

ZEE_Recommendation

January 23, 2025

0.1 About Zee

ZEE5 is an Indian subscription video on demand and over-the-top streaming service, owned by Zee Entertainment Enterprises. It was launched in India on 14 February 2018 with content in 12 languages. The ZEE5 mobile app is available on Web, Android, iOS, Smart TVs, among other devices. ZEE5 claimed 56 million monthly active users in December 2019.

0.2 Business Problem

The primary objective is to develop a robust Recommender System that personalizes movie recommendations for users of the Zee OTT platform. The system aims to enhance user experience by suggesting movies based on user ratings, viewing history, and similarities with other users.

0.3 Importing Required Libraries

```
[1]: import pandas as pd
import numpy as np

from sklearn.preprocessing import LabelEncoder

import matplotlib.pyplot as plt
import seaborn as sns

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

0.4 Read Dataset

0.4.1 Movie Dataset

```
[2]: movies_df = pd.read_csv('./data/zee-movies.dat', delimiter='::',
    encoding='ISO-8859-1')
movies_df.head()
```

```
[2]:
```

	Movie ID	Title	Genres
0	1	Toy Story (1995)	Animation Children's Comedy

1	2	Jumanji (1995)	Adventure Children's Fantasy
2	3	Grumpier Old Men (1995)	Comedy Romance
3	4	Waiting to Exhale (1995)	Comedy Drama
4	5	Father of the Bride Part II (1995)	Comedy

```
[3]: print(f"Shape of the dataset: {movies_df.shape}")
      movies_df.info()
```

```
Shape of the dataset: (3883, 3)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 3 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Movie ID    3883 non-null   int64
1   Title       3883 non-null   object
2   Genres      3883 non-null   object
dtypes: int64(1), object(2)
memory usage: 91.1+ KB
```

```
[4]: movies_df.isna().sum()
```

```
[4]: Movie ID    0
      Title      0
      Genres     0
      dtype: int64
```

```
[5]: movies_df['Genres'] = movies_df['Genres'].str.split('|')
      movies_df['Release_Year'] = movies_df['Title'].str.extract(r'\((\d{4})\)')
      movies_df.head()
```

```
[5]:   Movie ID      Title \
0      1      Toy Story (1995)
1      2      Jumanji (1995)
2      3  Grumpier Old Men (1995)
3      4  Waiting to Exhale (1995)
4      5  Father of the Bride Part II (1995)

      Genres Release_Year
0  [Animation, Children's, Comedy]      1995
1  [Adventure, Children's, Fantasy]      1995
2              [Comedy, Romance]      1995
3              [Comedy, Drama]      1995
4              [Comedy]      1995
```

```
[6]: print(f"No. of Movie in the given dataset: {movies_df['Title'].nunique()}")
      print(f"No. of Duplicate Movie in the given dataset: {movies_df['Title'].
      ↪ duplicated().sum()}")
```

```
print(f"No. of Unique Genres in the given dataset: {movies_df['Genres'].
↳explode().nunique()}")
print(f"Earliest Movie in the dataset: {movies_df['Release_Year'].min()}")
print(f"Latest Movie in the dataset: {movies_df['Release_Year'].max()}")
```

No. of Movie in the given dataset: 3883
 No. of Duplicate Movie in the given dataset: 0
 No. of Unique Genres in the given dataset: 18
 Earliest Movie in the dataset: 1919
 Latest Movie in the dataset: 2000

0.4.2 User Dataset

```
[7]: users_df = pd.read_csv('./data/zee-users.dat', delimiter='::',
↳encoding='ISO-8859-1')
users_df.head()
```

```
[7]:
```

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117
3	4	M	45	7	02460
4	5	M	25	20	55455

```
[8]: print(f"Shape of the dataset: {users_df.shape}")
users_df.info()
```

```
Shape of the dataset: (6040, 5)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6040 entries, 0 to 6039
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   UserID          6040 non-null   int64
1   Gender          6040 non-null   object
2   Age             6040 non-null   int64
3   Occupation      6040 non-null   int64
4   Zip-code        6040 non-null   object
dtypes: int64(3), object(2)
memory usage: 236.1+ KB
```

```
[9]: users_df.isna().sum()
```

```
[9]: UserID          0
Gender            0
Age              0
Occupation       0
Zip-code         0
```

dtype: int64

```
[10]: print(f"No. of Users in the given dataset: {users_df['UserID'].nunique()}")
      print(f"No. of Duplicate Users in the given dataset: {users_df['UserID'].
      ↪ duplicated().sum()}")
```

No. of Users in the given dataset: 6040

No. of Duplicate Users in the given dataset: 0

0.4.3 Rating Dataset

```
[11]: ratings_df = pd.read_csv('./data/zee-ratings.dat', delimiter='::',
      ↪ encoding='ISO-8859-1')
      ratings_df.head()
```

```
[11]:  UserID  MovieID  Rating  Timestamp
      0      1      1193      5  978300760
      1      1      661      3  978302109
      2      1      914      3  978301968
      3      1     3408      4  978300275
      4      1     2355      5  978824291
```

```
[12]: print(f"Shape of the dataset: {ratings_df.shape}")
      ratings_df.info()
```

Shape of the dataset: (1000209, 4)

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 1000209 entries, 0 to 1000208

Data columns (total 4 columns):

#	Column	Non-Null Count	Dtype
0	UserID	1000209 non-null	int64
1	MovieID	1000209 non-null	int64
2	Rating	1000209 non-null	int64
3	Timestamp	1000209 non-null	int64

dtypes: int64(4)

memory usage: 30.5 MB

```
[13]: print(f"No. of Unique Movies rated in the given dataset: {ratings_df['MovieID'].
      ↪ nunique()}")
      print(f"No. of Duplicate rating in the given dataset: {ratings_df.duplicated().
      ↪ sum()}")
```

No. of Unique Movies rated in the given dataset: 3706

No. of Duplicate rating in the given dataset: 0

0.4.4 Observations

Movie Dataset:

- No. of Movie in the given dataset: 3883
- No. of Duplicate Movie in the given dataset: 0
- No. of Unique Genres in the given dataset: 18
- Earliest Movie in the dataset: 1919
- Latest Movie in the dataset: 2000

User Dataset:

- No. of Users in the given dataset: 6040
- No. of Duplicate Users in the given dataset: 0

Rating Dataset:

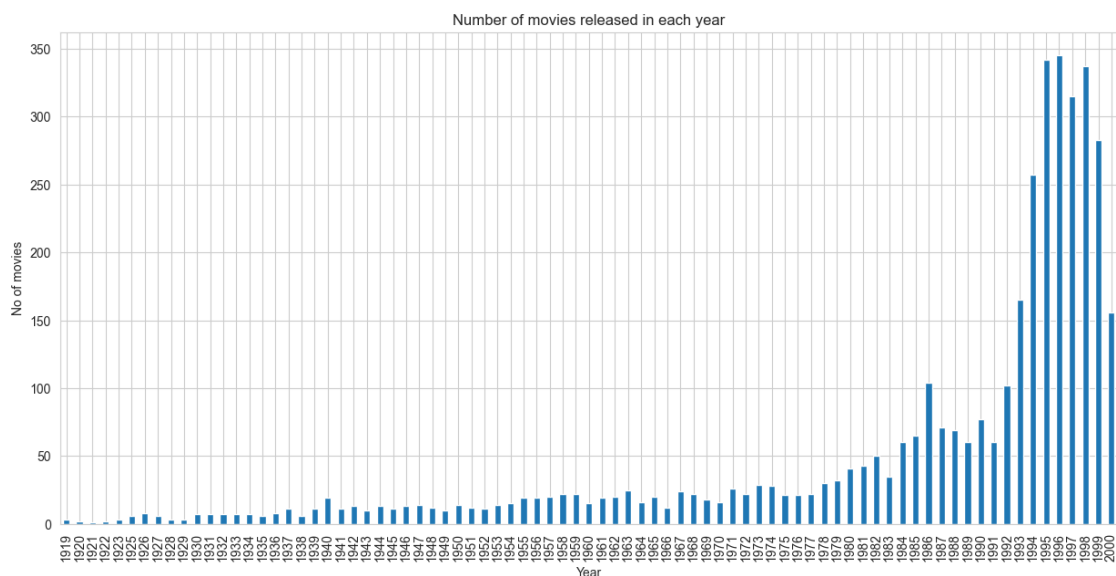
- Shape of the dataset: (1000209, 4)
- No. of Unique Movies rated in the given dataset: 3706
- No. of Duplicate rating in the given dataset: 0

0.5 Exploratory Data Analysis

0.5.1 Movie Dataset

```
[14]: # No of movies released in each year
sns.set_style('whitegrid')
plt.figure(figsize=(15, 7))

movies_df.groupby('Release_Year').size().plot(kind='bar')
plt.title('Number of movies released in each year')
plt.ylabel('No of movies')
plt.xlabel('Year')
plt.show()
```



```
[15]: movies_df['Release_Decade'] = movies_df['Release_Year'].apply(lambda x:
    ↪str(x)[2:-1] + "0's")
movies_df.head()
```

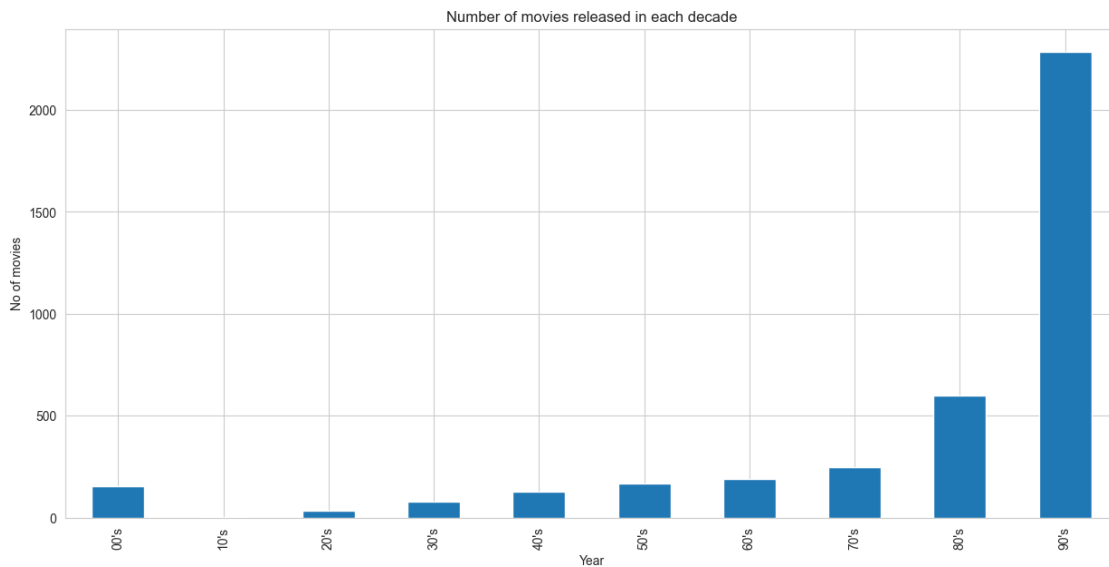
```
[15]:
```

	Movie ID	Title \
0	1	Toy Story (1995)
1	2	Jumanji (1995)
2	3	Grumpier Old Men (1995)
3	4	Waiting to Exhale (1995)
4	5	Father of the Bride Part II (1995)

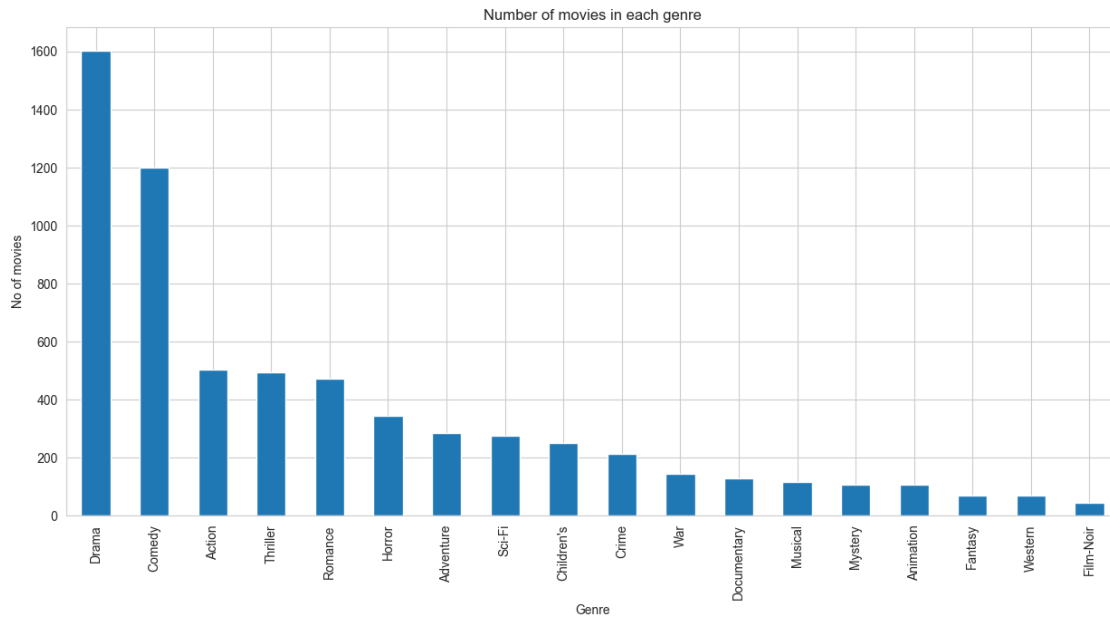
	Genres	Release_Year	Release_Decade
0	[Animation, Children's, Comedy]	1995	90's
1	[Adventure, Children's, Fantasy]	1995	90's
2	[Comedy, Romance]	1995	90's
3	[Comedy, Drama]	1995	90's
4	[Comedy]	1995	90's

```
[16]: # No of movies released in each decade
sns.set_style('whitegrid')
plt.figure(figsize=(15, 7))

movies_df.groupby('Release_Decade').size().plot(kind='bar')
plt.title('Number of movies released in each decade')
plt.ylabel('No of movies')
plt.xlabel('Year')
plt.show()
```



```
[17]: # No of movies in each genre
plt.figure(figsize=(15, 7))
genre_count = movies_df['Genres'].explode().value_counts()
genre_count.plot(kind='bar')
plt.title('Number of movies in each genre')
plt.ylabel('No of movies')
plt.xlabel('Genre')
plt.show()
```



```
[18]: # create a binary matrix for genres of each movie
genre_matrix = pd.get_dummies(movies_df['Genres'].explode()).groupby(level=0).
    ↪sum()
genre_matrix.head()

# merge the genre matrix with the movies dataframe
movies_df = pd.concat([movies_df, genre_matrix], axis=1)
movies_df.head()
```

```
[18]:
```

	Movie ID	Title \
0	1	Toy Story (1995)
1	2	Jumanji (1995)
2	3	Grumpier Old Men (1995)
3	4	Waiting to Exhale (1995)
4	5	Father of the Bride Part II (1995)

	Genres	Release_Year	Release_Decade	Action	\
0	[Animation, Children's, Comedy]	1995	90's	0	
1	[Adventure, Children's, Fantasy]	1995	90's	0	
2	[Comedy, Romance]	1995	90's	0	
3	[Comedy, Drama]	1995	90's	0	
4	[Comedy]	1995	90's	0	

	Adventure	Animation	Children's	Comedy	...	Fantasy	Film-Noir	Horror	\
0	0	1	1	1	...	0	0	0	
1	1	0	1	0	...	1	0	0	
2	0	0	0	1	...	0	0	0	
3	0	0	0	1	...	0	0	0	
4	0	0	0	1	...	0	0	0	

	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	1	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0

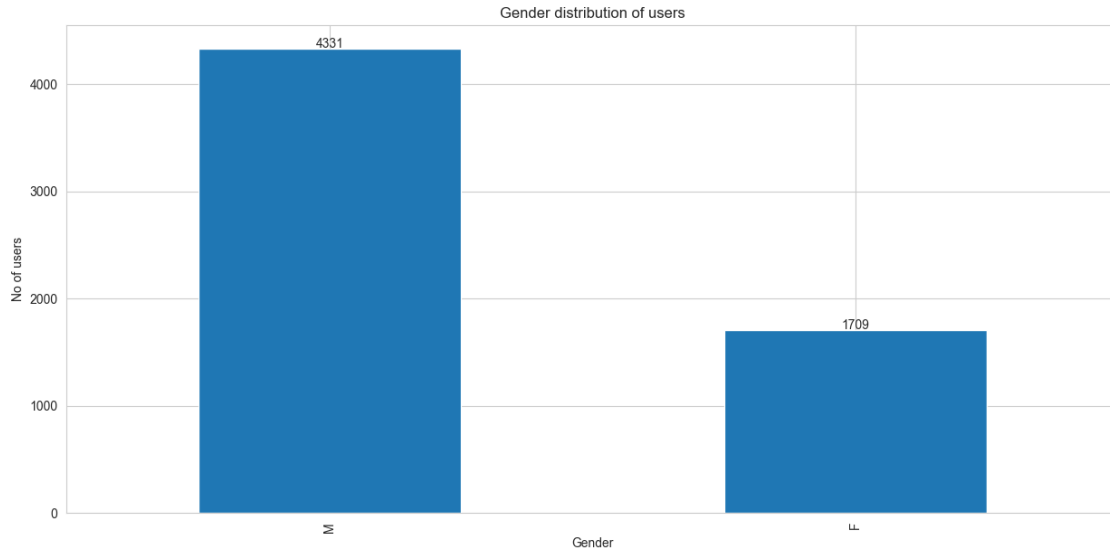
[5 rows x 23 columns]

0.5.2 Observations :

- The number of movies released each year has shown a notable increase starting from 1992.
- The 1990s saw the highest number of movie releases compared to other decades.
- Drama is the most popular movie genre, with Comedy, Action, Thriller, and Romance following in popularity.

0.5.3 User Dataset

```
[19]: # Gender distribution of users
sns.set_style('whitegrid')
plt.figure(figsize=(15, 7))
users_df['Gender'].value_counts().plot(kind='bar')
for i, v in enumerate(users_df['Gender'].value_counts()):
    plt.text(i, v + 10, str(v), ha='center')
plt.title('Gender distribution of users')
plt.ylabel('No of users')
plt.xlabel('Gender')
plt.show()
```

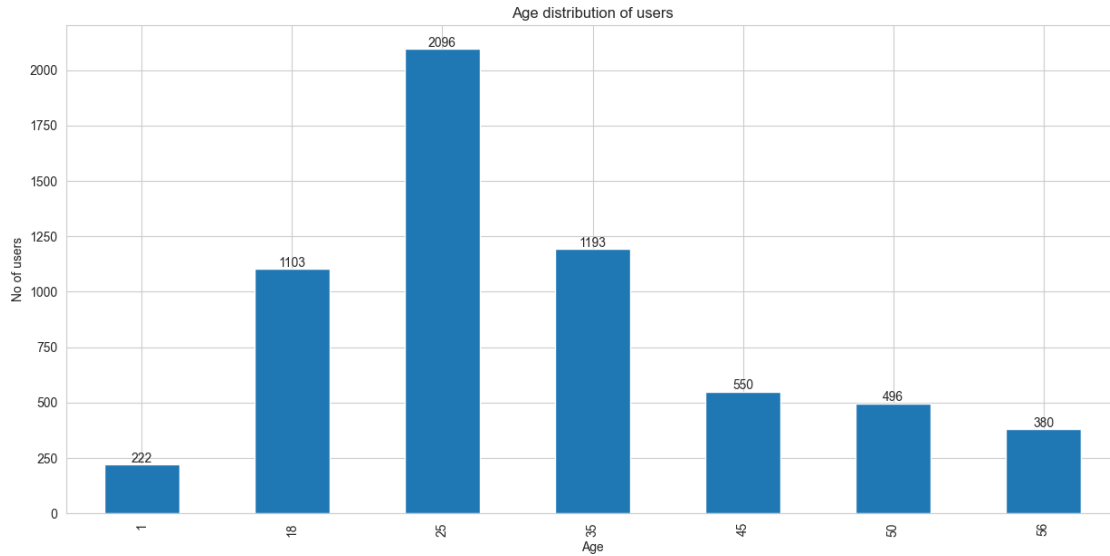



```
[20]: le = LabelEncoder()

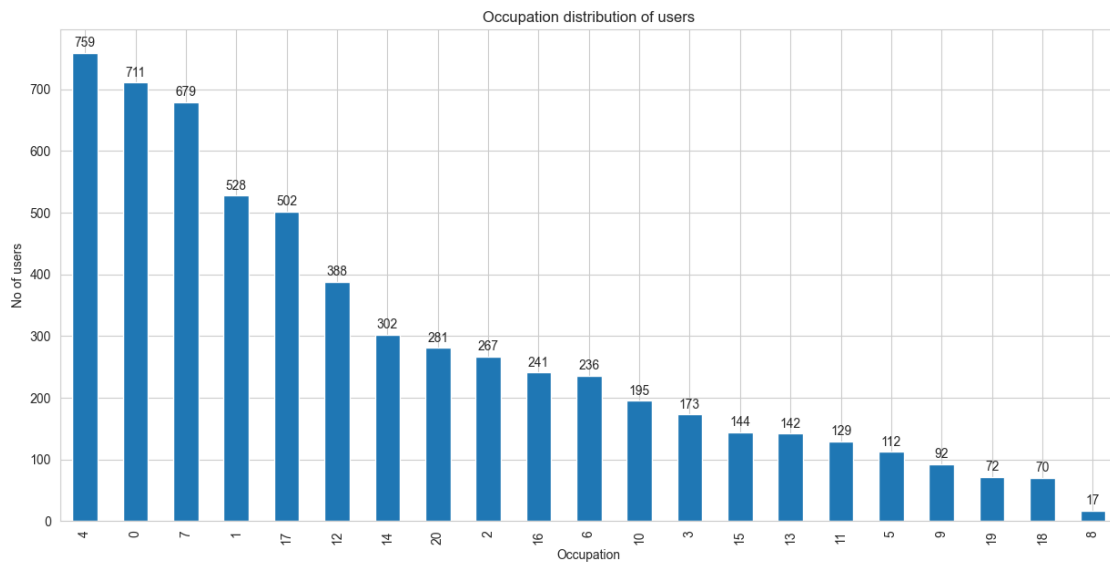
users_df['Gender'] = le.fit_transform(users_df['Gender'])
users_df.head()
```

```
[20]:   UserID  Gender  Age  Occupation  Zip-code
0       1       0    1         10     48067
1       2       1   56         16     70072
2       3       1   25         15     55117
3       4       1   45          7     02460
4       5       1   25         20     55455
```

```
[21]: # Age distribution of users
sns.set_style('whitegrid')
plt.figure(figsize=(15, 7))
users_df['Age'].value_counts().sort_index().plot(kind='bar')
for i, v in enumerate(users_df['Age'].value_counts().sort_index()):
    plt.text(i, v + 10, str(v), ha='center')
plt.title('Age distribution of users')
plt.ylabel('No of users')
plt.xlabel('Age')
plt.show()
```



```
[22]: # Occupation distribution of users
sns.set_style('whitegrid')
plt.figure(figsize=(15, 7))
users_df['Occupation'].value_counts().plot(kind='bar')
for i, v in enumerate(users_df['Occupation'].value_counts()):
    plt.text(i, v + 10, str(v), ha='center')
plt.title('Occupation distribution of users')
plt.ylabel('No of users')
plt.xlabel('Occupation')
plt.show()
```



0.5.4 Observations :

- Male users constitute 71% of the user base.
 - The majority of users fall within the age range of 25-34, followed by those aged 35-44 and 18-24.
 - Most users in our dataset have a college or graduate education, followed by those with unspecified or other, and those in executive or managerial positions.
-

0.5.5 Rating Dataset

```
[23]: ratings_df.head()
```

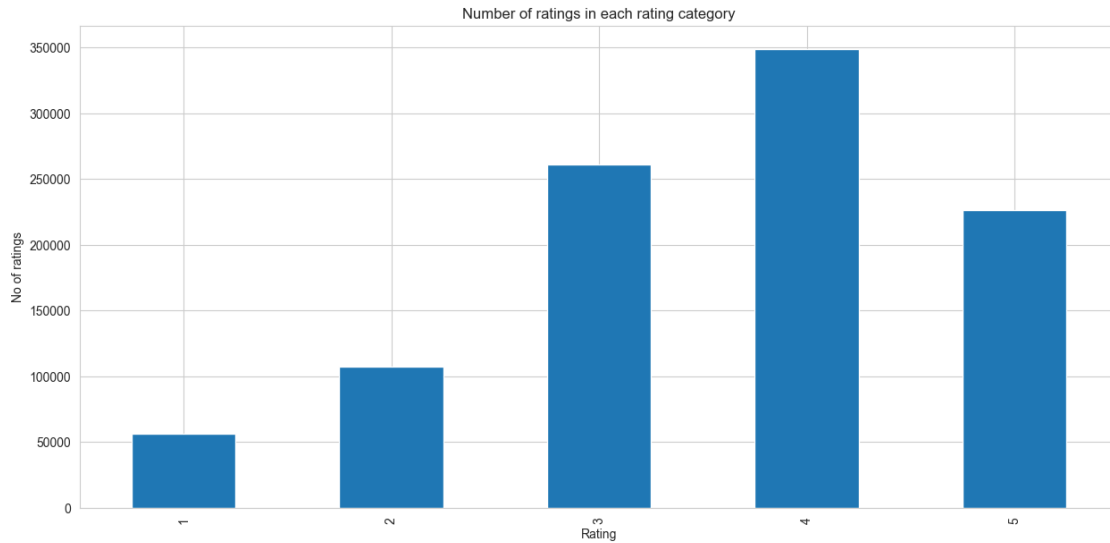
```
[23]:   UserID  MovieID  Rating  Timestamp
0        1    1193        5  978300760
1        1     661        3  978302109
2        1     914        3  978301968
3        1    3408        4  978300275
4        1    2355        5  978824291
```

```
[24]: ratings_df['Timestamp'] = pd.to_datetime(ratings_df['Timestamp'], unit='s')
ratings_df
```

```
[24]:   UserID  MovieID  Rating  Timestamp
0        1    1193        5  2000-12-31 22:12:40
1        1     661        3  2000-12-31 22:35:09
2        1     914        3  2000-12-31 22:32:48
3        1    3408        4  2000-12-31 22:04:35
4        1    2355        5  2001-01-06 23:38:11
...     ...     ...     ...     ...
1000204   6040    1091        1  2000-04-26 02:35:41
1000205   6040    1094        5  2000-04-25 23:21:27
1000206   6040     562        5  2000-04-25 23:19:06
1000207   6040    1096        4  2000-04-26 02:20:48
1000208   6040    1097        4  2000-04-26 02:19:29
```

[1000209 rows x 4 columns]

```
[25]: ratings_df.groupby('Rating').size()
sns.set_style('whitegrid')
plt.figure(figsize=(15, 7))
ratings_df.groupby('Rating').size().plot(kind='bar')
plt.title('Number of ratings in each rating category')
plt.ylabel('No of ratings')
plt.xlabel('Rating')
plt.show()
```



```
[26]: ratings_df.groupby('UserID').size().sort_values(ascending=False)
```

```
[26]: UserID
4169    2314
1680    1850
4277    1743
1941    1595
1181    1521
...
5725     20
3407     20
1664     20
4419     20
3021     20
Length: 6040, dtype: int64
```

```
[27]: ratings_df.groupby('UserID').size().describe()
```

```
[27]: count    6040.000000
mean      165.597517
std       192.747029
min       20.000000
25%       44.000000
50%       96.000000
75%      208.000000
max      2314.000000
dtype: float64
```

```
[28]: ratings_df.groupby('MovieID').size().sort_values(ascending=False)
```

```
[28]: MovieID
      2858    3428
      260    2991
      1196    2990
      1210    2883
      480    2672
      ...
      3237     1
      763     1
      624     1
      2563     1
      3290     1
      Length: 3706, dtype: int64
```

```
[29]: ratings_df.groupby('MovieID').size().describe()
```

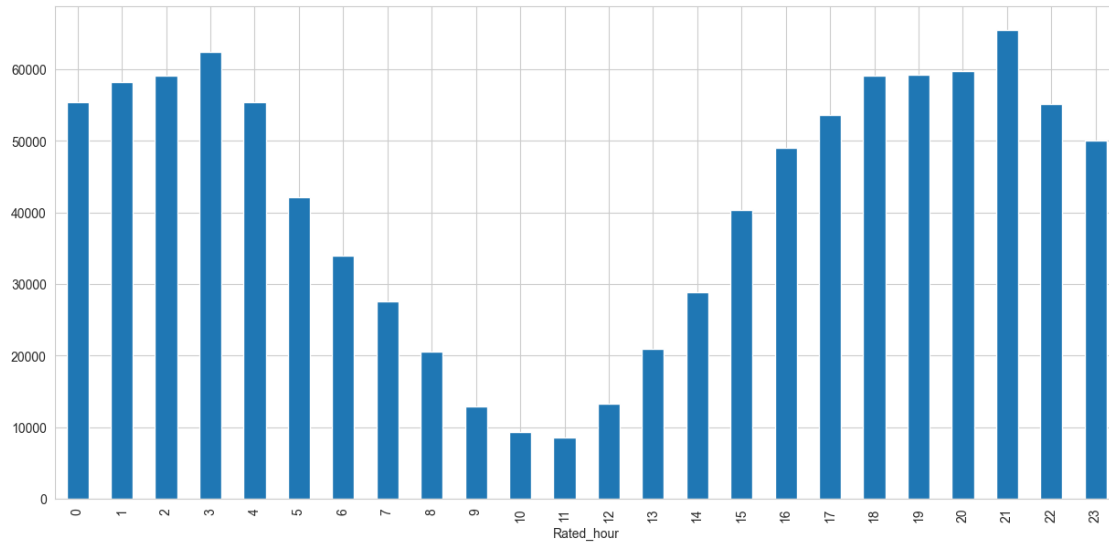
```
[29]: count    3706.000000
      mean      269.889099
      std       384.047838
      min        1.000000
      25%        33.000000
      50%       123.500000
      75%       350.000000
      max      3428.000000
      dtype: float64
```

```
[30]: ratings_df['Rated_hour'] = ratings_df['Timestamp'].dt.hour
      ratings_df['Rated_day'] = ratings_df['Timestamp'].dt.day_name()
      ratings_df.head()
```

```
[30]:   UserID  MovieID  Rating      Timestamp  Rated_hour  Rated_day
0      1      1193      5 2000-12-31 22:12:40          22    Sunday
1      1       661      3 2000-12-31 22:35:09          22    Sunday
2      1       914      3 2000-12-31 22:32:48          22    Sunday
3      1      3408      4 2000-12-31 22:04:35          22    Sunday
4      1      2355      5 2001-01-06 23:38:11          23  Saturday
```

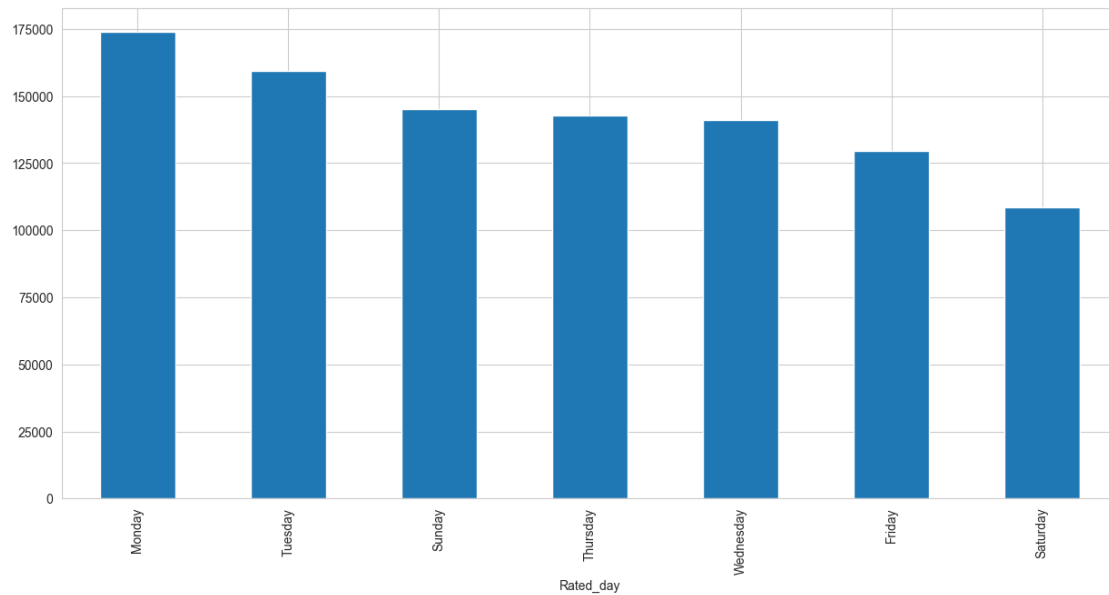
```
[31]: ratings_df['Rated_hour'].value_counts().sort_index().plot(kind='bar',
      ↪figsize=(15, 7))
```

```
[31]: <Axes: xlabel='Rated_hour'>
```



```
[32]: ratings_df['Rated_day'].value_counts().plot(kind='bar', figsize=(15, 7))
```

```
[32]: <Axes: xlabel='Rated_day'>
```



0.5.6 Observations :

- The most frequent ratings are 4 stars, followed by 3 stars and 5 stars.
- Users have rated as many as 2,314 movies and as few as 20 movies.
- 50% of users have rated up to 96 movies.

- Movies have been rated by as many as 3,428 users and at least by 1 user.
- The majority of ratings have been given between 5 PM and 10 PM, followed by the period from 12 AM to 4 AM.
- Most ratings are given on Mondays, followed by Tuesdays and Sundays.

0.5.7 Merging Datasets

```
[33]: df = pd.merge(ratings_df, users_df, on='UserID')
df = pd.merge(df, movies_df, left_on='MovieID', right_on='Movie ID')
df.head()
```

```
[33]:   UserID  MovieID  Rating      Timestamp  Rated_hour  Rated_day  Gender  \
0        1      1193        5  2000-12-31  22:12:40         22   Sunday        0
1        1        661        3  2000-12-31  22:35:09         22   Sunday        0
2        1        914        3  2000-12-31  22:32:48         22   Sunday        0
3        1      3408        4  2000-12-31  22:04:35         22   Sunday        0
4        1      2355        5  2001-01-06  23:38:11         23  Saturday        0
```

```
   Age  Occupation  Zip-code  ...  Fantasy  Film-Noir  Horror  Musical  Mystery  \
0    1           10    48067  ...         0          0        0         0         0
1    1           10    48067  ...         0          0        0         1         0
2    1           10    48067  ...         0          0        0         1         0
3    1           10    48067  ...         0          0        0         0         0
4    1           10    48067  ...         0          0        0         0         0
```

```
   Romance  Sci-Fi  Thriller  War  Western
0         0       0         0    0         0
1         0       0         0    0         0
2         1       0         0    0         0
3         0       0         0    0         0
4         0       0         0    0         0
```

[5 rows x 33 columns]

```
[34]: df.shape
```

```
[34]: (1000209, 33)
```

```
[35]: # Average rating of each movie
average_rating = df.groupby('Title')['Rating'].agg(['mean', 'count'])
average_rating.reset_index(inplace=True)
average_rating.columns = ['Title', 'Average_Rating', 'No_of_ratings']
average_rating.head()
```

```
[35]:   Title  Average_Rating  No_of_ratings
0  $1,000,000 Duck (1971)         3.027027         37
```

1	'Night Mother (1986)	3.371429	70
2	'Til There Was You (1997)	2.692308	52
3	'burbs, The (1989)	2.910891	303
4	...And Justice for All (1979)	3.713568	199

```
[36]: movie_user_rating = df.pivot_table(index='UserID', columns='Title',
      ↪values='Rating')
movie_user_rating.fillna(0, inplace=True)
movie_user_rating.head()
```

```
[36]: Title    $1,000,000 Duck (1971)  'Night Mother (1986)  \
UserID
1                0.0                0.0
2                0.0                0.0
3                0.0                0.0
4                0.0                0.0
5                0.0                0.0
```

```
Title    'Til There Was You (1997)  'burbs, The (1989)  \
UserID
1                0.0                0.0
2                0.0                0.0
3                0.0                0.0
4                0.0                0.0
5                0.0                0.0
```

```
Title    ...And Justice for All (1979)  1-900 (1994)  \
UserID
1                0.0                0.0
2                0.0                0.0
3                0.0                0.0
4                0.0                0.0
5                0.0                0.0
```

```
Title    10 Things I Hate About You (1999)  101 Dalmatians (1961)  \
UserID
1                0.0                0.0
2                0.0                0.0
3                0.0                0.0
4                0.0                0.0
5                0.0                0.0
```

```
Title    101 Dalmatians (1996)  12 Angry Men (1957)  ...  \
UserID                ...
1                0.0                0.0  ...
2                0.0                0.0  ...
3                0.0                0.0  ...
```


4	0.0	0.0 ...
5	0.0	0.0 ...

Title	Young Poisoner's Handbook, The (1995)	Young Sherlock Holmes (1985)	\
UserID			
1	0.0	0.0	
2	0.0	0.0	
3	0.0	0.0	
4	0.0	0.0	
5	0.0	0.0	

Title	Young and Innocent (1937)	Your Friends and Neighbors (1998)	\
UserID			
1	0.0	0.0	
2	0.0	0.0	
3	0.0	0.0	
4	0.0	0.0	
5	0.0	0.0	

Title	Zachariah (1971)	Zed & Two Noughts, A (1985)	Zero Effect (1998)	\
UserID				
1	0.0	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	
5	0.0	0.0	0.0	

Title	Zero Kelvin (Kjærlighetens kjøtere) (1995)	Zeus and Roxanne (1997)	\
UserID			
1	0.0	0.0	
2	0.0	0.0	
3	0.0	0.0	
4	0.0	0.0	
5	0.0	0.0	

Title	eXistenZ (1999)
UserID	
1	0.0
2	0.0
3	0.0
4	0.0
5	0.0

[5 rows x 3706 columns]

0.6 Recommendation System

0.6.1 Recommending movies based on pearson correlation

```
[37]: # Recommending movies based on correlation
correlation = movie_user_rating.corr(method='pearson', min_periods=100)
correlation
```

```
[37]: Title                                $1,000,000 Duck (1971) \
Title
$1,000,000 Duck (1971)                1.000000
'Night Mother (1986)                  0.065338
'Til There Was You (1997)              0.030805
'burbs, The (1989)                    0.065478
...And Justice for All (1979)          0.048708
...
Zed & Two Noughts, A (1985)            0.040590
Zero Effect (1998)                    0.024165
Zero Kelvin (Kjærlighetens kjøtere) (1995) -0.001332
Zeus and Roxanne (1997)                0.116574
eXistenZ (1999)                        0.009243

Title                                'Night Mother (1986) \
Title
$1,000,000 Duck (1971)                0.065338
'Night Mother (1986)                  1.000000
'Til There Was You (1997)              0.107374
'burbs, The (1989)                    0.096778
...And Justice for All (1979)          0.144480
...
Zed & Two Noughts, A (1985)            0.085001
Zero Effect (1998)                    0.054343
Zero Kelvin (Kjærlighetens kjøtere) (1995) -0.001852
Zeus and Roxanne (1997)                -0.005825
eXistenZ (1999)                        0.054699

Title                                'Til There Was You (1997) \
Title
$1,000,000 Duck (1971)                0.030805
'Night Mother (1986)                  0.107374
'Til There Was You (1997)              1.000000
'burbs, The (1989)                    0.082706
...And Justice for All (1979)          0.051965
...
Zed & Two Noughts, A (1985)            0.016935
Zero Effect (1998)                    0.062262
Zero Kelvin (Kjærlighetens kjøtere) (1995) -0.001571
Zeus and Roxanne (1997)                0.042842
```

eXistenZ (1999) 0.043483

Title 'burbs, The (1989) \

Title

\$1,000,000 Duck (1971) 0.065478

'Night Mother (1986) 0.096778

'Til There Was You (1997) 0.082706

'burbs, The (1989) 1.000000

...And Justice for All (1979) 0.110790

...

...

Zed & Two Noughts, A (1985) 0.042862

Zero Effect (1998) 0.121617

Zero Kelvin (Kjærlighetens kjøtere) (1995) -0.003858

Zeus and Roxanne (1997) 0.022249

eXistenZ (1999) 0.062471

Title ...And Justice for All (1979) \

Title

\$1,000,000 Duck (1971) 0.048708

'Night Mother (1986) 0.144480

'Til There Was You (1997) 0.051965

'burbs, The (1989) 0.110790

...And Justice for All (1979) 1.000000

...

...

Zed & Two Noughts, A (1985) 0.075720

Zero Effect (1998) 0.075804

Zero Kelvin (Kjærlighetens kjøtere) (1995) 0.072283

Zeus and Roxanne (1997) -0.010171

eXistenZ (1999) 0.071000

Title 1-900 (1994) \

Title

\$1,000,000 Duck (1971) -0.001319

'Night Mother (1986) -0.001834

'Til There Was You (1997) 0.079011

'burbs, The (1989) -0.003821

...And Justice for All (1979) -0.003203

...

...

Zed & Two Noughts, A (1985) -0.001186

Zero Effect (1998) -0.003931

Zero Kelvin (Kjærlighetens kjøtere) (1995) -0.000322

Zeus and Roxanne (1997) -0.001011

eXistenZ (1999) 0.036301

Title 10 Things I Hate About You (1999) \

Title

\$1,000,000 Duck (1971) 0.036612

'Night Mother (1986)	0.046122
'Til There Was You (1997)	0.105672
'burbs, The (1989)	0.133881
...And Justice for All (1979)	0.018614
...	...
Zed & Two Noughts, A (1985)	-0.009530
Zero Effect (1998)	0.114230
Zero Kelvin (Kjærlighetens kjøtere) (1995)	-0.006235
Zeus and Roxanne (1997)	0.042612
eXistenZ (1999)	0.089419

Title	101 Dalmatians (1961) \
\$1,000,000 Duck (1971)	0.176528
'Night Mother (1986)	0.123378
'Til There Was You (1997)	0.091422
'burbs, The (1989)	0.198168
...And Justice for All (1979)	0.151020
...	...
Zed & Two Noughts, A (1985)	0.030622
Zero Effect (1998)	0.088855
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.032238
Zeus and Roxanne (1997)	0.084739
eXistenZ (1999)	0.051587

Title	101 Dalmatians (1996) \
\$1,000,000 Duck (1971)	0.159973
'Night Mother (1986)	0.074706
'Til There Was You (1997)	0.108952
'burbs, The (1989)	0.134041
...And Justice for All (1979)	0.078917
...	...
Zed & Two Noughts, A (1985)	0.003318
Zero Effect (1998)	0.047345
Zero Kelvin (Kjærlighetens kjøtere) (1995)	-0.004277
Zeus and Roxanne (1997)	0.059812
eXistenZ (1999)	0.007314

Title	12 Angry Men (1957) ... \
\$1,000,000 Duck (1971)	0.075665 ...
'Night Mother (1986)	0.083988 ...
'Til There Was You (1997)	0.054821 ...
'burbs, The (1989)	0.113112 ...
...And Justice for All (1979)	0.160556 ...
...

Zed & Two Noughts, A (1985)	0.019564 ...
Zero Effect (1998)	0.070705 ...
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.032880 ...
Zeus and Roxanne (1997)	0.043186 ...
eXistenZ (1999)	0.023730 ...

Title	Young Poisoner's Handbook, The
(1995) \	

Title
\$1,000,000 Duck (1971)
0.030758
'Night Mother (1986)
0.042061
'Til There Was You (1997)
0.019685
'burbs, The (1989)
0.092597
...And Justice for All (1979)
0.071819

...

...

Zed & Two Noughts, A (1985)
0.040208
Zero Effect (1998)
0.159991
Zero Kelvin (Kjærlighetens kjøtere) (1995)
0.046727
Zeus and Roxanne (1997)
-0.006375
eXistenZ (1999)
0.091692

Title	Young Sherlock Holmes (1985) \
-------	--------------------------------

Title	
\$1,000,000 Duck (1971)	0.060574
'Night Mother (1986)	0.065333
'Til There Was You (1997)	0.043294
'burbs, The (1989)	0.165666
...And Justice for All (1979)	0.115402

...

...

Zed & Two Noughts, A (1985)	0.059839
Zero Effect (1998)	0.124075
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.043840
Zeus and Roxanne (1997)	0.034016
eXistenZ (1999)	0.128434

Title	Young and Innocent (1937) \
-------	-----------------------------

Title	
\$1,000,000 Duck (1971)	-0.002833
'Night Mother (1986)	0.060202
'Til There Was You (1997)	-0.003341
'burbs, The (1989)	0.012226
...And Justice for All (1979)	0.061253
...	...
Zed & Two Noughts, A (1985)	0.068069
Zero Effect (1998)	0.013451
Zero Kelvin (Kjærlighetens kjøtere) (1995)	-0.000690
Zeus and Roxanne (1997)	-0.002171
eXistenZ (1999)	0.015540

Title	Your Friends and Neighbors (1998) \
Title	
\$1,000,000 Duck (1971)	0.035056
'Night Mother (1986)	0.124593
'Til There Was You (1997)	0.068935
'burbs, The (1989)	0.114837
...And Justice for All (1979)	0.088616
...	...
Zed & Two Noughts, A (1985)	0.134474
Zero Effect (1998)	0.185265
Zero Kelvin (Kjærlighetens kjøtere) (1995)	-0.002315
Zeus and Roxanne (1997)	0.017447
eXistenZ (1999)	0.123249

Title	Zachariah (1971) \
Title	
\$1,000,000 Duck (1971)	-0.001237
'Night Mother (1986)	-0.001719
'Til There Was You (1997)	-0.001459
'burbs, The (1989)	-0.003582
...And Justice for All (1979)	-0.003002
...	...
Zed & Two Noughts, A (1985)	-0.001112
Zero Effect (1998)	-0.003684
Zero Kelvin (Kjærlighetens kjøtere) (1995)	-0.000301
Zeus and Roxanne (1997)	-0.000948
eXistenZ (1999)	-0.004228

Title	Zed & Two Noughts, A (1985) \
Title	
\$1,000,000 Duck (1971)	0.040590
'Night Mother (1986)	0.085001
'Til There Was You (1997)	0.016935
'burbs, The (1989)	0.042862

...And Justice for All (1979)	0.075720
...	...
Zed & Two Noughts, A (1985)	1.000000
Zero Effect (1998)	0.071585
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.124038
Zeus and Roxanne (1997)	-0.003766
eXistenZ (1999)	0.125207

Title	Zero Effect (1998) \
Title	
\$1,000,000 Duck (1971)	0.024165
'Night Mother (1986)	0.054343
'Til There Was You (1997)	0.062262
'burbs, The (1989)	0.121617
...And Justice for All (1979)	0.075804
...	...
Zed & Two Noughts, A (1985)	0.071585
Zero Effect (1998)	1.000000
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.056690
Zeus and Roxanne (1997)	0.004788
eXistenZ (1999)	0.199973

Title	Zero Kelvin (Kjærlighetens kjøtere)
(1995) \	
Title	
\$1,000,000 Duck (1971)	
-0.001332	
'Night Mother (1986)	
-0.001852	
'Til There Was You (1997)	
-0.001571	
'burbs, The (1989)	
-0.003858	
...And Justice for All (1979)	
0.072283	
...	
...	
Zed & Two Noughts, A (1985)	
0.124038	
Zero Effect (1998)	
0.056690	
Zero Kelvin (Kjærlighetens kjøtere) (1995)	
1.000000	
Zeus and Roxanne (1997)	
-0.001021	
eXistenZ (1999)	
0.042534	

Title	Zeus and Roxanne (1997) \
\$1,000,000 Duck (1971)	0.116574
'Night Mother (1986)	-0.005825
'Til There Was You (1997)	0.042842
'burbs, The (1989)	0.022249
...And Justice for All (1979)	-0.010171
...	...
Zed & Two Noughts, A (1985)	-0.003766
Zero Effect (1998)	0.004788
Zero Kelvin (Kjærlighetens kjøtere) (1995)	-0.001021
Zeus and Roxanne (1997)	1.000000
eXistenZ (1999)	0.031481

Title	eXistenZ (1999)
\$1,000,000 Duck (1971)	0.009243
'Night Mother (1986)	0.054699
'Til There Was You (1997)	0.043483
'burbs, The (1989)	0.062471
...And Justice for All (1979)	0.071000
...	...
Zed & Two Noughts, A (1985)	0.125207
Zero Effect (1998)	0.199973
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.042534
Zeus and Roxanne (1997)	0.031481
eXistenZ (1999)	1.000000

[3706 rows x 3706 columns]

```
[38]: movie_name = 'Toy Story (1995)'
similar_movies = correlation[movie_name]

similar_movies = similar_movies.sort_values(ascending=False)
similar_movies = similar_movies.dropna()
similar_movies = similar_movies.to_frame()
similar_movies = similar_movies.reset_index()
similar_movies.columns = ['Title', 'Correlation']
# similar_movies = pd.merge(similar_movies, average_rating, on='Title')
similar_movies = similar_movies[similar_movies['Title'] != movie_name]
similar_movies = similar_movies.sort_values('Correlation', ascending=False)
similar_movies = pd.merge(similar_movies, average_rating, on='Title')
similar_movies = similar_movies[similar_movies['No_of_ratings'] > 100]
similar_movies[['Title', 'Correlation', 'Average_Rating', 'No_of_ratings']].
    ↪head(5)
```



```
[38]:
```

	Title	Correlation	Average_Rating	No_of_ratings
0	Toy Story 2 (1999)	0.487370	4.218927	1585
1	Aladdin (1992)	0.470753	3.788305	1351
2	Lion King, The (1994)	0.411131	3.860839	1121
3	Groundhog Day (1993)	0.407547	3.953029	2278
4	Bug's Life, A (1998)	0.402679	3.854375	1703

0.6.2 Recommender System based on Cosine Similarity

```
[39]: # item-item similarity matrix and user-user similarity matrix
from sklearn.metrics.pairwise import cosine_similarity

item_item_similarity = cosine_similarity(movie_user_rating.T)
item_item_similarity = pd.DataFrame(item_item_similarity,
    ↪ index=movie_user_rating.columns, columns=movie_user_rating.columns)
item_item_similarity
```

```
[39]: Title                                $1,000,000 Duck (1971) \
Title
$1,000,000 Duck (1971)                    1.000000
'Night Mother (1986)                     0.072357
'Til There Was You (1997)                 0.037011
'burbs, The (1989)                       0.079291
...And Justice for All (1979)             0.060838
...
Zed & Two Noughts, A (1985)               0.045280
Zero Effect (1998)                       0.039395
Zero Kelvin (Kjærlighetens kjøtere) (1995) 0.000000
Zeus and Roxanne (1997)                  0.120242
eXistenZ (1999)                          0.027003

Title                                'Night Mother (1986) \
Title
$1,000,000 Duck (1971)                   0.072357
'Night Mother (1986)                     1.000000
'Til There Was You (1997)                 0.115290
'burbs, The (1989)                       0.115545
...And Justice for All (1979)             0.159526
...
Zed & Two Noughts, A (1985)               0.091150
Zero Effect (1998)                       0.074787
Zero Kelvin (Kjærlighetens kjøtere) (1995) 0.000000
Zeus and Roxanne (1997)                  0.000000
eXistenZ (1999)                          0.077807

Title                                'Til There Was You (1997) \
```

Title	
\$1,000,000 Duck (1971)	0.037011
'Night Mother (1986)	0.115290
'Til There Was You (1997)	1.000000
'burbs, The (1989)	0.098756
...And Justice for All (1979)	0.066301
...	...
Zed & Two Noughts, A (1985)	0.022594
Zero Effect (1998)	0.079261
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.000000
Zeus and Roxanne (1997)	0.047526
eXistenZ (1999)	0.063284

Title	'burbs, The (1989) \
Title	
\$1,000,000 Duck (1971)	0.079291
'Night Mother (1986)	0.115545
'Til There Was You (1997)	0.098756
'burbs, The (1989)	1.000000
...And Justice for All (1979)	0.143620
...	...
Zed & Two Noughts, A (1985)	0.055704
Zero Effect (1998)	0.161174
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.000000
Zeus and Roxanne (1997)	0.033567
eXistenZ (1999)	0.110525

Title	...And Justice for All (1979) \
Title	
\$1,000,000 Duck (1971)	0.060838
'Night Mother (1986)	0.159526
'Til There Was You (1997)	0.066301
'burbs, The (1989)	0.143620
...And Justice for All (1979)	1.000000
...	...
Zed & Two Noughts, A (1985)	0.086080
Zero Effect (1998)	0.110867
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.074317
Zeus and Roxanne (1997)	0.000000
eXistenZ (1999)	0.111040

Title	1-900 (1994) \
Title	
\$1,000,000 Duck (1971)	0.000000
'Night Mother (1986)	0.000000
'Til There Was You (1997)	0.080250
'burbs, The (1989)	0.000000

...And Justice for All (1979)	0.000000
...	...
Zed & Two Noughts, A (1985)	0.000000
Zero Effect (1998)	0.000000
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.000000
Zeus and Roxanne (1997)	0.000000
eXistenZ (1999)	0.039561
Title	10 Things I Hate About You (1999) \
Title	
\$1,000,000 Duck (1971)	0.058619
'Night Mother (1986)	0.076798
'Til There Was You (1997)	0.127895
'burbs, The (1989)	0.192191
...And Justice for All (1979)	0.075093
...	...
Zed & Two Noughts, A (1985)	0.012702
Zero Effect (1998)	0.175771
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.000000
Zeus and Roxanne (1997)	0.058708
eXistenZ (1999)	0.162060
Title	101 Dalmatians (1961) \
Title	
\$1,000,000 Duck (1971)	0.189965
'Night Mother (1986)	0.147437
'Til There Was You (1997)	0.112654
'burbs, The (1989)	0.246927
...And Justice for All (1979)	0.194154
...	...
Zed & Two Noughts, A (1985)	0.048761
Zero Effect (1998)	0.146381
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.036113
Zeus and Roxanne (1997)	0.097530
eXistenZ (1999)	0.120084
Title	101 Dalmatians (1996) \
Title	
\$1,000,000 Duck (1971)	0.172254
'Night Mother (1986)	0.095922
'Til There Was You (1997)	0.125670
'burbs, The (1989)	0.175885
...And Justice for All (1979)	0.116379
...	...
Zed & Two Noughts, A (1985)	0.018537
Zero Effect (1998)	0.094669
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.000000

Zeus and Roxanne (1997)	0.071169
eXistenZ (1999)	0.063491

Title	12 Angry Men (1957)	...	\
Title		...	
\$1,000,000 Duck (1971)	0.094785	...	
'Night Mother (1986)	0.111413	...	
'Til There Was You (1997)	0.079115	...	
'burbs, The (1989)	0.170719	...	
...And Justice for All (1979)	0.205486	...	
...	
Zed & Two Noughts, A (1985)	0.039344	...	
Zero Effect (1998)	0.133061	...	
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.036867	...	
Zeus and Roxanne (1997)	0.058692	...	
eXistenZ (1999)	0.098731	...	

Title	Young Poisoner's Handbook, The
(1995) \	
Title	
\$1,000,000 Duck (1971)	
0.038725	
'Night Mother (1986)	
0.053010	
'Til There Was You (1997)	
0.029200	
'burbs, The (1989)	
0.113386	
...And Justice for All (1979)	
0.089998	
...	
...	
Zed & Two Noughts, A (1985)	
0.047282	
Zero Effect (1998)	
0.179315	
Zero Kelvin (Kjærlighetens kjøtere) (1995)	
0.048440	
Zeus and Roxanne (1997)	
0.000000	
eXistenZ (1999)	
0.115734	

Title	Young Sherlock Holmes (1985)	\
Title		
\$1,000,000 Duck (1971)	0.076474	
'Night Mother (1986)	0.087828	

'Til There Was You (1997)	0.062893
'burbs, The (1989)	0.207897
...And Justice for All (1979)	0.153006
...	...
Zed & Two Noughts, A (1985)	0.073996
Zero Effect (1998)	0.169677
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.046892
Zeus and Roxanne (1997)	0.046658
eXistenZ (1999)	0.180174

Title	Young and Innocent (1937) \
Title	
\$1,000,000 Duck (1971)	0.000000
'Night Mother (1986)	0.063758
'Til There Was You (1997)	0.000000
'burbs, The (1989)	0.019962
...And Justice for All (1979)	0.067009
...	...
Zed & Two Noughts, A (1985)	0.070409
Zero Effect (1998)	0.021362
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.000000
Zeus and Roxanne (1997)	0.000000
eXistenZ (1999)	0.024437

Title	Your Friends and Neighbors (1998) \
Title	
\$1,000,000 Duck (1971)	0.044074
'Night Mother (1986)	0.135962
'Til There Was You (1997)	0.079187
'burbs, The (1989)	0.138064
...And Justice for All (1979)	0.109029
...	...
Zed & Two Noughts, A (1985)	0.141537
Zero Effect (1998)	0.206870
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.000000
Zeus and Roxanne (1997)	0.024489
eXistenZ (1999)	0.149749

Title	Zachariah (1971) \
Title	
\$1,000,000 Duck (1971)	0.0
'Night Mother (1986)	0.0
'Til There Was You (1997)	0.0
'burbs, The (1989)	0.0
...And Justice for All (1979)	0.0
...	...
Zed & Two Noughts, A (1985)	0.0

Zero Effect (1998)	0.0
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.0
Zeus and Roxanne (1997)	0.0
eXistenZ (1999)	0.0

Title	Zed & Two Noughts, A (1985) \
\$1,000,000 Duck (1971)	0.045280
'Night Mother (1986)	0.091150
'Til There Was You (1997)	0.022594
'burbs, The (1989)	0.055704
...And Justice for All (1979)	0.086080
...	...
Zed & Two Noughts, A (1985)	1.000000
Zero Effect (1998)	0.084020
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.124939
Zeus and Roxanne (1997)	0.000000
eXistenZ (1999)	0.137372

Title	Zero Effect (1998) \
\$1,000,000 Duck (1971)	0.039395
'Night Mother (1986)	0.074787
'Til There Was You (1997)	0.079261
'burbs, The (1989)	0.161174
...And Justice for All (1979)	0.110867
...	...
Zed & Two Noughts, A (1985)	0.084020
Zero Effect (1998)	1.000000
Zero Kelvin (Kjærlighetens kjøtere) (1995)	0.059228
Zeus and Roxanne (1997)	0.016838
eXistenZ (1999)	0.242043

Title	Zero Kelvin (Kjærlighetens kjøtere)
(1995) \	
\$1,000,000 Duck (1971)	0.000000
'Night Mother (1986)	0.000000
'Til There Was You (1997)	0.000000
'burbs, The (1989)	0.000000
...And Justice for All (1979)	0.074317
...	

```

...
Zed & Two Noughts, A (1985)
0.124939
Zero Effect (1998)
0.059228
Zero Kelvin (Kjærlighetens kjøtere) (1995)
1.000000
Zeus and Roxanne (1997)
0.000000
eXistenZ (1999)
0.045644

Title                                Zeus and Roxanne (1997) \
Title
$1,000,000 Duck (1971)                0.120242
'Night Mother (1986)                  0.000000
'Til There Was You (1997)              0.047526
'burbs, The (1989)                    0.033567
...And Justice for All (1979)          0.000000
...
Zed & Two Noughts, A (1985)            0.000000
Zero Effect (1998)                    0.016838
Zero Kelvin (Kjærlighetens kjøtere) (1995) 0.000000
Zeus and Roxanne (1997)                1.000000
eXistenZ (1999)                       0.044335

Title                                eXistenZ (1999)
Title
$1,000,000 Duck (1971)                0.027003
'Night Mother (1986)                  0.077807
'Til There Was You (1997)              0.063284
'burbs, The (1989)                    0.110525
...And Justice for All (1979)          0.111040
...
Zed & Two Noughts, A (1985)            0.137372
Zero Effect (1998)                    0.242043
Zero Kelvin (Kjærlighetens kjøtere) (1995) 0.045644
Zeus and Roxanne (1997)                0.044335
eXistenZ (1999)                       1.000000

```

[3706 rows x 3706 columns]

```

[40]: user_user_similarity = cosine_similarity(movie_user_rating)
user_user_similarity = pd.DataFrame(user_user_similarity,
    ↪ index=movie_user_rating.index, columns=movie_user_rating.index)
user_user_similarity

```

```
[40]: UserID      1          2          3          4          5          6          7      \
UserID
1      1.000000  0.096382  0.120610  0.132455  0.090158  0.179222  0.059678
2      0.096382  1.000000  0.151479  0.171176  0.114394  0.100865  0.305787
3      0.120610  0.151479  1.000000  0.151227  0.062907  0.074603  0.138332
4      0.132455  0.171176  0.151227  1.000000  0.045094  0.013529  0.130339
5      0.090158  0.114394  0.062907  0.045094  1.000000  0.047449  0.126257
...      ...      ...      ...      ...      ...      ...
6036   0.186329  0.228241  0.143264  0.170583  0.293365  0.093583  0.122441
6037   0.135979  0.206274  0.107744  0.127464  0.172686  0.065788  0.111673
6038   0.000000  0.066118  0.120234  0.062907  0.020459  0.065711  0.000000
6039   0.174604  0.066457  0.094675  0.064634  0.027689  0.167303  0.014977
6040   0.133590  0.218276  0.133144  0.137968  0.241437  0.083436  0.080680

UserID      8          9         10      ...      6031      6032      6033      \
UserID
1      0.138241  0.226148  0.255288  ...      0.170588  0.082006  0.069807
2      0.203337  0.190198  0.226861  ...      0.112503  0.091222  0.268565
3      0.077656  0.126457  0.213655  ...      0.092960  0.125864  0.161507
4      0.100856  0.093651  0.120738  ...      0.163629  0.093041  0.382803
5      0.220817  0.261330  0.117052  ...      0.100652  0.035732  0.061806
...      ...      ...      ...      ...      ...      ...
6036   0.227400  0.239607  0.338072  ...      0.131294  0.209843  0.186426
6037   0.144395  0.225055  0.246902  ...      0.142309  0.276134  0.129985
6038   0.019242  0.093470  0.113789  ...      0.108837  0.106897  0.040689
6039   0.044660  0.046434  0.296776  ...      0.118776  0.250994  0.053750
6040   0.148123  0.215819  0.255793  ...      0.154574  0.291988  0.115540

UserID      6034      6035      6036      6037      6038      6039      6040
UserID
1      0.033663  0.114877  0.186329  0.135979  0.000000  0.174604  0.133590
2      0.014286  0.183384  0.228241  0.206274  0.066118  0.066457  0.218276
3      0.000000  0.097308  0.143264  0.107744  0.120234  0.094675  0.133144
4      0.000000  0.082097  0.170583  0.127464  0.062907  0.064634  0.137968
5      0.054151  0.179083  0.293365  0.172686  0.020459  0.027689  0.241437
...      ...      ...      ...      ...      ...
6036   0.103431  0.267405  1.000000  0.341462  0.124174  0.219115  0.411891
6037   0.118749  0.141676  0.341462  1.000000  0.049015  0.252146  0.428240
6038   0.000000  0.063967  0.124174  0.049015  1.000000  0.161714  0.099300
6039   0.102168  0.068399  0.219115  0.252146  0.161714  1.000000  0.228332
6040   0.118840  0.168997  0.411891  0.428240  0.099300  0.228332  1.000000

[6040 rows x 6040 columns]
```

```
[41]: # Top 5 recommendations for a movie
def get_top_5_recommendations(movie_name):
    similar_movies = item_item_similarity[movie_name]
```



```

similar_movies = similar_movies.sort_values(ascending=False)
similar_movies = similar_movies.dropna()
similar_movies = similar_movies.to_frame()
similar_movies = similar_movies.reset_index()
similar_movies.columns = ['Title', 'Similarity']
similar_movies = similar_movies[similar_movies['Title'] != movie_name]
similar_movies = similar_movies.head(5)
return similar_movies

```

```

[42]: movie_name = 'Toy Story (1995)'
      get_top_5_recommendations(movie_name)

```

```

[42]:
      Title  Similarity
1  Toy Story 2 (1999)    0.633104
2  Groundhog Day (1993)  0.610826
3    Aladdin (1992)    0.605849
4  Bug's Life, A (1998)  0.579382
5  Back to the Future (1985) 0.570125

```

0.6.3 Recommender System based on Matrix Factorization

```

[43]: # # Use cmfrec/Surprise library to run matrix factorization. (Show results with
      ↪d=4).

      # from surprise import Dataset
      # from surprise import Reader
      # from surprise import SVD
      # from surprise.model_selection import cross_validate

      # reader = Reader(rating_scale=(1, 5))
      # data = Dataset.load_from_df(ratings_df[['UserID', 'MovieID', 'Rating']],
      ↪reader)

      # algo = SVD(n_factors=4)
      # cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)

      # from surprise.model_selection import train_test_split

      # trainset, testset = train_test_split(data, test_size=0.25)
      # algo.fit(trainset)
      # predictions = algo.test(testset)

      # from surprise import accuracy
      # accuracy.rmse(predictions)

```

```
# accuracy.mae(predictions)

# # Predict rating for a user and movie
# uid = 1 # user id
# iid = 1091 # item id
# pred = algo.predict(uid, iid, verbose=True)
# pred
```

0.6.4 Questionnaire

[44]: df

```
[44]:      UserID  MovieID  Rating      Timestamp  Rated_hour  Rated_day \
0          1    1193      5  2000-12-31 22:12:40         22    Sunday
1          1     661      3  2000-12-31 22:35:09         22    Sunday
2          1     914      3  2000-12-31 22:32:48         22    Sunday
3          1    3408      4  2000-12-31 22:04:35         22    Sunday
4          1    2355      5  2001-01-06 23:38:11         23  Saturday
...      ...      ...      ...      ...      ...      ...
1000204    6040    1091      1  2000-04-26 02:35:41          2  Wednesday
1000205    6040    1094      5  2000-04-25 23:21:27         23   Tuesday
1000206    6040     562      5  2000-04-25 23:19:06         23   Tuesday
1000207    6040    1096      4  2000-04-26 02:20:48          2  Wednesday
1000208    6040    1097      4  2000-04-26 02:19:29          2  Wednesday
```

```
      Gender  Age  Occupation  Zip-code  ...  Fantasy  Film-Noir  Horror  \
0          0    1          10    48067  ...      0          0          0
1          0    1          10    48067  ...      0          0          0
2          0    1          10    48067  ...      0          0          0
3          0    1          10    48067  ...      0          0          0
4          0    1          10    48067  ...      0          0          0
...      ...  ...      ...      ...  ...      ...      ...
1000204    1    25           6    11106  ...      0          0          0
1000205    1    25           6    11106  ...      0          0          0
1000206    1    25           6    11106  ...      0          0          0
1000207    1    25           6    11106  ...      0          0          0
1000208    1    25           6    11106  ...      1          0          0
```

```
      Musical  Mystery  Romance  Sci-Fi  Thriller  War  Western
0          0          0          0          0          0          0
1          1          0          0          0          0          0
2          1          0          1          0          0          0
3          0          0          0          0          0          0
4          0          0          0          0          0          0
...      ...      ...      ...      ...      ...      ...
```

1000204	0	0	0	0	0	0	0
1000205	0	0	1	0	0	1	0
1000206	0	0	0	0	0	0	0
1000207	0	0	0	0	0	0	0
1000208	0	0	0	1	0	0	0

[1000209 rows x 33 columns]

```
[45]: # Users of which age group have watched and rated the most number of movies?
most Rated movies = df.groupby('Age')['Title'].count().
↳sort_values(ascending=False)
most Rated movies
```

```
[45]: Age
25    395556
35    199003
18    183536
45     83633
50     72490
56     38780
1      27211
Name: Title, dtype: int64
```

```
[46]: # Users belonging to which profession have watched and rated the most movies?

most Rated movies = df.groupby('Occupation')['Title'].count().
↳sort_values(ascending=False)
most Rated movies
```

```
[46]: Occupation
4      131032
0      130499
7      105425
1       85351
17     72816
20     60397
12     57214
2      50068
14     49109
16     46021
6      37205
3      31623
10     23290
15     22951
5      21850
11     20563
19     14904
```

```

13      13754
18      12086
9       11345
8        2706
Name: Title, dtype: int64

```

[47]: *# Most of the users in our dataset who've rated the movies are Male.*

```

most Rated movies = df.groupby('Gender')['Title'].count().
↳sort_values(ascending=False)
most Rated movies

```

[47]: Gender

```

1      753769
0      246440
Name: Title, dtype: int64

```

[48]: *# Most of the movies present in our dataset were released in which decade?*

```

most Rated movies = movies_df.groupby('Release_Decade')['Title'].count().
↳sort_values(ascending=False)
most Rated movies

```

[48]: Release_Decade

```

90's      2283
80's       598
70's       247
60's       191
50's       168
00's       156
40's       126
30's        77
20's        34
10's         3
Name: Title, dtype: int64

```

[49]: *# The movie with maximum number of ratings*

```

most Rated movies = df.groupby('Title')['Rating'].count().
↳sort_values(ascending=False)
most Rated movies

```

[49]: Title

American Beauty (1999)	3428
Star Wars: Episode IV - A New Hope (1977)	2991
Star Wars: Episode V - The Empire Strikes Back (1980)	2990
Star Wars: Episode VI - Return of the Jedi (1983)	2883

```

Jurassic Park (1993)                2672
Target (1995)                        ...
I Don't Want to Talk About It (De eso no se habla) (1993)  1
An Unforgettable Summer (1994)      1
Never Met Picasso (1996)            1
Full Speed (1996)                   1
Name: Rating, Length: 3706, dtype: int64

```

[50]: *# Name the top 3 movies similar to 'Liar Liar' on the item-based approach.*

```

movie_name = 'Liar Liar (1997)'
get_top_5_recommendations(movie_name)

```

```

[50]:
      Title  Similarity
1  Mrs. Doubtfire (1993)    0.557067
2  Ace Ventura: Pet Detective (1994)  0.516861
3    Dumb & Dumber (1994)    0.512585
4    Home Alone (1990)    0.511204
5  Wayne's World (1992)    0.499368

```

Answers:

1. Users of which age group have watched and rated the most number of movies? - **25-34**
2. Users belonging to which profession have watched and rated the most movies? - **college or graduate**
3. Most of the users in our dataset who've rated the movies are Male. (T/F) - **True**
4. Most of the movies present in our dataset were released in which decade? - **90s**
5. The movie with maximum number of ratings is **American Beauty (1999)** has **3428**.
6. Name the top 3 movies similar to 'Liar Liar' on the item-based approach.
 - Mrs. Doubtfire (1993)
 - Ace Ventura: Pet Detective (1994)
 - Dumb & Dumber (1994)
7. On the basis of approach, Collaborative Filtering methods can be classified into user-based and item-based.
8. Pearson Correlation ranges between **-1** to **1** whereas, Cosine Similarity belongs to the interval between **0** to **1**.
9. Mention the RMSE and MAPE that you got while evaluating the Matrix Factorization model.
10. Give the sparse 'row' matrix representation for the following dense matrix: $\begin{bmatrix} 1 & 0 \\ 3 & 7 \end{bmatrix}$
 - data = [1, 3, 7]
 - col_index = [0, 0, 1]
 - row_ptr = [0, 1, 3]