Problem Statement

Build a Recommender System for an Indian subscription video on-demand and over-the-top streaming service, to show personalized movie recommendations based on ratings given by a user and other users similar to them based on user attributes like Age, Gender & Occupation in order to improve user experience.

In [226…

```
#importing required libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from sklearn.metrics.pairwise import cosine_similarity
from cmfrec import CMF
from sklearn.metrics import mean_squared_error as mse
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import NearestNeighbors
from sklearn.metrics import mean_absolute_percentage_error as mape
from scipy.sparse import csr_matrix
from numpy import array
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
```

In [19]:

```
#importing data set

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

In [20]:

```
#formtting data file movies

movies.head()
```

Out[20]:

	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 [21]:

```
movies.columns
```

Out[21]:

```
Index(['Movie ID::Title::Genres', 'Unnamed: 1', 'Unnamed: 2'], dtype='objec
t')
```

In [22]:

```
delimitter = '::'
movies = movies['Movie ID::Title::Genres'].str.split(delimitter, expand=Tru
```

```
movies.columns = ['MovieID', 'Title', 'Genres']
movies.head(2)
```

Out[22]:

	MovieID	Title	Genres
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy

In [23]:

```
#formtting data file ratings

ratings.head()
```

Out[23]:

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

In [24]:

```
ratings.columns
```

Out[24]:

```
Index(['UserID::MovieID::Rating::Timestamp'], dtype='object')
```

In [25]:

```
delimitter = '::'
ratings = ratings['UserID::MovieID::Rating::Timestamp'].str.split(delimitte
ratings.columns = ['UserID', 'MovieID', 'Rating', 'Timestamp']
ratings.head(2)
```

Out[25]:

	UserID	MovieID	Rating	Timestamp
0	1	1193	5	978300760
1	1	661	3	978302109

In [26]:

```
#formtting data file users

users.head()
```

Out[26]:

	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 [27]:

```
users.columns
```

Out[27]:

```
Index(['UserID::Gender::Age::Occupation::Zip-code'], dtype='object')
```

In [28]:
```
delimitter = '::'
users = users['UserID::Gender::Age::Occupation::Zip-code'].str.split(delimi
users.columns = ['UserID', 'Gender', 'Age', 'Occupation', 'Zip-code']
users.head(2)
```

Out[28]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	48067
1	2	M	56	16	70072

In [29]:
```
#movies data overiew

movies.shape
```

Out[29]:
```
(3883, 3)
```

In [30]:
```
#non-null counts and data types

movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   MovieID  3883 non-null   object
 1   Title    3883 non-null   object
 2   Genres   3858 non-null   object
dtypes: object(3)
memory usage: 91.1+ KB
```

In [31]:
```
#percentage of null values in each column

movies.isnull().sum()*100/movies.isnull().count()
```

Out[31]:
```
MovieID    0.000000
Title      0.000000
Genres     0.643832
dtype: float64
```

In [32]:
```
#number of unique values

movies.nunique()
```

Out[32]:
```
MovieID    3883
Title      3883
Genres      360
dtype: int64
```

In [33]:
```
#ratings data overiew

ratings.shape
```

Out[33]:
```
(1000209, 4)
```

In [34]:
```
#non-null counts and data types

ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 4 columns):
 #   Column     Non-Null Count    Dtype 
---  ------     --------------    ----- 
 0   UserID     1000209 non-null  object
 1   MovieID    1000209 non-null  object
 2   Rating     1000209 non-null  object
 3   Timestamp  1000209 non-null  object
dtypes: object(4)
memory usage: 30.5+ MB
```

In [35]:
```
#percentage of null values in each column

ratings.isnull().sum()*100/ratings.isnull().count()
```

Out[35]:
```
UserID       0.0
MovieID      0.0
Rating       0.0
Timestamp    0.0
dtype: float64
```

In [36]:
```
#number of unique values

ratings.nunique()
```

Out[36]:
```
UserID         6040
MovieID        3706
Rating            5
Timestamp    458455
dtype: int64
```

In [37]:
```
#users data overiew

users.shape
```

Out[37]:
```
(6040, 5)
```

In [38]:
```
#non-null counts and data types

users.info()
```

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

In [39]:
```
#percentage of null values in each column

users.isnull().sum()*100/users.isnull().count()
```

Out[39]:
```
UserID        0.0
Gender        0.0
Age           0.0
Occupation    0.0
Zip-code      0.0
dtype: float64
```

In [40]:
```
#number of unique values

users.nunique()
```

Out[40]:
```
UserID        6040
Gender           2
Age              7
Occupation      21
Zip-code      3439
dtype: int64
```

Data Overview

1. **Movies**

- There are 3883 rows and 3 columns in the dataset
- Each row represents a movie and its features; MovieID, Title(and Release Year) and Genres
- All the three columns are categorical variables of type object
- 0.64% or 25 movies have null values for column genres

2. **Users**

- There are 6040 rows and 5 columns in the dataset
- Each row represents a user and their features; UserID, Gender, Age, Occupation and Zip-code
- All the five columns are categorical variables of type object
- No missing values are present in the dataset

3. **Ratings**

- There are 1,000,209 rows and 4 columns in the dataset
- Each row represents the rating, movie, the user who is rated and the timestamp
- All the four columns are of type object however, rating and timestamp can be converted into numerical features
- No missing values are present in the dataset

Exploratory Data Analysis

In [41]:
```
#dropping 25 movies with no genres
```

```
movies = movies.dropna()
movies.shape
```

Out[41]: (3858, 3)

In [42]:

```
#creating new feature Release_year

movies['Release_year'] = movies['Title'].apply(lambda s: int(s.rstrip("*")|
```

In [43]:

```
#creating movie_age feature from Release_year

movies['MovieAge'] = movies['Release_year'].apply(lambda x: 2022 - int(x))
movies.head(2)
```

Out[43]:

	MovieID	Title	Genres	Release_year	MovieAge
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995	27
1	2	Jumanji (1995)	Adventure|Children's|Fantasy	1995	27

In [44]:

```
#converting timestamp to hour and ratings to int type

ratings['Rating'] = ratings['Rating'].astype('int')
ratings['Hour'] = ratings['Timestamp'].apply(lambda x: datetime.fromtimesta
ratings.head(2)
```

Out[44]:

	UserID	MovieID	Rating	Timestamp	Hour
0	1	1193	5	978300760	3
1	1	661	3	978302109	4

In [45]:

```
#converting US zip codes to city codes

users['Zip-code'] = users['Zip-code'].apply(lambda x: x[:3])
users.head(2)
```

Out[45]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	480
1	2	M	56	16	700

In [46]:

```
#merging movies and ratings

df = pd.merge(movies, ratings, on='MovieID')
df.head(2)
```

Out[46]:

	MovieID	Title	Genres	Release_year	MovieAge	UserID	Rating	Timest
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995	27	1	5	97882
1	1	Toy Story (1995)	Animation|Children's|Comedy	1995	27	6	4	97823

In [47]:

```
#merging df and users

df = pd.merge(df, users, on='UserID')
df.head(2)
```

Out[47]:

	MovieID	Title	Genres	Release_year	MovieAge	UserID	R
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995	27	1	
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1995	27	1	

In [48]:

```
df.shape
```

Out[48]: (996144, 13)

In [49]:

```
#min number of ratings for a user

df.groupby(['UserID'])['MovieID'].count().min()
```

Out[49]: 19

In [50]:

```
#number of unique values

df.nunique()
```

Out[50]:

```
MovieID           3682
Title             3682
Genres             358
Release_year        81
MovieAge            81
UserID            6040
Rating               5
Timestamp       457632
Hour                24
Gender               2
Age                  7
Occupation          21
Zip-code           678
dtype: int64
```

In [51]:

```
df.describe()
```

Out[51]:

	Release_year	MovieAge	Rating	Hour
count	996144.000000	996144.000000	996144.000000	996144.000000
mean	1986.758458	35.241542	3.579985	9.730529
std	14.314470	14.314470	1.116849	7.293934
min	1919.000000	22.000000	1.000000	0.000000
25%	1982.000000	25.000000	3.000000	4.000000
50%	1992.000000	30.000000	4.000000	8.000000
75%	1997.000000	40.000000	4.000000	15.000000
max	2000.000000	103.000000	5.000000	23.000000

In [52]:

```
#splitting genres to get different genres

m = movies.copy()
m['Genres'] = m['Genres'].str.split('|')
m = m.explode('Genres')
m = m.pivot(index='MovieID', columns='Genres', values='Title')
m = ~m.isna()
m = m.astype(int)
m.head(2)
```

Out[52]:

Genres		A	Acti	Action	Adv	Advent	Adventu	Adventur	Adventure	Animati	...	Sci-Fi	Th
MovieID													
1	0	0	0	0	0	0	0	0	0	0	...	0	(
10	0	0	0	1	0	0	0	0	1	0	...	0	(

2 rows × 63 columns

In [53]:

```
#cleaning genres for consistency

m['action'] = m[['A', 'Acti', 'Action']].agg(sum, axis=1)
m['adventure'] = m[['Adv', 'Advent', 'Adventu', 'Adventur', 'Adventure']].a
m['animation'] = m[['Animati', 'Animation']].agg(sum, axis=1)
m['childrens'] = m[['Chi', 'Chil', 'Childr', 'Childre', 'Children', "Child
m['comedy'] = m[['Com', 'Come', 'Adventu', 'Comed', 'Comedy']].agg(sum, axi
m['crime'] = m[['Crime']].agg(sum, axis=1)
m['documentary'] = m[['D', 'Docu', 'Documen', 'Document', 'Documentary']].a
m['drama'] = m[['Dr', 'Dram', 'Drama']].agg(sum, axis=1)
m['fantasy'] = m[['F', 'Fant', 'Fantas', 'Fantasy']].agg(sum, axis=1)
m['film-noir'] = m[['Film-Noir']].agg(sum, axis=1)
m['horror'] = m[['Horr', 'Horro', 'Horror']].agg(sum, axis=1)
m['musical'] = m[['Music', 'Musical']].agg(sum, axis=1)
m['mystery'] = m[['Mystery']].agg(sum, axis=1)
m['romance'] = m[['R', 'Ro', 'Rom', 'Roma', 'Roman', 'Romance']].agg(sum, a
m['sci-fi'] = m[['S', 'Sci', 'Sci-', 'Sci-F', 'Sci-Fi']].agg(sum, axis=1)
m['thriller'] = m[['Th', 'Thri', 'Thrille', 'Thriller']].agg(sum, axis=1)
m['war'] = m[['Wa', 'War']].agg(sum, axis=1)
m['western'] = m[['Wester', 'Western']].agg(sum, axis=1)
m = m.drop(columns=['', 'A', 'Acti', 'Action', 'Adv', 'Advent', 'Adventu',
       'Adventure', 'Animati', 'Animation', 'Chi', 'Chil', 'Childr', 'Chilc
       'Children', "Children'", "Children's", 'Com', 'Come', 'Comed', 'Come
       'Crime', 'D', 'Docu', 'Documen', 'Document', 'Documenta', 'Documenta
```

```
        'Dr', 'Dram', 'Drama', 'F', 'Fant', 'Fantas', 'Fantasy', 'Film-Noir'
        'Horr', 'Horro', 'Horror', 'Music', 'Musical', 'Mystery', 'R', 'Ro',
        'Rom', 'Roma', 'Roman', 'Romance', 'S', 'Sci', 'Sci-', 'Sci-F',
        'Sci-Fi', 'Th', 'Thri', 'Thrille', 'Thriller', 'Wa', 'War', 'We',
        'Wester', 'Western'])
m.head(2)
```

Out[53]:

Genres	action	adventure	animation	childrens	comedy	crime	documentary	drama	fantasy
MovieID									
1	0	0	1	1	1	0	0	0	0
10	1	1	0	0	0	0	0	0	0

In [54]:

```
m.columns
```

Out[54]:

```
Index(['action', 'adventure', 'animation', 'childrens', 'comedy', 'crime',
       'documentary', 'drama', 'fantasy', 'film-noir', 'horror', 'musical',
       'mystery', 'romance', 'sci-fi', 'thriller', 'war', 'western'],
      dtype='object', name='Genres')
```

In [55]:

```
#avg_rating and no.of rating by movies

movie_rating = ratings.groupby('MovieID').agg({'Rating':['mean', 'count']})
    columns={'mean':'rate_avg', 'count':'rate_ct'})
movie_rating.columns = movie_rating.columns.droplevel()
```

In [56]:

```
#merging m with movies and adding avg rating

movies_df = pd.merge(movies, m, on='MovieID')
movies_df = pd.merge(movies_df, movie_rating, on='MovieID')
movies_df.head(2)
```

Out[56]:

	MovieID	Title	Genres	Release_year	MovieAge	action	adventure	ani
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995	27	0	0	
1	2	Jumanji (1995)	Adventure|Children's|Fantasy	1995	27	0	1	

2 rows × 25 columns

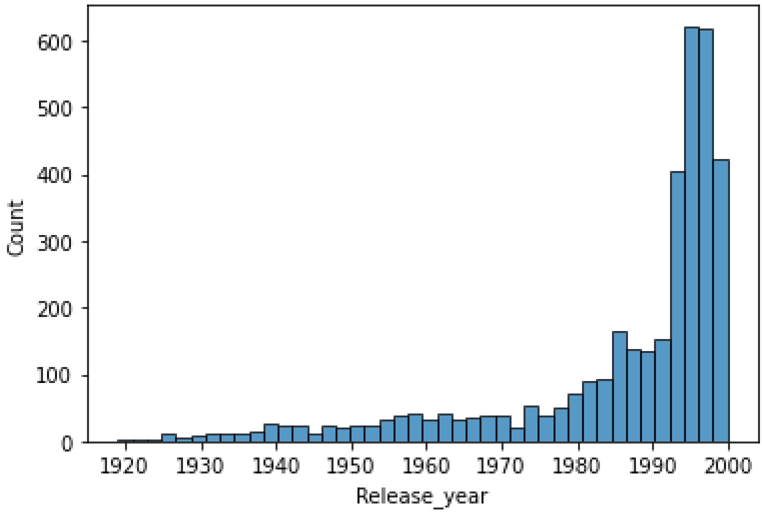
In [57]:

```
#checking column Release_year

movies_df['Release_year'].value_counts()
```

Out[57]:
```
1998    313
1996    311
1995    310
1997    304
1999    271
       ... 
1928      2
1923      2
1922      1
1920      1
1921      1
Name: Release_year, Length: 81, dtype: int64
```

In [58]:
```
sns.histplot(data=movies_df, x='Release_year')
plt.show()
```



In [59]:
```
#checking genres count

cols = ['action', 'adventure', 'animation', 'childrens', 'comedy',
       'crime', 'documentary', 'drama', 'fantasy', 'film-noir', 'horror',
       'musical', 'mystery', 'romance', 'sci-fi', 'thriller', 'war',
       'western']
dic = {}
for col in cols:
    dic[col] = movies_df[col].sum()
dict(sorted(dic.items(), key=lambda item: item[1]))
```

Out[59]:
```
{'film-noir': 44,
 'fantasy': 63,
 'western': 66,
 'mystery': 103,
 'animation': 104,
 'documentary': 108,
 'musical': 112,
 'war': 137,
 'crime': 200,
 'childrens': 248,
 'sci-fi': 263,
 'adventure': 280,
 'horror': 336,
 'romance': 450,
 'thriller': 482,
 'action': 495,
 'comedy': 1154,
 'drama': 1472}
```

In [60]:
```
#checking genres count post 2000

dic = {}
for col in cols:
    dic[col] = movies_df[movies_df['Release_year'] >= 2000][col].sum()
dict(sorted(dic.items(), key=lambda item: item[1]))
```

Out[60]:
```
{'film-noir': 0,
 'western': 0,
 'fantasy': 1,
 'musical': 1,
 'mystery': 1,
 'war': 2,
 'adventure': 6,
 'documentary': 7,
 'animation': 8,
 'crime': 8,
 'horror': 8,
 'childrens': 9,
 'sci-fi': 10,
 'romance': 16,
 'action': 19,
 'thriller': 25,
 'drama': 53,
 'comedy': 67}
```

In [61]:
```
#Movies rated by most number of peoples

movies_df[['MovieID', 'Title','rate_ct', 'rate_avg']].sort_values(by='rate_
```

Out[61]:

	MovieID	Title	rate_ct	rate_avg
2635	2858	American Beauty (1999)	3428	4.317386
251	260	Star Wars: Episode IV - A New Hope (1977)	2991	4.453694
1097	1196	Star Wars: Episode V - The Empire Strikes Back...	2990	4.292977
1111	1210	Star Wars: Episode VI - Return of the Jedi (1983)	2883	4.022893
462	480	Jurassic Park (1993)	2672	3.763847
1837	2028	Saving Private Ryan (1998)	2653	4.337354
571	589	Terminator 2: Judgment Day (1991)	2649	4.058513
2362	2571	Matrix, The (1999)	2590	4.315830
1169	1270	Back to the Future (1985)	2583	3.990321
575	593	Silence of the Lambs, The (1991)	2578	4.351823

In [62]:
```
#Movies with highest ratings and rated by atleast 10 people

movies_df[movies_df['rate_ct']>=10][['MovieID', 'Title','rate_ct', 'rate_av
    by='rate_avg', ascending=False).head(10)
```

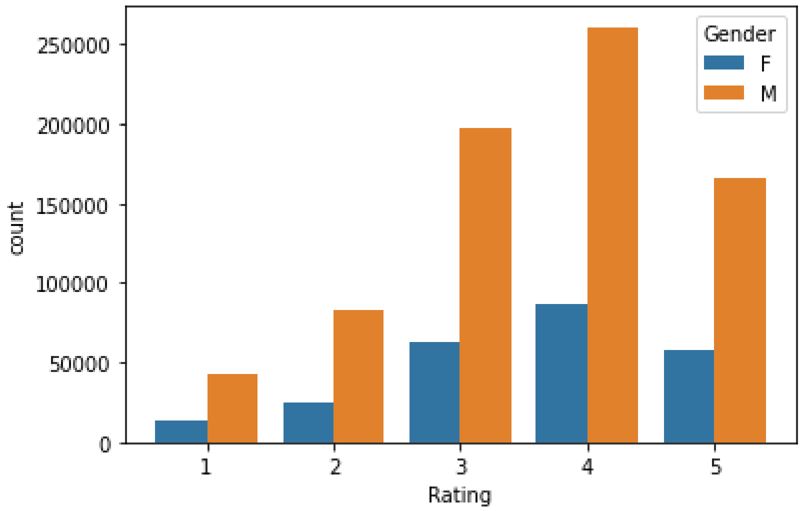
Out[62]:

	MovieID	Title	rate_ct	rate_avg
2682	2905	Sanjuro (1962)	69	4.608696
307	318	Shawshank Redemption, The (1994)	2227	4.554558
795	858	Godfather, The (1972)	2223	4.524966
703	745	Close Shave, A (1995)	657	4.520548
49	50	Usual Suspects, The (1995)	1783	4.517106
509	527	Schindler's List (1993)	2304	4.510417
1059	1148	Wrong Trousers, The (1993)	882	4.507937
854	922	Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)	470	4.491489
1099	1198	Raiders of the Lost Ark (1981)	2514	4.477725
836	904	Rear Window (1954)	1050	4.476190

In [63]:

```
sns.countplot(data=df, x='Rating', hue='Gender')
plt.plot()
```

Out[63]: []



In [64]:

```
#checking users

users.info()
```

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

In [65]:

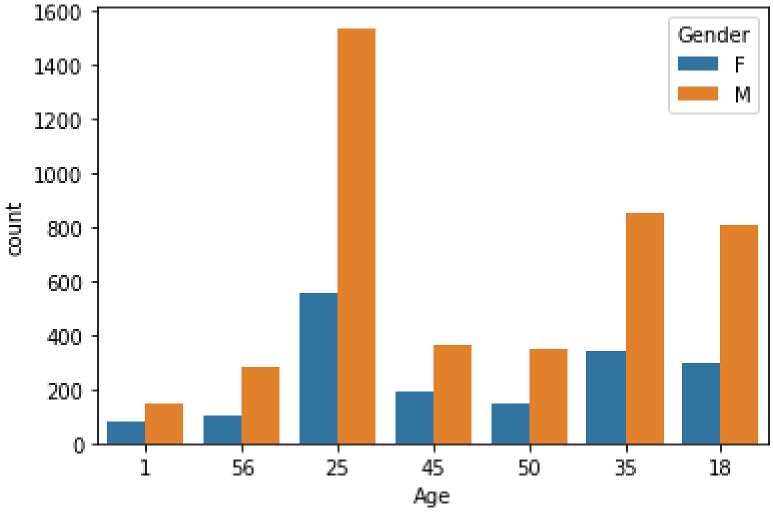
```
users['Gender'].value_counts()
```

Out[65]:
```
M    4331
F    1709
Name: Gender, dtype: int64
```

In [66]:
```
users['Age'].value_counts()
```

Out[66]:
```
25    2096
35    1193
18    1103
45     550
50     496
56     380
1      222
Name: Age, dtype: int64
```

In [67]:
```
sns.countplot(data=users, x='Age', hue='Gender')
plt.show()
```



In [68]:
```
users['Occupation'].value_counts()
```

Out[68]:
```
4     759
0     711
7     679
1     528
17    502
12    388
14    302
20    281
2     267
16    241
6     236
10    195
3     173
15    144
13    142
11    129
5     112
9      92
19     72
18     70
8      17
Name: Occupation, dtype: int64
```

In [69]:
```
users['Zip-code'].value_counts().head(10)
```

Out[69]:
```
554    172
100    162
551    146
941    137
021    109
606    104
900    103
481     95
981     90
921     72
Name: Zip-code, dtype: int64
```

Build a Recommender System based on Pearson Correlation

In [70]:
```
#creating item-user matrix

item_user = ratings.pivot(index = 'UserID', columns ='MovieID', values = 'R
item_user.head()
```

Out[70]:

MovieID	1	10	100	1000	1002	1003	1004	1005	1006	1007	...	99	990	991	992	993
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
10	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
100	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
1000	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
1001	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

5 rows × 3706 columns

In [71]:
```
# item similarity matrix using Pearson correlation

item_sim = item_user.corr()
```

In [72]:
```
item_sim.shape
```

Out[72]:
```
(3706, 3706)
```

Query - List of 5 movies to recommend to a user who has liked 'The Shawshank Redemption (1994)' MovieID - 318

In [73]:
```
movies[movies['MovieID']=='318']
```

Out[73]:

	MovieID	Title	Genres	Release_year	MovieAge
315	318	Shawshank Redemption, The (1994)	Drama	1994	28

In [74]:
```
print("Here is a list of 5 movies to recommend to a user who has liked 'Sha
lt = list(pd.DataFrame(item_sim['307'].sort_values(ascending=False).iloc[1:
```

```
item_sim['307'].sort_values(ascending=False).iloc[1:6]
```

Out[74]:
```
Here is a list of 5 movies to recommend to a user who has liked 'Shawshank
Redemption, The (1994)'
MovieID
308     0.675480
306     0.593413
1176    0.298589
535     0.293932
194     0.272502
Name: 307, dtype: float64
```

In [75]:
```
movies[movies['MovieID'].isin(lt)]
```

Out[75]:

	MovieID	Title	Genres	Release_year	MovieAge
192	194	Smoke (1995)	Drama	1995	27
303	306	Three Colors: Red (1994)	Drama	1994	28
305	308	Three Colors: White (1994)	Drama	1994	28
531	535	Short Cuts (1993)	Drama	1993	29

Build a Recommender System based on Cosine Similarity

In [76]:
```
# Create user-item matrix

user_item = ratings.pivot(index = 'UserID', columns ='MovieID', values = 'F
user_item.head()
```

Out[76]:

MovieID	1	10	100	1000	1002	1003	1004	1005	1006	1007	...	99	990	991	992	993
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
10	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
100	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
1000	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
1001	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

5 rows × 3706 columns

In [77]:
```
# User similarity matrix using cosine similarity

user_sim = cosine_similarity(user_item)
user_sim = pd.DataFrame(user_sim, index=user_item.index, columns=user_item.
user_sim
```

Out[77]:

UserID	1	10	100	1000	1001	1002	1003	1004	100
UserID									
1	1.000000	0.255288	0.123967	0.207800	0.139061	0.110320	0.121384	0.179143	0.10313
10	0.255288	1.000000	0.258047	0.278753	0.154858	0.112222	0.141111	0.428224	0.18856
100	0.123967	0.258047	1.000000	0.297539	0.075597	0.110450	0.358686	0.236065	0.17160
1000	0.207800	0.278753	0.297539	1.000000	0.094710	0.047677	0.201722	0.353782	0.32358
1001	0.139061	0.154858	0.075597	0.094710	1.000000	0.164551	0.053788	0.149019	0.13733
...	...	...	...	...	...	...	...	...	.
995	0.035731	0.145650	0.033754	0.044404	0.109499	0.072578	0.031406	0.088304	0.06100
996	0.170184	0.300175	0.344290	0.330748	0.221710	0.224779	0.185226	0.349899	0.28586
997	0.159267	0.160346	0.204302	0.172803	0.100597	0.068980	0.170771	0.171951	0.10552
998	0.119356	0.132506	0.113522	0.098456	0.269456	0.218905	0.141829	0.075084	0.11121
999	0.122059	0.246251	0.306104	0.245292	0.175194	0.177989	0.198117	0.331558	0.16312

6040 rows × 6040 columns

In [78]:

```
user_sim.shape
```

Out[78]:

```
(6040, 6040)
```

Query - List of 5 users similar to the user with userID - 1

In [79]:

```
users[users['UserID']=='1']
```

Out[79]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	480

In [80]:

```
print("Here is a list of 5 users similar to the user with userID - 1")
lt = list(pd.DataFrame(user_sim['1'].sort_values(ascending=False).iloc[1:6]
user_sim['1'].sort_values(ascending=False).iloc[1:6]
```

Out[80]:

```
Here is a list of 5 users similar to the user with userID - 1
UserID
5343    0.412117
5190    0.411899
1481    0.392110
1283    0.386597
5705    0.360898
Name: 1, dtype: float64
```

In [81]:

```
users[users['UserID'].isin(lt)]
```

Out[81]:

	UserID	Gender	Age	Occupation	Zip-code
1282	1283	F	18	1	946
1480	1481	M	35	17	770
5189	5190	F	35	0	850
5342	5343	F	25	9	602
5704	5705	F	18	4	900

In [147…

```
#item-based similarity matrix based on KNN and Cosine Similarity

movies_df.head(2)
```

Out[147]:

	MovieID	Title	Genres	Release_year	MovieAge	action	adventure	ai
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995	27	0	0	
1	2	Jumanji (1995)	Adventure|Children's|Fantasy	1995	27	0	1	

2 rows × 25 columns

In [148…

```
movies_train = movies_df.drop(columns=['MovieID', 'Title', 'Genres', 'Relea
movies_train.head(2)
```

Out[148]:

	MovieAge	action	adventure	animation	childrens	comedy	crime	documentary	drama	fa
0	27	0	0	1	1	1	0	0	0	
1	27	0	1	0	1	0	0	0	0	

2 rows × 21 columns

In [149…

```
movies_train.shape
```

Out[149]: (3682, 21)

In [150…

```
##scaling data
scaler = StandardScaler()
scaler.fit(movies_train[movies_train.columns])
movies_cleaned = movies_train.copy()
X = scaler.transform(movies_train[movies_train.columns])  # returns numpy.r

X
```

Out[150]:
```
array([[-0.53391391, -0.39318803, -0.28688766, ..., -0.13510075,
         1.35278064,  4.69953471],
       [-0.53391391, -0.39318803,  3.48568501, ..., -0.13510075,
        -0.05554765,  1.11984014],
       [-0.53391391, -0.39318803, -0.28688766, ..., -0.13510075,
        -0.33016022,  0.53970069],
       ...,
       [-0.83486474, -0.39318803, -0.28688766, ..., -0.13510075,
         0.63770502, -0.56334473],
       [-0.83486474, -0.39318803, -0.28688766, ..., -0.13510075,
         0.98518111, -0.59976604],
       [-0.83486474, -0.39318803, -0.28688766, ..., -0.13510075,
         0.80786084,  0.30556369]])
```

In [151…
```
X.shape
```

Out[151]:
```
(3682, 21)
```

In [152…
```
# Item similarity matrix using cosine similarity

item_cosine_sim = cosine_similarity(X)
item_cosine_sim = pd.DataFrame(item_cosine_sim, index=movies_df.MovieID, co
item_cosine_sim
```

Out[152]:

MovieID	1	2	3	4	5	6	7	8
MovieID								
1	1.000000	0.206599	0.101794	-0.088609	0.106230	0.094914	0.120728	0.208012
2	0.206599	1.000000	-0.084843	-0.184710	-0.107904	-0.038795	-0.088067	0.534626
3	0.101794	-0.084843	1.000000	0.183101	0.451199	-0.139913	0.985042	-0.135685
4	-0.088609	-0.184710	0.183101	1.000000	0.559063	-0.362684	0.130525	-0.191480
5	0.106230	-0.107904	0.451199	0.559063	1.000000	-0.205943	0.423882	-0.097538
...	...	...	...	...	...	...	...	...
3948	0.435081	-0.013099	0.416313	0.283719	0.755764	0.063513	0.447125	-0.138885
3949	-0.021710	-0.101692	-0.257068	0.176128	-0.198856	-0.072609	-0.161752	-0.136008
3950	-0.239761	-0.147750	-0.302572	0.330082	-0.177010	-0.219685	-0.247340	-0.100236
3951	-0.209562	-0.141424	-0.301314	0.261922	-0.192284	-0.186220	-0.222576	-0.102040
3952	-0.042877	-0.100012	-0.257851	0.018279	-0.280474	0.326783	-0.218145	-0.157792

3682 rows × 3682 columns

In [153…
```
item_cosine_sim.shape
```

Out[153]:
```
(3682, 3682)
```

Query - List of 5 movies to recommend to a user who has liked 'The Shawshank Redemption (1994)' MovieID - 318

In [154…
```
movies[movies['MovieID']=='318']
```

Out[154]:

	MovieID	Title	Genres	Release_year	MovieAge	Decade
315	318	Shawshank Redemption, The (1994)	Drama	1994	28	1990

In [155…

```
print("Here is a list of 5 movies to recommend to a user who has liked 'Sha
lt = list(pd.DataFrame(item_cosine_sim['318'].sort_values(ascending=False).
item_cosine_sim['318'].sort_values(ascending=False).iloc[1:6]
```

```
Here is a list of 5 movies to recommend to a user who has liked 'Shawshank
Redemption, The (1994)'
```

Out[155]:

```
MovieID
1704    0.986775
2959    0.977749
1961    0.975023
1225    0.971536
1193    0.968353
Name: 318, dtype: float64
```

In [91]:

```
movies[movies['MovieID'].isin(lt)]
```

Out[91]:

	MovieID	Title	Genres	Release_year	MovieAge
1176	1193	One Flew Over the Cuckoo's Nest (1975)	Drama	1975	47
1207	1225	Amadeus (1984)	Drama	1984	38
1656	1704	Good Will Hunting (1997)	Drama	1997	25
1892	1961	Rain Man (1988)	Drama	1988	34
2890	2959	Fight Club (1999)	Drama	1999	23

Build a Recommender System based on Matrix Factorization

In [92]:

```
rm = ratings.pivot(index = 'UserID', columns ='MovieID', values = 'Rating')
rm.head()
```

Out[92]:

MovieID	1	10	100	1000	1002	1003	1004	1005	1006	1007	...	99	990	991	992	993
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
10	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
100	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
1000	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
1001	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

5 rows × 3706 columns

In [93]:

```
um_mf = ratings[['UserID', 'MovieID', 'Rating']].copy()
um_mf.columns = ['UserId', 'ItemId', 'Rating']  # Lib requires specific co
um_mf.head(2)
```

Out[93]:

	UserId	ItemId	Rating
0	1	1193	5
1	1	661	3

In [94]:
```
#Use cmfrec library to run matrix factorization. (Show results with d=4)

model = CMF(method="als", k=4, lambda_=0.1, user_bias=False, item_bias=Fals
```

In [95]:
```
model.fit(um_mf)
```

Out[95]:
```
Collective matrix factorization model
(explicit-feedback variant)
```

In [96]:
```
model.A_.shape, model.B_.shape
```

Out[96]:
```
((6040, 4), (3706, 4))
```

In [97]:
```
um_mf.Rating.mean(), model.glob_mean_
```

Out[97]:
```
(3.581564453029317, 3.581564426422119)
```

In [98]:
```
#RMSE

rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_
mse(rm.values[rm > 0], rm__[rm > 0])**0.5
```

Out[98]:
```
1.4183050661062944
```

In [99]:
```
#MAPE

mape(rm.values[rm > 0], rm__[rm > 0])
```

Out[99]:
```
0.41151258874570046
```

In [100…
```
ratings.loc[ratings.UserID=='1'].head()
```

Out[100]:

	UserID	MovieID	Rating	Timestamp	Hour
0	1	1193	5	978300760	3
1	1	661	3	978302109	4
2	1	914	3	978301968	4
3	1	3408	4	978300275	3
4	1	2355	5	978824291	5

In [101…
```
#Get d=2 embeddings, and plot the results

#Use cmfrec library to run matrix factorization. (Show results with d=2)

model = CMF(method="als", k=2, lambda_=0.1, user_bias=False, item_bias=Fals
```

In [102…
```
model.fit(um_mf)
```
Out[102]:
```
Collective matrix factorization model
(explicit-feedback variant)
```
In [103…
```
model.A_.shape, model.B_.shape
```
Out[103]:
```
((6040, 2), (3706, 2))
```
In [104…
```
um_mf.Rating.mean(), model.glob_mean_
```
Out[104]:
```
(3.581564453029317, 3.581564426422119)
```
In [105…
```
#RMSE

rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_
mse(rm.values[rm > 0], rm__[rm > 0])**0.5
```
Out[105]:
```
1.3570806112486162
```
In [106…
```
#MAPE

mape(rm.values[rm > 0], rm__[rm > 0])
```
Out[106]:
```
0.40771761654281075
```

Build a Recommender System based Pearson Correlation (Optional)

In [184…
```
#Ask the user to rate a few movies and create a dataframe of the user’s cho
df_997 = df[df['UserID'] == '997']
df_997.head(2)
```
Out[184]:

	MovieID	Title	Genres	Release_year	MovieAge	UserID	Rating	T
88414	1	Toy Story (1995)	Animation|Children's|Comedy	1995	27	997	4	(
88415	34	Babe (1995)	Children's|Comedy|Drama	1995	27	997	4	(

In [185…
```
df_997.shape[0]
```
Out[185]:
```
30
```
In [218…
```
#Find other users who’ve watched the same movies as the new user.
m_lt = list(df_997['MovieID'].values)
```

In [219…

```
#Sort the old users by the count of most movies in common with the new user
#Take the top 100 users
u_lt = list(pd.DataFrame(df[df['MovieID'].isin(m_lt)].groupby('UserID')['Mo
    by='MovieID', ascending=False).head(100).index)
```

In [240…

```
#calculate a Similarity Score for each user using the Pearson Correlation i
user_train = users[users['UserID'].isin(u_lt)]
user_train.head()
```

Out[240]:

	UserID	Gender	Age	Occupation	Zip-code
47	48	M	25	4	921
194	195	M	25	12	104
300	301	M	18	4	618
301	302	M	18	4	049
307	308	M	25	2	100

In [241…

```
#label encode features

le = LabelEncoder()
user_train['Gender'] = le.fit_transform(user_train['Gender'])
```

```
/tmp/ipykernel_195599/3818497058.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  user_train['Gender'] = le.fit_transform(user_train['Gender'])
```

In [242…

```
user_train['Age'] = user_train['Age'].map(
{'1':15, '18':21, '25':30, '35':40, '45':47, '50':52, '56':60})
```

```
/tmp/ipykernel_195599/3605105142.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  user_train['Age'] = user_train['Age'].map(
```

In [244…

```
X_user = user_train.drop(columns=['UserID', 'Occupation', 'Zip-code'])
X_user.head()
```

Out[244]:

	Gender	Age
47	1	30
194	1	30
300	1	21
301	1	21
307	1	30

In [248…

```
##scaling data
scaler = StandardScaler()
scaler.fit(X_user[X_user.columns])
users_cleaned = X_user.copy()
X_u = scaler.transform(X_user[X_user.columns])  # returns numpy.ndarray no

X_u[:5]
```

Out[248]:

```
array([[ 0.531085  ,  0.08834502],
       [ 0.531085  ,  0.08834502],
       [ 0.531085  , -0.93102062],
       [ 0.531085  , -0.93102062],
       [ 0.531085  ,  0.08834502]])
```

In [249…

```
X_u.shape
```

Out[249]:

```
(100, 2)
```

In [258…

```
# User similarity matrix using cosine similarity

user_cosine_sim = cosine_similarity(X_u)
user_cosine_sim = pd.DataFrame(user_cosine_sim, index=user_train.UserID, co
user_cosine_sim
```

Out[258]:

UserID	48	195	301	302	308	355	424	528	
UserID									
48	1.000000	1.000000	0.346237	0.346237	1.000000	0.346237	1.000000	-0.956988	-
195	1.000000	1.000000	0.346237	0.346237	1.000000	0.346237	1.000000	-0.956988	-
301	0.346237	0.346237	1.000000	1.000000	0.346237	1.000000	0.346237	-0.059162	-
302	0.346237	0.346237	1.000000	1.000000	0.346237	1.000000	0.346237	-0.059162	-
308	1.000000	1.000000	0.346237	0.346237	1.000000	0.346237	1.000000	-0.956988	-
...	...	...	...	...	...	...	...	...	
5689	1.000000	1.000000	0.346237	0.346237	1.000000	0.346237	1.000000	-0.956988	-
5795	1.000000	1.000000	0.346237	0.346237	1.000000	0.346237	1.000000	-0.956988	-
5812	-0.977670	-0.977670	-0.535652	-0.535652	-0.977670	-0.535652	-0.977670	0.874650	
5831	1.000000	1.000000	0.346237	0.346237	1.000000	0.346237	1.000000	-0.956988	-
5878	-0.977670	-0.977670	-0.535652	-0.535652	-0.977670	-0.535652	-0.977670	0.874650	

100 rows × 100 columns

In [275…

```
#Get the top 10 users with the highest similarity indices, all the movies i
#and add Weighted movie Ratings by Multiplying the Rating to the Similarity
df_sim = pd.DataFrame(user_cosine_sim['997']).sort_values(by='997', ascendi
df_sim.rename({'997':'sim_score'}, axis=1)
```

Out[275]:

	sim_score
UserID	
5555	1.000000
997	1.000000
881	0.980091
1112	0.980091
3729	0.980091
1246	0.980091
3471	0.980091
1447	0.980091
3391	0.980091
2010	0.980091

In [284…

```
#top 5 recommended movies for user 881
df_881 = pd.DataFrame()
df_881['Movie'] = df_997['Title']
df_881['score'] = df_997['Rating']*0.980091
df_881.sort_values(by='score', ascending=False).head()
```

Out[284]:

	Movie	score
88427	Princess Bride, The (1987)	4.900455
88417	Shawshank Redemption, The (1994)	4.900455
88418	Forrest Gump (1994)	4.900455
88436	Matrix, The (1999)	4.900455
88431	Saving Private Ryan (1998)	4.900455

Questionnaire

In [116…

```
df.head(2)
```

Out[116]:

	MovieID	Title	Genres	Release_year	MovieAge	UserID	I
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995	27	1	
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1995	27	1	

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

In [125…

```
df.groupby(by='Age')['MovieID'].count()
```

Out[125]:
```
Age
1      27132
18    183047
25    394105
35    198084
45     83161
50     72071
56     38544
Name: MovieID, dtype: int64
```

Ans: Users of age group 25-34 (25) have watched and rated most number of movies

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

In [143…
```
df.groupby(by='Occupation')['MovieID'].count()
```

Out[143]:
```
Occupation
0     130001
1      84936
10     23238
11     20462
12     56931
13     13658
14     48952
15     22821
16     45815
17     72534
18     12050
19     14841
2      49823
20     60098
3      31520
4     130626
5      21781
6      37040
7     105013
8       2692
9      11312
Name: MovieID, dtype: int64
```

Ans: Users belonging to college/grad students (4) have watched and rated the most number of movies

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

In [122…
```
df.groupby(by='Gender')['MovieID'].count()
```

Out[122]:
```
Gender
F    245554
M    750590
Name: MovieID, dtype: int64
```

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 [130…
```
movies['Decade'] = movies['Release_year'].apply(lambda x: (x//10)*10)
movies.groupby(by='Decade')['MovieID'].count()
```

Out[130]:
```
Decade
1910       3
1920      34
1930      76
1940     126
1950     167
1960     188
1970     244
1980     592
1990    2272
2000     156
Name: MovieID, dtype: int64
```

Ans: (b-90s) Most of the movies present in our dataset were released 90s

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

In [140…
```
movies_df[['MovieID','Title','rate_ct']].sort_values(by='rate_ct', ascendir
```

Out[140]:

	MovieID	Title	rate_ct
2635	2858	American Beauty (1999)	3428
251	260	Star Wars: Episode IV - A New Hope (1977)	2991
1097	1196	Star Wars: Episode V - The Empire Strikes Back...	2990
1111	1210	Star Wars: Episode VI - Return of the Jedi (1983)	2883
462	480	Jurassic Park (1993)	2672

Ans: The movie with maximum no. of ratings is 'American Beauty (1999)'

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

In [146…
```
movies[movies['Title'] == 'Liar Liar (1997)']
```

Out[146]:

	MovieID	Title	Genres	Release_year	MovieAge	Decade
1455	1485	Liar Liar (1997)	Comedy	1997	25	1990

In [158…
```
print("Here is a list of top 3 movies similar to 'Liar Liar'")
lt = list(pd.DataFrame(item_cosine_sim['1455'].sort_values(ascending=False)
item_cosine_sim['1455'].sort_values(ascending=False).iloc[1:4]
```

```
Here is a list of top 3 movies similar to 'Liar Liar'
```

Out[158]:
```
MovieID
295     0.999822
1550    0.998767
499     0.998463
Name: 1455, dtype: float64
```

In [159…
```
movies[movies['MovieID'].isin(lt)]
```

Out[159]:

	MovieID	Title	Genres	Release_year	MovieAge	Decade
292	295	Pyromaniac's Love Story, A (1995)	Comedy|Romance	1995	27	1990
495	499	Mr. Wonderful (1993)	Comedy|Romance	1993	29	1990
1511	1550	Trial and Error (1997)	Comedy|Romance	1997	25	1990

Ans: The top 3 movies similar to 'Liar Liar' are

A Pyromaniac's Love Story

Mr. Wonderful

Trial and Error

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

Ans: On the basis of approach, Collaborative Filtering methods can be classified into Item-Item-based, User-User-based and User-Item-based

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

Ans: Pearson Correlation ranges between -1 to 1 and, Cosine Similarity also belongs to the interval between -1 to 1.

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

Ans: RMSE - 1.357 MAPE - 0.408

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

In [162…

```
m =  [[1, 0], [3, 7]]
```

In [170…

```
# dense to sparse
A = array(m)

# convert to sparse matrix (CSR method)
S = csr_matrix(A)
print(S)
```

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

Ans:

(0, 0) 1

(1, 0) 3

(1, 1) 7

In [ ]: