MovieLens Recommender System

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- Student pace: self paced
- Scheduled project review date/time: 01/04/2022
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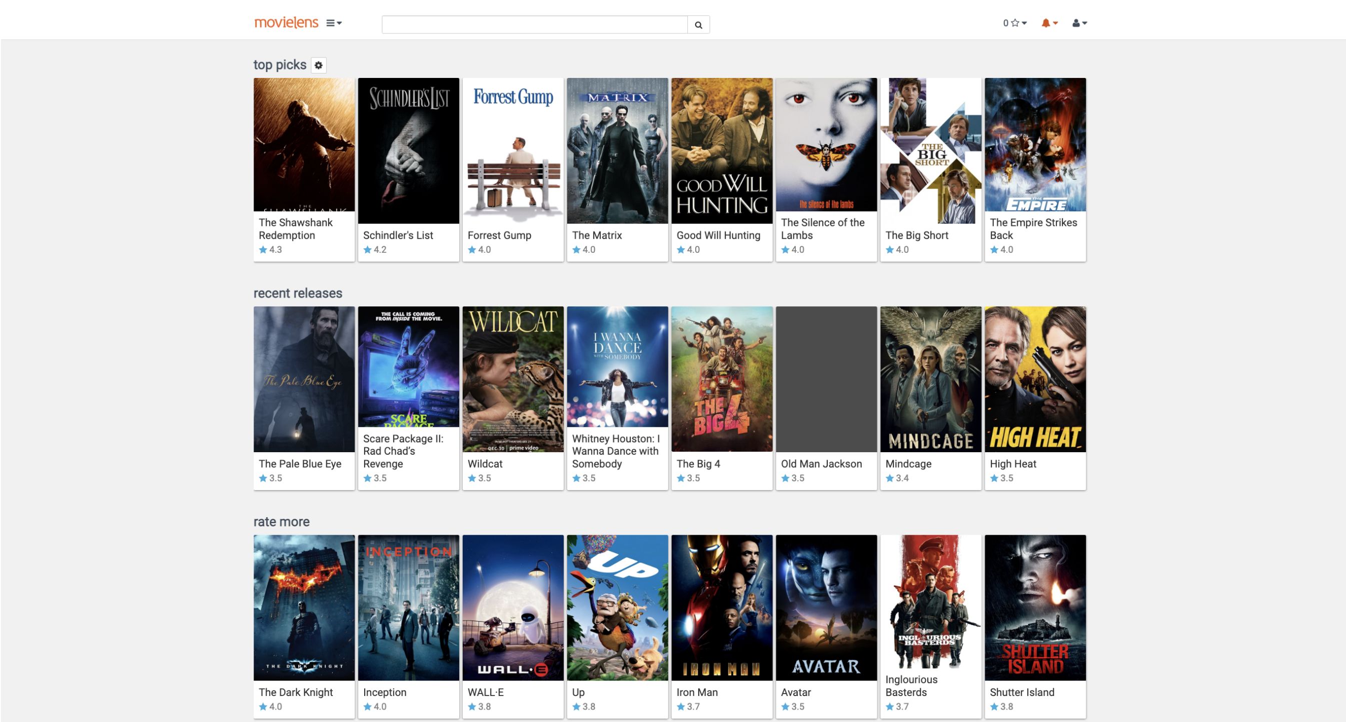
Overview



In this project ,I chose the MovieLens dataset and managed to create a movie recommendation system that somehow simulates some of the most successful recommendation engine products, such as Spotify, YouTube, and Netflix.

This notebook is going to explain how I worked throughout the entire life cycle of this project, and provide my solutions to some technical issues.

For the recommender system I will use Content-based, Collaborative and Model Based.Recommender systems are built on MovieLens dataset with 100,000 movie ratings. These Recommender systems were built using Pandas operations and by fitting Machine Learning models to suggest movies for the users based on similar users and for queries specific to genre, user, movie, rating.

Business Understanding

MovieLens wants to improve it's movie recommendation system that is located on users' homepages.

The goal is to use users movie ratings and recommend other movies. This may save the user time when deciding which movie they would like to watch

Data Understanding

https://grouplens.org/datasets/movielens/latest/

This dataset (ml-latest-small) describes 5-star rating and free-text tagging activity from MovieLens, a movie recommendation service. It contains 100836 ratings and 943 users informations across 9742 movies.

Users were selected at random for inclusion. All selected users had rated at least 20 movies.

The data are contained in the files **u.user**, **movies.csv** and **ratings.csv**.

- **movies.csv**: Movie information is contained in the file movies.csv. Each line of this file after the header row represents one movie, and has the following format:

movieId: Unique id for each movie

title: Name of movies followed by their year of release

genres: categories that a movie might fall into separated by |

- **ratings.csv**: A table that records all the users' rating behaviors, covering their rates and the time stamp when they posted the rates.

userId: Unique id for each user

movieId: Unique id for each movie

rating: Rating given by userId for movieId. Ratings are made on a 5-star scale with 0.5 increments.

timestamp: Time when rating was given

- **u.user**: A table that records each user's unique ID , age , sex, occupation and zip code.

Importing Libraries

```
# importing necessary libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')

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

Loading Dataset

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=Tru
```

```
path = "/content/drive/MyDrive/Project/ml-latest-small/movies.csv"
movie_df = pd.read_csv(path)
movie_df.head()
```

	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

```
movie_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   movieId  9742 non-null   int64 
 1   title    9742 non-null   object
 2   genres   9742 non-null   object
```

```
dtypes: int64(1), object(2)
memory usage: 228.5+ KB
```

```
path = "/content/drive/MyDrive/Project/ml-latest-small/ratings.csv"
rating_df = pd.read_csv(path)
rating_df.head()
```

	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

```
rating_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100836 entries, 0 to 100835
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   userId     100836 non-null  int64
 1   movieId    100836 non-null  int64
 2   rating     100836 non-null  float64
 3   timestamp  100836 non-null  int64
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
```

```
# I will use this data only for EDA
u_cols = ['userId', 'age', 'sex', 'occupation', 'zip_code']
path = "/content/drive/MyDrive/Project/ml-latest-small/u.user"
users_df = pd.read_csv(path, sep='|', names=u_cols,
                       encoding='latin-1', parse_dates=True)
```

```
users_df
```

	userId	age	sex	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
...	...	...	...	...	...
938	939	26	F	student	33319
939	940	32	M	administrator	02215
940	941	20	M	student	97229
941	942	48	F	librarian	78209
942	943	22	M	student	77841

943 rows × 5 columns

```
users_df['age'].value_counts()
```

```
30    39
25    38
22    37
28    36
27    35
      ..
7      1
66     1
11     1
10     1
```

```
73     1
Name: age, Length: 61, dtype: int64
```

```
users_df['occupation'].value_counts()
```

```
student          196
other            105
educator          95
administrator     79
engineer          67
programmer        66
librarian         51
writer            45
executive         32
scientist         31
artist            28
technician        27
marketing         26
entertainment     18
healthcare        16
retired           14
lawyer            12
salesman          12
none               9
homemaker          7
doctor             7
Name: occupation, dtype: int64
```

```
users_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 943 entries, 0 to 942
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   userId      943 non-null    int64
 1   age         943 non-null    int64
 2   sex         943 non-null    object
 3   occupation  943 non-null    object
 4   zip_code    943 non-null    object
dtypes: int64(2), object(3)
memory usage: 37.0+ KB
```

Some observation from dataset:

- Genres column has several genres , we need seperate them to do meaningful analysis
- users_df has **zip_code** columns we dont use this feature for the future analysis. it can be dropped.

Exploratory Data Analysis and Data Cleaning

```
# Merging ratings and movies data

merged_movies = pd.merge(movie_df, rating_df, on='movieId', how='inner')
merged_movies
```

	movieId	title	genres	userId	rating	timestamp

```
# Dropping the timestamp column
merged_movies = merged_movies.drop('timestamp', axis=1)
```

2	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	7	4.5	1106635946

```
merged_movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100836 entries, 0 to 100835
Data columns (total 5 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   movieId  100836 non-null  int64  
 1   title    100836 non-null  object 
 2   genres   100836 non-null  object 
 3   userId   100836 non-null  int64  
 4   rating   100836 non-null  float64
dtypes: float64(1), int64(2), object(2)
memory usage: 4.6+ MB
```

100836 rows × 6 columns

- There are no null values in the dataset.

```
merged_movies['userId'].value_counts()
```

```
414    2698
599    2478
474    2108
448    1864
274    1346
       ... 
53       20
207      20
431      20
442      20
189      20
Name: userId, Length: 610, dtype: int64
```

```
# Droppping zipcode column
df_merged =  pd.merge(merged_movies, users_df, on='userId')
df_merged = df_merged.drop('zip_code' , axis =1)
df_merged
```

	movieId	title	genres	userId	rating	age	sex	occupation
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	1	4.0	24	M	technician
1	3	Grumpier Old Men (1995)	Comedy|Romance	1	4.0	24	M	technician
2	6	Heat (1995)	Action|Crime|Thriller	1	4.0	24	M	technician
3	47	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller	1	5.0	24	M	technician
4	50	Usual Suspects, The (1995)	Crime|Mystery|Thriller	1	5.0	24	M	technician
...	...	...	...	...	...	...	...	...
100831	193579	Jon Stewart Has Left the Building (2015)	Documentary	184	3.5	37	M	librarian
100832	193581	Black Butler: Book of the Atlantic (2017)	Action|Animation|Comedy|Fantasy	184	4.0	37	M	librarian
100833	193583	No Game No Life: Zero (2017)	Animation|Comedy|Fantasy	184	3.5	37	M	librarian
100834	193585	Flint (2017)	Drama	184	3.5	37	M	librarian
100835	193587	Bungo Stray Dogs: Dead Apple (2018)	Action|Animation	184	3.5	37	M	librarian

100836 rows × 8 columns

```
df_merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100836 entries, 0 to 100835
Data columns (total 8 columns):
 #   Column      Non-Null Count   Dtype  
---  ------      --------------   -----  
 0   movieId     100836 non-null  int64  
 1   title       100836 non-null  object 
 2   genres      100836 non-null  object 
 3   userId      100836 non-null  int64  
```

```
 4   rating      100836 non-null  float64
 5   age         100836 non-null  int64
 6   sex         100836 non-null  object
 7   occupation  100836 non-null  object
dtypes: float64(1), int64(3), object(4)
memory usage: 6.9+ MB
```

```
df_merged.isna().sum()
```

```
movieId       0
title         0
genres        0
userId        0
rating        0
age           0
sex           0
occupation    0
dtype: int64
```

```
# Extracting release year from movie title
df_merged['year'] = df_merged['title'].str.extract('.*\((.*)\).*',expand = False)
df_merged['year'].unique()
```

```
array(['1995', '1996', '1994', '1977', '1993', '1990', '1989', '1991',
       '1940', '1939', '1941', '1938', '1947', '1975', '1968', '1945',
       '1963', '1971', '1951', '1979', '1992', '1986', '1982', '1980',
       '1987', '1981', '1983', '1960', '1952', '1984', '1933', '1985',
       '1974', '1922', '1997', '1998', '1930', '1976', '1942', '1967',
       '1959', '1946', '1978', '1973', '1988', '1999', '1931', '1964',
       '1962', '1965', '1969', '2000', '1970', '1937', '1954', '2001',
       '2002', '2003', '2004', '2005', '2006', '1972', '1961', '2007',
       '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015',
       '2016', '1966', '1944', '1957', '1949', '1955', '1936', '2017',
       '1958', '1935', '1943', '1927', '1953', '1926', '1950', '1956',
       '1923', '1902', '1920', '2018', '1948', '1928', '1934', '1916',
       '1908', '1932', '1925', '1921', '1915', '1924', '1929', '1903',
       '1919', nan, '1917', '2006–2007'], dtype=object)
```

```
# Changing 2006-2007 to 2007
df_merged['year'] = df_merged['year'].replace("2006–2007","2007")
df_merged['year'].unique()
```

```
array(['1995', '1996', '1994', '1977', '1993', '1990', '1989', '1991',
       '1940', '1939', '1941', '1938', '1947', '1975', '1968', '1945',
       '1963', '1971', '1951', '1979', '1992', '1986', '1982', '1980',
       '1987', '1981', '1983', '1960', '1952', '1984', '1933', '1985',
       '1974', '1922', '1997', '1998', '1930', '1976', '1942', '1967',
       '1959', '1946', '1978', '1973', '1988', '1999', '1931', '1964',
       '1962', '1965', '1969', '2000', '1970', '1937', '1954', '2001',
       '2002', '2003', '2004', '2005', '2006', '1972', '1961', '2007',
       '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015',
       '2016', '1966', '1944', '1957', '1949', '1955', '1936', '2017',
       '1958', '1935', '1943', '1927', '1953', '1926', '1950', '1956',
       '1923', '1902', '1920', '2018', '1948', '1928', '1934', '1916',
       '1908', '1932', '1925', '1921', '1915', '1924', '1929', '1903',
       '1919', nan, '1917'], dtype=object)
```

```
# df_merged[df_merged['year'] == "nan"]
df_nan = df_merged[pd.isna(df_merged['year'])]
df_nan
```

	movieId	title	genres	userId	rating	age	sex	occupation	year
33055	140956	Ready Player One	Action|Sci-Fi|Thriller	380	3.0	32	M	engineer	NaN
37532	167570	The OA	(no genres listed)	414	4.0	24	M	programmer	NaN
40842	143410	Hyena Road	(no genres listed)	448	2.0	23	M	entertainment	NaN
41839	162414	Moonlight	Drama	462	5.0	19	F	student	NaN
48424	140956	Ready Player One	Action|Sci-Fi|Thriller	514	3.0	27	M	programmer	NaN
49731	40697	Babylon 5	Sci-Fi	528	0.5	18	M	student	NaN
52739	156605	Paterson	(no genres listed)	567	4.5	24	M	entertainment	NaN

```
df_merged = df_merged.dropna(subset=['year'],how='any')
df_merged['year'].unique()
```

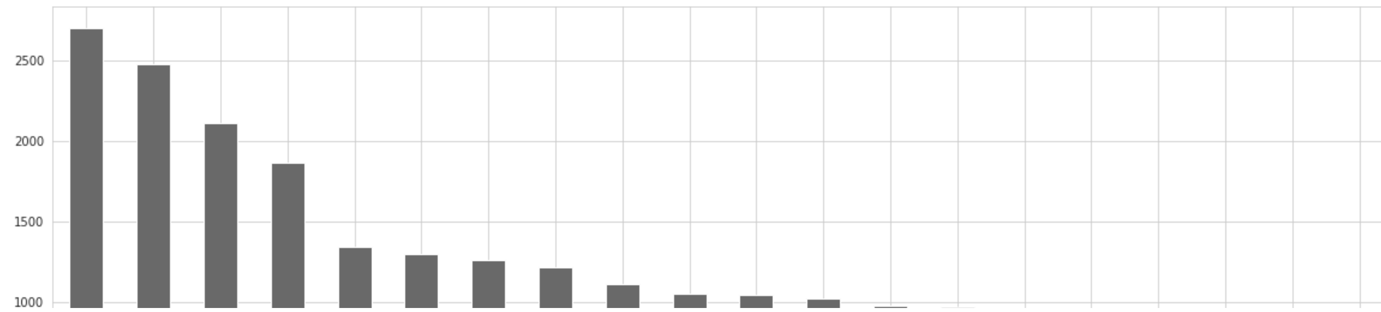
```
array(['1995', '1996', '1994', '1977', '1993', '1990', '1989', '1991',
       '1940', '1939', '1941', '1938', '1947', '1975', '1968', '1945',
       '1963', '1971', '1951', '1979', '1992', '1986', '1982', '1980',
       '1987', '1981', '1983', '1960', '1952', '1984', '1933', '1985',
       '1974', '1922', '1997', '1998', '1930', '1976', '1942', '1967',
       '1959', '1946', '1978', '1973', '1988', '1999', '1931', '1964',
       '1962', '1965', '1969', '2000', '1970', '1937', '1954', '2001',
       '2002', '2003', '2004', '2005', '2006', '1972', '1961', '2007',
       '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015',
       '2016', '1966', '1944', '1957', '1949', '1955', '1936', '2017',
       '1958', '1935', '1943', '1927', '1953', '1926', '1950', '1956',
       '1923', '1902', '1920', '2018', '1948', '1928', '1934', '1916',
       '1908', '1932', '1925', '1921', '1915', '1924', '1929', '1903',
       '1919', '1917'], dtype=object)
```

```
df_merged['genres'] = df_merged['genres'].replace('(no genres listed)', np.nan)
print('Number of missing values in genres column:',df_merged['genres'].isna().sum())

# dropping rows with missing genres
df_merged= df_merged.dropna(subset=['genres'],how='any')
df_merged= df_merged.reset_index(drop=True)

df_merged.info()
```

```
Number of missing values in genres column: 38
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100781 entries, 0 to 100780
Data columns (total 9 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   movieId     100781 non-null  int64
 1   title       100781 non-null  object
 2   genres      100781 non-null  object
 3   userId      100781 non-null  int64
 4   rating      100781 non-null  float64
 5   age         100781 non-null  int64
 6   sex         100781 non-null  object
 7   occupation  100781 non-null  object
 8   year        100781 non-null  object
dtypes: float64(1), int64(3), object(5)
memory usage: 6.9+ MB
```

```
df_merged.to_csv('df_merged.csv',index=False)
```

```
#Grouping the rating based on user

ratings_by_users = df_merged.groupby('userId').agg({'rating': [np.size, np.mean]})
ratings_by_users['rating']['size'].sort_values(ascending = False).head(20).plot(kind = 'bar', figsize = (20,7), color = 'dimgray')
```



- This graph shows us the users who rated mostly.
- ratings are not evenly distributed across users and users at most provided around 2,700 ratings

```
# in this table we can see that user_414' rated movies and demographic information
user_414 = df_merged[df_merged['userId'] == 414]
user_414.head()
```

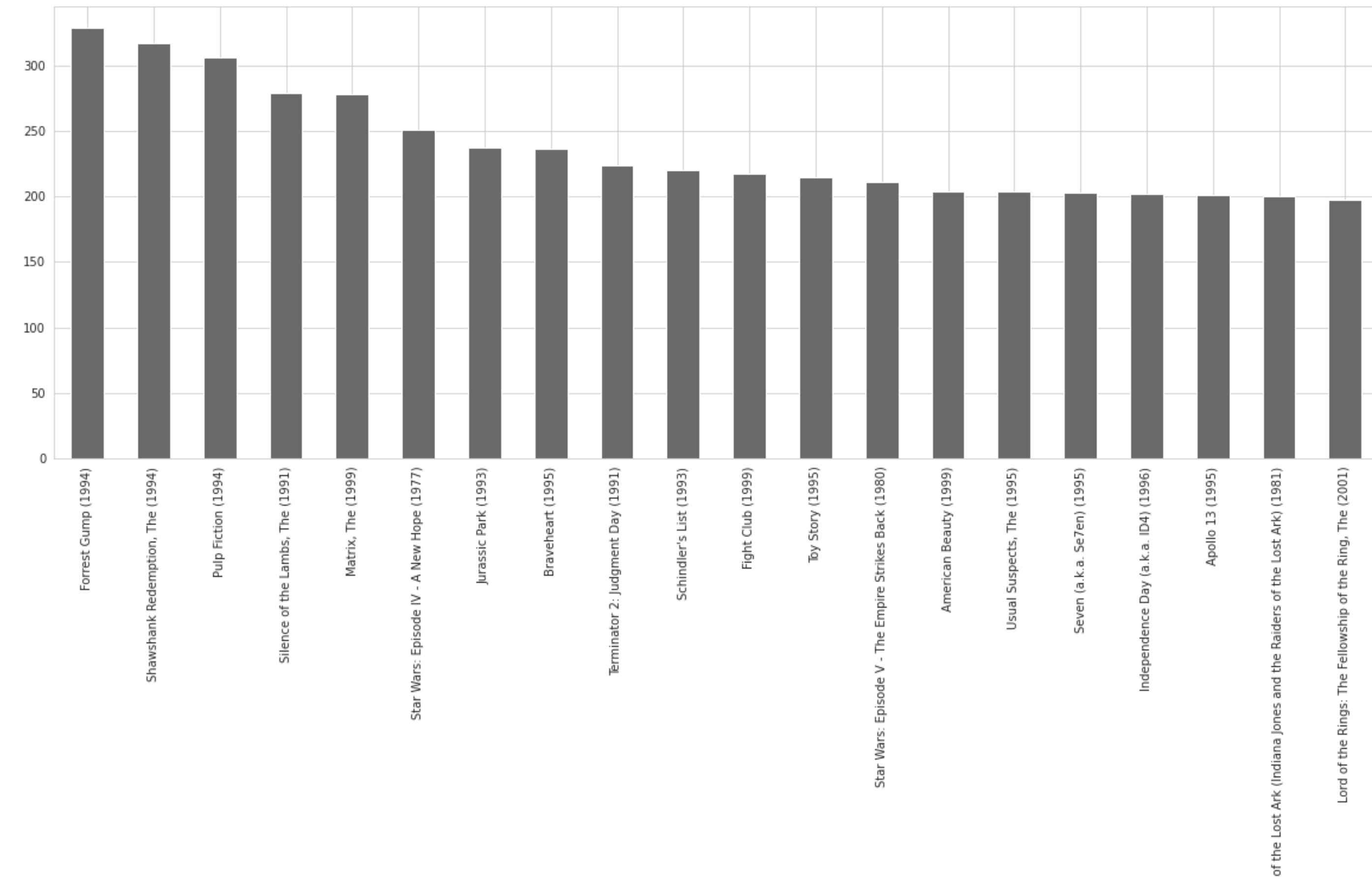
	movieId	title	genres	userId	rating	age	sex	occupation	year
34855	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	414	4.0	24	M	programmer	1995
34856	2	Jumanji (1995)	Adventure|Children|Fantasy	414	3.0	24	M	programmer	1995
34857	3	Grumpier Old Men (1995)	Comedy|Romance	414	4.0	24	M	programmer	1995
34858	5	Father of the Bride Part II (1995)	Comedy	414	2.0	24	M	programmer	1995
34859	6	Heat (1995)	Action|Crime|Thriller	414	3.0	24	M	programmer	1995

```
# Grouping the ratings based on movies
ratings_by_movies = df_merged.groupby('title').agg({'rating': [np.size, np.mean]})
ratings_by_movies
```

	rating	
	size	mean
title		
'71 (2014)	1	4.000000
'Hellboy': The Seeds of Creation (2004)	1	4.000000
'Round Midnight (1986)	2	3.500000
'Salem's Lot (2004)	1	5.000000
'Til There Was You (1997)	2	4.000000
...	...	...
eXistenZ (1999)	22	3.863636
xXx (2002)	24	2.770833
xXx: State of the Union (2005)	5	2.000000
¡Three Amigos! (1986)	26	3.134615
À nous la liberté (Freedom for Us) (1931)	1	1.000000

9681 rows × 2 columns

```
# Most rated movies
ratings_by_movies['rating']['size'].sort_values(ascending = False).head(20).plot(kind = 'bar', figsize = (20,7), color = 'dimgrey'
```



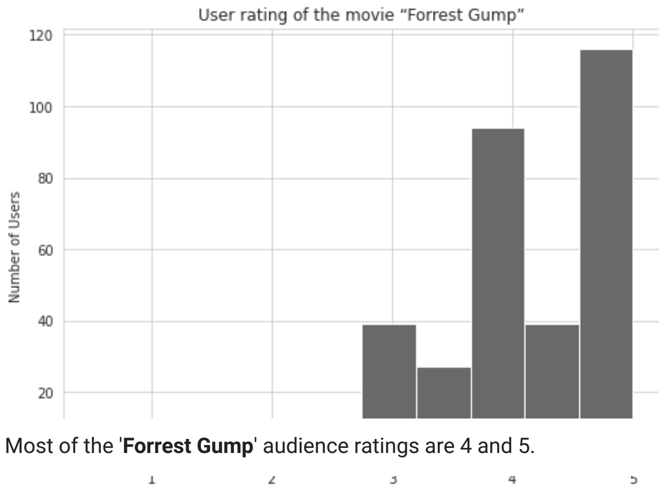
- ratings are not evenly distributed among movies and the most rated movies is “Forrest Gump” which has no more than 350 ratings

```
# We can consider high average rated movies as popular movies
pop_ratings_by_movies = ratings_by_movies[ratings_by_movies['rating']['size']>200]
pop_ratings_by_movies['rating']['mean'].sort_values( ascending=False).head(10)
```

```
title
Shawshank Redemption, The (1994)                         4.429022
Fight Club (1999)                                        4.272936
Usual Suspects, The (1995)                               4.237745
Star Wars: Episode IV - A New Hope (1977)                4.231076
Schindler's List (1993)                                  4.225000
Star Wars: Episode V - The Empire Strikes Back (1980)    4.215640
Pulp Fiction (1994)                                      4.197068
Matrix, The (1999)                                       4.192446
Forrest Gump (1994)                                      4.164134
Silence of the Lambs, The (1991)                         4.161290
Name: mean, dtype: float64
```

- **ratings_by_users** and **ratings_by_movies** tables would allow us to understand which movie is well loved or reviewed in our database. I will make use of this information in the following sections.

```
# User rating of the movie “Forrest Gump”

plt.figure(figsize=(8,6))
movies_grouped = df_merged.groupby('title')
Forrest_Gump = movies_grouped.get_group('Forrest Gump (1994)')
Forrest_Gump['rating'].hist(color = 'dimgray')
plt.title('User rating of the movie “Forrest Gump”')
plt.xlabel('Rating')
plt.ylabel('Number of Users')

plt.show()
```



- Most of the '**Forrest Gump**' audience ratings are 4 and 5.

```
# Checking duplicates if there is any
df_merged.duplicated().sum()
```

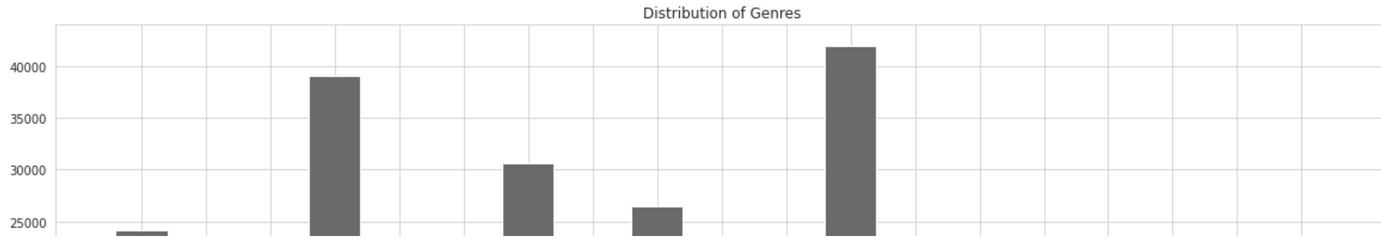
```
0
```

Visual Representations of Data

```
genre_popularity = (movie_df.genres.str.split('|')
                      .explode()
                      .value_counts()
                      .sort_values(ascending=False))
genre_popularity.head(10)
```

```
Drama        4361
Comedy       3756
Thriller     1894
Action       1828
Romance      1596
Adventure    1263
Crime        1199
Sci-Fi        980
Horror        978
Fantasy       779
Name: genres, dtype: int64
```

```
# Distribution of Genres

plt.figure(figsize=(20,7))
genres = df_merged['genres'].apply(lambda genres_movie : str(genres_movie).split("|"))

genres_count = {}
for genres_movie in genres:
    for genre in genres_movie:
        if(genres_count.get(genre,False)):
            genres_count[genre]=genres_count[genre]+1
        else:
            genres_count[genre] = 1
plt.bar(genres_count.keys(),genres_count.values(),color='dimgray');
plt.title('Distribution of Genres');
```

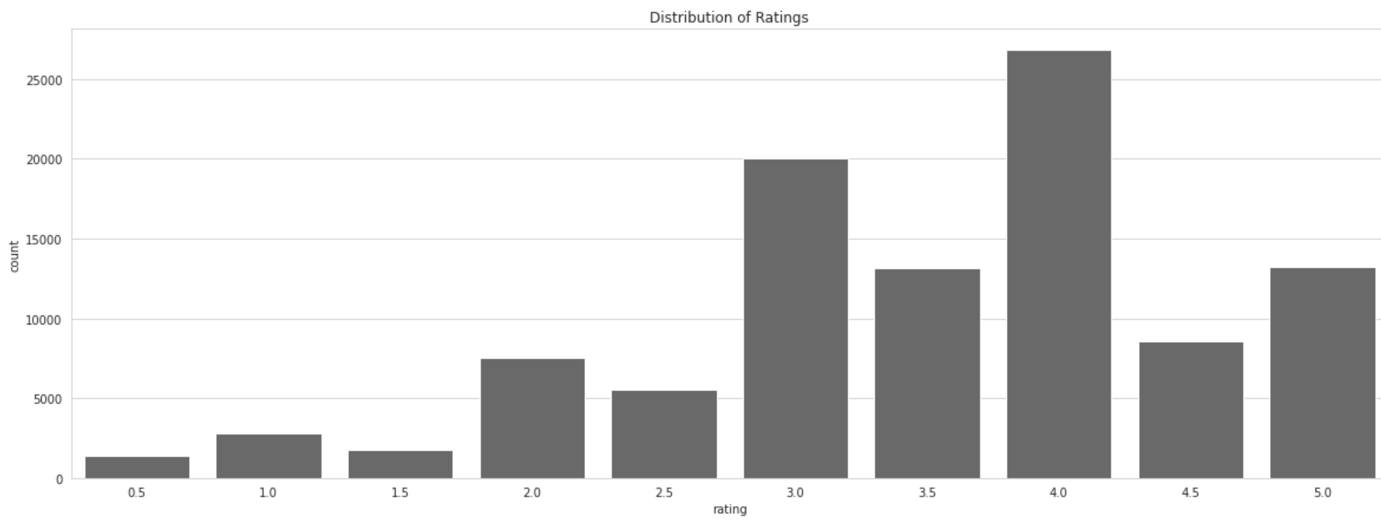


- We can see that most of the movies belong to movie genre : **Drama** followed by **Comedy** then **Action**, **Thriller** and **Adventure**

```
df_merged.rating.mean()
```

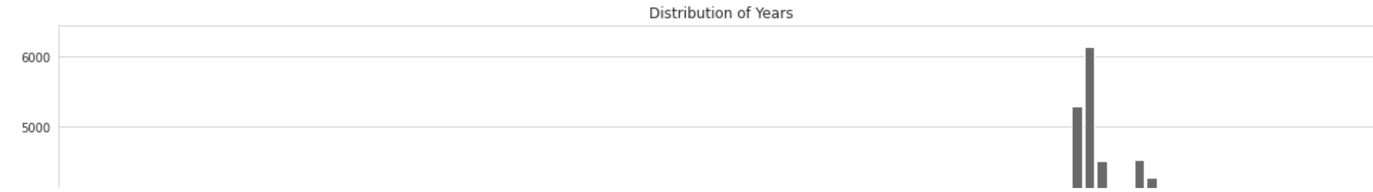
```
3.501577678332225
```

```
# Distribution of Ratings
plt.figure(figsize=(20,7))
sns.countplot(df_merged['rating'], color = 'dimgray')
plt.title('Distribution of Ratings');
```



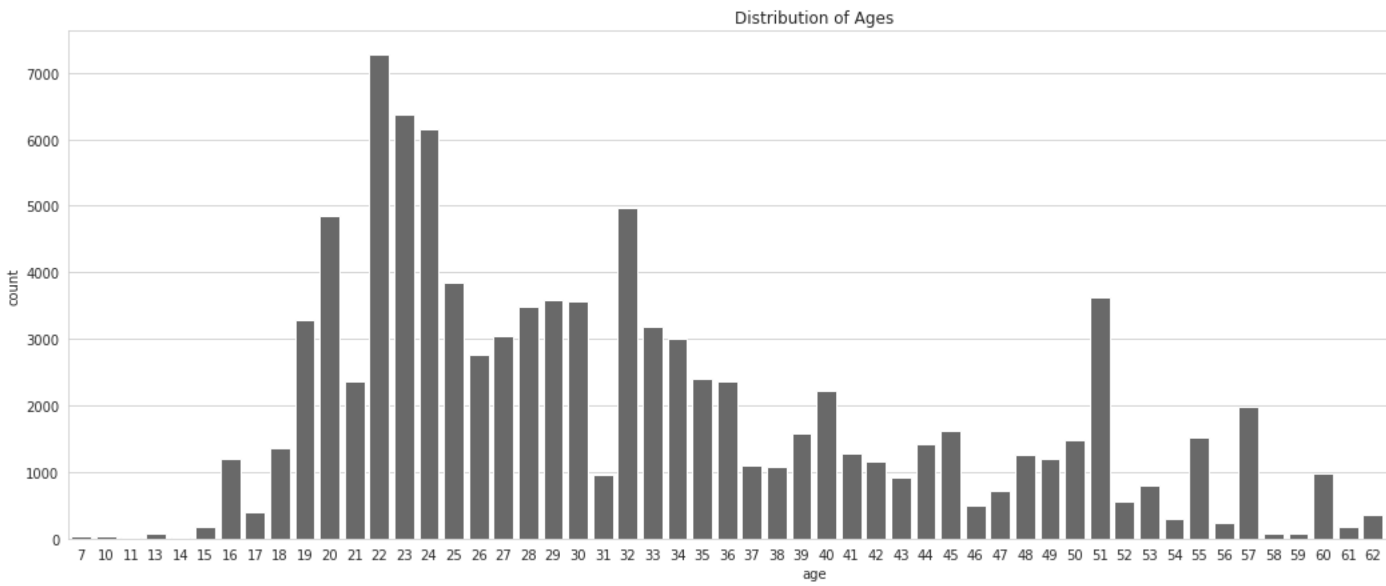
- It appears that ratings are not normally distibuted.
- The mean rating is 3.50 on a scale of 5.
- Almost half the movies have a rating of 4 and 5

```
# Distribution of Year
df_year_asc = df_merged.sort_values('year' , ascending = True)
plt.figure(figsize=(20,7))
sns.countplot(df_year_asc['year'], color = 'dimgray')
plt.xticks(rotation=90)
plt.title('Distribution of Years');
```



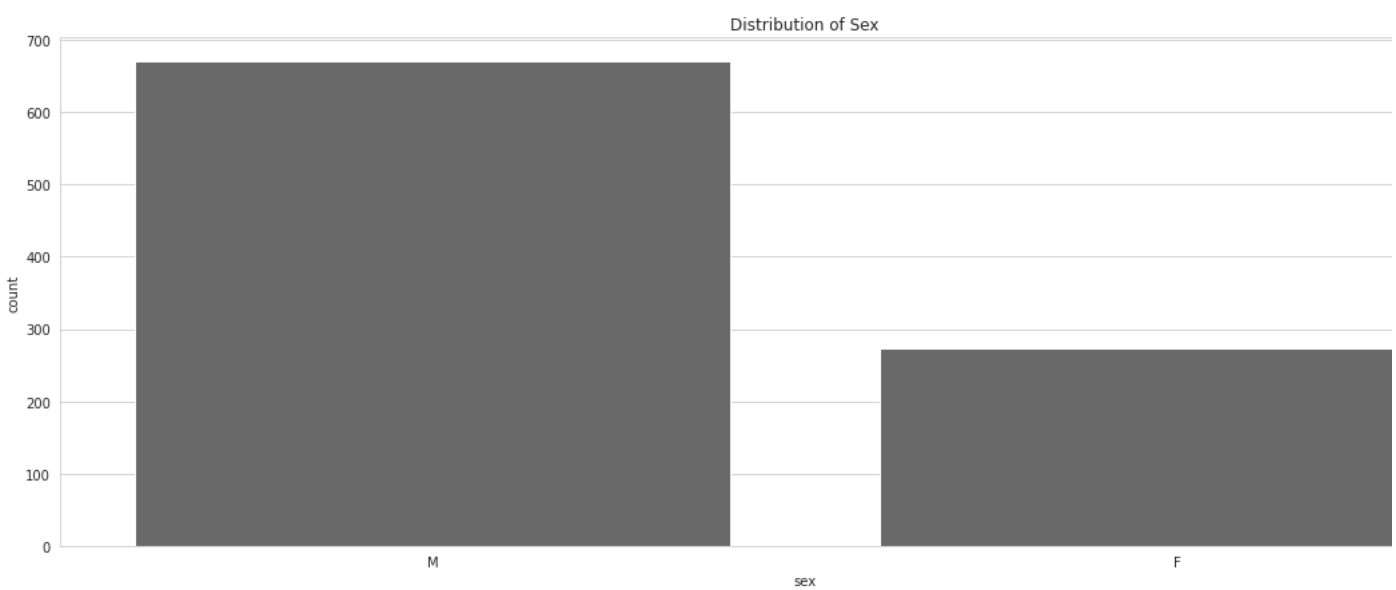
- In this dataset, we have movies starting as early as 1902 and the latest movie is from 2018. The year with the maximum number of rated movies in this dataset between 1995 - 2005

```
# Distribution of Ages
plt.figure(figsize=(20,7))
sns.countplot(df_merged['age'], color = 'dimgray')
plt.title('Distribution of Ages');
```



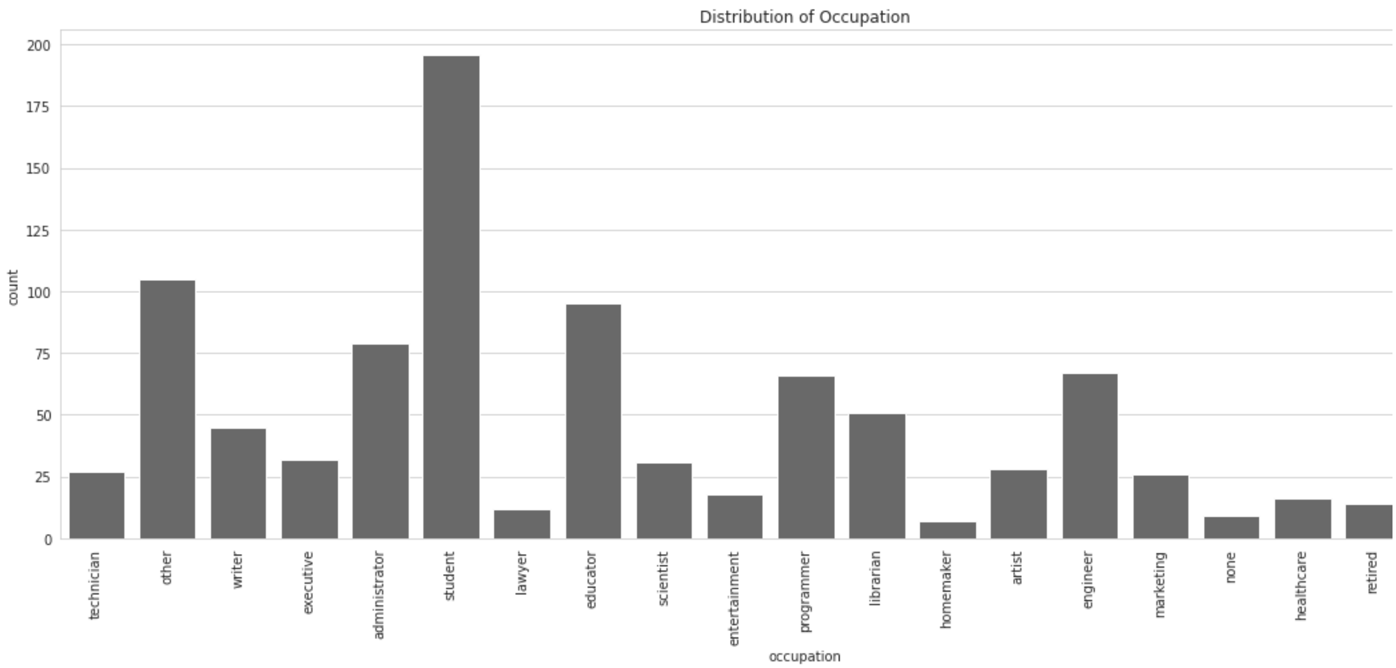
- User age is highest in the 22-24 age group and ranges mostly between 19 years old to 34/35 years of age

```
# Distribution of Sex
plt.figure(figsize=(20,7))
sns.countplot(users_df['sex'], color = 'dimgray')
plt.title('Distribution of Sex');
```



- it shows that number of the male raters are doubled female raters

```
# Distribution of Sex
plt.figure(figsize=(20,7))
sns.countplot(users_df['occupation'], color = 'dimgray')
plt.title('Distribution of Occupation')
plt.xticks(rotation=90);
```



- Most of the raters are students , followed by educaters and administrators.