

# Rudra\_Ronit\_CS422\_HW4\_Practicum

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## 0.0.1 Importing Modules

```
In [1]: import numpy as np
import pandas as pd
from sklearn.metrics.pairwise import cosine_distances, cosine_similarity
```

## 0.0.2 Read in required data (Referenced from Notebook5)

```
In [2]: rating_cols = ['user_id',
                        'movie_id',
                        'rating',
                        'timestamp']
ratings = pd.read_csv('ml-100k/u.data', sep='\t', names=rating_cols)

user_cols = ['user_id',
             'age',
             'gender',
             'occupation',
             'zip_code']
users = pd.read_csv('ml-100k/u.user', sep='|', names=user_cols)

item_cols = ['movie id',
             'movie title',
             'release date',
             'video release date',
             'IMDb URL',
             'Unknown',
             'Action',
             'Adventure',
             'Animation',
             'Childrens',
             'Comedy',
             'Crime',
             'Documentary',
             'Drama',
             'Fantasy',
             'FilmNoir',
             'Horror',
```

```

        'Musical',
        'Mystery',
        'Romance',
        'SciFi',
        'Thriller',
        'War',
        'Western']
items = pd.read_csv('ml-100k/u.item',
                    sep='|',
                    names=item_cols,
                    encoding='latin-1')

```

In [3]: users.head()

```

Out[3]:
   user_id  age gender  occupation  zip_code
0         1   24      M  technician    85711
1         2   53      F      other    94043
2         3   23      M      writer    32067
3         4   24      M  technician    43537
4         5   33      F      other    15213

```

In [4]: ratings.head()

```

Out[4]:
   user_id  movie_id  rating  timestamp
0        196       242        3  881250949
1        186       302        3  891717742
2         22       377        1  878887116
3        244        51        2  880606923
4        166       346        1  886397596

```

In [5]: items.head()

```

Out[5]:
   movie id      movie title  release date  video release date  \
0         1  Toy Story (1995)  01-Jan-1995                NaN
1         2  GoldenEye (1995)  01-Jan-1995                NaN
2         3  Four Rooms (1995)  01-Jan-1995                NaN
3         4  Get Shorty (1995)  01-Jan-1995                NaN
4         5   Copycat (1995)  01-Jan-1995                NaN

   IMDb URL  Unknown  Action  \
0  http://us.imdb.com/M/title-exact?Toy%20Story%2...      0      0
1  http://us.imdb.com/M/title-exact?GoldenEye%20(...      0      1
2  http://us.imdb.com/M/title-exact?Four%20Rooms%...      0      0
3  http://us.imdb.com/M/title-exact?Get%20Shorty%...      0      1
4  http://us.imdb.com/M/title-exact?Copycat%20(1995)      0      0

   Adventure  Animation  Childrens  ...  Fantasy  FilmNoir  Horror  \
0           0          1          1  ...        0          0      0
1           1          0          0  ...        0          0      0

```

2	0	0	0	...	0	0	0
3	0	0	0	...	0	0	0
4	0	0	0	...	0	0	0

	Musical	Mystery	Romance	SciFi	Thriller	War	Western
0	0	0	0	0	0	0	0
1	0	0	0	0	1	0	0
2	0	0	0	0	1	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	1	0	0

[5 rows x 24 columns]

```
In [6]: utility = ratings.pivot(index='user_id',
                                columns='movie_id',
                                values='rating')
```

```
In [7]: # user id and movie id is index+1 and column+1
utility.head(10)
```

```
Out[7]: movie_id  1      2      3      4      5      6      7      8      9     10     ...
user_id
1             5.0    3.0    4.0    3.0    3.0    5.0    4.0    1.0    5.0    3.0    ...
2             4.0    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    2.0    ...
3             NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    ...
4             NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    ...
5             4.0    3.0    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    ...
6             4.0    NaN    NaN    NaN    NaN    NaN    NaN    2.0    4.0    4.0    NaN    ...
7             NaN    NaN    NaN    5.0    NaN    NaN    NaN    5.0    5.0    5.0    4.0    ...
8             NaN    NaN    NaN    NaN    NaN    NaN    NaN    3.0    NaN    NaN    NaN    ...
9             NaN    NaN    NaN    NaN    NaN    NaN    5.0    4.0    NaN    NaN    NaN    ...
10            4.0    NaN    NaN    4.0    NaN    NaN    NaN    4.0    NaN    4.0    NaN    ...
```

movie_id	1673	1674	1675	1676	1677	1678	1679	1680	1681	1682
user_id										
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

[10 rows x 1682 columns]

# 1 Question 1

Load the Movielens 100k dataset ( ml-100k.zip ) into Python using Pandas dataframes. Build a user profile on unscaled data for both users 200 and 15 , and calculate the cosine similarity and distance between the user's preferences and the item/movie 95. Which user would a recommender system suggest this movie to?

## 1.0.1 Extract ratings for users 200 and 15

```
In [8]: user_200 = ratings.iloc[np.where(ratings["user_id"]==200)]
        user_15 = ratings.iloc[np.where(ratings["user_id"]==15)]
        #extract list of movie ids rated for each user
        user_200_movies = np.array(user_200["movie_id"])
        user_15_movies = np.array(user_15["movie_id"])
```

```
In [9]: user_200.head()
```

```
Out[9]:
```

	user_id	movie_id	rating	timestamp
12	200	222	5	876042340
189	200	673	5	884128554
243	200	318	5	884128458
326	200	304	5	876041644
367	200	96	5	884129409

## 1.0.2 Extract genre features

Only the columns containing genre are extracted.

```
In [10]: features = items.iloc[:,5:]
```

```
In [11]: # Movie id is index + 1
        features.head()
```

```
Out[11]:
```

	Unknown	Action	Adventure	Animation	Childrens	Comedy	Crime	\
0	0	0	0	1	1	1	0	
1	0	1	1	0	0	0	0	
2	0	0	0	0	0	0	0	
3	0	1	0	0	0	1	0	
4	0	0	0	0	0	0	1	

  

	Documentary	Drama	Fantasy	FilmNoir	Horror	Musical	Mystery	Romance
0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	
3	0	1	0	0	0	0	0	
4	0	1	0	0	0	0	0	

  

	SciFi	Thriller	War	Western
0	0	0	0	0

1	0	1	0	0
2	0	1	0	0
3	0	0	0	0
4	0	1	0	0

### 1.0.3 Average out utility matrix

Take row averages of the utility matrix to center it for each user.

```
In [12]: user_means = utility.mean(axis=1)
utility_centered = utility - user_means
utility_centered = utility_centered.where((pd.notnull(utility_centered)), 0)
```

```
In [13]: utility_centered.head()
```

```
Out [13]:
```

	1	2	3	4	5	6	7
user_id							
1	1.389706	-0.709677	1.203704	-1.333333	0.125714	1.364929	0.034
2	0.389706	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
5	0.389706	-0.709677	0.000000	0.000000	0.000000	0.000000	0.000

  

	8	9	10	...	1673	1674	1675	1676	1677
user_id				...					
1	-2.79661	0.727273	-1.206522	...	0.0	0.0	0.0	0.0	0.0
2	0.00000	0.000000	-2.206522	...	0.0	0.0	0.0	0.0	0.0
3	0.00000	0.000000	0.000000	...	0.0	0.0	0.0	0.0	0.0
4	0.00000	0.000000	0.000000	...	0.0	0.0	0.0	0.0	0.0
5	0.00000	0.000000	0.000000	...	0.0	0.0	0.0	0.0	0.0

  

	1678	1679	1680	1681	1682
user_id					
1	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0

[5 rows x 1682 columns]

### 1.0.4 Generate user profiles for users 200 and 15

Multiply the centered utility matrix row of both users to the feature dataframe containing feature vector for each movie. Since the movies not rated by the user will have rating of zero, the profile generated would not be counted towards the overall user profile. This makes it safe to multiply the ratings with the entire feature dataframe. Note that the row indices are user id - 1.

```
In [14]: user_200_profile=((features.values*utility_centered.iloc[199,
                        :].values.reshape(-1,1)).sum(axis=0)).reshape(1,-1)
        user_15_profile=((features.values*utility_centered.iloc[14,
                        :].values.reshape(-1,1)).sum(axis=0)).reshape(1,-1)
```

### 1.0.5 Extract vector for item 95

```
In [15]: item_95 = features.iloc[95,:].reshape(1,-1)
```

```
In [16]: print("For User 200:")
        print("Cosine Distance is %s and Cosine Similarity is %s"
              % (cosine_distances(user_200_profile,item_95)[0,0],cosine_similarity
```

For User 200:

Cosine Distance is 0.293108142037 and Cosine Similarity is 0.706891857963

```
In [17]: print("For User 15:")
        print("Cosine Distance is %s and Cosine Similarity is %s"
              % (cosine_distances(user_15_profile,item_95)[0,0],cosine_similarity
```

For User 15:

Cosine Distance is 1.62448866308 and Cosine Similarity is -0.624488663084

The system would recommend movie/item 95 to user 200 as the similarity score is higher/distance score is lower.

## 2 Question 2

### 2.0.1 Utility matrix for data has already been generated

```
In [18]: utility_centered.head()
```

```
Out[18]:
```

	1	2	3	4	5	6	7
user_id							
1	1.389706	-0.709677	1.203704	-1.333333	0.125714	1.364929	0.034
2	0.389706	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
5	0.389706	-0.709677	0.000000	0.000000	0.000000	0.000000	0.000

  

	8	9	10	...	1673	1674	1675	1676	1677
user_id				...					
1	-2.79661	0.727273	-1.206522	...	0.0	0.0	0.0	0.0	0.0
2	0.00000	0.000000	-2.206522	...	0.0	0.0	0.0	0.0	0.0
3	0.00000	0.000000	0.000000	...	0.0	0.0	0.0	0.0	0.0
4	0.00000	0.000000	0.000000	...	0.0	0.0	0.0	0.0	0.0
5	0.00000	0.000000	0.000000	...	0.0	0.0	0.0	0.0	0.0

	1678	1679	1680	1681	1682
user_id					
1	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0

[5 rows x 1682 columns]

## 2.0.2 Find similar users for user 1

```
In [19]: similar_users=cosine_similarity(utility_centered.iloc[0,
      :].values.reshape(1,-1),utility_centered.values).reshape(-1,)
```

```
In [20]: users['similarity'] = pd.Series(similar_users, index=users.index)
```

```
In [21]: users = users.sort_values("similarity",ascending=0)
```

Top 10 users similar to User 1 are:

```
In [22]: users.iloc[1:11,:]
```

```
Out[22]:
```

	user_id	age	gender	occupation	zip_code	similarity
737	738	35	M	technician	95403	0.291487
591	592	18	M	student	97520	0.278402
275	276	21	M	student	95064	0.268151
266	267	23	M	engineer	83716	0.264761
642	643	39	M	scientist	55122	0.264003
756	757	26	M	student	55104	0.262368
456	457	33	F	salesman	30011	0.262337
605	606	28	M	programmer	63044	0.260847
915	916	27	M	engineer	N2L5N	0.255624
43	44	26	M	technician	46260	0.252954

```
In [23]: top_10=np.array(users.iloc[1:11,:]["user_id"].index)
```

Ratings of these similar users for item 508 are:

```
In [24]: utility.iloc[top_10,507]
```

```
Out[24]: user_id
738      NaN
592      5.0
276      5.0
267      NaN
643      4.0
757      NaN
```

```
457      NaN
606      4.0
916      NaN
44       NaN
Name: 508, dtype: float64
```

Note that item id = column index + 1

```
In [25]: print("The Expected Rating of User 1 for Item 508:")
         print("based on average rating of it's similar users is %s."
               % (utility.iloc[top_10,507].mean()))
```

```
The Expected Rating of User 1 for Item 508:
based on average rating of it's similar users is 4.5.
```