Comedy|Romance
2	442	524	2.0	1331560506	Rudy (1993)	Drama
12	442	2908	2.0	1331560472	Boys Don't Cry (1999)	Drama
17	442	3752	2.0	1331560582	Me, Myself & Irene (2000)	Adventure|Comedy

Euclidean Distance- Recommending Movies to User 2 based on Top Movies rated by User 442

As Highest rating given by `User 442` is 2.5, recommending movies to `User 2` by having filter that check movies with rating greater than or equal to 2.

In [29]:
```
rated_by_442_not_watched_by_2 = (wide.loc[442] >= 2) & (wide.loc[2] != '-1.0')
print(wide.loc[2][rated_by_442_not_watched_by_2])
print(wide.loc[442][rated_by_442_not_watched_by_2])
```

```
movieId
362    -1.0
524    -1.0
2145   -1.0
2908   -1.0
3752   -1.0
4361   -1.0
Name: 2, dtype: float64
movieId
362     2.5
524     2.0
2145    2.0
2908    2.0
3752    2.0
4361    2.5
Name: 442, dtype: float64
```

Cosine Distance

In [30]:
```
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[30]:
```
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
```

`User 341` which was next similar user to `User 2` using Pearson Correlation is not the closest user using Cosine Distance.

In [31]:
```
cosine_df.loc[2].sort_values().loc[341]
```

Out[31]:
```
0.0892952689103661
```

Cosine Distance like Euclidean Distance has `User 442` as next similar user to `User 2`

Checking Top Movie ratings given by `User 442` for recommending movies to `User 2`

In [32]:
```
#  Getting Top Rating Given by User 442 and Index of it.
print(wide.loc[442].max())
print(wide.loc[442].argmax())
```

```
2.5
320
```

In [33]:
```
# Getting Top Movies by User 442
user_442_rating = ratings[ratings['userId'] == 442]
user442_top_movies = pd.merge(user_442_rating, movies, on='movieId')
user442_top_movies.sort_values(by='rating', ascending=False).head()
```

Out[33]:

	userId	movieId	rating	timestamp	title	genres
0	442	362	2.5	1331560498	Jungle Book, The (1994)	Adventure|Children|Romance
19	442	4361	2.5	1331560492	Tootsie (1982)	Comedy|Romance
2	442	524	2.0	1331560506	Rudy (1993)	Drama
12	442	2908	2.0	1331560472	Boys Don't Cry (1999)	Drama
17	442	3752	2.0	1331560582	Me, Myself & Irene (2000)	Adventure|Comedy

Cosine Distance- Recommending Movies to User 2 based on Top Movies rated by User 442

As Highest rating given by `User 442` is 2.5, recommending movies to `User 2` by having filter that check movies with rating greater than or equal to 2.

In [34]:
```
rated_by_442_not_watched_by_2 = (wide.loc[442] >= 2) & (wide.loc[2] != '-1.0')
print(wide.loc[2][rated_by_442_not_watched_by_2])
print(wide.loc[442][rated_by_442_not_watched_by_2])
```

```
movieId
362    -1.0
524    -1.0
2145   -1.0
2908   -1.0
3752   -1.0
4361   -1.0
Name: 2, dtype: float64
movieId
362     2.5
524     2.0
2145    2.0
2908    2.0
3752    2.0
4361    2.5
Name: 442, dtype: float64
```

Movies Recommendations

Yes, recommendations from Cosine Distance, Euclidean Distance and Pearson Correlation make sense.

User 2 top movies are mostly Adventure, Comedy and Drama. And those Genres movies are recommended.

As `User 442` was closest to `User 2` using Cosine and Euclidean Method. Below Movies are recommended.

In [35]:
```
#Movies recommended by Cosine and Euclidean Method based on closest user User442 Data
movies[movies['movieId'].isin([362, 524, 2145, 2908, 3752, 4361])]
```

Out[35]:

	movieId	title	genres
320	362	Jungle Book, The (1994)	Adventure|Children|Romance
459	524	Rudy (1993)	Drama
1603	2145	Pretty in Pink (1986)	Comedy|Drama|Romance
2190	2908	Boys Don't Cry (1999)	Drama
2807	3752	Me, Myself & Irene (2000)	Adventure|Comedy
3229	4361	Tootsie (1982)	Comedy|Romance

Analysis/Summary

First I loaded movies and ratings data. Then worked on finding Number of movies watched by `User 2` , it was found that `User 2` has watched `29` movies. Then plotted Bar Chart of Movie Ratings for `User 2` . `User 2` has rating count more in Rating "4". Also plotted Bar Chart of Movie Ratings for `All Users` and it shows that count of Rating "4" is more compared to other ratings.

Worked on getting User 2's Top Movies and it shows `User 2` has watched mostly Adventure, Drama and Comedy movies. `User 2` gave top 5 Movies rating of "5".

Transformed ratings DataFrame to "Wide" format for calculating similarities between users. Pearson Correlation method shows that `User 341` is closest to `User 2` . Based on `User 341` Data got recommendation of movies for `User 2` .

Cosine and Euclidean method showed that `User 442` is closest to `User 2` . As `User 442` highest rating is "2.5" filtered movies with rating greater than or equal to "2". 6 Movies were recommended and those movies are similar to movies that `User 2` has rated high.

References

Gannous, A. (2022) MSDS 600 - From the Experts: Recommender Systems. World Class. Anderson College of Business & Computing. Regis University.

George, N. (2021) MSDS 600 - From the Experts: Recommender Systems.. World Class. Anderson College of Business & Computing. Regis University.

In [ ]:

```

```