

# **CMPE 257 - PROJECT PROPOSAL**

**Project Title:** Movie Recommender System

## **About Data:**

**Dataset Name:** Investigating Serendipity in Recommender Systems Based on Real User Feedback

**Source:** <https://grouplens.org/datasets/serendipity-2018/>

**Data Summary:** GroupLens Research group at the University of Minnesota and the University of Jyväskylä conducted an experiment in MovieLens (<http://movielens.org>) where users were asked how serendipitous particular movies were to them. This dataset contains user answers to GroupLens' questions and additional information, such as past ratings of these users, recommendations they received before replying to the survey and movie descriptions. The dataset was generated on January 15, 2018. The data are contained in the files 'answers.csv', 'movies.csv', 'recommendations.csv', 'tag\_genome.csv', 'tags.csv' and 'training.csv'. Overall, there are 10,000,000 ratings (2,150 ratings stored in 'answers.csv' and 9,997,850 in 'training.csv').

## **Problem Description:**

- To find k-similar users to every user and k-similar items (movies) to every item in the dataset
- To create user profile and movie profile to identify similarities between these vectors for prediction
- To analyze the effect of various movie features such as genres, actors, directors, release date (metadata/content) on the rating prediction
- To design a model which predicts the ratings for users based on user/item similarity and content
- To provide movie recommendation to users based on the predicted ratings and perform a qualitative comparison of different approaches

## **Potential Methods:**

- Similarity metrics such as Cosine, Raw Cosine, Pearson similarity coefficient etc.
- User-based collaborative-filtering using similarity among different users
- Item-based collaborative-filtering using similarity among different items (movies)
- Content-based recommendation system using feature vector for movies (user-item profile)
- Latent-matrix factorization-based recommendation system using other metadata

## **Preprocessing:**

Following steps are performed in data-wrangling

- Remove unnecessary features that are not planned to be used such as timestamp, IMDB ID etc.
- Find dimensions and statistical summary (min, max, mean, median, range, count, etc.) of the dataset
- Check for missing values and handle them
- Check and duplicate observations and handle them
- Factor numerical and categorical columns
- One-hot encoding for categorical column - Movie Genre
- Some visualization for movies and users

## **Challenges:**

- Dataset sampling - Possibility of missing out on relevant information.
- Feature engineering - What attributes are irrelevant to the problem statement?
- Class imbalance - Are all the classes represented equally?
- Missing data - How do different imputation methods affect the model accuracy?
- Data splitting – How to ensure proportional user representation and reliable test and train dataset sizes?

**Github Repository:**

<https://github.com/ankdeshm/CMPE257-MovieRecommenderSystem>

**References:**

- [1] Denis Kotkov, Joseph A. Konstan, Qian Zhao, and Jari Veijalainen. 2018. Investigating Serendipity in Recommender Systems Based on Real User Feedback. In Proceedings of SAC 2018: Symposium on Applied Computing , Pau, France, April 9–13, 2018 (SAC 2018), 10 pages. DOI: 10.1145/3167132.3167276
- [2] Jesse Vig, Shilad Sen, and John Riedl. 2012. The Tag Genome: Encoding Community Knowledge to Support Novel Interaction. ACM Trans. Interact. Intell. Syst. 2, 3: 13:1–13:44. <https://doi.org/10.1145/2362394.2362395>

## Import necessary modules

```
In [7]: #data analysis libraries
import numpy as np
import pandas as pd
from sklearn.preprocessing import MultiLabelBinarizer

#visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

#ignore warnings
import warnings
warnings.filterwarnings('ignore')

# Enable multiple output cells
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

```
In [8]: # Load dataset
movies_full = pd.read_csv("/Users/ankitadeshmukh/Desktop/SJSU/Academic/Fall22/CMPE257/Project/Dataset/serendipity-sac2018/movies.csv", on_bad_lines='skip')
movies_full.head()
```

```
Out[8]:
```

	movieId	title	releaseDate	directedBy	starring	imdbId	tmdbId	genres
0	1	Toy Story (1995)	19/11/95	John Lasseter	Tim Allen, Tom Hanks, Don Rickles, Jim Varney,...	114709	862.0	Adventure,Animation,Children,Comedy,Fantasy
1	2	Jumanji (1995)	15/12/95	Joe Johnston	Jonathan Hyde, Bradley Pierce, Robin Williams,...	113497	8844.0	Adventure,Children,Fantasy
2	3	Grumpier Old Men (1995)	01/01/95	Howard Deutch	Jack Lemmon, Walter Matthau, Ann-Margret , Sop...	113228	15602.0	Comedy,Romance
3	4	Waiting to Exhale (1995)	15/01/96	Forest Whitaker	Angela Bassett, Loretta Devine, Whitney Housto...	114885	31357.0	Comedy,Drama,Romance
4	5	Father of the Bride Part II (1995)	08/12/95	Charles Shyer	Steve Martin, Martin Short, Diane Keaton, Kimb...	113041	11862.0	Comedy

```
In [9]: # Drop unnecessary columns
cols_to_drop = ['imdbId', 'tmdbId']
movies_full.drop(cols_to_drop, axis = 1, inplace = True)
movies_full.head()
```

```
Out[9]:
```

	movieId	title	releaseDate	directedBy	starring	genres
0	1	Toy Story (1995)	19/11/95	John Lasseter	Tim Allen, Tom Hanks, Don Rickles, Jim Varney,...	Adventure,Animation,Children,Comedy,Fantasy
1	2	Jumanji (1995)	15/12/95	Joe Johnston	Jonathan Hyde, Bradley Pierce, Robin Williams,...	Adventure,Children,Fantasy
2	3	Grumpier Old Men (1995)	01/01/95	Howard Deutch	Jack Lemmon, Walter Matthau, Ann-Margret , Sop...	Comedy,Romance
3	4	Waiting to Exhale (1995)	15/01/96	Forest Whitaker	Angela Bassett, Loretta Devine, Whitney Housto...	Comedy,Drama,Romance
4	5	Father of the Bride Part II (1995)	08/12/95	Charles Shyer	Steve Martin, Martin Short, Diane Keaton, Kimb...	Comedy

```
In [10]: # Find numerical columns
movies_full.select_dtypes(exclude=['object']).columns.tolist()
# Find categorical columns
movies_full.select_dtypes(include=['object']).columns.tolist()
# Check for missing values
movies_full.isnull().sum()
# Check for duplicate values
```

```

movies_full.duplicated().sum()

Out[10]: ['movieId']

Out[10]: ['title', 'releaseDate', 'directedBy', 'starring', 'genres']

Out[10]: movieId      0
          title      2
          releaseDate 0
          directedBy 1462
          starring    3547
          genres     3312
          dtype: int64

Out[10]: 0

```

1 numerical columns and 5 categorical columns

No duplicate observations but some missing values

```

In [11]: # Since our dataset is large, removing the rows with missing values won't hurt.
movies_full.dropna(inplace=True)
# Check for missing values again
movies_full.isnull().sum()

Out[11]: movieId      0
          title      0
          releaseDate 0
          directedBy 0
          starring    0
          genres     0
          dtype: int64

In [12]: # Find the dimensions of this dataset
movies_full.shape

Out[12]: (43018, 6)

```

Now we have 43018 unique movies in our dataset with 6 features

Let's use one-hot-encoding to find the movie genres

```

In [13]: seperated_ratings = []

for col in movies_full["genres"]:
    try:
        col = col.split(",")
    except:
        col = ["Null"]
    seperated_ratings.append(col)

data = {'Seperated_genres': seperated_ratings}
test = pd.DataFrame(data)

one_hot = MultiLabelBinarizer()
res = one_hot.fit_transform(seperated_ratings)
classes = one_hot.classes_

df = pd.DataFrame(res, columns=classes)

```

```
movies_full = movies_full.drop('genres', axis=1)
movies_full = movies_full.join(df)
movies_full.head()
```

Out[13]:

[illegible]

5 rows  $\times$  24 columns

```
In [14]: movies_full.shape
```

```
Out[14]: (43018, 24)
```

Now we have additional 18 features compared to previous data which means we have 18 movie genres.

```
In [15]: movies_full.columns
```

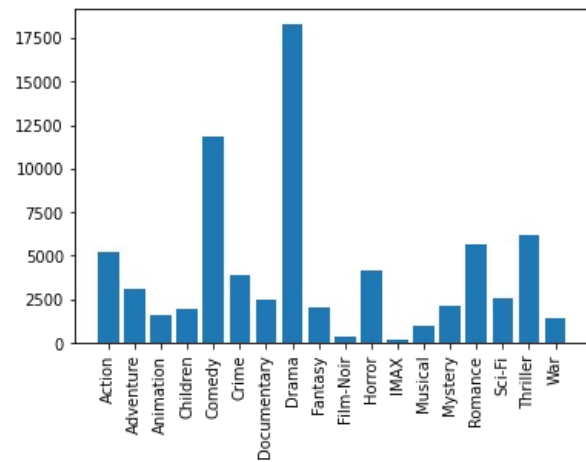
```
Out[15]: Index(['movieId', 'title', 'releaseDate', 'directedBy', 'starring', 'Action',
        'Adventure', 'Animation', 'Children', 'Comedy', 'Crime', 'Documentary',
        'Drama', 'Fantasy', 'Film-Noir', 'Horror', 'IMAX', 'Musical', 'Mystery',
        'Romance', 'Sci-Fi', 'Thriller', 'War', 'Western'],
        dtype='object')
```

```
In [16]: movies_full.describe()
```

Out[16]:

[illegible]





Most of the movies from the dataset belong to Drama genre followed by Comedy.

```
In [20]: # Load training dataset which contains the ratings for movies by different users
training_full = pd.read_csv("/Users/ankitadeshmukh/Desktop/SJSU/Academic/Fall22/CMPE257/Project/Dataset/serendipity-sac2018/training.csv")
training_full.head()
```

```
Out[20]:
```

	userId	movieId	rating	timestamp
0	142882	91658	2.5	1515209647000
1	142882	4344	1.0	1515209646000
2	142882	45720	2.0	1515209643000
3	142882	4734	2.0	1515209641000
4	142882	91542	2.0	1515209637000

```
In [21]: # Drop unnecessary columns
cols_to_drop = ['timestamp']
training_full.drop(cols_to_drop, axis = 1, inplace = True)
training_full.head()
```

```
Out[21]:
```

	userId	movieId	rating
0	142882	91658	2.5
1	142882	4344	1.0
2	142882	45720	2.0
3	142882	4734	2.0
4	142882	91542	2.0

```
In [22]: # Find numerical colums
training_full.select_dtypes(exclude=['object']).columns.tolist()
# Find categorical colums
training_full.select_dtypes(include=['object']).columns.tolist()
# Check for missing values
training_full.isnull().sum()
# Check for duplicate values
training_full.duplicated().sum()
```

```
Out[22]: ['userId', 'movieId', 'rating']
```

```
Out[22]: []
```

```
Out[22]:
```

userId	0
movieId	0
rating	0

dtype: int64

```
Out[22]: 0
```

3 numerical columns and 0 categorical columns

No missing values and no duplicate observations

```
In [23]: # Merge movies and training file based on movieId
movie_ratings_df = pd.merge(training_full, movies_full, on='movieId')
movie_ratings_df.head()
```



Out[23]:

	userId	movieId	rating	title	releaseDate	directedBy	starring	Action	Adventure	Animation	...	Film-Noir	Horror	IMAX	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
0	142882	91658	2.5	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	142911	91658	5.0	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	142893	91658	3.0	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	142884	91658	4.0	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	142322	91658	4.0	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 26 columns

In [25]: `#Extracting the year from the Title`  
`movie_ratings_df['Year'] = movie_ratings_df['title'].str.extract('.*\((.*)\).*',expand = False)`  
`movie_ratings_df.head()`

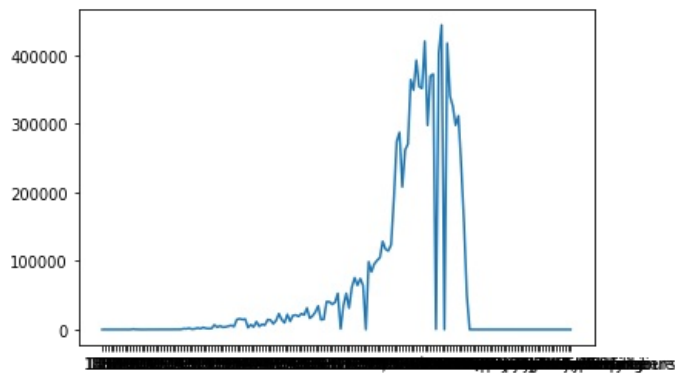
Out[25]:

	userId	movieId	rating	title	releaseDate	directedBy	starring	Action	Adventure	Animation	...	Horror	IMAX	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western	Year
0	142882	91658	2.5	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2011
1	142911	91658	5.0	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2011
2	142893	91658	3.0	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2011
3	142884	91658	4.0	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2011
4	142322	91658	4.0	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	1.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2011

5 rows × 27 columns

In [117...]: `#Ploting a Graph with number of Movies each Year corresponding to its Year`  
`plt.plot(movie_ratings_df.groupby('Year').title.count())`  
`plt.show()`  
`a=movie_ratings_df.groupby('Year').title.count()`  
`print('Max No.of Movies Relesed =',a.max())`  
`for i in a.index:`  
`if a[i] == a.max():`  
`print('Year =',i)`  
`a.describe()`

Out[117]: `[<matplotlib.lines.Line2D at 0x26751f700>]`



Max No.of Movies Relesed = 443747  
Year = 2009

```
Out[117]: count    168.000000
          mean    59120.642857
          std     113861.704637
          min       1.000000
          25%       8.750000
          50%     3557.000000
          75%    40391.250000
          max    443747.000000
          Name: title, dtype: float64
```

Now we know that the maximum number of movies were in 2009 with count = 443747. On an average, 59120 movies are released every year.

```
In [134]: avg_rating_df = movie_ratings_df.groupby(['movieId']).agg (avg_rating = ('rating', 'mean'))
count_df = new_df.groupby(['movieId']).agg (user_count = ('userId', 'count'))
movie_ratings_df = pd.merge(movie_ratings_df, avg_rating_df, how='outer', on='movieId')
movie_ratings_df = pd.merge(movie_ratings_df, count_df, how='outer', on='movieId')
new_df = movie_ratings_df.drop(['rating', 'releaseDate', 'directedBy', 'starring', 'genres', 'Year'],axis = 1)
new_df.head()
```

```
Out[134]:
```

	userId	movieId	title	avg_rating	user_count
0	142882	91658	Girl with the Dragon Tattoo, The (2011)	3.817041	7652
1	142911	91658	Girl with the Dragon Tattoo, The (2011)	3.817041	7652
2	142893	91658	Girl with the Dragon Tattoo, The (2011)	3.817041	7652
3	142884	91658	Girl with the Dragon Tattoo, The (2011)	3.817041	7652
4	142322	91658	Girl with the Dragon Tattoo, The (2011)	3.817041	7652

```
In [136]: new_df.sort_values(['user_count', 'avg_rating'],ascending=False)
```

Out[136]:

	userid	movieId	title	avg_rating	user_count
2338286	142914	2571	Matrix, The (1999)	4.107004	42120
2338287	142913	2571	Matrix, The (1999)	4.107004	42120
2338288	142905	2571	Matrix, The (1999)	4.107004	42120
2338289	142911	2571	Matrix, The (1999)	4.107004	42120
2338290	142909	2571	Matrix, The (1999)	4.107004	42120
...	...	...	...	...	...
9935277	154955	1561	Wedding Bell Blues (1996)	0.500000	1
9935278	154955	1424	Inside (1996)	0.500000	1
9935281	154955	8095	Cucaracha, La (1998)	0.500000	1
9935282	154955	3541	Third World Cop (1999)	0.500000	1
9935320	153352	1789	Sadness of Sex, The (1995)	0.500000	1

9935346 rows × 5 columns

## Movies with the highest ratings

```
In [138]: # selecting rows based on condition
rslt_df = new_df.loc[new_df['avg_rating'] == 5.0].sort_values(['user_count'],ascending=False)
rslt_df
```

Out[138]:

	userid	movieId	title	avg_rating	user_count
9929785	102667	51571	Hazaaron Khwaishein Aisi	5.0	2
9908020	126685	166028	What Remains of Us (2004)	5.0	2
9925813	114386	151569	The Old Fairy Tale: When the Sun Was God (2003)	5.0	2
9928380	110773	144192	¡Cuba Si! (1961)	5.0	2
9886032	101983	140369	War Arrow (1954)	5.0	2
...	...	...	...	...	...
9839502	137276	175727	Cure for Pain: The Mark Sandman Story (2011)	5.0	1
9839501	137276	175729	Itinéraire bis (2011)	5.0	1
9839500	137276	175731	The Box (2004)	5.0	1
9839481	137276	175737	Ducoboo (2011)	5.0	1
9935340	144534	5814	Rising Place, The (2002)	5.0	1

412 rows × 5 columns

Most of the movies which are rated 5 stars are only rated by 1 or 2 people.

## Top-10 most watched movies

```
In [150]: rating_count = movie_ratings_df.groupby('title')['user_count']
rating_count = rating_count.count().sort_values(ascending=False)
```

```
rating_count[:10]
```

```
Out[150]: title
Matrix, The (1999) 42120
Shawshank Redemption, The (1994) 40889
Inception (2010) 37947
Dark Knight, The (2008) 34531
Fight Club (1999) 34290
Forrest Gump (1994) 33854
Lord of the Rings: The Return of the King, The (2003) 32509
Lord of the Rings: The Fellowship of the Ring, The (2001) 31634
Star Wars: Episode IV - A New Hope (1977) 29141
Pulp Fiction (1994) 29140
Name: avg_rating, dtype: int64
```

The most watched movie from our dataset is "The Matrix" with 42120 views. It is also the highest rated movie considering user ratings and viewer count.

Let's find out how different users rated "The Matrix".

```
In [157]: plt.figure(figsize=(8,6))
movies_grouped = movie_ratings_df.groupby('title')
the_matrix = movies_grouped.get_group('Matrix, The (1999)')
the_matrix['rating'].hist()
plt.title('User rating of the movie "The Matrix"')
plt.xlabel('Rating')
plt.ylabel('Number of Users')

plt.show()
```

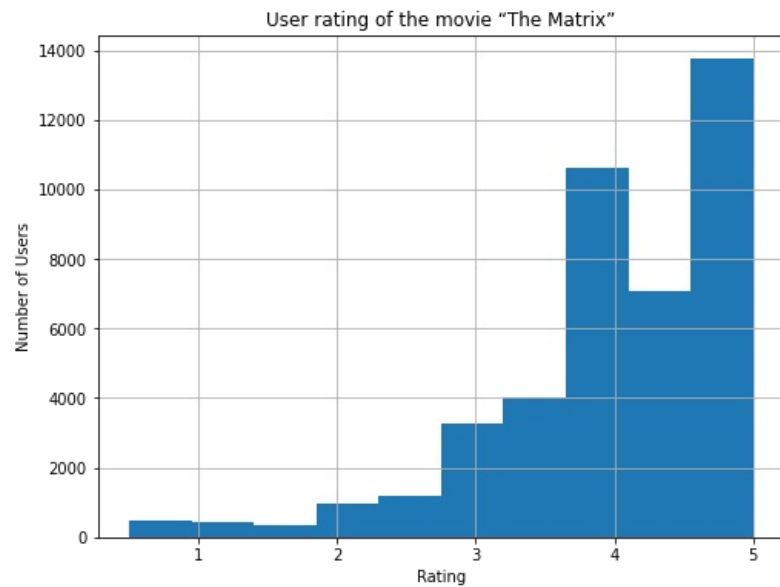
```
Out[157]: <Figure size 576x432 with 0 Axes>
```

```
Out[157]: <AxesSubplot:>
```

```
Out[157]: Text(0.5, 1.0, 'User rating of the movie "The Matrix"')
```

```
Out[157]: Text(0.5, 0, 'Rating')
```

```
Out[157]: Text(0, 0.5, 'Number of Users')
```



```
In [158.. # unique_movies_df = movie_ratings_df.drop_duplicates('movieId')
# unique_movies_df
```

Let's see which user voted for the most number of movies.

```
In [160.. user_rating_df = movie_ratings_df.groupby(['userId']).agg (avg_user_rating = ('rating', 'mean'))
user_count_df = movie_ratings_df.groupby(['userId']).agg (avg_user_count = ('rating', 'count'))
user_ratings_df = pd.merge(movie_ratings_df, user_rating_df, how='outer', on='userId')
user_ratings_df = pd.merge(user_ratings_df, user_count_df, how='outer', on='userId')
user_ratings_df.head()
```

Out[160]:	userId	movieId	rating	title	releaseDate	directedBy	starring	genres	Year	avg_rating	user_count	avg_user_rating	avg_user_count
0	142882	91658	2.5	Girl with the Dragon Tattoo, The (2011)	21/12/11	David Fincher	Daniel Craig, Rooney Mara, Christopher Plummer...	Drama,Thriller	2011	3.817041	7652	2.598077	780
1	142882	4344	1.0	Swordfish (2001)	08/06/01	Dominic Sena	Hugh Jackman, John Travolta, Halle Berry, Don ...	Action,Crime,Drama	2001	3.129220	2755	2.598077	780
2	142882	45720	2.0	Devil Wears Prada, The (2006)	30/06/06	David Frankel	Anne Hathaway, Meryl Streep, Adrian Grenier, S...	Comedy,Drama	2006	3.491760	5704	2.598077	780
3	142882	4734	2.0	Jay and Silent Bob Strike Back (2001)	24/08/01	Kevin Smith	Jason Mewes, Kevin Smith, Ben Affleck, Jeff An...	Adventure,Comedy	2001	3.224567	2654	2.598077	780
4	142882	91542	2.0	Sherlock Holmes: A Game of Shadows (2011)	16/12/11	Guy Ritchie	Robert Downey Jr., Jude Law, Rachel McAdams, N...	Action,Adventure,Comedy,Crime,Mystery,Thriller	2011	3.739130	7866	2.598077	780

```
In [164]: new_user_df = user_ratings_df.drop(['rating', 'releaseDate', 'directedBy', 'starring', 'genres', 'Year', 'user_count'],axis = 1)
new_user_df.sort_values(by = "avg_user_count", ascending=False).head(10)
```

Out[164]:	userId	movieId	title	avg_rating	avg_user_rating	avg_user_count
1382129	148071	110512	My Lady Margarine (Die Austernprinzessin) (Oys...	3.285714	3.166769	17923
1378006	148071	81660	1990: The Bronx Warriors (1990: I guerrieri de...	2.720000	3.166769	17923
1378016	148071	61941	Humboldt County (2008)	3.318182	3.166769	17923
1378015	148071	5636	Welcome to Collinwood (2002)	3.192308	3.166769	17923
1378014	148071	6410	Car Wash (1976)	2.819444	3.166769	17923
1378013	148071	48159	Everyone's Hero (2006)	2.975610	3.166769	17923
1378012	148071	54254	Come Early Morning (2006)	3.192308	3.166769	17923
1378011	148071	55729	King of California (2007)	3.339161	3.166769	17923
1378010	148071	61991	Miracle at St. Anna (2008)	2.993056	3.166769	17923
1378009	148071	65045	Alien Raiders (2008)	2.734043	3.166769	17923

## Top-10 users who voted the most number of movies

```
In [165]: rating_count = new_user_df.groupby('userId')['avg_user_count']
rating_count = rating_count.count().sort_values(ascending=False)
rating_count[:10]
```

```
Out[165]:
userId
148071    17923
184994     7705
121660     5720
149977     5575
119645     5485
138634     4950
113476     4941
183041     4831
154364     4806
129944     4589
Name: avg_user_count, dtype: int64
```

## Rating pattern of User 148071

```
In [169]: plt.figure(figsize=(8,6))
users_grouped = user_ratings_df.groupby('userId')
user_148071 = users_grouped.get_group(148071)
user_148071['rating'].hist()
plt.title('User rating for different movies')
plt.xlabel('Rating')
plt.ylabel('No of movies rated bu User 148071')
plt.show()
```

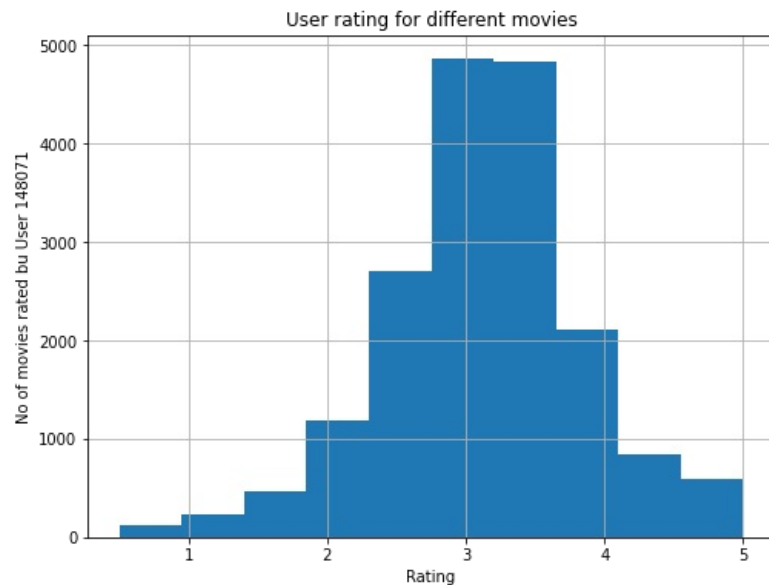
Out[169]: <Figure size 576x432 with 0 Axes>

Out[169]: <AxesSubplot:>

Out[169]: Text(0.5, 1.0, 'User rating for different movies')

Out[169]: Text(0.5, 0, 'Rating')

Out[169]: Text(0, 0.5, 'No of movies rated bu User 148071')



There are other files like tags.csv, tag\_genome.csv, answers.csv and we might use some of those files as metadata for content-based recommendations and latent-matrix factorization.