Business Case:Zee Recommender Systems

Problem Statement:

Create a Recommender System to show personalized movie recommendations based on ratings given by a user and other users similar to them in order to improve user experience.

Recommendation Systems

Recommendation engines are a subclass of machine learning which generally deal with ranking or rating products / users. Loosely defined, a recommender system is a system which predicts ratings a user might give to a specific item. These predictions will then be ranked and returned back to the user.

There are many different ways to build recommender systems, some use algorithmic and formulaic approaches like Page Rank while others use more modelling centric approaches like collaborative filtering, content based, link prediction, etc

Collaborative Filtering Systems

Collaborative filtering is the process of predicting the interests of a user by identifying preferences and information from many users. This is done by filtering data for information or patterns using techniques involving collaboration among multiple agents, data sources, etc. The underlying intuition behind collaborative filtering is that if users A and B have similar taste in a product, then A and B are likely to have similar taste in other products as well.

Content Based Systems

Content based systems generate recommendations based on the users preferences and profile. They try to match users to items which they've liked previously. The level of similarity between items is generally established based on attributes of items liked by the user. Unlike most collaborative filtering models which leverage ratings between target user and other users, content based models focus on the ratings provided by the target user themselves. In essence, the content based approach leverages different sources of data to generate recommendations.

Data Dictionary:

RATINGS FILE DESCRIPTION:

All ratings are contained in the file "ratings.dat" and are in the following format:

UserID::MovieID::Rating::Timestamp

- UserIDs range between 1 and 6040
- MovieIDs range between 1 and 3952
- Ratings are made on a 5-star scale (whole-star ratings only)
- Timestamp is represented in seconds
- Each user has at least 20 ratings

USERS FILE DESCRIPTION:

User information is in the file "users.dat" and is in the following format:

UserID::Gender::Age::Occupation::Zip-code

All demographic information is provided voluntarily by the users and is not checked for accuracy. Only users who have provided some demographic information are included in this data set.

- Gender is denoted by a "M" for male and "F" for female
- Age is chosen from the following ranges:

```
1: "Under 18"
18: "18-24"
25: "25-34"
35: "35-44"
45: "45-49"
50: "50-55"
56: "56+"
```

- Occupation is chosen from the following choices:

```
0: "other" or not specified
1: "academic/educator"
2: "artist"
3: "clerical/admin"
4: "college/grad student"
5: "customer service"
6: "doctor/health care"
7: "executive/managerial"
8: "farmer"
9: "homemaker"
10: "K-12 student"
11: "lawyer"
12: "programmer"
13: "retired"
14: "sales/marketing"
15: "scientist"
16: "self-employed"
17: "technician/engineer"
18: "tradesman/craftsman"
19: "unemployed"
20: "writer"
```

MOVIES FILE DESCRIPTION:

Movie information is in the file "movies.dat" and is in the following format:

MovieID::Title::Genres

- Titles are identical to titles provided by the IMDB (including year of release)
- Genres are pipe-separated and are selected from the following genres:

```
Action
Adventure
Animation
Children's
Comedy
Crime
Documentary
Drama
Fantasy
Film-Noir
Horror
Musical
Mystery
Romance
Sci-Fi
Thriller
War
Western
```

In [ ]:

```
# Analysis
#Importing Required Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm
from datetime import datetime

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

In [ ]:

```
movies = pd.read_fwf('zee-movies.dat', encoding='ISO-8859-1')
ratings = pd.read_fwf('zee-ratings.dat', encoding='ISO-8859-1')
users = pd.read_fwf('zee-users.dat', encoding='ISO-8859-1')
```

Data Formatting

In [ ]:

```
#Formatting Movies Dataset
movies.head()
```

Out[ ]:

	Movie ID::Title::Genres	Unnamed: 1	Unnamed: 2
0	1::Toy Story (1995)::Animation|Children's|Comedy	NaN	NaN
1	2::Jumanji (1995)::Adventure|Children's|Fantasy	NaN	NaN
2	3::Grumpier Old Men (1995)::Comedy|Romance	NaN	NaN
3	4::Waiting to Exhale (1995)::Comedy|Drama	NaN	NaN
4	5::Father of the Bride Part II (1995)::Comedy	NaN	NaN

In [ ]:
```
#Dropping Unnamed column which is not Required
movies.drop(columns=['Unnamed: 1','Unnamed: 2'], axis=1, inplace=True)
```

In [ ]:
```
movies=movies['Movie ID::Title::Genres'].str.split('::',expand=True)
movies.columns=['Movie ID','Title','Genres']
```

In [ ]:
```
movies.rename(columns={'Movie ID':'MovieID'},inplace=True)
```

In [ ]:
```
movies.head(5)
```

Out[ ]:

	MovieID	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

In [ ]:
```
mov=movies.copy()
mov.dropna(inplace=True)
mov.Genres=mov.Genres.str.split('|')
```

In [ ]:
```
for i in mov['Genres']:
  for j in range(len(i)):
    if i[j]=='Ro' or i[j]=='Rom' or i[j]=='R' or i[j]=='Roman' or i[j]=='Roma':
      i[j]='Romance'
    elif i[j]=='Chil' or i[j]=='Childre' or i[j]=='Childr' or i[j]=="Children'" or
      i[j]="Children's"
    elif i[j]=='Fantas' or i[j]=='Fant' or i[j]=='F':
      i[j]='Fantasy'
    elif i[j]=='Dr' or i[j]=='Dram' or i[j]=='D':
      i[j]='Drama'
    elif i[j]=='Documenta' or i[j]=='Docu' or i[j]=='Document' or i[j]=='Documen':
      i[j]='Documentary'
    elif i[j]=='Wester' or i[j]=='We':
      i[j]='Western'
    elif i[j]=='Animati':
      i[j]='Animation'
    elif i[j]=='Come' or i[j]=='Comed' or i[j]=='Com':
      i[j]='Comdey'
    elif i[j]=='Sci-F' or i[j]=='S' or i[j]=='Sci-' or i[j]=='Sci':
      i[j]='Sci-Fi'
    elif i[j]=='Adv' or i[j]=='Adventu' or i[j]=='Adventur' or i[j]=='A' or i[j]==
      i[j]='Adventure'
    elif i[j]=='Horro' or i[j]=='Horr':
```

```
        i[j]='Horror'
      elif i[j]=='Th' or i[j]=='Thri' or i[j]=='Thrille':
        i[j]='Thriller'
      elif i[j]=='Acti':
        i[j]='Action'
      elif i[j]=='Wa':
        i[j]='War'
      elif i[j]=='Music':
        i[j]='Musical'
      elif i[j]=='':
        i[j]='No Genre'
```

In [ ]:

```
#Formatting Ratings Dataset
ratings.head()
```

Out[ ]:

	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

In [ ]:

```
ratings=ratings['UserID::MovieID::Rating::Timestamp'].str.split('::',expand=True)
ratings.columns=['UserID','MovieID','Rating','Timestamp']
```

In [ ]:

```
ratings.head()
```

Out[ ]:

	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

In [ ]:

```
#Formatting Ratings Dataset
users.head()
```

Out[ ]:

	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

In [ ]:

```
users=users['UserID::Gender::Age::Occupation::Zip-code'].str.split('::',expand=Tru
users.columns=['UserID','Gender','Age','Occupation','Zip-code']
```

In [ ]:

```
users.head()
```

Out[ ]:

	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

In [ ]:

```
users.replace({'Age':{'1':"Under 18",
                      '18':"18-24",
                      '25':"25-34",
                      '35':"35-44",
                      '45':"45-49",
                      '50':"50-55",
                      '56':"56+"}},inplace=True)
```

In [ ]:

```
users.replace({'Occupation':{'0': "other",
    '1': "academic/educator",
    '2': "artist",
    '3': "clerical/admin",
    '4': "college/grad student",
    '5': "customer service",
    '6': "doctor/health care",
    '7': "executive/managerial",
    '8': "farmer",
    '9': "homemaker",
    '10': "K-12 student",
    '11': "lawyer",
    '12': "programmer",
    '13': "retired",
    '14': "sales/marketing",
    '15': "scientist",
    '16': "self-employed",
    '17': "technician/engineer",
    '18': "tradesman/craftsman",
    '19': "unemployed",
    '20': "writer"
}},inplace=True)
```

In [ ]:

```
users.head()
```

Out[ ]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	Under 18	K-12 student	48067
1	2	M	56+	self-employed	70072
2	3	M	25-34	scientist	55117
3	4	M	45-49	executive/managerial	02460
4	5	M	25-34	writer	55455

In [ ]:

```
#Merging the DataFrames
df_1=pd.merge(mov,ratings,how='inner',on='MovieID')
```

```
df_1.head()
```

Out[ ]:

	MovieID	Title	Genres	UserID	Rating	Timestamp
0	1	Toy Story (1995)	[Animation, Children's, Comedy]	1	5	978824268
1	1	Toy Story (1995)	[Animation, Children's, Comedy]	6	4	978237008
2	1	Toy Story (1995)	[Animation, Children's, Comedy]	8	4	978233496
3	1	Toy Story (1995)	[Animation, Children's, Comedy]	9	5	978225952
4	1	Toy Story (1995)	[Animation, Children's, Comedy]	10	5	978226474

In [ ]:

```
df=pd.merge(df_1,users,how='inner',on='UserID')
df.head()
```

Out[ ]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	index	Gender	Age	Occupati
0	1	Toy Story (1995)	[Animation, Children's, Comedy]	1	5	978824268	0	F	Under 18	K-stude
1	48	Pocahontas (1995)	[Animation, Children's, Musical, Romance]	1	5	978824351	0	F	Under 18	K-stude
2	150	Apollo 13 (1995)	[Drama]	1	5	978301777	0	F	Under 18	K-stude
3	260	Star Wars: Episode IV - A New Hope (1977)	[Action, Adventure, Fantasy]	1	4	978300760	0	F	Under 18	K-stude
4	527	Schindler's List (1993)	[Drama, War]	1	5	978824195	0	F	Under 18	K-stude

In [ ]:

```
df.shape
```

Out[ ]:

```
(996144, 10)
```

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 996144 entries, 0 to 996143
Data columns (total 10 columns):
 #   Column      Non-Null Count   Dtype 
---  ------      --------------   ----- 
 0   MovieID     996144 non-null  object
 1   Title       996144 non-null  object
 2   Genres      996144 non-null  object
 3   UserID      996144 non-null  object
 4   Rating      996144 non-null  object
 5   Timestamp   996144 non-null  object
 6   Gender      996144 non-null  object
 7   Age         996144 non-null  object
 8   Occupation  996144 non-null  object
 9   Zip-code    996144 non-null  object
dtypes: object(10)
memory usage: 83.6+ MB
```

In [ ]:
```
df.isnull().sum()
```

Out[ ]:
```
MovieID       0
Title         0
Genres        0
UserID        0
Rating        0
Timestamp     0
Gender        0
Age           0
Occupation    0
Zip-code      0
dtype: int64
```

Observations:

- There are No missing Values after Merging all DataFrames

Feature Engineering and Data Cleaning

In [ ]:
```
#extracting Release Year
df['Release_Year']=df['Title'].apply(lambda x:x.split("(")[-1].split(')')[0])
```

In [ ]:
```
# convert string to an integer
df['MovieID'] = df['MovieID'].astype(int)
df['UserID'] = df['UserID'].astype(int)
df['Rating'] = df['Rating'].astype(int)
df['Timestamp'] = df['Timestamp'].astype(int)
df['Release_Year'] = df['Release_Year'].astype(int)
```

In [ ]:
```
df['Release_Year'].unique()
```

Out[ ]:
```
array([1995, 1977, 1993, 1992, 1937, 1991, 1996, 1964, 1939, 1958, 1950,
       1941, 1965, 1982, 1975, 1987, 1962, 1989, 1985, 1959, 1997, 1998,
       1988, 1942, 1947, 1999, 1980, 1983, 1986, 1990, 2000, 1994, 1978,
       1961, 1984, 1972, 1976, 1981, 1973, 1974, 1940, 1952, 1954, 1953,
       1944, 1968, 1957, 1946, 1949, 1951, 1963, 1971, 1979, 1967, 1966,
       1948, 1933, 1970, 1969, 1930, 1955, 1956, 1920, 1925, 1938, 1960,
       1935, 1932, 1931, 1945, 1943, 1934, 1936, 1929, 1926, 1927, 1922,
       1919, 1921, 1923, 1928])
```

In [ ]:
```
bins=[1919,1929,1939,1949,1959,1969,1979,1989,2000]
labels=['20s','30s','40s','50s','60s','70s','80s','90s']
```

```
df['Release_Decade']=pd.cut(df['Release_Year'],bins=bins,labels=labels)
```

In [ ]:
```
df['Title']=df['Title'].apply(lambda x:x.split("(")[0])
```

In [ ]:
```
import re
def preprocess_string(string):
    new_string= re.sub('[^A-Za-z ]+', '', string).lower().strip()
    return new_string
```

In [ ]:
```
#TO remove special characters and space from Title column after splitting
df['Title']=df['Title'].apply(lambda x: preprocess_string(str(x)))
```

In [ ]:
```
from datetime import datetime

#Reducing Timestamp which are in seconds to Hour
df['Timestamp'] = df['Timestamp'].apply(lambda x: datetime.fromtimestamp(x).hour)
```

In [ ]:
```
df['Zip-code']=df['Zip-code'].apply(lambda x:x.split('-')[0])
```

In [ ]:
```
df.head(5)
```

Out[ ]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	index	Gender	Age	Occupati
0	1	toy story	[Animation, Children's, Comedy]	1	5	23	0	F	Under 18	K-stude
1	48	pocahontas	[Animation, Children's, Musical, Romance]	1	5	23	0	F	Under 18	K-stude
2	150	apollo	[Drama]	1	5	22	0	F	Under 18	K-stude
3	260	star wars episode iv a new hope	[Action, Adventure, Fantasy]	1	4	22	0	F	Under 18	K-stude
4	527	schindlers list	[Drama, War]	1	5	23	0	F	Under 18	K-stude

Calculating Average Time spent and ratings done by users

In [ ]:
```
users1=df.groupby('UserID').agg({'Rating':'mean','Timestamp':'mean'}).rename(colum

users1=users1.reset_index()
```

In [ ]:
```
users2=df.groupby('UserID').agg({'Rating':'count'}).rename(columns={'Rating':'Rati
users2=users2.reset_index()
```

In [ ]:
```
users3=pd.merge(users1,users2,how='left',on='UserID')
users3
```

Out[ ]:

	UserID	Average_Rating	Average_Timestamp	Rating_Counts
0	1	4.188679	22.245283	53
1	2	3.713178	21.155039	129
2	3	3.901961	21.000000	51
3	4	4.190476	20.000000	21
4	5	3.146465	6.015152	198
...	...	...	...	...
6035	6036	3.297052	5.236961	882
6036	6037	3.715000	1.595000	200
6037	6038	3.800000	7.400000	20
6038	6039	3.875000	22.550000	120
6039	6040	3.566766	11.359050	337

6040 rows × 4 columns

In [ ]:

```
# Merging this data to Main Dataframe
df=pd.merge(df,users3,how='left',on='UserID')
df.head(5)
```

Out[ ]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	index	Gender	Age	Occupati
0	1	toy story	[Animation, Children's, Comedy]	1	5	23	0	F	Under 18	K-stud
1	48	pocahontas	[Animation, Children's, Musical, Romance]	1	5	23	0	F	Under 18	K-stud
2	150	apollo	[Drama]	1	5	22	0	F	Under 18	K-stud
3	260	star wars episode iv a new hope	[Action, Adventure, Fantasy]	1	4	22	0	F	Under 18	K-stud
4	527	schindlers list	[Drama, War]	1	5	23	0	F	Under 18	K-stud

In [ ]:

```
df.shape
```

Out[ ]:

```
(996144, 16)
```

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 996144 entries, 0 to 996143
Data columns (total 15 columns):
 #   Column             Non-Null Count   Dtype   
---  ------             --------------   -----   
 0   MovieID            996144 non-null  int64   
 1   Title              996144 non-null  object  
 2   Genres             996144 non-null  object  
 3   UserID             996144 non-null  int64   
 4   Rating             996144 non-null  int64   
 5   Timestamp          996144 non-null  int64   
 6   Gender             996144 non-null  int64   
 7   Age                996144 non-null  object  
 8   Occupation         996144 non-null  object  
 9   Zip-code           996144 non-null  object  
 10  Release_Year       996144 non-null  int64   
 11  Release_Decade     996099 non-null  category
 12  Average_Rating     996144 non-null  float64 
 13  Average_Timestamp  996144 non-null  float64 
 14  Rating_Counts      996144 non-null  int64   
dtypes: category(1), float64(2), int64(7), object(5)
memory usage: 114.9+ MB
```

In [ ]:

```
df_numerical=df.select_dtypes(exclude='object')
df_categorical=df.select_dtypes(include='object')
```

In [ ]:

```
df_numerical.columns
```

Out[ ]:

```
Index(['MovieID', 'UserID', 'Rating', 'Timestamp', 'Gender', 'Release_Year',
       'Release_Decade', 'Average_Rating', 'Average_Timestamp',
       'Rating_Counts'],
      dtype='object')
```

In [ ]:

```
df_categorical.columns
```

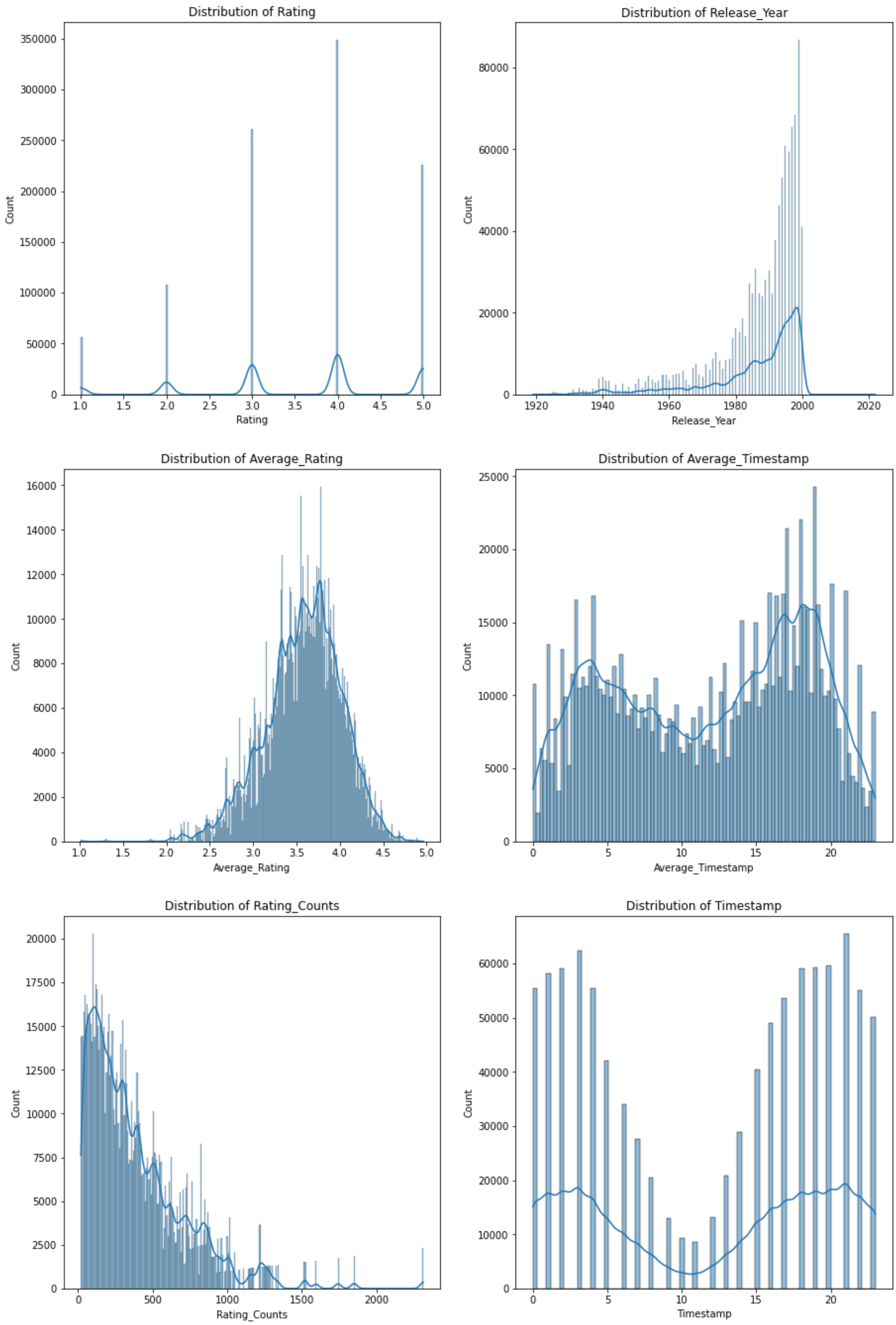
Out[ ]:

```
Index(['Title', 'Genres', 'Gender', 'Age', 'Occupation', 'Zip-code'], dtype='objec
t')
```

Univariate analysis

In [ ]:

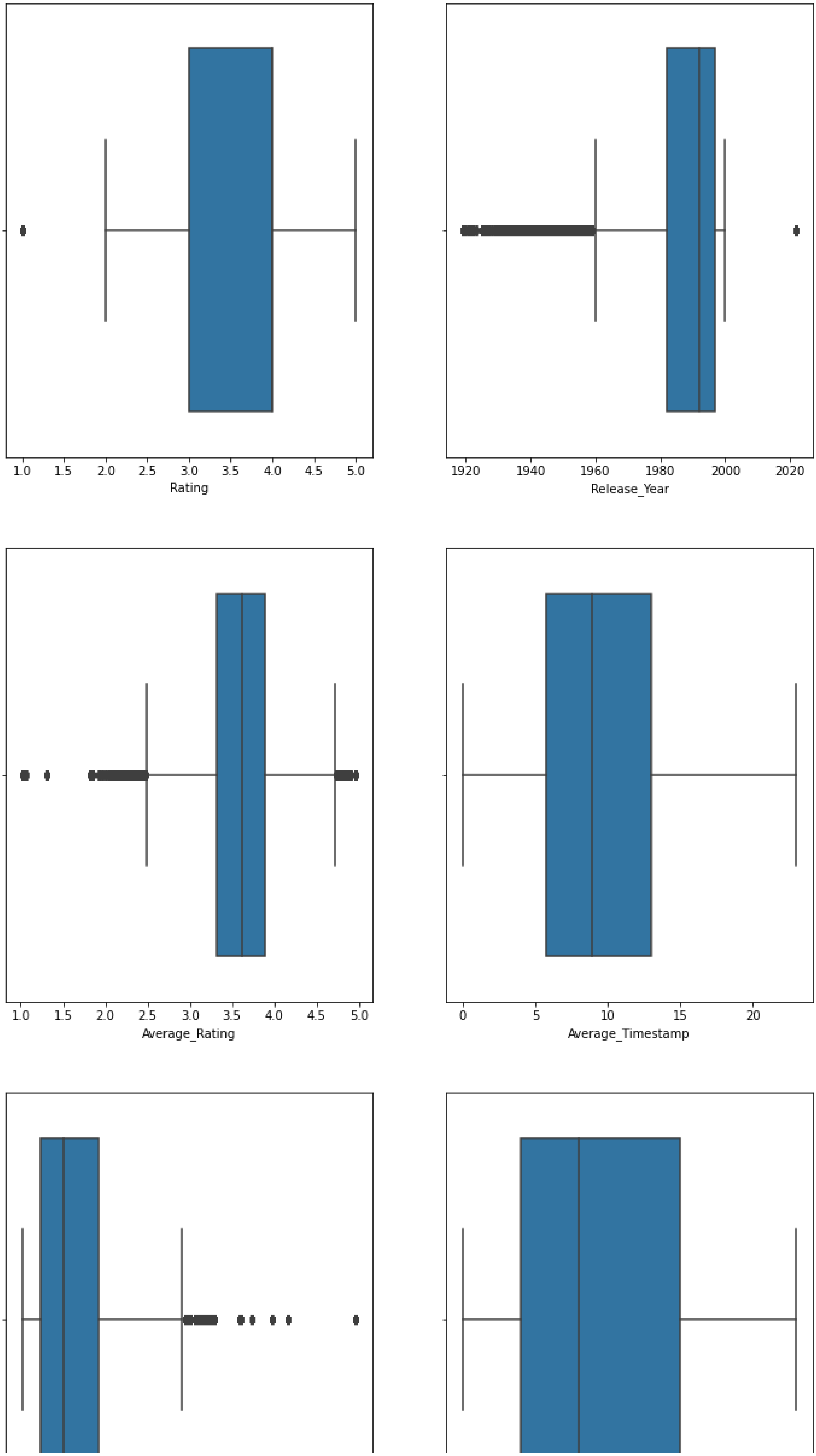
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(15, 10))
fig.subplots_adjust(top=1.9)

sns.histplot(data=df, x="Rating", kde=True, ax=axis[0,0])
axis[0,0].set_title('Distribution of Rating')
sns.histplot(data=df, x="Release_Year", kde=True, ax=axis[0,1])
axis[0,1].set_title('Distribution of Release_Year')
sns.histplot(data=df, x="Average_Rating", kde=True, ax=axis[1,0])
axis[1,0].set_title('Distribution of Average_Rating')
sns.histplot(data=df, x="Average_Timestamp", kde=True, ax=axis[1,1])
axis[1,1].set_title('Distribution of Average_Timestamp')
sns.histplot(data=df, x="Rating_Counts", kde=True, ax=axis[2,0])
axis[2,0].set_title('Distribution of Rating_Counts')
sns.histplot(data=df, x="Timestamp", kde=True, ax=axis[2,1])
axis[2,1].set_title('Distribution of Timestamp')
plt.show()
```



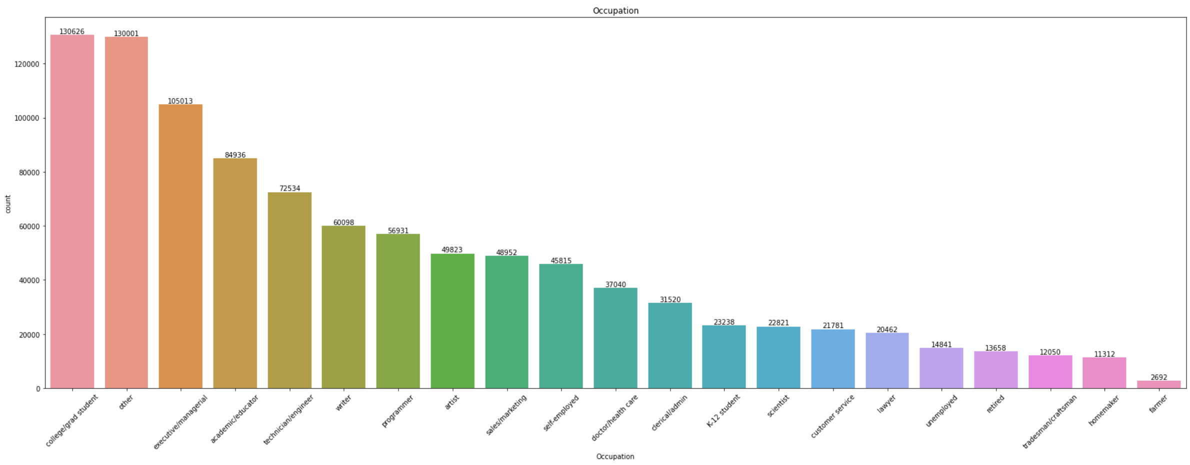
In [ ]:

```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.9)

sns.boxplot(data=df, x="Rating", ax=axis[0,0])
sns.boxplot(data=df, x="Release_Year", ax=axis[0,1])
sns.boxplot(data=df, x="Average_Rating", ax=axis[1,0])
sns.boxplot(data=df, x="Average_Timestamp", ax=axis[1,1])
sns.boxplot(data=df, x="Rating_Counts", ax=axis[2,0])
```

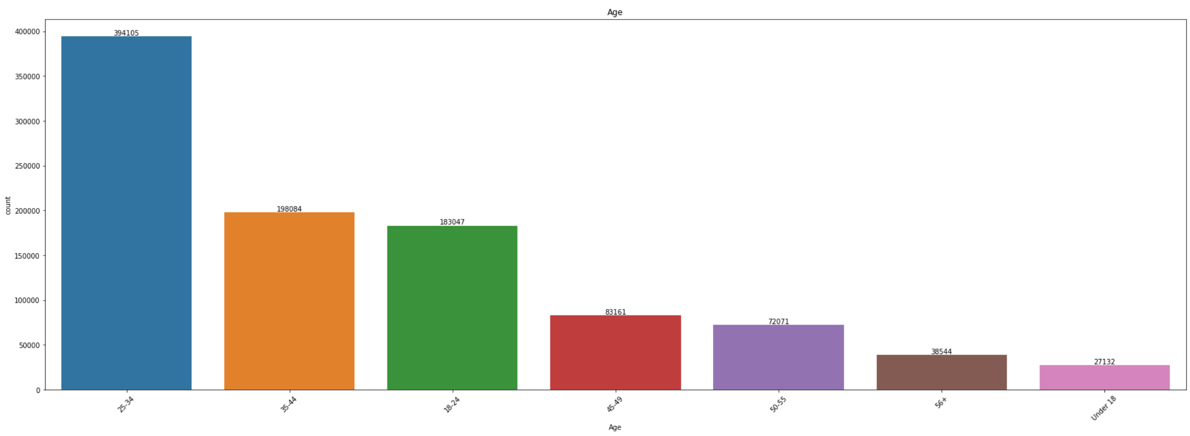
```
sns.boxplot(data=df, x="Timestamp", ax=axis[2,1])
plt.show()
```


1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
Rating
1920 1940 1960 1980 2000 2020
Release_Year
1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
Average_Rating
0 5 10 15 20
Average_Timestamp

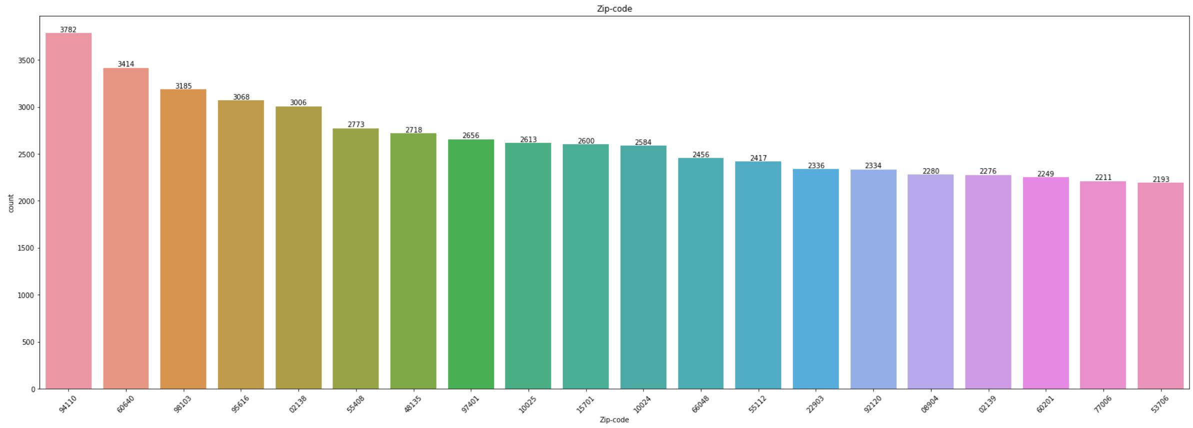
In [ ]:
```
plt.figure(figsize=(30,10))
ax = sns.countplot(data = df,
              x = 'Occupation',
              order = df['Occupation'].value_counts().index[:], linewidth=0.3)
ax.bar_label(ax.containers[0])
plt.title('Occupation')
plt.xticks(rotation=45)
plt.show()
```



In [ ]:
```
plt.figure(figsize=(30,10))
ax = sns.countplot(data = df,
              x = 'Age',
              order = df['Age'].value_counts().index[:], linewidth=0.3)
ax.bar_label(ax.containers[0])
plt.title('Age')
plt.xticks(rotation=45)
plt.show()
```

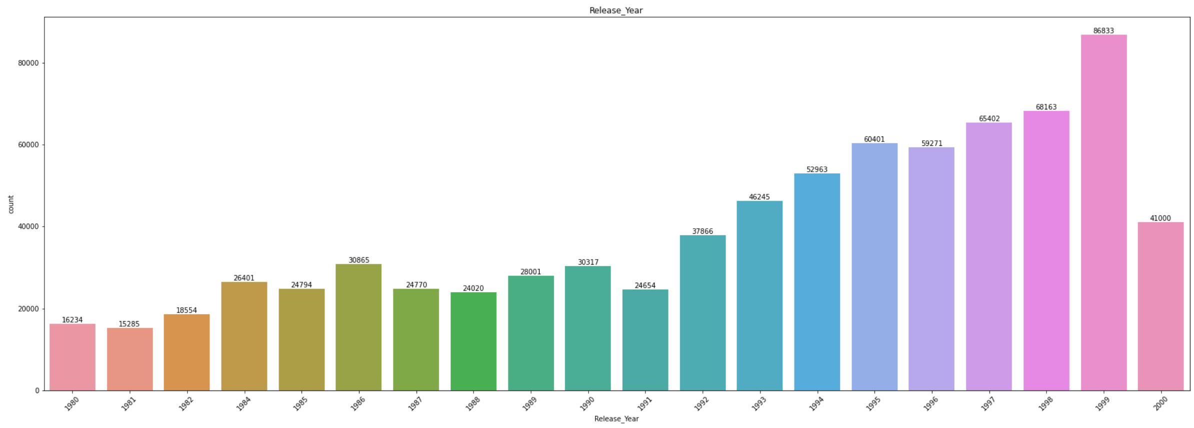


In [ ]:
```
plt.figure(figsize=(30,10))
ax = sns.countplot(data = df,
              x = 'Zip-code',
              order = df['Zip-code'].value_counts().index[:20], linewidth=0.3)
ax.bar_label(ax.containers[0])
plt.title('Zip-code')
plt.xticks(rotation=45)
plt.show()
```



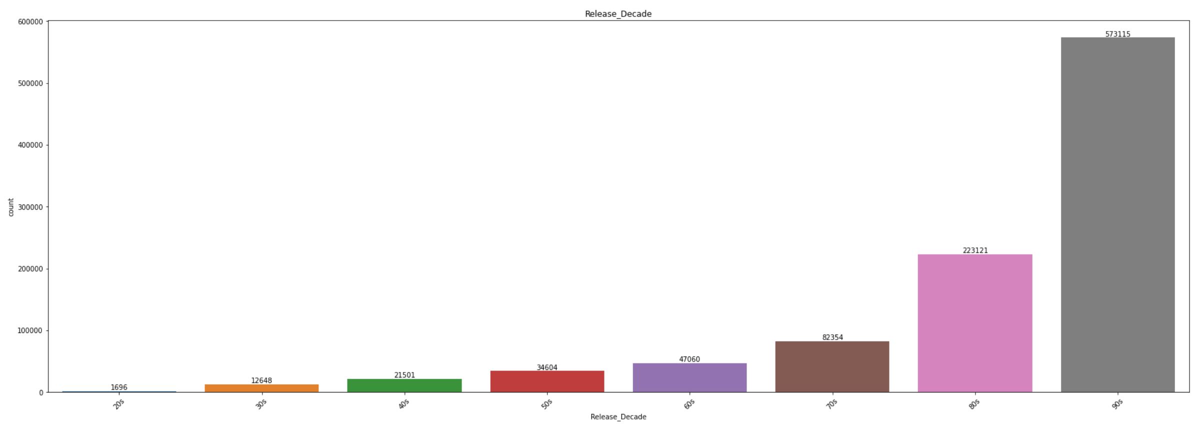
In [ ]:

```
plt.figure(figsize=(30,10))
ax = sns.countplot(data = df,
              x = 'Release_Year',
              order = sorted(df['Release_Year'].value_counts().index[:20]), linewi
ax.bar_label(ax.containers[0])
plt.title('Release_Year')
plt.xticks(rotation=45)
plt.show()
```



In [ ]:

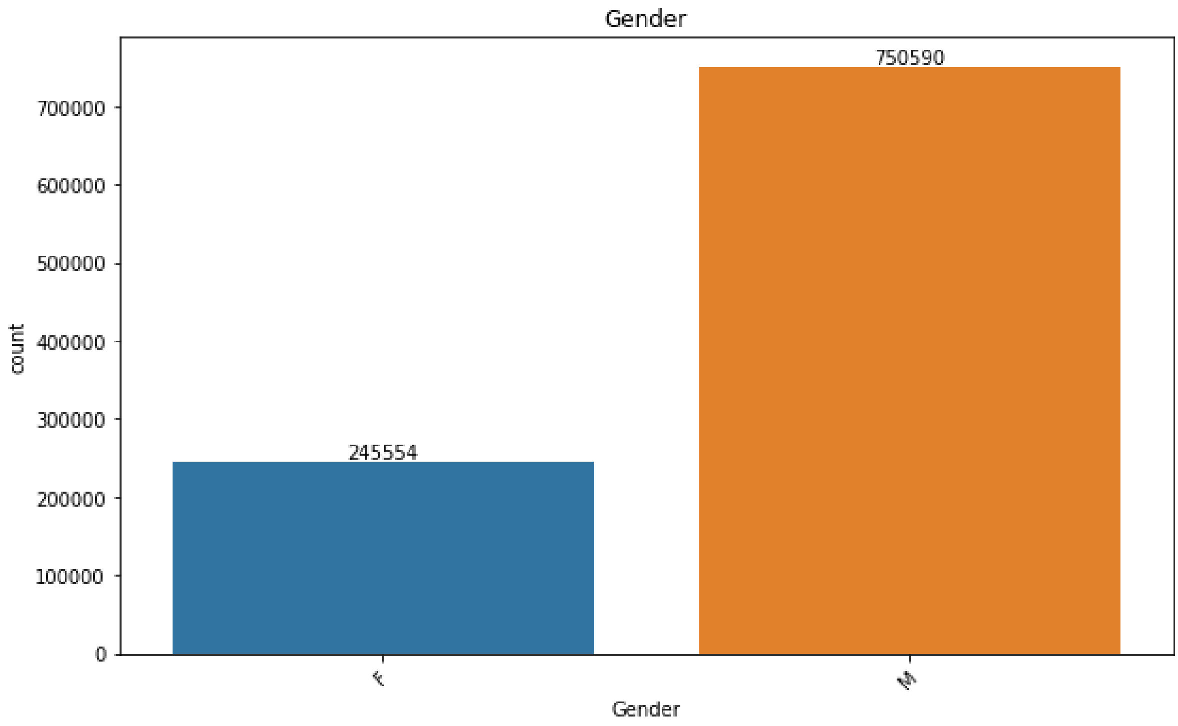
```
plt.figure(figsize=(30,10))
ax = sns.countplot(data = df,
              x = 'Release_Decade',
              order = sorted(df['Release_Decade'].value_counts().index[:20]), linew
ax.bar_label(ax.containers[0])
plt.title('Release_Decade')
plt.xticks(rotation=45)
plt.show()
```



In [ ]:

```
plt.figure(figsize=(10,6))
ax = sns.countplot(data = df,
              x = 'Gender',
              order = sorted(df['Gender'].value_counts().index[:]), linewidth=0.3)
```

```
ax.bar_label(ax.containers[0])
plt.title('Gender')
plt.xticks(rotation=45)
plt.show()
```



In [ ]:
```
#Replacing Gender with 0 and 1 for analysis
df.replace({'Gender':{'F':0,'M':1}},inplace=True)
```

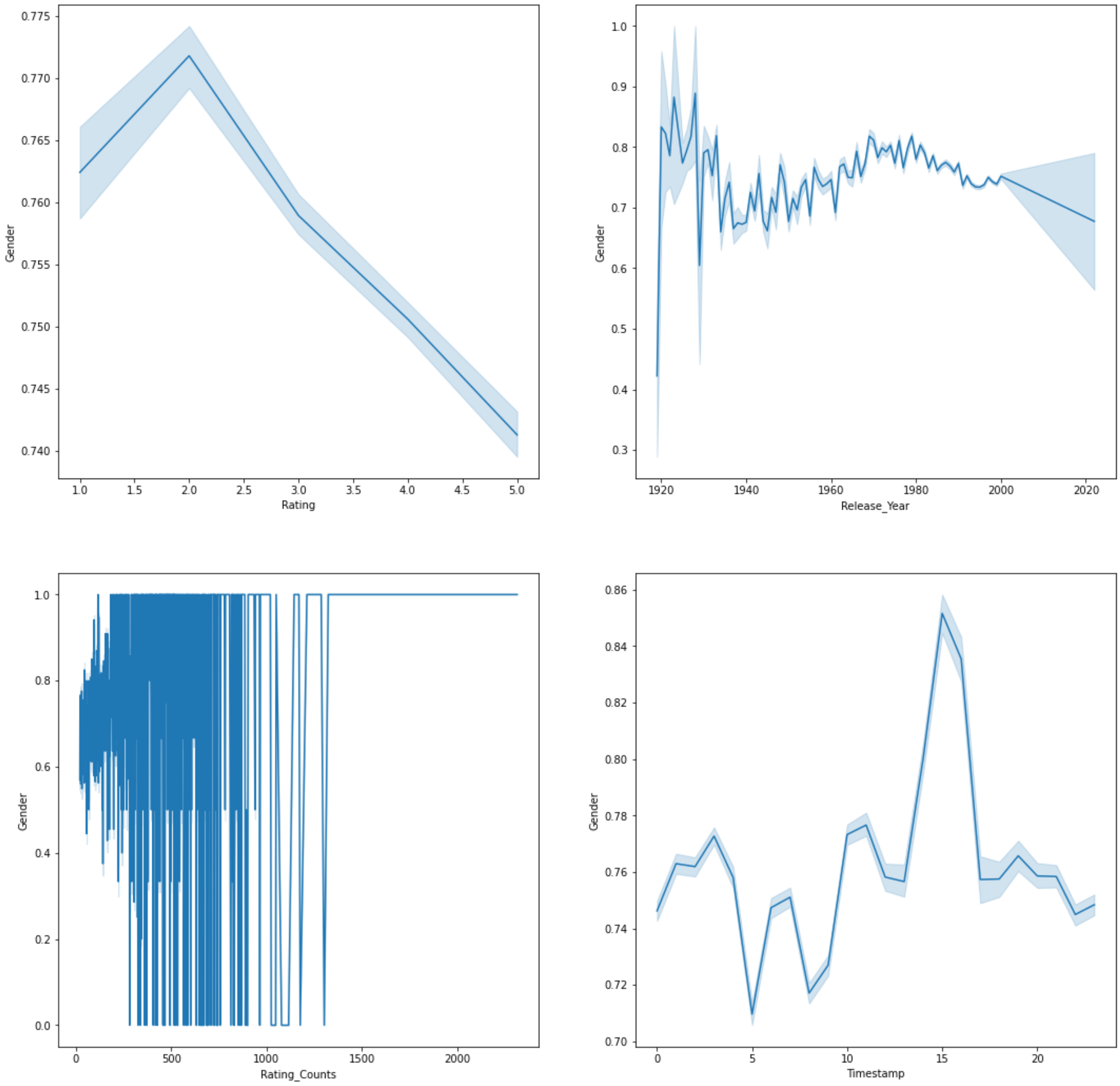
Observations:

1. Movies with Rating 4 are more.
2. More Movies are released on 90's.
3. More Users has Screen time more than 20 hours.
4. College/Grad Students are more to see the movie and Rate them.
5. More males users are watching Movies and rating them.
6. More Users are from Area zip code- 94110

Bivariate and Multivariate Analysis

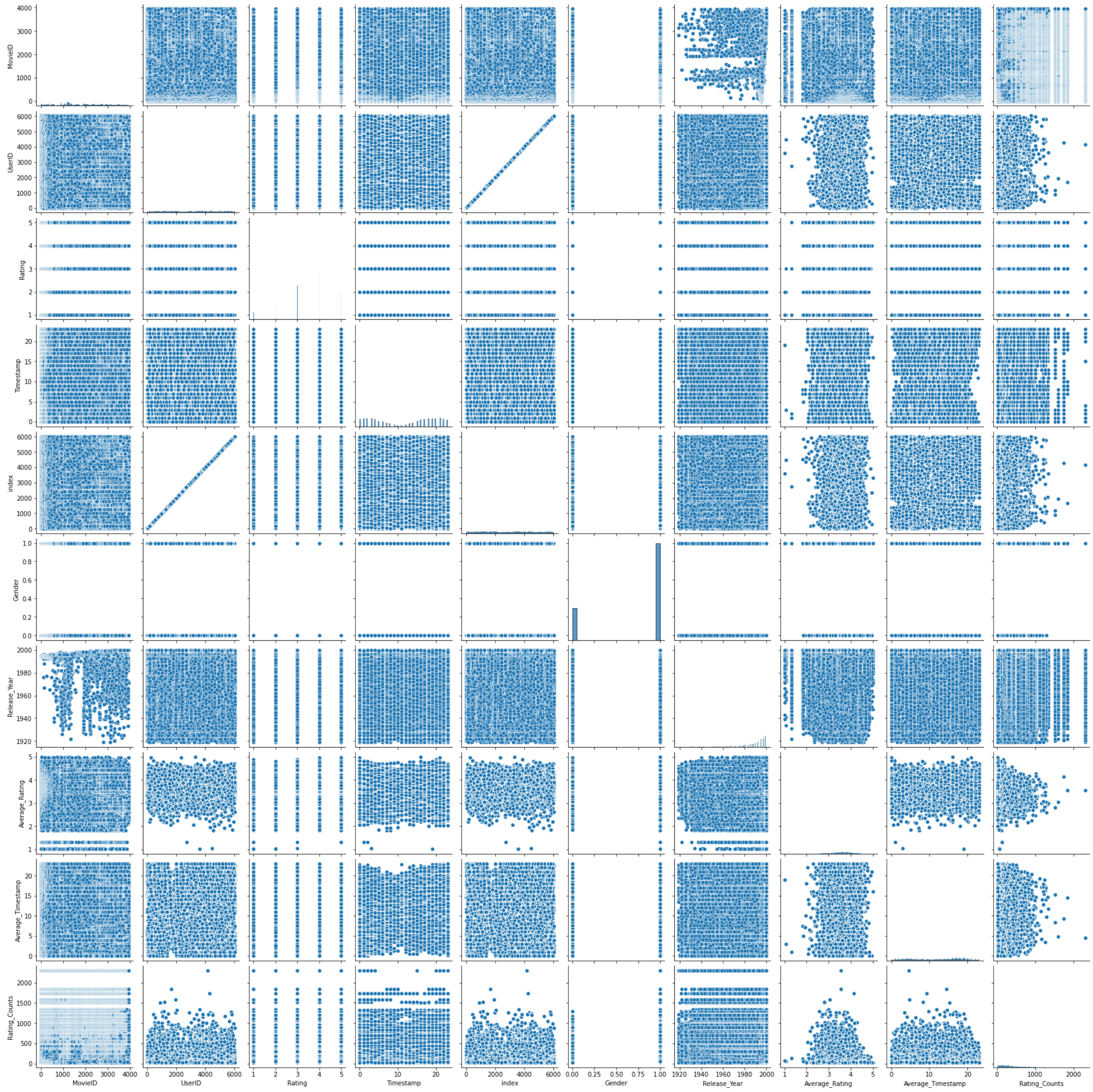
In [ ]:
```
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(18, 10))
fig.subplots_adjust(top=1.5)

sns.lineplot(x='Rating', y='Gender', data=df, ax=axis[0,0])
sns.lineplot(x='Release_Year',y='Gender', data=df, ax=axis[0,1])
sns.lineplot(x='Rating_Counts',y='Gender', data=df, ax=axis[1,0])
sns.lineplot(x='Timestamp',y='Gender', data=df, ax=axis[1,1])
```

Out[ ]:
```
<AxesSubplot:xlabel='Timestamp', ylabel='Gender'>
```



In [ ]:
```
sns.pairplot(df)
```

Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x7ff8883bea00>
```



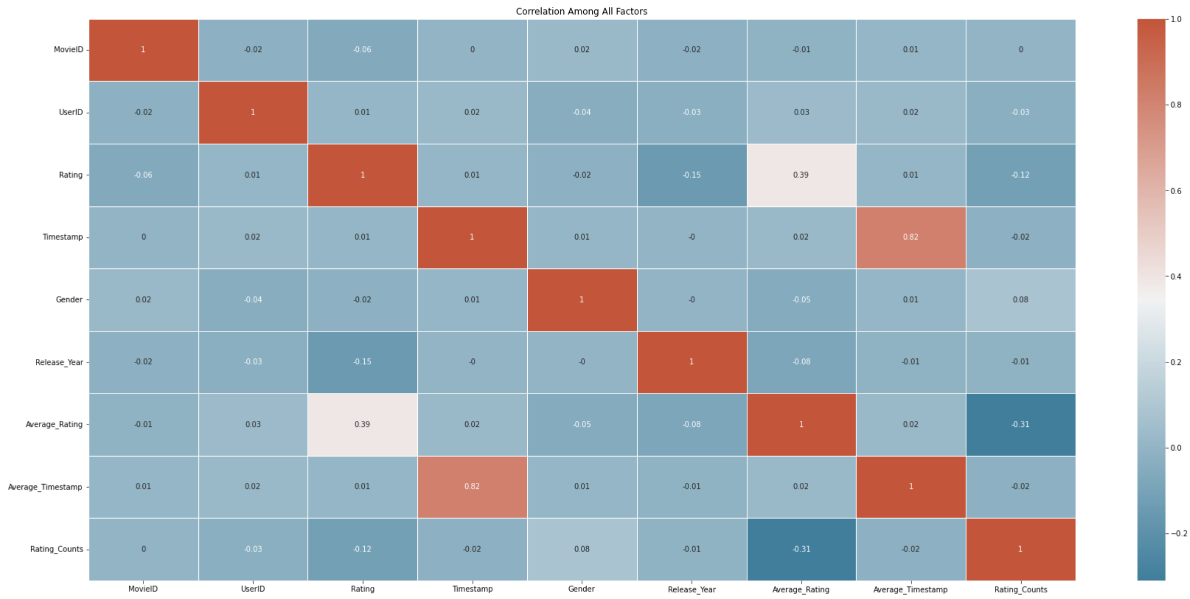
In [ ]:
```
## correlation matrix for heat map
df.corr()
```

Out[ ]:

	MovieID	UserID	Rating	Timestamp	Gender	Release_Year	Average
MovieID	1.000000	-0.017799	-0.063106	0.003628	0.021458	-0.015706	-0
UserID	-0.017799	1.000000	0.012142	0.019491	-0.035115	-0.031569	0
Rating	-0.063106	0.012142	1.000000	0.007323	-0.020160	-0.154817	0
Timestamp	0.003628	0.019491	0.007323	1.000000	0.007467	-0.004587	0
Gender	0.021458	-0.035115	-0.020160	0.007467	1.000000	-0.002147	-0
Release_Year	-0.015706	-0.031569	-0.154817	-0.004587	-0.002147	1.000000	-0
Average_Rating	-0.010083	0.031103	0.390367	0.017196	-0.051644	-0.083179	1
Average_Timestamp	0.005287	0.023725	0.008171	0.821552	0.009089	-0.008255	0
Rating_Counts	0.003087	-0.025659	-0.121329	-0.020170	0.083861	-0.010287	-0

In [ ]:
```
df_corr = df.corr()
plt.figure(figsize=(30,14))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
```

```python
plt.title('Correlation Among All Factors')
sns.heatmap(np.round(df_corr,2), annot=True, linewidths=.5, linecolor='white', cma
plt.show()
```

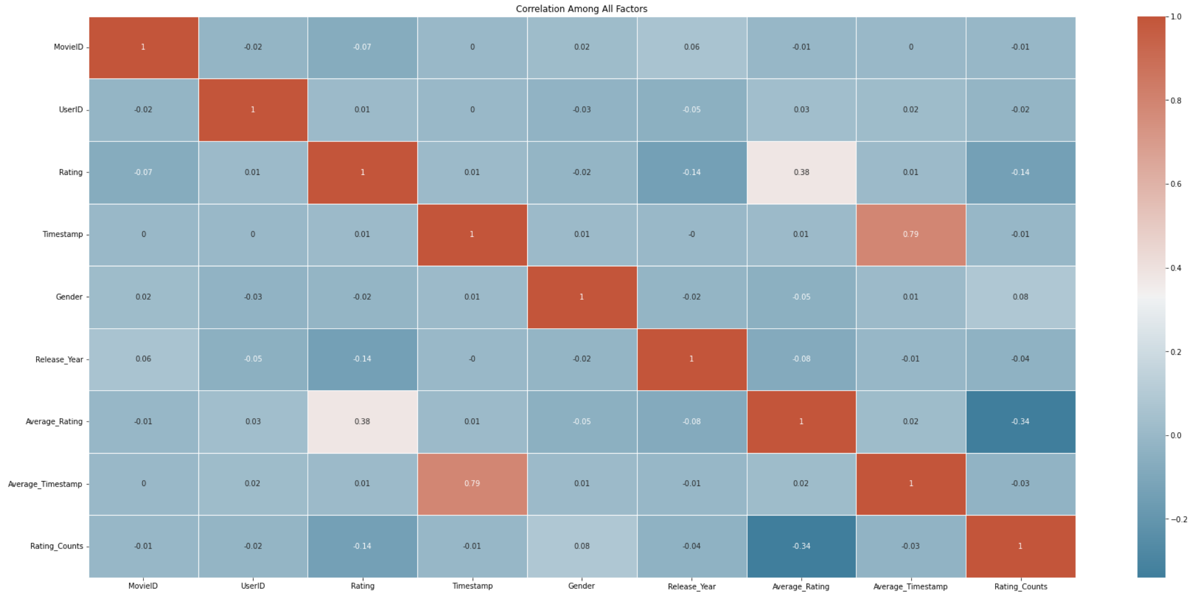


In [ ]:
```python
## spearman correlation matrix for heat map, used for better understanding
df.corr('spearman')
```

Out[ ]:

	MovieID	UserID	Rating	Timestamp	Gender	Release_Year	Average
MovieID	1.000000	-0.016434	-0.069092	0.003264	0.022019	0.059512	-0
UserID	-0.016434	1.000000	0.011713	0.002778	-0.034513	-0.046061	0
Rating	-0.069092	0.011713	1.000000	0.005091	-0.020896	-0.138091	0
Timestamp	0.003264	0.002778	0.005091	1.000000	0.007591	-0.001743	0
Gender	0.022019	-0.034513	-0.020896	0.007591	1.000000	-0.020077	-0
Release_Year	0.059512	-0.046061	-0.138091	-0.001743	-0.020077	1.000000	-0
Average_Rating	-0.011972	0.027265	0.377621	0.013200	-0.051988	-0.077341	1
Average_Timestamp	0.004774	0.018902	0.009248	0.794128	0.007681	-0.008256	0
Rating_Counts	-0.005130	-0.023144	-0.137660	-0.014541	0.076741	-0.037684	-0

In [ ]:
```python
df_corr = df.corr('spearman')
plt.figure(figsize=(30,14))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
plt.title('Correlation Among All Factors')
sns.heatmap(np.round(df_corr,2), annot=True, linewidths=.5, linecolor='white', cma
plt.show()
```



Observations:

1. No Correlation is seen between any Features.
2. There is no Evidence that More Screen time results more rating

ITEM BASED APPROACH

Build a Recommender System based on Pearson Correlation

In [ ]:
```
# Creates a pivot table dataframe
table1 = pd.pivot_table(df, index ='UserID',columns='Title',values='Rating', aggfu
table1.fillna(0,inplace=True)
table1
```

Out[ ]:

Title		a chef in love	a space odyssey	abbott and costello meet frankenstein	abominable snowman the	about adam	about last night	above the rim	absent minded professor the	absolute power
UserID										
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...
6036	2.0	0.0	5.0	0.0	0.0	0.0	2.0	0.0	0.0	3.0
6037	0.0	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6038	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6039	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6040	5.0	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

6040 rows × 3590 columns

In [ ]:

```
#checking data sparsity
n_users=df['UserID'].nunique()
n_movies=df['MovieID'].nunique()
sparsity=round(1.0-df.shape[0]/float(n_users*n_movies),3)
print('Sparsity of dataset:'+ str(sparsity*100)+'%')
```

```
Sparsity of dataset:95.5%
```

In [ ]:

```
#Top similar 5 movies for movie 'adam adam'
print("here are a list of 5 movies to recommend to a user who has liked 'about adar
print(table1.corr()['about adam'].sort_values(ascending=False).iloc[1:6])
```

```
here are a list of 5 movies to recommend to a user who has liked 'about adam'
Title
identification of a woman        0.387823
separation the                   0.369745
cheetah                          0.269400
safe passage                     0.267653
smiling fish and goat on fire    0.242155
Name: about adam, dtype: float64
```

In [ ]:

```
# Take input from user
print("please input the Movie name:")
a=input()
#Printing Top 5 similar Movies for recommendation
print("The Top 5 Similar Movies are:")
print(table1.corr()[a].sort_values(ascending=False).iloc[1:6])
```

```
please input the Movie name:
liar liar
The Top 5 Similar Movies are:
Title
mrs doubtfire                 0.499927
dumb  dumber                  0.459601
ace ventura pet detective     0.458654
home alone                    0.453982
wedding singer the            0.429222
Name: liar liar, dtype: float64
```

Build a Recommender System based on Cosine Similarity

In [ ]:
```
matrix=table1
```

In [ ]:
```
from sklearn.metrics.pairwise import cosine_similarity
user_similarity=cosine_similarity(matrix)
item_similarity=cosine_similarity(matrix.T)
```

In [ ]:
```
user_similarity #user-user similarity using Cosine similarity
```

Out[ ]:
```
array([[1.        , 0.09744712, 0.12365275, ..., 0.        , 0.17878902,
        0.13558235],
       [0.09744712, 1.        , 0.1514786 , ..., 0.06611767, 0.07366603,
        0.22524253],
       [0.12365275, 0.1514786 , 1.        , ..., 0.12023352, 0.09588437,
        0.13889985],
       ...,
       [0.        , 0.06611767, 0.12023352, ..., 1.        , 0.16377988,
        0.10020251],
       [0.17878902, 0.07366603, 0.09588437, ..., 0.16377988, 1.        ,
        0.22495658],
       [0.13558235, 0.22524253, 0.13889985, ..., 0.10020251, 0.22495658,
        1.        ]])
```

In [ ]:
```
item_similarity #item-item similarity using cosine similarity
```

Out[ ]:
```
array([[1.        , 0.08103149, 0.47713092, ..., 0.19422964, 0.0499589 ,
        0.02627491],
       [0.08103149, 1.        , 0.08124235, ..., 0.07031233, 0.        ,
        0.        ],
       [0.47713092, 0.08124235, 1.        , ..., 0.21344055, 0.03333554,
        0.04487888],
       ...,
       [0.19422964, 0.07031233, 0.21344055, ..., 1.        , 0.05922839,
        0.01683785],
       [0.0499589 , 0.        , 0.03333554, ..., 0.05922839, 1.        ,
        0.        ],
       [0.02627491, 0.        , 0.04487888, ..., 0.01683785, 0.        ,
        1.        ]])
```

In [ ]:
```
user_sim_matrix=pd.DataFrame(user_similarity,index=matrix.index,columns=matrix.ind
user_sim_matrix.head()
```

Out[ ]:

UserID	1	2	3	4	5	6	7	8	9
UserID									
1	1.000000	0.097447	0.123653	0.133919	0.091155	0.181273	0.060338	0.138379	0.212825
2	0.097447	1.000000	0.151479	0.194308	0.114394	0.102000	0.305787	0.211120	0.200854
3	0.123653	0.151479	1.000000	0.151227	0.062907	0.088017	0.138332	0.086531	0.139331
4	0.133919	0.194308	0.151227	1.000000	0.045094	0.013681	0.130339	0.100856	0.094285
5	0.091155	0.114394	0.062907	0.045094	1.000000	0.047983	0.126257	0.220817	0.263097

5 rows × 6040 columns

In [ ]:

```
# NearestNeighbors to find similar movies to recommend
from sklearn.neighbors import NearestNeighbors
knn = NearestNeighbors(metric='cosine', algorithm='brute', n_neighbors=6, n_jobs=-
knn.fit(matrix.T)
```

Out[ ]:

```
NearestNeighbors
NearestNeighbors(algorithm='brute', metric='cosine', n_jobs=-1, n_neighbo
rs=3)
```

In [ ]:

```
distances , indices = knn.kneighbors(matrix.T,n_neighbors=6)
```

In [ ]:

```
result=pd.DataFrame(indices,columns=['Title1','Title2','Title3','Title4','Title5',
result.head()
```

Out[ ]:

	Title1	Title2	Title3	Title4	Title5	Title6
0	0	2	383	668	954	667
1	1	839	2578	1808	148	2323
2	2	668	383	667	62	3043
3	3	739	1633	3426	1060	2680
4	4	2189	1520	2244	2171	2170

In [ ]:

```
result2=result.copy()
for i in range(1,7):
  mov=pd.DataFrame(matrix.T.index).reset_index()
  mov=mov.rename(columns={'index':f'Title{i}'})
  result2=pd.merge(result2,mov,on=[f'Title{i}'],how='left')
  result2=result2.drop(f'Title{i}',axis=1)
  result2=result2.rename(columns={'Title':f'Title{i}'})

result2.rename(columns = {'Title1':'Title','Title2':'Nearest_title1','Title3':'Nea
                          'Title4':'Nearest_title4','Title5':'Nearest_title4','Tit
result2[1:6]
```

Out[ ]:

	Title	Nearest_title1	Nearest_title2	Nearest_title4	Nearest_title4	Nearest_title5
1	a chef in love	death in the garden	proposition the	last of the high kings the	another mans poison	number seventeen
2	a space odyssey	close encounters of the third kind	blade runner	clockwork orange a	alien	star wars episode iv a new hope
3	abbott and costello meet frankenstein	creature from the black lagoon the	invisible man the	voyage to the bottom of the sea	fantastic voyage	return of the fly
4	abominable snowman the	mutters courage	house of dracula	nemesis nebula	mummys hand the	mummys ghost the
5	about adam	identification of a woman	separation the	cheetah	safe passage	smiling fish and goat on fire

In [ ]:

```
# Take input from user
print("please input the Movie name:")
movie_name=input()
#Printing Top 5 similar Movies for recommendation
print("The Top 5 Similar Movies are:")
result2.loc[result2['Title']==movie_name]
```

```
please input the Movie name:
liar liar
The Top 5 Similar Movies are:
```

Out[ ]:

	Title	Nearest_title1	Nearest_title2	Nearest_title4	Nearest_title4	Nearest_title5
1840	liar liar	mrs doubtfire	ace ventura pet detective	dumb dumber	home alone	waynes world

Build a Recommender System based on Matrix Factorization

In [ ]:

```
rm=df.pivot(index='UserID',columns='MovieID',values='Rating').fillna(0)
rm.head(5)
```

Out[ ]:

MovieID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948
UserID																	
1	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 3682 columns

In [ ]:

```
rm_raw = df[['UserID', 'MovieID', 'Rating']].copy()
rm_raw.columns = ['UserId', 'ItemId', 'Rating']  # Lib requires specific column nai
```

```
rm_raw.head(2)
```

Out[ ]:

	UserId	ItemId	Rating
0	1	1	5
1	1	48	5

In [ ]:
```
from cmfrec import CMF
model = CMF(method="als", k=4, lambda_=0.1, user_bias=False, item_bias=False, verb
model.fit(rm_raw)
```

Out[ ]:
```
Collective matrix factorization model
(explicit-feedback variant)
```

In [ ]:
```
model.A_.shape, model.B_.shape
```

Out[ ]:
```
((6040, 4), (3682, 4))
```

In [ ]:
```
rm_raw.Rating.mean(), model.glob_mean_
```

Out[ ]:
```
(3.57998542379415, 3.5799853801727295)
```

In [ ]:
```
# calculating Predicted Ratings
rm_=np.dot(model.A_, model.B_.T)+ model.glob_mean_
```

In [ ]:
```
# RMSE Error
from sklearn.metrics import mean_squared_error

rmse=mean_squared_error(rm.values[rm>0],rm_[rm>0],squared=False)
print ('RMSE: ' + str(rmse))
```

```
RMSE: 1.475653561527743
```

In [ ]:
```
# MAPE Error
from sklearn.metrics import mean_absolute_percentage_error

mape=mean_absolute_percentage_error(rm.values[rm>0],rm_[rm>0])
print ('MAPE: ' + str(mape))
```

```
MAPE: 0.42228753211692427
```

In [ ]:
```
# User-User embedding
User_User_embedding=cosine_similarity(model.A_)
User_User_embedding
```

Out[ ]:
```
array([[ 0.99999994, -0.08807255,  0.36307815, ..., -0.31150767,
         0.9453766 ,  0.27851325],
       [-0.08807255,  0.99999994, -0.51266956, ..., -0.00825458,
        -0.40687895,  0.6629223 ],
       [ 0.36307815, -0.51266956,  1.0000001 , ...,  0.23402148,
         0.50284976,  0.27974468],
       ...,
       [-0.31150767, -0.00825458,  0.23402148, ...,  0.99999994,
        -0.25871277,  0.31190187],
       [ 0.9453766 , -0.40687895,  0.50284976, ..., -0.25871277,
         1.0000001 ,  0.04626301],
       [ 0.27851325,  0.6629223 ,  0.27974468, ...,  0.31190187,
         0.04626301,  1.        ]], dtype=float32)
```

In [ ]:
```
user_sim_matrix=pd.DataFrame(User_User_embedding,index=matrix.index,columns=matrix
user_sim_matrix.head()
```

Out[ ]:

UserID	1	2	3	4	5	6	7	8	
UserID									
1	1.000000	-0.088073	0.363078	-0.249395	0.718838	0.332625	-0.010086	-0.625572	-0.44
2	-0.088073	1.000000	-0.512670	0.060343	0.581220	0.332946	0.154381	-0.569656	0.04
3	0.363078	-0.512670	1.000000	0.659688	-0.069559	0.485552	0.656270	0.443274	0.45
4	-0.249395	0.060343	0.659688	1.000000	-0.195940	0.542990	0.924487	0.580668	0.89
5	0.718838	0.581220	-0.069559	-0.195940	1.000000	0.596940	-0.019081	-0.878569	-0.45

5 rows × 6040 columns

In [ ]:

```
# Item-Item embedding
Item_Item_embedding=cosine_similarity(model.B_)
Item_Item_embedding
```

Out[ ]:

```
array([[ 1.0000001 , -0.058749  ,  0.95450747, ...,  0.76212126,
        -0.653695  ,  0.6034498 ],
       [-0.058749  ,  1.        ,  0.0850298 , ..., -0.03379729,
         0.2730069 , -0.37590423],
       [ 0.95450747,  0.0850298 ,  1.        , ...,  0.8809599 ,
        -0.6711108 ,  0.683148  ],
       ...,
       [ 0.76212126, -0.03379729,  0.8809599 , ...,  1.        ,
        -0.861548  ,  0.91796774],
       [-0.653695  ,  0.2730069 , -0.6711108 , ..., -0.861548  ,
         0.9999999 , -0.92368925],
       [ 0.6034498 , -0.37590423,  0.683148  , ...,  0.91796774,
        -0.92368925,  1.        ]], dtype=float32)
```

In [ ]:

```
item_sim_matrix=pd.DataFrame(Item_Item_embedding,index=rm_raw['ItemId'].unique(),c
item_sim_matrix.head()
```

Out[ ]:

	1	48	150	260	527	531	588	594	595
1	1.000000	-0.058749	0.954507	0.911087	0.952640	0.666721	0.909237	0.764234	0.882831
48	-0.058749	1.000000	0.085030	-0.385942	-0.355209	0.483500	0.360928	0.375136	0.379983
150	0.954507	0.085030	1.000000	0.880058	0.879090	0.571414	0.934890	0.666851	0.876782
260	0.911087	-0.385942	0.880058	1.000000	0.975596	0.313627	0.697035	0.438496	0.621809
527	0.952640	-0.355209	0.879090	0.975596	1.000000	0.454423	0.743251	0.583664	0.709877

5 rows × 3682 columns

In [ ]:

```
movie_name=150
movie_rating=item_sim_matrix[movie_name]
print(movie_rating)
```

```
1       0.954507
48      0.085030
150     1.000000
260     0.880058
527     0.879090
          ...
3280   -0.576731
642     0.199331
1915    0.880960
3779   -0.671111
1832    0.683148
Name: 150, Length: 3682, dtype: float32
```

In [ ]:
```
similar_movies=item_sim_matrix.corrwith(movie_rating)

sim_df=pd.DataFrame(similar_movies,columns=['Correlation'])
```

In [ ]:
```
item_mov=df[['MovieID','Title']]
item_mov.drop_duplicates(inplace=True)
item_mov.reset_index(drop=True,inplace=True)

sim_df1=sim_df.copy()
sim_df1.reset_index(inplace=True)
sim_df1.rename(columns={'index':'MovieID'},inplace=True)
sim_mov=pd.merge(sim_df1,item_mov,on="MovieID",how='inner')
sim_mov.head(6)
```

Out[ ]:

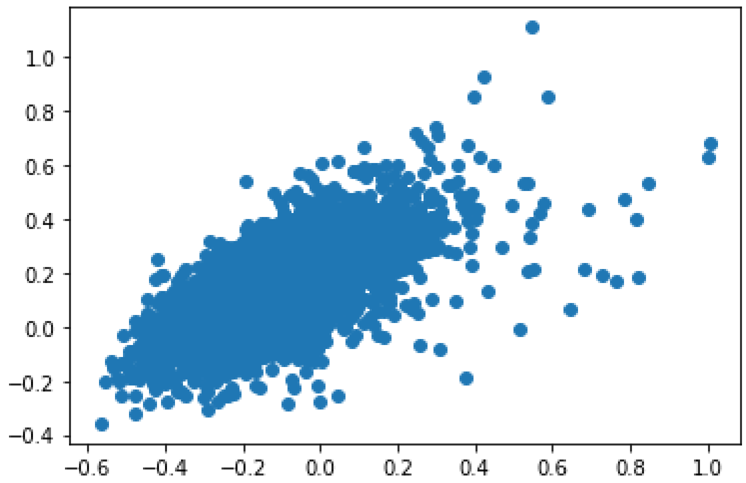
	MovieID	Correlation	Title
0	1	0.953083	toy story
1	48	-0.289414	pocahontas
2	150	1.000000	apollo
3	260	0.921454	star wars episode iv a new hope
4	527	0.906801	schindlers list
5	531	0.632564	secret garden the

In [ ]:
```
# For d=2 Matrix Factorization using Embeddings
from cmfrec import CMF
model1 = CMF(method="als", k=2, lambda_=0.1, user_bias=False, item_bias=False, verl
model1.fit(rm_raw)
```

Out[ ]:
```
Collective matrix factorization model
(explicit-feedback variant)
```

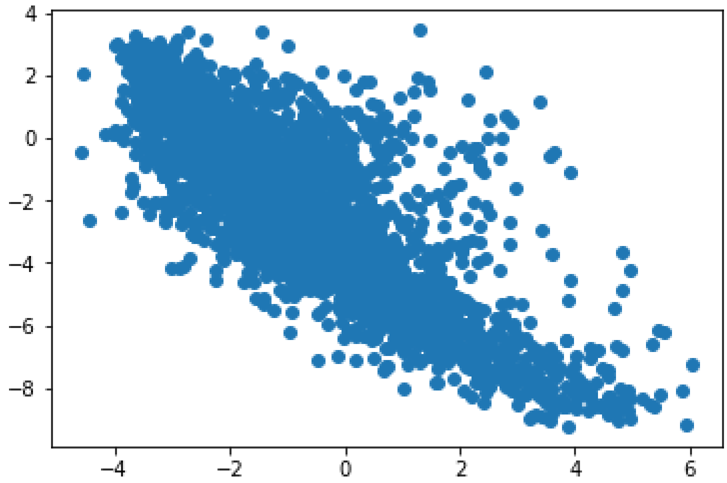
In [ ]:
```
plt.scatter(model1.A_[:,0],model1.A_[:,1],cmap='hot')
```

Out[ ]:
```
<matplotlib.collections.PathCollection at 0x7ff8607cb340>
```



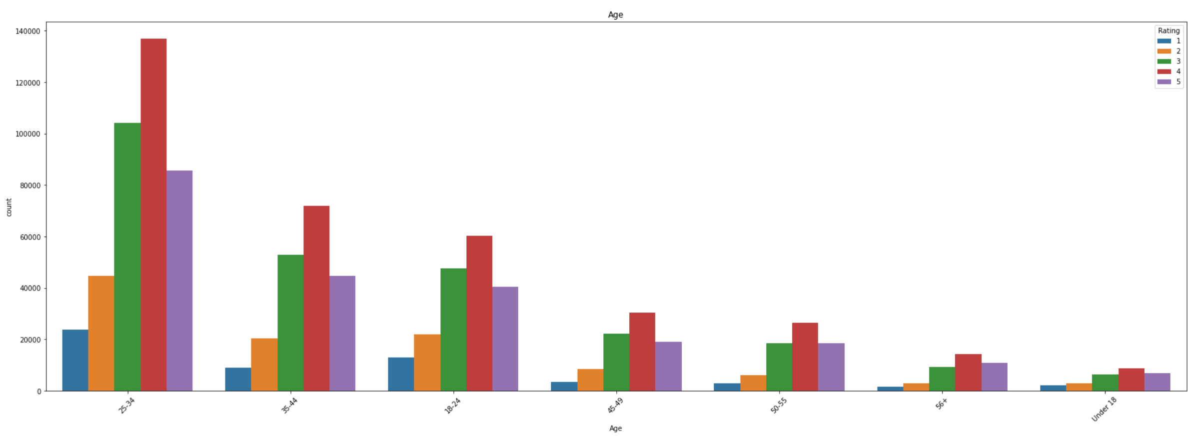
```
In [ ]: plt.scatter(model1.B_[:,0],model1.B_[:,1],cmap='hot')
```

```
Out[ ]: <matplotlib.collections.PathCollection at 0x7ff860567760>
```



1. Users of which age group have watched and rated the most number of movies?

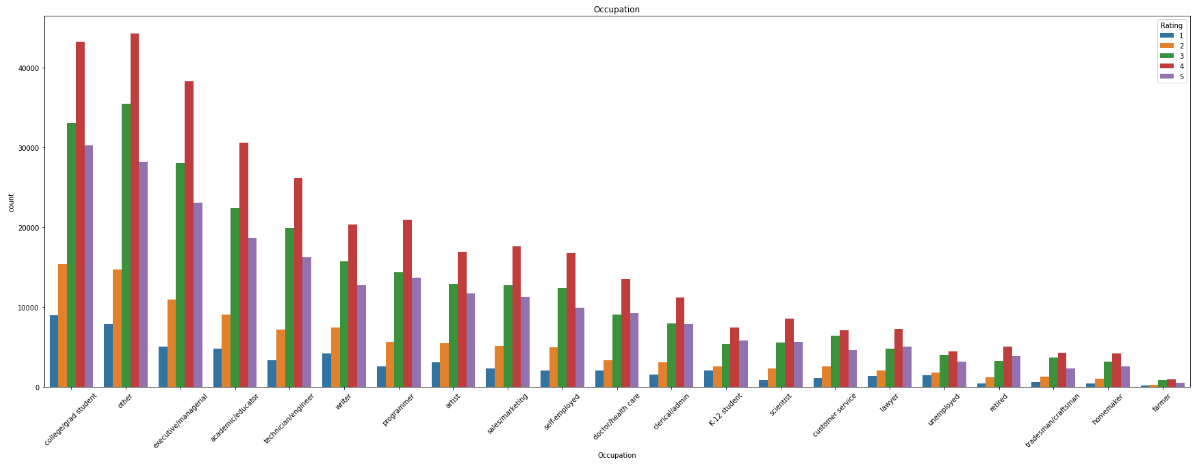
```
In [ ]: plt.figure(figsize=(30,10))
        ax = sns.countplot(data = df,
                      x = 'Age',hue='Rating',
                      order = df['Age'].value_counts().index[:], linewidth=0.3)
        plt.title('Age')
        plt.xticks(rotation=45)
        plt.show()
```



ANS: Age Group of 25-34 watched more and rated more.

2.Users belonging to which profession have watched and rated the most movies?

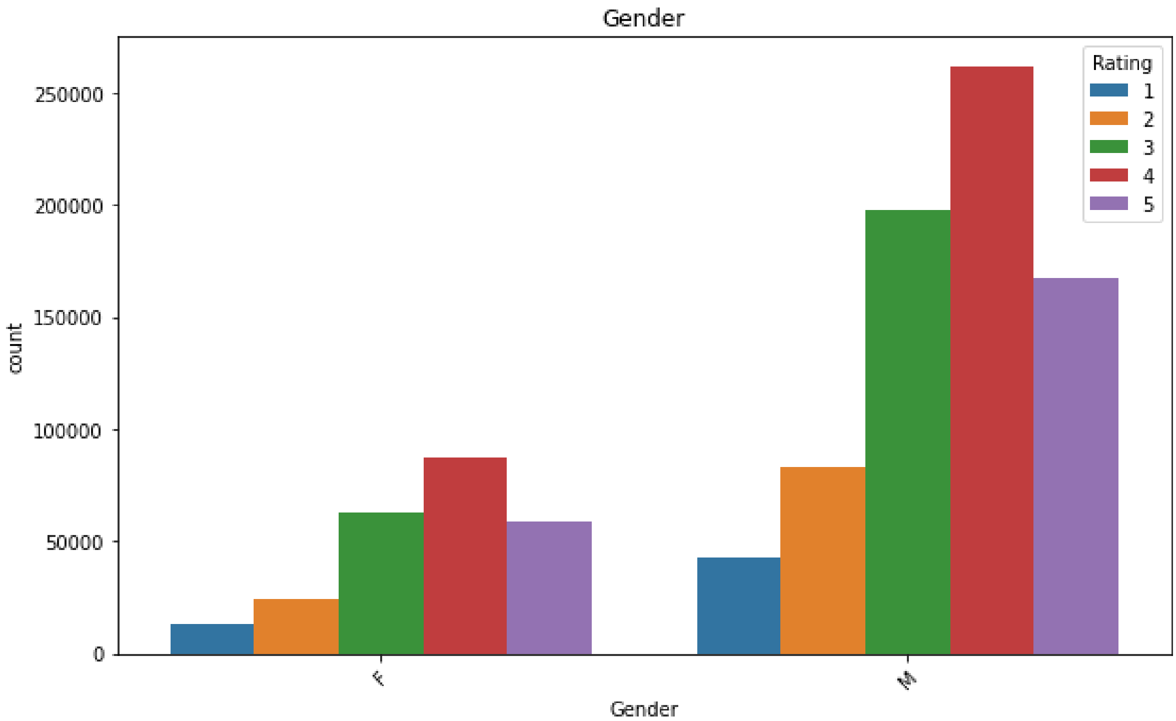
In [ ]:
```
plt.figure(figsize=(30,10))
ax = sns.countplot(data = df,
              x = 'Occupation', hue='Rating',
              order = df['Occupation'].value_counts().index[:], linewidth=0.3)
plt.title('Occupation')
plt.xticks(rotation=45)
plt.show()
```



ANS: College/Grad Student had Rated more movies and watched more compared to other.

3.Most of the users in our dataset who've rated the movies are Male. (T/F)

In [ ]:
```
plt.figure(figsize=(10,6))
ax = sns.countplot(data = df,
              x = 'Gender',hue='Rating',
              order = sorted(df['Gender'].value_counts().index[:]), linewidth=0.3)
plt.title('Gender')
plt.xticks(rotation=45)
plt.show()
```



ANS: **TRUE**

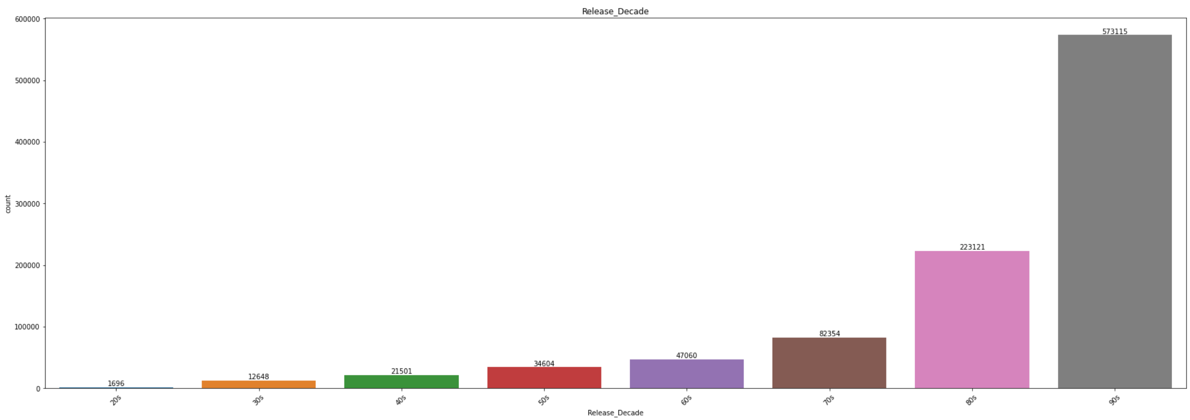
4. Most of the movies present in our dataset were released in which decade?

```
**a.70s b. 90s c. 50s d.80s **
```

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['MovieID', 'Title', 'Genres', 'UserID', 'Rating', 'Timestamp', 'index',
       'Gender', 'Age', 'Occupation', 'Zip-code', 'Release_Year',
       'Release_Decade', 'Average_Rating', 'Average_Timestamp',
       'Rating_Counts'],
      dtype='object')
```

In [ ]:
```
plt.figure(figsize=(30,10))
ax = sns.countplot(data = df,
              x = 'Release_Decade',
              order = sorted(df['Release_Decade'].value_counts().index[:20]), linew
ax.bar_label(ax.containers[0])
plt.title('Release_Decade')
plt.xticks(rotation=45)
plt.show()
```



ANS: **B(90's)**

5.The movie with maximum no. of ratings is ___?

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['MovieID', 'Title', 'Genres', 'UserID', 'Rating', 'Timestamp', 'Gender',
       'Age', 'Occupation', 'Zip-code', 'Release_Year', 'Release_Decade',
       'Average_Rating', 'Average_Timestamp', 'Rating_Counts'],
      dtype='object')
```

In [ ]:
```
ans=df.groupby('Title').agg({'Rating':'sum'})
ans=ans.reset_index()
ans.sort_values('Rating').tail(5)
```

Out[ ]:

	Title	Rating
3044	star wars episode v the empire strikes back	12836
3043	star wars episode iv a new hope	13321
1837	lethal weapon	14619
89	american beauty	14800
3301	toy story	15300

ANS: **toy story with 15300 ratings**

6.Name the top 3 movies similar to 'Liar Liar' on the item-based approach?

In [ ]:

```
# Take input from user
print("please input the Movie name:")
a=input()
#Printing Top 5 similar Movies for recommendation
print("The Top 5 Similar Movies are:")
print(table1.corr()[a].sort_values(ascending=False).iloc[1:6])
```

```
please input the Movie name:
liar liar
The Top 5 Similar Movies are:
Title
mrs doubtfire                0.499927
dumb  dumber                 0.459601
ace ventura pet detective    0.458654
home alone                   0.453982
wedding singer the           0.429222
Name: liar liar, dtype: float64
```

7.On the basis of approach, Collaborative Filtering methods can be classified into -*based and* -based?

Memory-based collaborative filtering uses all the data in the database to generate a prediction.

model-based collaborative filtering uses the data in the database to create a model that can then be used to generate predictions

8.Pearson Correlation ranges between *to* whereas, Cosine Similarity belongs to the interval between *to* ?

Pearson Correlation ranges from -1 to 1

cosine similarity ranges from 0 to 1

9.Mention the RMSE and MAPE that you got while evaluating the Matrix Factorization model.

RMSE: 1.475653561527743

MAPE: 0.42228753211692427

10. Give the sparse ‘row’ matrix representation for the following dense matrix -

[[1 0] [3 7]]

In [ ]:
```
from scipy.sparse import csr_matrix

a= np.array([[1,0],[3,7]])
sparse_matrix = csr_matrix(a)
print(sparse_matrix)
```

```
  (0, 0)	1
  (1, 0)	3
  (1, 1)	7
```

Insights:

1. Movies with Rating 4 are more.
2. Age Group of 25-34 watched more and rated more
3. More Movies are released on 90's.
4. More Users has Screen time more than 20 hours.
5. College/Grad Students are more to see the movie and Rate them.
6. More males users are watching Movies and rating them.
7. More Users are from Area zip code- 94110
8. No Correlation is seen between any Features.
9. There is no Evidence that More Screen time results more rating
10. Movie 'saboteur' got highest number of ratings i.e 2314 ratings.
11. RMSE: 1.475653561527743
12. MAPE: 0.42228753211692427

Recommendations For Zee To Improve Business:

1. Company should Focus College and grad students by offering some Discount as they are most viewers according to data.
2. Company should Recommend Most rating Films to others who love similar Genres.
3. Comapany need to Focus on Zip code area 94110 as ther are more watch Hours from that area.
4. Company Should Target Audience with Age Group of 25-34.

In [ ]:
```

```