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.

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

import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (12,8)
import warnings
warnings.filterwarnings("ignore")

pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 10000)
```

In [298]:
```
Path = r"C:\Users\mayan\Desktop\Project - ZEE\ZEE-data"
movies = pd.read_fwf(r"{}\zee-movies.dat".format(Path),encoding="ISO-8859-1")
ratings = pd.read_fwf(r"{}\zee-ratings.dat".format(Path),encoding="ISO-8859-1")
users = pd.read_fwf(r"{}\zee-users.dat".format(Path),encoding="ISO-8859-1")
```

In [85]:
```
movies
```

	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
...	...	...	...
3878	3948	Meet the Parents (2000)	Comedy
3879	3949	Requiem for a Dream (2000)	Drama
3880	3950	Tigerland (2000)	Drama
3881	3951	Two Family House (2000)	Drama
3882	3952	Contender, The (2000)	Drama|Thriller

3883 rows × 3 columns

In [86]:
```
rating
```

	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
...	...
1000204	6040::1091::1::956716541
1000205	6040::1094::5::956704887
1000206	6040::562::5::956704746
1000207	6040::1096::4::956715648
1000208	6040::1097::4::956715569

1000209 rows × 1 columns

In [87]:
```
users
```

	UserID	Gender	Age	Occupation	Zipcode
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
...	...	...	...	...	...
6035	6036	F	25-34	scientist	32603
6036	6037	F	45-49	academic/educator	76006
6037	6038	F	56+	academic/educator	14706
6038	6039	F	45-49	other	01060
6039	6040	M	25-34	doctor/health care	11106

6040 rows × 5 columns

In [299]:
```
movies.shape,ratings.shape,users.shape
```

Out[299]:
```
((3883, 3), (1000209, 1), (6040, 1))
```

In [ ]:
```
# user_splited = pd.DataFrame(columns=users.columns[0].split("::"))
# for i in range(len(users)):
#     user_splited.loc[i,:] = users.loc[i,:].values[0].split("::")
# user_splited
```

In [300]:
```
delimiter ="::"

movies = movies["Movie ID::Title::Genres"].str.split(delimiter,expand = True)
movies.columns = ["MovieID","Title","Genres"]

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

users = users["UserID::Gender::Age::Occupation::Zip-code"].str.split(delimiter,expand = True)
users.columns = ["UserID","Gender","Age","Occupation","Zipcode"]
users["Age"].replace({"1": "Under 18","18": "18-24","25": "25-34",
                      "35": "35-44","45": "45-49","50": "50-55","56": "56+"},inplace=True)
users["Occupation"] = users["Occupation"].astype(int).replace({0: "other",1: "academic/educator",2: "artist",
                                                               3: "clerical/admin",4: "college/grad student",
                                                    5: "customer service",6: "doctor/health care",7: "executive/manageri
                                                    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.shape,ratings.shape,users.shape
```

Out[300]:
```
((3883, 3), (1000209, 4), (6040, 5))
```

In [301]:
```
movies # need to take care of Genres .
```

Out[301]:

	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
...	...	...	...
3878	3948	Meet the Parents (2000)	Comedy
3879	3949	Requiem for a Dream (2000)	Drama
3880	3950	Tigerland (2000)	Drama
3881	3951	Two Family House (2000)	Drama
3882	3952	Contender, The (2000)	Drama|Thriller

3883 rows × 3 columns

In [302]:
```
ratings # need to convert timestamp to hrs.
```

Out[302]:

	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
...	...	...	...	...
1000204	6040	1091	1	956716541
1000205	6040	1094	5	956704887
1000206	6040	562	5	956704746
1000207	6040	1096	4	956715648
1000208	6040	1097	4	956715569

1000209 rows × 4 columns

In [90]:
```
users
```

Out[90]:

	UserID	Gender	Age	Occupation	Zipcode
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
...	...	...	...	...	...
6035	6036	F	25-34	scientist	32603
6036	6037	F	45-49	academic/educator	76006
6037	6038	F	56+	academic/educator	14706
6038	6039	F	45-49	other	01060
6039	6040	M	25-34	doctor/health care	11106

6040 rows × 5 columns

In [ ]:
```
# movies["Title"].str.split("(",expand=True)[1].str.split(")",expand=True)[0]
```

In [303]:
```
# taking out the release year from the title column from movie table :

movies["Release_year"] = movies["Title"].str.extract('^(.+)\s\(([0-9]*)\)$',expand = True)[1]
movies["Title"] = movies["Title"].str.split("(").apply(lambda x:x[0])


# Converting timestamp to hours

from datetime import datetime
ratings["Watch_Hour"] =ratings["Timestamp"].apply(lambda x:datetime.fromtimestamp(int(x)).hour)
ratings.drop(["Timestamp"],axis = 1,inplace=True)
```

In [304]:
```
movies
```

Out[304]:

	MovieID	Title	Genres	Release_year
0	1	Toy Story	Animation|Children's|Comedy	1995
1	2	Jumanji	Adventure|Children's|Fantasy	1995
2	3	Grumpier Old Men	Comedy|Romance	1995
3	4	Waiting to Exhale	Comedy|Drama	1995
4	5	Father of the Bride Part II	Comedy	1995
...	...	...	...	...
3878	3948	Meet the Parents	Comedy	2000
3879	3949	Requiem for a Dream	Drama	2000
3880	3950	Tigerland	Drama	2000
3881	3951	Two Family House	Drama	2000
3882	3952	Contender, The	Drama|Thriller	2000

3883 rows × 4 columns

Merging all the tables into one data frame :

In [305]:
```
df = users.merge(movies.merge(ratings,on="MovieID",how="outer"),on="UserID",how="outer")
```

In [129]:
```
df.shape
```

Out[129]: (1000386, 11)

In [295]:
```
df
```

Out[295]:

	UserID	Gender	Age	Occupation	Zipcode	MovieID	Title	Genres	Release_year	Rating	Watc
0	1	F	Under 18	K-12 student	48067	1	Toy Story	Animation|Children's|Comedy	1995	5	
1	1	F	Under 18	K-12 student	48067	48	Pocahontas	Animation|Children's|Musical|Romance	1995	5	
2	1	F	Under 18	K-12 student	48067	150	Apollo 13	Drama	1995	5	
3	1	F	Under 18	K-12 student	48067	260	Star Wars: Episode IV - A New Hope	Action|Adventure|Fantas	1977	4	
4	1	F	Under 18	K-12 student	48067	527	Schindler's List	Drama|War	1993	5	
...	...	...	...	...	...	...	...	...	...	...	...
1000381	NaN	NaN	NaN	NaN	NaN	3650	Anguish	Horror	1986	NaN	
1000382	NaN	NaN	NaN	NaN	NaN	3750	Boricua's Bond	Drama	2000	NaN	
1000383	NaN	NaN	NaN	NaN	NaN	3829	Mad About Mambo	Comedy|Romance	2000	NaN	
1000384	NaN	NaN	NaN	NaN	NaN	3856	Autumn Heart	Drama	1999	NaN	
1000385	NaN	NaN	NaN	NaN	NaN	3907	Prince of Central Park, The	Drama	1999	NaN	

1000386 rows × 11 columns

In [135]:
```
df_ = df.copy()
```

In [136]:
```
df_.dropna(inplace=True)
```

In [137]:
```
df_.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 996144 entries, 0 to 1000208
Data columns (total 11 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   UserID        996144 non-null  object 
 1   Gender        996144 non-null  object 
 2   Age           996144 non-null  object 
 3   Occupation    996144 non-null  object 
 4   Zipcode       996144 non-null  object 
 5   MovieID       996144 non-null  object 
 6   Title         996144 non-null  object 
 7   Genres        996144 non-null  object 
 8   Release_year  996144 non-null  object 
 9   Rating        996144 non-null  object 
 10  Watch_Hour    996144 non-null  float64
dtypes: float64(1), object(10)
memory usage: 91.2+ MB
```

In [138]:
```
df_['Release_year']=df_['Release_year'].astype('int32')
df_['Rating']=df_['Rating'].astype('int32')
```

In [139]:
```
bins = [1919, 1929, 1939, 1949, 1959, 1969, 1979, 1989, 2000]
labels = ['20s', '30s', '40s', '50s', '60s', '70s', '80s', '90s']
df_["Released_In"] =  pd.cut(df_['Release_year'], bins=bins, labels=labels)
df_
```

Out[139]:

	UserID	Gender	Age	Occupation	Zipcode	MovieID	Title	Genres	Release_year	Rating	Watc
0	1	F	Under 18	K-12 student	48067	1	Toy Story	Animation|Children's|Comedy	1995	5	
1	1	F	Under 18	K-12 student	48067	48	Pocahontas	Animation|Children's|Musical|Romance	1995	5	
2	1	F	Under 18	K-12 student	48067	150	Apollo 13	Drama	1995	5	
3	1	F	Under 18	K-12 student	48067	260	Star Wars: Episode IV - A New Hope	Action|Adventure|Fantas	1977	4	
4	1	F	Under 18	K-12 student	48067	527	Schindler's List	Drama|War	1993	5	
...	...	...	...	...	...	...	...	...	...	...	...
1000204	6040	M	25-34	doctor/health care	11106	3683	Blood Simple	Drama|Film-Noir	1984	4	
1000205	6040	M	25-34	doctor/health care	11106	3703	Mad Max 2	Action|Sci-Fi	1981	4	
1000206	6040	M	25-34	doctor/health care	11106	3735	Serpico	Crime|Drama	1973	4	
1000207	6040	M	25-34	doctor/health care	11106	3751	Chicken Run	Animation|Children's|Comedy	2000	4	
1000208	6040	M	25-34	doctor/health care	11106	3819	Tampopo	Comedy	1986	5	

996144 rows × 12 columns

Average user rating distribution :

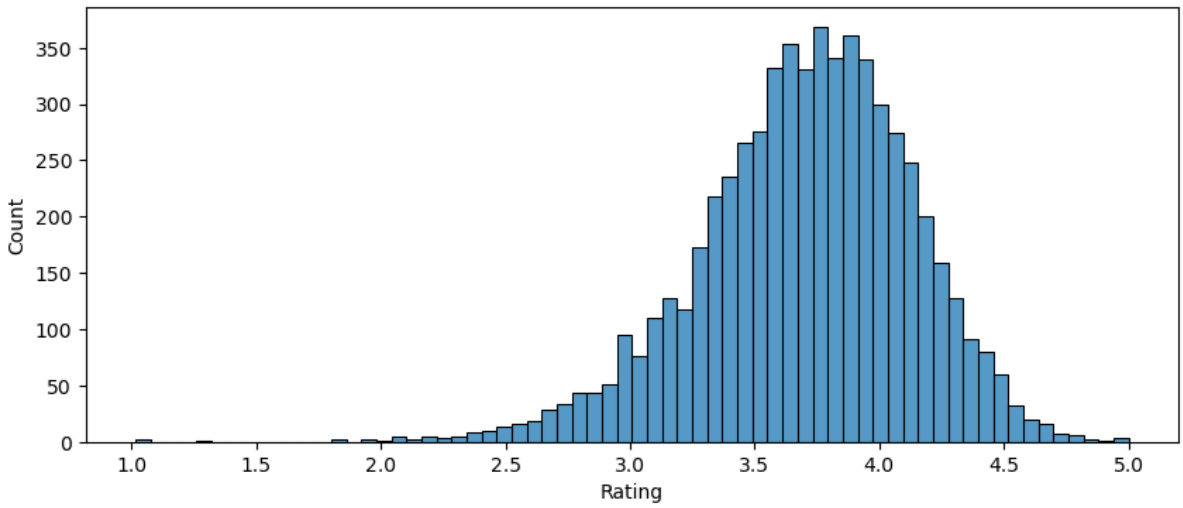
In [140]:
```
import seaborn as sns
```

In [187]:
```
plt.rcParams["figure.figsize"] = (10,4)
```

In [190]:
```
sns.histplot(df_[['UserID','Rating']].groupby('UserID').mean()["Rating"])

# average ratings given by each user distribution
```

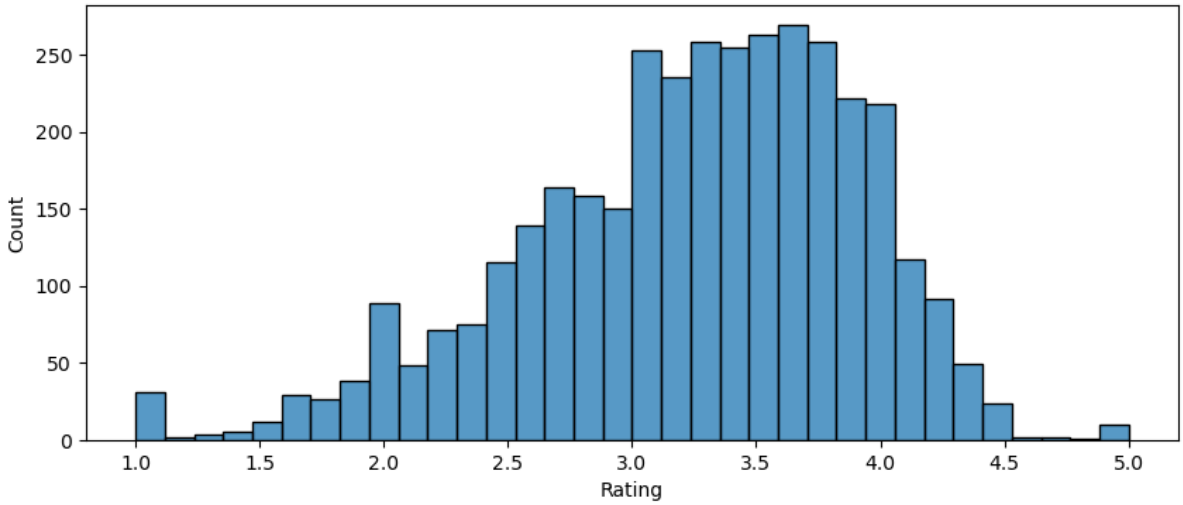
Out[190]: <Axes: xlabel='Rating', ylabel='Count'>



In [189]:
```
sns.histplot(df_[['MovieID','Rating']].groupby('MovieID').mean()["Rating"])

# average rating , that each movie has receieved by users .
```

Out[189]: <Axes: xlabel='Rating', ylabel='Count'>



In [143]:
```
df_["MovieID"].nunique()
```

Out[143]: 3682

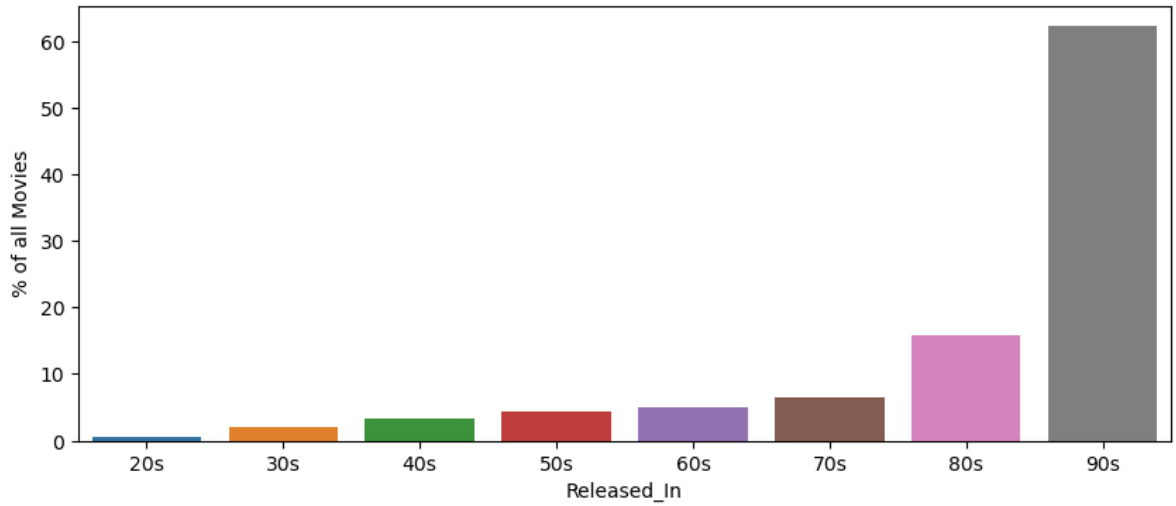
In [145]:
```
movies_per_decade = df_[['MovieID','Released_In']].groupby('Released_In').nunique()
movies_per_decade["% of all Movies"] = round((movies_per_decade["MovieID"]/(df_["MovieID"].nunique())) * 100,2)
movies_per_decade
```

Out[145]:

Released_In	MovieID	% of all Movies
20s	23	0.62
30s	71	1.93
40s	120	3.26
50s	164	4.45
60s	184	5.00
70s	237	6.44
80s	586	15.92
90s	2294	62.30

In [188]:
```
sns.barplot(x=movies_per_decade.index, y=movies_per_decade["% of all Movies"])
```

Out[188]: <Axes: xlabel='Released_In', ylabel='% of all Movies'>



In [307]:
```
m = movies[["MovieID","Title","Genres"]]
m["Genres"] = m["Genres"].str.split("|")
m = m.explode("Genres")
m["Genres"] = m["Genres"].replace({"":"Other","Horro":"Horror","Sci-":"Sci-Fi","Sci":"Sci-Fi","Sci-F":"Sci-Fi","D
                    "Wester":"Western","Fant":"Fantasy","Chil":"Children's","R":"Romance","D":"Drama","Rom":"Rom
                    "Fantas":"Fantasy","Come":"Comedy","Dram":"Drama","S":"Sci-Fi","Roma":"Romance","A":"Adventu
                     "Wa":"War","Thrille"  :"Thriller","Com":"Comedy","Comed":"Comedy","Acti":"Action","Advent":
                       "Chi":"Children's","Ro":"Romance","F":"Fantasy","We":"Western","Documen":"Documentary","M
                    "Children'":"Children's","Roman":"Romance","Docu":"Documentary","Th":"Thriller","Document":"
                   })
m = m.pivot_table(values="Title", index="MovieID", columns="Genres", aggfunc= np.size,).fillna(0)


def apply(x):
  if x >= 1:
    return 1
  else:
    return 0

m["Adventure"] = m["Adventure"].apply(apply)
m = m.astype(int)
```

In [311]:
```
final_data = df.merge(m,on="MovieID",how="left").drop(["Genres"],axis = 1)
```

In [171]:
```
final_data
```

Out[171]:

	UserID	Gender	Age	Occupation	Zipcode	MovieID	Title	Release_year	Rating	Watch_Hour	Action	Adventure	Ani
0	1	F	Under 18	K-12 student	48067	1	Toy Story	1995	5	5.0	0.0	0.0	
1	1	F	Under 18	K-12 student	48067	48	Pocahontas	1995	5	5.0	0.0	0.0	
2	1	F	Under 18	K-12 student	48067	150	Apollo 13	1995	5	3.0	0.0	0.0	
3	1	F	Under 18	K-12 student	48067	260	Star Wars: Episode IV - A New Hope	1977	4	3.0	1.0	1.0	
4	1	F	Under 18	K-12 student	48067	527	Schindler's List	1993	5	5.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...

In [172]:
```
final_data.MovieID = final_data.MovieID.astype(int)
final_data.UserID = final_data.UserID.astype(float)
final_data.Release_year = final_data.Release_year.astype(float)
```

In [173]:
```
final_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000386 entries, 0 to 1000385
Data columns (total 29 columns):
 #   Column        Non-Null Count    Dtype  
---  ------        --------------    -----  
 0   UserID        1000209 non-null  float64
 1   Gender        1000209 non-null  object 
 2   Age           1000209 non-null  object 
 3   Occupation    1000209 non-null  object 
 4   Zipcode       1000209 non-null  object 
 5   MovieID       1000386 non-null  int32  
 6   Title         1000386 non-null  object 
 7   Release_year  996606 non-null   float64
 8   Rating        1000209 non-null  object 
 9   Watch_Hour    1000209 non-null  float64
 10  Action        996320 non-null   float64
 11  Adventure     996320 non-null   float64
 12  Animation     996320 non-null   float64
 13  Children's    996320 non-null   float64
 14  Comedy        996320 non-null   float64
 15  Crime         996320 non-null   float64
 16  Documentary   996320 non-null   float64
 17  Drama         996320 non-null   float64
 18  Fantasy       996320 non-null   float64
 19  Film-Noir     996320 non-null   float64
 20  Horror        996320 non-null   float64
 21  Musical       996320 non-null   float64
 22  Mystery       996320 non-null   float64
 23  Other         996320 non-null   float64
 24  Romance       996320 non-null   float64
 25  Sci-Fi        996320 non-null   float64
 26  Thriller      996320 non-null   float64
 27  War           996320 non-null   float64
 28  Western       996320 non-null   float64
dtypes: float64(22), int32(1), object(6)
memory usage: 225.2+ MB
```

In [174]:
```
final_data.describe()
```

Out[174]:

	UserID	MovieID	Release_year	Watch_Hour	Action	Adventure	Animation	Children's	Comed
count	1.000209e+06	1.000386e+06	996606.000000	1.000209e+06	996320.000000	996320.000000	996320.000000	996320.000000	996320.00000
mean	3.024512e+03	1.865526e+03	1986.758010	9.730487e+00	0.257534	0.134088	0.043107	0.072154	0.35489
std	1.728413e+03	1.096030e+03	14.314345	7.294195e+00	0.437276	0.340747	0.203097	0.258742	0.47848
min	1.000000e+00	1.000000e+00	1919.000000	0.000000e+00	0.000000	0.000000	0.000000	0.000000	0.00000
25%	1.506000e+03	1.030000e+03	1982.000000	4.000000e+00	0.000000	0.000000	0.000000	0.000000	0.00000
50%	3.070000e+03	1.835000e+03	1992.000000	8.000000e+00	0.000000	0.000000	0.000000	0.000000	0.00000
75%	4.476000e+03	2.770000e+03	1997.000000	1.500000e+01	1.000000	0.000000	0.000000	0.000000	1.00000
max	6.040000e+03	3.952000e+03	2000.000000	2.300000e+01	1.000000	1.000000	1.000000	1.000000	1.00000

In [175]:
```
final_data.describe(include="object")
```

Out[175]:

	Gender	Age	Occupation	Zipcode	Title	Rating
count	1000209	1000209	1000209	1000209	1000386	1000209
unique	2	7	21	3439	3833	5
top	M	25-34	college/grad student	94110	American Beauty	4
freq	753769	395556	131032	3802	3428	348971

In [176]:
```
final_data.nunique()
```

Out[176]:
```
UserID          6040
Gender             2
Age                7
Occupation        21
Zipcode         3439
MovieID         3883
Title           3833
Release_year      81
Rating             5
Watch_Hour        24
Action             2
Adventure          2
Animation          2
Children's         2
Comedy             2
Crime              2
Documentary        2
Drama              2
Fantasy            2
Film-Noir          2
Horror             2
Musical            2
Mystery            2
Other              2
Romance            2
Sci-Fi             2
Thriller           2
War                2
Western            2
dtype: int64
```

Unique values present in data

- 6040 unique UserID
- 7 different age groups
- 21 occupations
- 3439 different locations of users
- 3883 unique movies

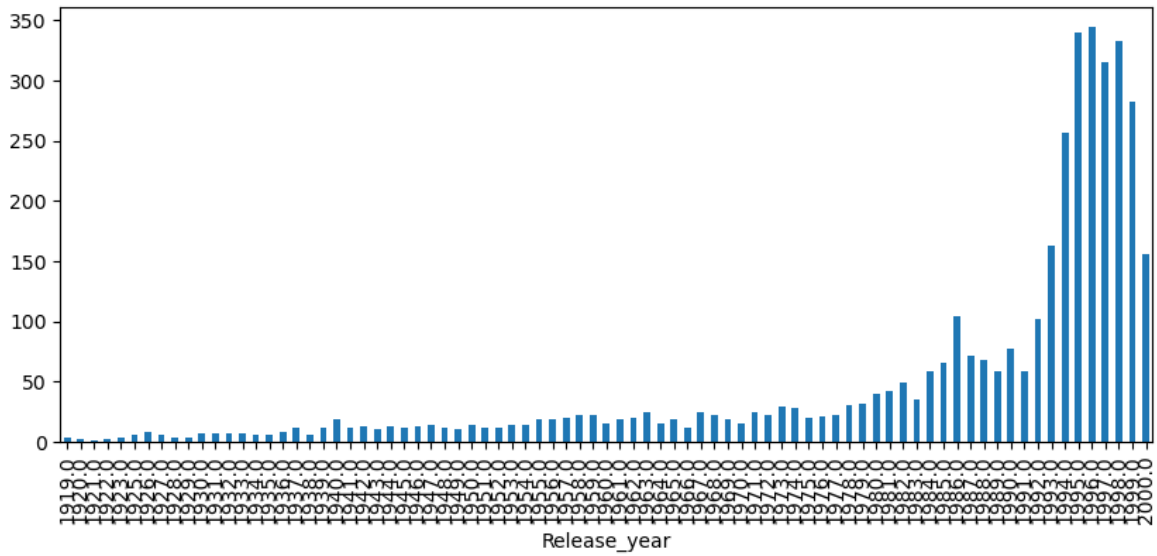
- There are movies available in database , which were never been watched by any user before .
- Thats is the reason we have lots of NaN values in our final dataset.

In [177]:
```
final_data.shape
```

Out[177]:
```
(1000386, 29)
```

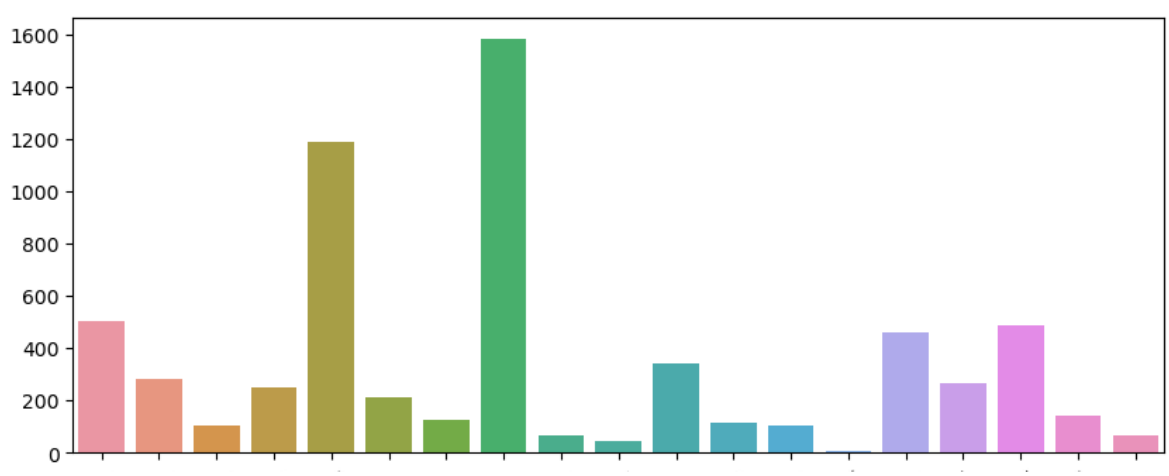
Most of the movies present in our dataset were released in year:

In [202]:
```
final_data.groupby("Release_year")["Title"].nunique().plot(kind="bar")
plt.xticks(rotation=90)
plt.show()
```



In [200]:
```
# Number of Movies per Genres:

sns.barplot(x=m.sum(axis= 0).index,y=m.sum(axis= 0))
plt.xticks(rotation=70)
plt.show()
```



In [205]:
```
m.sum(axis= 0)
```

Out[205]:
```
Genres
Action          501
Adventure       283
Animation       104
Children's      249
Comedy         1189
Crime           210
Documentary     124
Drama          1585
Fantasy          63
Film-Noir        44
Horror          340
Musical         113
Mystery         105
Other             8
Romance         462
Sci-Fi          265
Thriller        488
War             139
Western          68
dtype: int64
```

In [206]:
```
final_data["Rating"].count()
```

Out[206]:
```
1000209
```

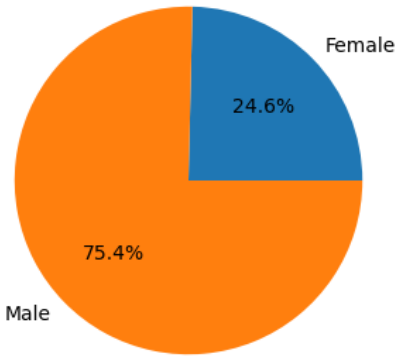
Number of movies Rated by each Gender type :

In [207]:
```
# Gender %

asd = final_data.groupby("Gender")["Rating"].count() / final_data["Rating"].count() * 100
asd
```

Out[207]:
```
Gender
F    24.63885
M    75.36115
Name: Rating, dtype: float64
```

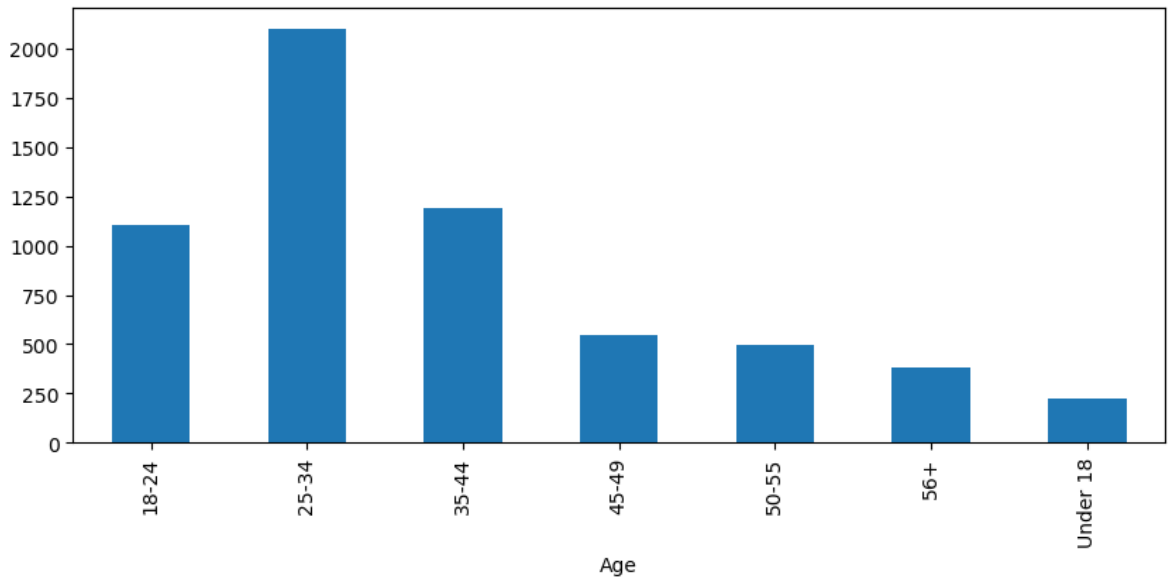
In [209]:
```
plt.pie(asd, labels = ["Female", "Male"],autopct='%1.1f%%')
plt.show()
```



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

In [213]:
```
plt.rcParams["figure.figsize"] = (10,4)
final_data.groupby("Age")["UserID"].nunique().plot(kind="bar")
```

Out[213]:
```
<Axes: xlabel='Age'>
```



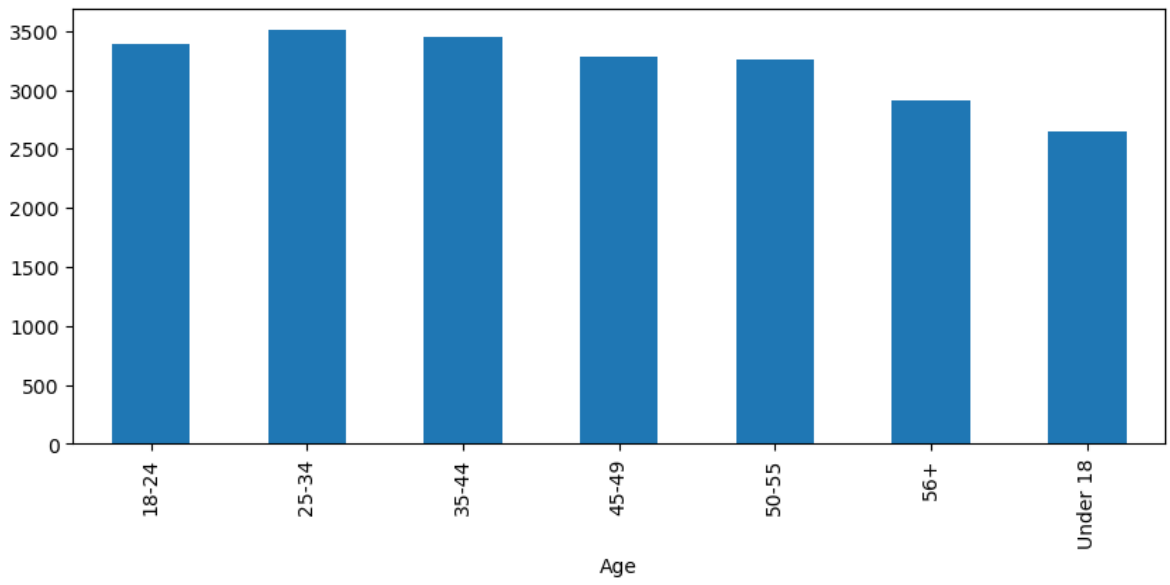
- in DataSet : majority of the viewers are in age group of 25-34
- out of all , 25-34 age group have rated and watched the maximum number of movies.
- for other age groups data are as below:

In [211]:
```
final_data.groupby("Age")["MovieID"].nunique()
```

Out[211]:
```
Age
18-24       3393
25-34       3508
35-44       3447
45-49       3288
50-55       3258
56+         2913
Under 18    2650
Name: MovieID, dtype: int64
```

In [214]:
```
plt.rcParams["figure.figsize"] = (10,4)
final_data.groupby("Age")["MovieID"].nunique().plot(kind="bar")
```

Out[214]: <Axes: xlabel='Age'>



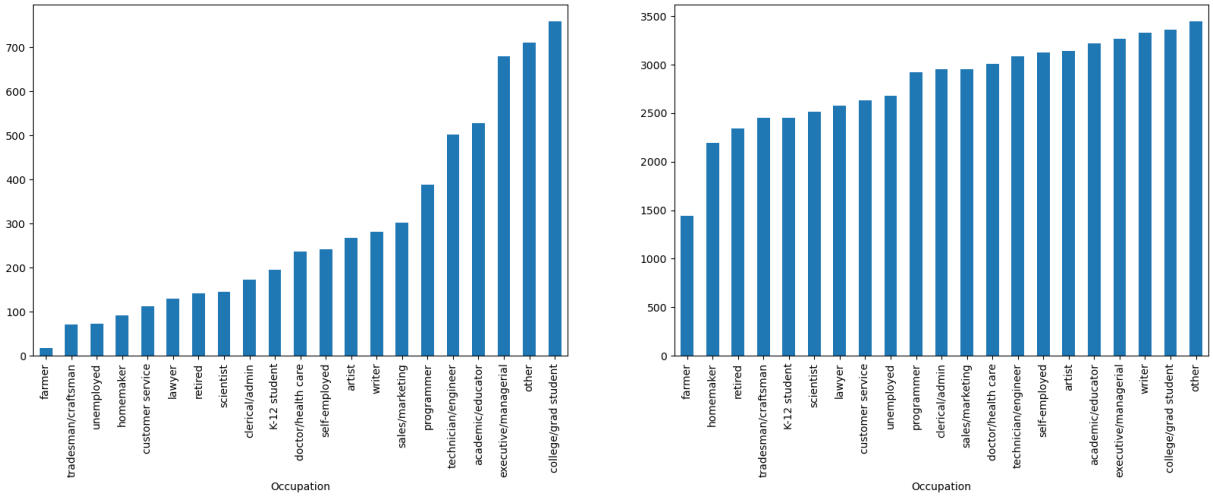
Users belonging to which profession have watched and rated the most movies?

In [237]:
```
plt.rcParams["figure.figsize"] = (20,6)

plt.subplot(121) #211
final_data.groupby("Occupation")["UserID"].nunique().sort_values().plot(kind="bar")
plt.subplot(122) #212
final_data.groupby("Occupation")["MovieID"].nunique().sort_values().plot(kind="bar")

# The syntax of plt.subplot() is plt.subplot(nrows, ncols, index) where:
# nrows specifies the number of rows in the grid.
# ncols specifies the number of columns in the grid.
# index specifies the position of the subplot within the grid.
```

Out[237]: <Axes: xlabel='Occupation'>



- Majority of the Users are College Graduates and Students , followed by Executives, educators and engineers. y of the Users are College Graduates and Students , followed by Executives, educators and engineers.

- Maximum movies are watched and rated by user's occupations are College graduate students , writers , executives, educator and artists.

In [238]:
```
final_data.groupby("Occupation")["MovieID"].nunique().sort_values(ascending = False).head(6)
```

Out[238]:
```
Occupation
other                  3448
college/grad student   3363
writer                 3330
executive/managerial   3269
academic/educator      3218
artist                 3145
Name: MovieID, dtype: int64
```

In [239]:
```
final_data.columns
```

Out[239]:
```
Index(['UserID', 'Gender', 'Age', 'Occupation', 'Zipcode', 'MovieID', 'Title', 'Release_year', 'Rating', 'Watch_
Hour', 'Action', 'Adventure', 'Animation', 'Children's', 'Comedy', 'Crime', 'Documentary', 'Drama', 'Fantasy',
'Film-Noir', 'Horror', 'Musical', 'Mystery', 'Other', 'Romance', 'Sci-Fi', 'Thriller', 'War', 'Western'], dtype
='object')
```

Movie Recommendation based on Genres as per Majority Users occupation :

- below table shows the rank preference of each occupation users:
- higher the number more prefered .

In [ ]:
```
## Movie Recommendation based on Genre as per Majority Users :
```

In [240]:
```
np.argsort((final_data.groupby("Occupation")['Action', 'Adventure', 'Animation', "Children's",
                                             'Comedy', 'Crime','Documentary', 'Drama', 'Fantasy',
                                             'Film-Noir', 'Horror', 'Musical', 'Mystery', 'Other',
                                             'Romance', 'Sci-Fi', 'Thriller', 'War', 'Western'].mean())   *100,ax
```

Out[240]:

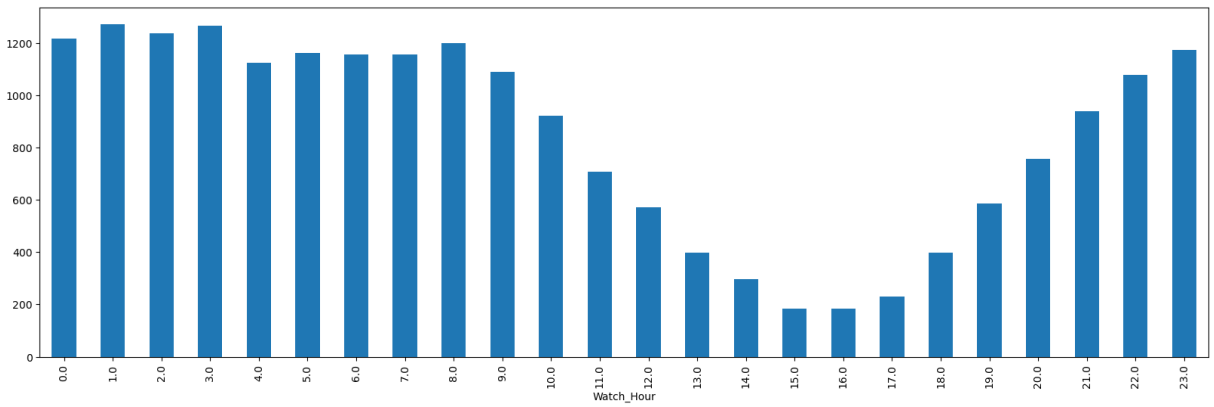
Occupation	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horror	Musical	Mys
writer	13	6	18	9	8	12	2	11	17	3	10	5	
artist	13	6	18	9	8	12	2	11	17	3	10	5	
academic/educator	13	6	18	9	8	2	12	11	10	17	3	5	
executive/managerial	13	6	9	18	8	2	11	12	3	17	10	5	
college/grad student	13	6	9	18	8	12	11	2	17	10	5	3	

- Writers , artists and educator most preferes to watch Animation, Fantasy and Science Fiction movies, followed by Romance , Action and rest of the genres.
- COllege Students most prefer to watch Children's , Science Fiction, Romance and Fantasy movies.
- Film-Noir is more prefered by the educators and Executive occupation users.

what is the traffic on OTT, based on watch hour :

In [241]:
```
final_data.groupby("Watch_Hour")["UserID"].nunique().plot(kind="bar")
```

Out[241]:
```
<Axes: xlabel='Watch_Hour'>
```



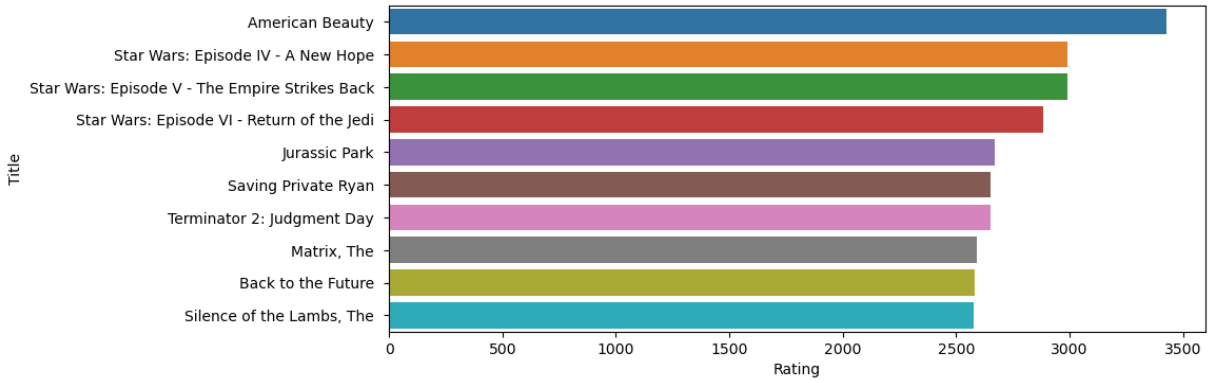
Top 10 Movies have got the most number of ratings :

In [242]:
```
top10_movies = final_data.groupby("Title")["Rating"].count().reset_index().sort_values(by="Rating",ascending=Fals
top10_movies
```

Out[242]:

	Title	Rating
127	American Beauty	3428
3261	Star Wars: Episode IV - A New Hope	2991
3262	Star Wars: Episode V - The Empire Strikes Back	2990
3263	Star Wars: Episode VI - Return of the Jedi	2883
1846	Jurassic Park	2672
2994	Saving Private Ryan	2653
3405	Terminator 2: Judgment Day	2649
2186	Matrix, The	2590
262	Back to the Future	2583
3090	Silence of the Lambs, The	2578

In [245]:
```
plt.figure(figsize=(10, 4))
sns.barplot(y = top10_movies["Title"],
            x = top10_movies["Rating"])
plt.show()
```



5 Top rated Recommended Movies per each genre :

In [247]:
```
Genres = ['Action', 'Adventure', 'Animation', "Children's", 'Comedy', 'Crime','Documentary', 'Drama', 'Fantasy',

for G in Genres:
  print(G)
  print("----------------------")
  print(final_data[final_data[G] == 1].groupby("Title")["Rating"].count().sort_values(ascending=False).head(5))
  print()
```

```
War
----------------------
Title
Saving Private Ryan     2653
Braveheart              2443
Schindler's List        2304
Forrest Gump            2194
Aliens                  1820
Name: Rating, dtype: int64

Western
----------------------
Title
Dances with Wolves                    1451
Butch Cassidy and the Sundance Kid    1419
Back to the Future Part III           1148
Blazing Saddles                       1119
Unforgiven                             997
Name: Rating, dtype: int64
```

Top 5 movie recommended as per age_Group based on ratings each age group provided

In [248]:
```
age_groups = final_data.Age.unique()
```

In [250]:
```
for age_ in age_groups:
  print(age_)
  print("------")
  print(final_data[final_data.Age == age_].groupby("Title")["Rating"].count().sort_values(ascending=False).head()
  print()
```

```
Under 18
------
Title
Toy Story                                   112
Sixth Sense, The                            109
Star Wars: Episode IV - A New Hope          101
Men in Black                                100
Star Wars: Episode VI - Return of the Jedi  100
Name: Rating, dtype: int64

56+
------
Title
American Beauty         184
Schindler's List        137
Shakespeare in Love     136
Godfather, The          122
Saving Private Ryan     121
Name: Rating, dtype: int64

25-34
------
Title
American Beauty                                 1334
Star Wars: Episode V - The Empire Strikes Back  1176
Star Wars: Episode VI - Return of the Jedi      1134
Star Wars: Episode IV - A New Hope              1128
Terminator 2: Judgment Day                      1087
Name: Rating, dtype: int64

45-49
------
Title
American Beauty                                 258
Star Wars: Episode IV - A New Hope              243
Star Wars: Episode V - The Empire Strikes Back  226
Jurassic Park                                   218
Shakespeare in Love                             217
Name: Rating, dtype: int64

50-55
------
Title
American Beauty                                 248
Star Wars: Episode IV - A New Hope              215
Star Wars: Episode V - The Empire Strikes Back  206
Fargo                                           199
Godfather, The                                  198
Name: Rating, dtype: int64

35-44
------
Title
Star Wars: Episode IV - A New Hope              626
Star Wars: Episode V - The Empire Strikes Back  598
American Beauty                                 597
Star Wars: Episode VI - Return of the Jedi      550
Back to the Future                              525
Name: Rating, dtype: int64

18-24
------
Title
American Beauty                                 715
Star Wars: Episode VI - Return of the Jedi      586
Star Wars: Episode V - The Empire Strikes Back  579
Matrix, The                                     567
Star Wars: Episode IV - A New Hope              562
Name: Rating, dtype: int64

nan
------
Series([], Name: Rating, dtype: int64)
```

Creating a user Movie average rating Matrix :

In [251]:
```
df_.columns
```

Out[251]:
```
Index(['UserID', 'Gender', 'Age', 'Occupation', 'Zipcode', 'MovieID', 'Title', 'Genres', 'Release_year', 'Ratin
g', 'Watch_Hour', 'Released_In'], dtype='object')
```

In [252]:
```
user_movie_rating_matrix = pd.pivot_table(df_,index = "UserID",
                columns = "Title",
                values = "Rating",
                aggfunc = "mean").fillna(0)
user_movie_rating_matrix.shape
```

Out[252]:
```
(6040, 3633)
```

In [253]:
```
user_movie_rating_matrix
```

0.0	0.0	0.0	0.0	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	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	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	0.0	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	0.0	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
0.0	0.0	0.0	5.0	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	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	3.0	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	0.0	0.0	0.0	3.0	3.0	0.0	0.0	0.0	0.0

item item similarity(hamming distance) based recommendation :

In [ ]:
```
m = movies[["MovieID","Title","Genres"]]
m["Genres"] = m["Genres"].str.split("|")
m = m.explode("Genres")
m["Genres"] = m["Genres"].replace({"":"Other","Horro":"Horror","Sci-":"Sci-Fi","Sci":"Sci-Fi","Sci-F":"Sci-Fi","D
                      "Wester":"Western","Fant":"Fantasy","Chil":"Children's","R":"Romance","D":"Drama","Rom":"Rom
                      "Fantas":"Fantasy","Come":"Comedy","Dram":"Drama","S":"Sci-Fi","Roma":"Romance","A":"Adventu
                       "Wa":"War","Thrille"  :"Thriller","Com":"Comedy","Comed":"Comedy","Acti":"Action","Advent":
                          "Chi":"Children's","Ro":"Romance","F":"Fantasy","We":"Western","Documen":"Documentary","M
                      "Children'":"Children's","Roman":"Romance","Docu":"Documentary","Th":"Thriller","Document":"
                     })

m = m.pivot_table(values="Title", index="MovieID", columns="Genres", aggfunc= np.size,).fillna(0)


def apply(x):
  if x >= 1:
    return 1
  else:
    return 0

m["Adventure"] = m["Adventure"].apply(apply)
m = m.astype(int)
```

In [ ]:
```
m
```

In [256]:

```
def Hamming_distance(x1,x2):
  return np.sum(abs(x1-x2))

Ranks = []
Query = "1"
for candidate in m.index:
  if candidate == Query:
    continue
  Ranks.append([Query,candidate,Hamming_distance(m.loc[Query],m.loc[candidate])])

Ranks = pd.DataFrame(Ranks,columns=["Query","Candidate","Hamming_distance"])
Ranks = Ranks.merge(movies[['MovieID', 'Title']], left_on='Query', right_on='MovieID').rename(columns={'Title': '
Ranks = Ranks.merge(movies[['MovieID', 'Title']], left_on='Candidate', right_on='MovieID').rename(columns={'Title
Ranks = Ranks.sort_values(by=['Query', 'Hamming_distance'])

Ranks.head(10)
```

Out[256]:

	Query	Candidate	Hamming_distance	query_tittle	candidate_tittle
71	1	1064	0	Toy Story	Aladdin and the King of Thieves
1208	1	2141	0	Toy Story	American Tail, An
1442	1	2354	0	Toy Story	Rugrats Movie, The
1443	1	2355	0	Toy Story	Bug's Life, A
2281	1	3114	0	Toy Story	Toy Story 2
2831	1	3611	0	Toy Story	Saludos Amigos
2981	1	3751	0	Toy Story	Chicken Run
7	1	1005	1	Toy Story	D3: The Mighty Ducks
13	1	1010	1	Toy Story	Love Bug, The
19	1	1016	1	Toy Story	Shaggy Dog, The

In [257]:

```
def Hamming_distance(x1,x2):
  return np.sum(abs(x1-x2))

Ranks = []
Query = "1485"
for candidate in m.index:
  if candidate == Query:
    continue
  Ranks.append([Query,candidate,Hamming_distance(m.loc[Query],m.loc[candidate])])

Ranks = pd.DataFrame(Ranks,columns=["Query","Candidate","Hamming_distance"])
Ranks = Ranks.merge(movies[['MovieID', 'Title']], left_on='Query', right_on='MovieID').rename(columns={'Title': '
Ranks = Ranks.merge(movies[['MovieID', 'Title']], left_on='Candidate', right_on='MovieID').rename(columns={'Title
Ranks = Ranks.sort_values(by=['Query', 'Hamming_distance'])


Ranks.head(10)
```

Out[257]:

	Query	Candidate	Hamming_distance	query_tittle	candidate_tittle
4	1485	1001	0	Liar Liar	Associate, The
5	1485	1002	0	Liar Liar	Ed's Next Move
13	1485	101	0	Liar Liar	Bottle Rocket
24	1485	102	0	Liar Liar	Mr. Wrong
25	1485	1020	0	Liar Liar	Cool Runnings
46	1485	104	0	Liar Liar	Happy Gilmore
49	1485	1042	0	Liar Liar	That Thing You Do!
82	1485	1075	0	Liar Liar	Sexual Life of the Belgians, The
86	1485	1079	0	Liar Liar	Fish Called Wanda, A
88	1485	1080	0	Liar Liar	Monty Python's Life of Brian

In [ ]:

```
movies = pd.read_fwf("/content/drive/Othercomputers/My Laptop/Data Science Studies/GitHub_Desktop/BusinessCase_Da
ratings =pd.read_fwf("/content/drive/Othercomputers/My Laptop/Data Science Studies/GitHub_Desktop/BusinessCase_Da
users = pd.read_fwf("/content/drive/Othercomputers/My Laptop/Data Science Studies/GitHub_Desktop/BusinessCase_Dat

delimiter ="::"

users = users["UserID::Gender::Age::Occupation::Zip-code"].str.split(delimiter,expand = True)
users.columns = ["UserID","Gender","Age","Occupation","Zipcode"]

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

users["Occupation"] = users["Occupation"].astype(int).replace({0: "other",1: "academic/educator",2: "artist",
                                                               3: "clerical/admin",4: "college/grad student",
                                                 5: "customer service",6: "doctor/health care",7: "executive/manageri
                                                 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"},
                                                )

delimiter ="::"

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


movies.drop(["Unnamed: 1","Unnamed: 2"],axis = 1,inplace=True)

delimiter ="::"

movies = movies["Movie ID::Title::Genres"].str.split(delimiter,expand = True)
movies.columns = ["MovieID","Title","Genres"]

movies.shape,ratings.shape,users.shape

movies["Release_year"] = movies["Title"].str.extract('^(.+)\s\(([0-9]*)\)$',expand = True)[1]
movies["Title"] = movies["Title"].str.split("(").apply(lambda x:x[0])

from datetime import datetime
ratings["Watch_Hour"] =ratings["Timestamp"].apply(lambda x:datetime.fromtimestamp(int(x)).hour)
ratings.drop(["Timestamp"],axis = 1,inplace=True)

df = users.merge(movies.merge(ratings,on="MovieID",how="outer"),on="UserID",how="outer")
df["Genres"] = df["Genres"].str.split("|")
df = df.explode('Genres')

df["Genres"] = df["Genres"].replace({"":"Other","Horro":"Horror","Sci-":"Sci-Fi","Sci":"Sci-Fi","Sci-F":"Sci-Fi",
                      "Wester":"Western","Fant":"Fantasy","Chil":"Children's","R":"Romance","D":"Drama","Rom":"Rom
                      "Fantas":"Fantasy","Come":"Comedy","Dram":"Drama","S":"Sci-Fi","Roma":"Romance","A":"Adventu
                       "Wa":"War","Thrille"  :"Thriller","Com":"Comedy","Comed":"Comedy","Acti":"Action","Advent":
                         "Chi":"Children's","Ro":"Romance","F":"Fantasy","We":"Western","Documen":"Documentary","M
                      "Children'":"Children's","Roman":"Romance","Docu":"Documentary","Th":"Thriller","Document":"
                     })
m = df.groupby(['MovieID','Genres'])['Title'].unique().str[0].unstack().reset_index().set_index('MovieID')
m = ~m.isna()
m = m.astype(int)
```

Cosine Similarity :

Item and User : -Cosine similarity Matrix :

In [258]:

```
from sklearn.metrics.pairwise import cosine_similarity
```

In [259]:
```
Item_similarity = cosine_similarity(user_movie_rating_matrix.T)
Item_similarity
```

Out[259]:
```
array([[1.        , 0.07235746, 0.03701053, ..., 0.        , 0.12024178,
        0.02700277],
       [0.07235746, 1.        , 0.11528952, ..., 0.        , 0.        ,
        0.07780705],
       [0.03701053, 0.11528952, 1.        , ..., 0.        , 0.04752635,
        0.0632837 ],
       ...,
       [0.        , 0.        , 0.        , ..., 1.        , 0.        ,
        0.04564448],
       [0.12024178, 0.        , 0.04752635, ..., 0.        , 1.        ,
        0.04433508],
       [0.02700277, 0.07780705, 0.0632837 , ..., 0.04564448, 0.04433508,
        1.        ]])
```

In [262]:
```
Item_similarity.shape
```

Out[262]:
```
(3633, 3633)
```

In [263]:
```
Item_similarty_matrix = pd.DataFrame(Item_similarity,
             index = user_movie_rating_matrix.columns,
             columns = user_movie_rating_matrix.columns)
Item_similarty_matrix
```

Out[263]:

Title	$1,000,000 Duck	'Night Mother	'Til There Was You	'burbs, The	...And Justice for All	1-900	10 Things I Hate About You	101 Dalmatians	12 Angry Men	13th Warrior, The	187	2 Days in the Valley	20 D
Title													
$1,000,000 Duck	1.000000	0.072357	0.037011	0.079291	0.060838	0.000000	0.058619	0.189843	0.094785	0.058418	0.028171	0.021295	0.01
'Night Mother	0.072357	1.000000	0.115290	0.115545	0.159526	0.000000	0.076798	0.137135	0.111413	0.046135	0.060254	0.108613	0.03
'Til There Was You	0.037011	0.115290	1.000000	0.098756	0.066301	0.080250	0.127895	0.128523	0.079115	0.066598	0.019914	0.067742	0.09
'burbs, The	0.079291	0.115545	0.098756	1.000000	0.143620	0.000000	0.192191	0.250140	0.170719	0.197808	0.103273	0.183970	0.04
...And Justice for All	0.060838	0.159526	0.066301	0.143620	1.000000	0.000000	0.075093	0.178928	0.205486	0.122431	0.114231	0.195255	0.03
...	...	...	...	...	...	...	...	...	...	...	...	...	
Zed & Two Noughts, A	0.045280	0.091150	0.022594	0.055704	0.086080	0.000000	0.012702	0.042295	0.039344	0.041324	0.021497	0.083057	0.00
Zero Effect	0.039395	0.074787	0.079261	0.161174	0.110867	0.000000	0.175771	0.157313	0.133061	0.156505	0.097833	0.273992	0.06
Zero Kelvin	0.000000	0.000000	0.000000	0.000000	0.074317	0.000000	0.000000	0.033120	0.036867	0.034797	0.000000	0.041621	0.00
Zeus and Roxanne	0.120242	0.000000	0.047526	0.033567	0.000000	0.000000	0.058708	0.089840	0.058692	0.034623	0.000000	0.000000	0.03
eXistenZ	0.027003	0.077807	0.063284	0.110525	0.111040	0.039561	0.162060	0.120762	0.098731	0.230799	0.036650	0.165736	0.12

3633 rows × 3633 columns

User Based Similartiy :

In [264]:
```
User_similarity = cosine_similarity(user_movie_rating_matrix)
User_similarity.shape
```

Out[264]:
```
(6040, 6040)
```

In [265]:
```
User_similarity
```

Out[265]:
```
array([[1.        , 0.25531859, 0.12396703, ..., 0.15926709, 0.11935626,
        0.12239079],
       [0.25531859, 1.        , 0.25964457, ..., 0.16569953, 0.13332665,
        0.24845029],
       [0.12396703, 0.25964457, 1.        , ..., 0.20430203, 0.11352239,
        0.30693676],
       ...,
       [0.15926709, 0.16569953, 0.20430203, ..., 1.        , 0.18657496,
        0.18563871],
       [0.11935626, 0.13332665, 0.11352239, ..., 0.18657496, 1.        ,
        0.10827118],
       [0.12239079, 0.24845029, 0.30693676, ..., 0.18563871, 0.10827118,
        1.        ]])
```

In [266]:
```
User_similarity_matrix = pd.DataFrame(User_similarity,
             index = user_movie_rating_matrix.index,
             columns = user_movie_rating_matrix.index)
User_similarity_matrix
```

Out[266]:

UserID	1	10	100	1000	1001	1002	1003	1004	1005	1006	1007	1008	1009	
UserID														
1	1.000000	0.255319	0.123967	0.207800	0.139317	0.110320	0.121384	0.180226	0.103896	0.052816	0.060032	0.102675	0.049839	0
10	0.255319	1.000000	0.259645	0.280479	0.158703	0.112917	0.141985	0.432536	0.194915	0.102487	0.161729	0.220798	0.118062	0
100	0.123967	0.259645	1.000000	0.306067	0.075736	0.110450	0.358686	0.237492	0.172872	0.099147	0.060103	0.043367	0.061238	0
1000	0.207800	0.280479	0.306067	1.000000	0.099117	0.047677	0.201722	0.355920	0.325966	0.130702	0.042828	0.077724	0.123638	0
1001	0.139317	0.158703	0.075736	0.099117	1.000000	0.164854	0.053887	0.152057	0.138602	0.134710	0.019576	0.083651	0.200411	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
995	0.035731	0.146552	0.033754	0.044404	0.109700	0.072578	0.031406	0.088838	0.061450	0.032265	0.000000	0.041055	0.019928	0
996	0.170184	0.304806	0.344290	0.330748	0.222119	0.224779	0.185226	0.352014	0.287965	0.164045	0.078759	0.117937	0.151984	0
997	0.159267	0.165700	0.204302	0.172803	0.103255	0.068980	0.170771	0.175488	0.106303	0.049536	0.037536	0.041037	0.031871	0
998	0.119356	0.133327	0.113522	0.098456	0.269952	0.218905	0.141829	0.075538	0.112029	0.052900	0.012658	0.056094	0.169102	0
999	0.122391	0.248450	0.306937	0.250564	0.178399	0.178474	0.198656	0.334470	0.164777	0.143866	0.054761	0.057473	0.107457	0

6040 rows × 6040 columns

Pearson Correlation

In [267]:
```
correlated_movie_matrix = m.T.corr()
```

In [268]:
```
correlated_movie_matrix
```

Out[268]:

MovieID	1	10	100	1000	1001	1002	1003	1004	1005	1006	1007	1008	
MovieID													
1	1.000000	-0.187500	-0.148522	-0.102062	0.544331	0.544331	-0.148522	-0.148522	0.792118	-0.102062	0.604167	-0.102062	0.
10	-0.187500	1.000000	0.321798	-0.102062	-0.102062	-0.102062	0.321798	0.792118	-0.148522	-0.102062	-0.187500	-0.102062	0.
100	-0.148522	0.321798	1.000000	-0.080845	-0.080845	-0.080845	1.000000	0.441176	-0.117647	0.687184	-0.148522	-0.080845	-0.
1000	-0.102062	-0.102062	-0.080845	1.000000	-0.055556	-0.055556	-0.080845	-0.080845	-0.080845	-0.055556	-0.102062	-0.055556	-0.
1001	0.544331	-0.102062	-0.080845	-0.055556	1.000000	1.000000	-0.080845	-0.080845	0.687184	-0.055556	0.544331	-0.055556	-0.
...	...	...	...	...	...	...	...	...	...	...	...	...	...
994	-0.102062	-0.102062	0.687184	-0.055556	-0.055556	-0.055556	0.687184	-0.080845	-0.080845	1.000000	-0.102062	-0.055556	-0.
996	-0.187500	0.208333	0.321798	-0.102062	-0.102062	-0.102062	0.321798	0.321798	-0.148522	0.544331	0.208333	0.544331	-0.
997	-0.148522	0.321798	1.000000	-0.080845	-0.080845	-0.080845	1.000000	0.441176	-0.117647	0.687184	-0.148522	-0.080845	-0.
998	-0.148522	0.321798	-0.117647	0.687184	-0.080845	-0.080845	-0.117647	0.441176	-0.117647	-0.080845	-0.148522	-0.080845	-0.
999	-0.102062	-0.102062	-0.080845	1.000000	-0.055556	-0.055556	-0.080845	-0.080845	-0.080845	-0.055556	-0.102062	-0.055556	-0.

3858 rows × 3858 columns

In [269]:
```
movies[movies.MovieID == "1"]["Title"][0]
```

Out[269]:
```
'Toy Story '
```

In [270]:
```
movies[movies.Title.str.contains("Toy Story")].iloc[0].MovieID
```

Out[270]:
```
'1'
```

In [271]:
```
def recommend_movie_based_on_correlation(movie):
    TITLE = movies[movies.Title.str.contains(movie)].iloc[0]["Title"]

    INDEX = movies[movies.Title.str.contains(movie)].iloc[0].MovieID

    print(TITLE)
    print(INDEX)

    print(movies[movies.MovieID.isin(correlated_movie_matrix[INDEX].sort_values(ascending=False).head(10).index.t
```

In [272]:
```
recommend_movie_based_on_correlation("Toy Story")
```

```
Toy Story
1
0                            Toy Story
584                            Aladdin
1050    Aladdin and the King of Thieves
2009                  Jungle Book, The
2072                 American Tail, An
2285                Rugrats Movie, The
2286                     Bug's Life, A
3045                       Toy Story 2
3542                     Saludos Amigos
3682                        Chicken Run
Name: Title, dtype: object
```

In [273]:
```
recommend_movie_based_on_correlation("Shawshank")
```

```
Shawshank Redemption, The
318
35             Dead Man Walking
384                   Boys Life
631                       Frisk
1555              Career Girls
2443    Ballad of Narayama, The
2451                    Airport
2452               Airport 1975
2453                Airport '77
3525               Center Stage
3529                     Hamlet
Name: Title, dtype: object
```

In [274]:
```
recommend_movie_based_on_correlation("Titanic")
```

```
Titanic
1721
200                  Total Eclipse
357         It Could Happen to You
1372                 Jerry Maguire
1466          Inventing the Abbotts
1951             Dangerous Liaisons
2106                       Déjà Vu
2247               Practical Magic
2850    Year of Living Dangerously
3086             Anna and the King
3599              Romeo and Juliet
Name: Title, dtype: object
```

In [275]:
```
recommend_movie_based_on_correlation("Braveheart")
```

```
Braveheart
110
461            Heaven & Earth
1204        Full Metal Jacket
1214                Boat, The
1222                    Glory
1959      Saving Private Ryan
2358       Thin Red Line, The
2993         Longest Day, The
3559            Flying Tigers
3574    Fighting Seabees, The
3585    Guns of Navarone, The
Name: Title, dtype: object
```

k - Nearest Neighbours

In [276]:
```
from sklearn.neighbors import NearestNeighbors
```

In [277]:
```
kNN_model = NearestNeighbors(metric='cosine')
kNN_model.fit(user_movie_rating_matrix.T)
```

Out[277]:
```
NearestNeighbors(metric='cosine')
```

In [278]:
```
distances, indices = kNN_model.kneighbors(user_movie_rating_matrix.T, n_neighbors= 5)
```

In [279]:
```
result = pd.DataFrame(indices)
result
```

Out[279]:

	0	1	2	3	4
0	0	731	414	285	582
1	1	803	72	2162	3029
2	2	1622	2524	3313	2583
3	3	1452	2164	1304	1043
4	4	26	723	890	493
...	...	...	...	...	...
3628	3628	2548	750	1582	2439
3629	3629	382	1699	482	1578
3630	3630	1328	1687	3393	2922
3631	3631	1609	1176	3225	2093
3632	3632	839	3126	2519	1278

3633 rows × 5 columns

In [280]:
```
result.index = user_movie_rating_matrix.columns
result
```

Out[280]:

	0	1	2	3	4
Title					
$1,000,000 Duck	0	731	414	285	582
'Night Mother	1	803	72	2162	3029
'Til There Was You	2	1622	2524	3313	2583
'burbs, The	3	1452	2164	1304	1043
...And Justice for All	4	26	723	890	493
...	...	...	...	...	...
Zed & Two Noughts, A	3628	2548	750	1582	2439
Zero Effect	3629	382	1699	482	1578
Zero Kelvin	3630	1328	1687	3393	2922
Zeus and Roxanne	3631	1609	1176	3225	2093
eXistenZ	3632	839	3126	2519	1278

3633 rows × 5 columns

In [281]:
```
result.loc["Zero Effect "].to_list()
```

Out[281]:
```
[3629, 382, 1699, 482, 1578]
```

In [282]:
```
movies.MovieID = movies.MovieID.astype("int32")
```

In [283]:
```
movies[movies.MovieID.isin( result.loc["Zero Effect "].to_list())]
```

Out[283]:

	MovieID	Title	Genres	Release_year
378	382	Wolf	Drama|Horror	1994
478	482	Killing Zoe	Thriller	1994
1537	1578	Innocent Sleep, The	Crime	1995
1652	1699	Butcher Boy, The	Drama	1998
3560	3629	Gold Rush, The	Comedy	1925

sparse 'row' matrix representation for the following dense matrix - [[1 0],[3 7]]

In [284]:
```
from scipy.sparse import csr_matrix

dense_matrix = [[1,0],
                [3,7]]
sparse_matrix = csr_matrix(dense_matrix)
```

In [285]:
```
print(sparse_matrix.data)
print(sparse_matrix.indices)
print(sparse_matrix.indptr)
```

```
[1 3 7]
[0 0 1]
[0 1 3]
```

Questions and Answers :

1. Users of which age group have watched and rated the most number of movies?
   - age group 25-35
2. Users belonging to which profession have watched and rated the most movies?
   - College Graduate Students and Other category
3. Most of the users in our dataset who've rated the movies are Male. (T/F)
   - Male
4. Most of the movies present in our dataset were released in which decade?
   - 90s
5. The movie with maximum no. of ratings is ___.
   - American Beauty
6. Name the top 3 movies similar to 'Liar Liar' on the item-based approach.
   - The Associate
   - Ed's Next Move
   - Bottle Rocket
   - Mr. Wrong
   - Cool Runnings
   - Happy Gilmore
   - That Thing You Do!
7. On the basis of approach, Collaborative Filtering methods can be classified into ___-based and ___-based.
   - Memory based and Model based
8. Pearson Correlation ranges between ___ to ___ whereas, Cosine Similarity belongs to the interval between ___ to ___.
   - Pearson Correlation ranges between -1 to +1
   - Cosine Similarity belongs to the interval between -1 to 1
   - similarity of 1 means that the vectors are identical,
   - a similarity of -1 means that the vectors are dissimilar,
   - and a similarity of 0 means that the vectors are not similar.
9. Mention the RMSE and MAPE that you got while evaluating the Matrix Factorization model.
   - Item-based Model :
   - RMSE: 0.8926
   - User-based Model :
   - RMSE: 0.9345
10. Give the sparse 'row' matrix representation for the following dense matrix -
    - [[1 0],[3 7]]

```
ans  :
        [1 3 7]
        [0 0 1]
```