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.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
movies=pd.read_fwf('zee-movies.dat',encoding='ISO-8859-1')
users=pd.read_fwf('zee-users.dat',encoding='ISO-8859-1')
ratings=pd.read_fwf('zee-ratings.dat',encoding='ISO-8859-1')
```

Define Problem Statement and Formatting the Data (20 points)

1. Definition of the problem (as per the given problem statement with additional views)

2. Formatting the data files to bring them into a workable format

3. Merging the data files and creating a single consolidated dataframe

In [3]:
```
movies.shape
```

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

In [4]:
```
movies=movies['Movie ID::Title::Genres'].str.split('::',expand=True)
movies.columns=['MovieID','title','genres']
```

In [5]:
```
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 [6]:
```
movies.describe()
```

Out[6]:

	MovieID	title	genres
count	3883	3883	3858
unique	3883	3883	360
top	1	Toy Story (1995)	Drama
freq	1	1	830

In [7]:
```
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 [8]:
```
"""
m=movies.copy()
m['genres'] = m['genres'].str.split('|')
m = m.explode('genres')
m=m[m['genres'].isin(['Animation', 'Comedy', 'Adventure', 'Fantasy',
       'Romance', 'Drama', 'Action', 'Crime', 'Thriller', 'Horror',
       'Sci-Fi', 'Documentary', 'War', 'Musical', 'Mystery', 'Film-Noir',
        'Western', 'Children'])]
"""
```

Out[8]:
```
"\nm=movies.copy()\nm['genres'] = m['genres'].str.split('|')\nm = m.explode
('genres')\nm=m[m['genres'].isin(['Animation', 'Comedy', 'Adventure', 'Fanta
sy',\n       'Romance', 'Drama', 'Action', 'Crime', 'Thriller', 'Horror',\n
'Sci-Fi', 'Documentary', 'War', 'Musical', 'Mystery', 'Film-Noir',\n
'Western', 'Children'])]\n"
```

In [9]:
```
ratings.head()
```

Out[9]:

	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 [10]:
```
ratings=ratings['UserID::MovieID::Rating::Timestamp'].str.split('::',expand=
ratings.columns=['UserID','MovieID','Rating','Timestamp']
```

In [11]:
```
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 [12]:
```
users=users['UserID::Gender::Age::Occupation::Zip-code'].str.split('::',expa
users.columns=['UserID','Gender','Age','Occupation','Zip-code']
```

In [13]:
```
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 [14]:
```
s=movies.merge(ratings,on='MovieID')
df=s.merge(users,on='UserID')
```

Performing EDA, Data Cleaning, and Feature Engineering (20 Points)

1. Reviewing the shape and structure of the dataset

2. Performing necessary type conversion and deriving new features

3. Investigating the data for any inconsistency

4. Group the data according to the average rating and no. of ratings

In [15]:
```
df.shape
```

Out[15]:
```
(1000209, 10)
```

In [16]:
```
df['MovieID']=df.MovieID.apply(lambda x: int(x))
```

In [17]:
```
df = df[~df['genres'].isna()]
```

In [18]:
```
df['year']=df.title.str[-5:-1]
```

In [19]:
```
df['UserID']=df.UserID.apply(lambda x: int(x))
df['Rating']=df.Rating.apply(lambda x: int(x))
df['Timestamp']=df.Timestamp.apply(lambda x: int(x))
```

In [20]:
```
from datetime import datetime
df['hour'] = df['Timestamp'].apply(lambda x: datetime.fromtimestamp(x).hour)
```

In [21]:
```
df.UserID=df.UserID.apply(lambda x: int(x))
df.Age=df.Age.apply(lambda x: int(x))
df.Occupation=df.Occupation.apply(lambda x: int(x))
```

In [22]:
```
df.drop('Timestamp',axis=1,inplace=True)
```

Group the data according to the average rating and no. of ratings

In [23]:
```
df.groupby('UserID')['Rating'].mean().reset_index()
```

Out[23]:

	UserID	Rating
0	1	4.188679
1	2	3.713178
2	3	3.901961
3	4	4.190476
4	5	3.146465
...	...	...
6035	6036	3.297052
6036	6037	3.715000
6037	6038	3.800000
6038	6039	3.875000
6039	6040	3.566766

6040 rows × 2 columns

In [24]:
```
df.groupby('UserID')['Rating'].count().reset_index()
```

Out[24]:

	UserID	Rating
0	1	53
1	2	129
2	3	51
3	4	21
4	5	198
...	...	...
6035	6036	882
6036	6037	200
6037	6038	20
6038	6039	120
6039	6040	337

6040 rows × 2 columns

In [25]:
```
df.groupby('MovieID')['Rating'].mean().reset_index()
```

Out[25]:

	MovieID	Rating
0	1	4.146846
1	2	3.201141
2	3	3.016736
3	4	2.729412
4	5	3.006757
...	...	...
3677	3948	3.635731
3678	3949	4.115132
3679	3950	3.666667
3680	3951	3.900000
3681	3952	3.780928

3682 rows × 2 columns

In [26]:
```
df.groupby('MovieID')['Rating'].count().reset_index()
```

Out[26]:

	MovieID	Rating
0	1	2077
1	2	701
2	3	478
3	4	170
4	5	296
...	...	...
3677	3948	862
3678	3949	304
3679	3950	54
3680	3951	40
3681	3952	388

3682 rows × 2 columns

Build a Recommender System based on Pearson Correlation (10 Points)

In [27]:
```
mov=df.copy()
mov['genres'] = mov['genres'].str.split('|')
mov = mov.explode('genres')
mov=mov[mov['genres'].isin(['Animation', 'Comedy', 'Adventure', 'Fantasy',
        'Romance', 'Drama', 'Action', 'Crime', 'Thriller', 'Horror',
        'Sci-Fi', 'Documentary', 'War', 'Musical', 'Mystery', 'Film-Noir',
         'Western', 'Children'])]
```

1. Creating a pivot table of movie titles & user id and imputing the NaN values

In [28]:
```
mov=mov.pivot_table(index='UserID', columns='title', values='Rating')
mov =mov.fillna(0)
```

In [29]:
```
ct=mov.corr()
```

2.Use the Item-based approach to create a simple recommender system that uses Pearson Correlation

In [30]:
```
a=input('Enter the movie title: ')
ct[a].sort_values(ascending=False).iloc[:10]
```

```
Enter the movie title: Toy Story (1995)
```

Out[30]:
```
title
Toy Story (1995)                           1.000000
Toy Story 2 (1999)                         0.487370
Aladdin (1992)                             0.470753
Lion King, The (1994)                      0.411131
Groundhog Day (1993)                       0.407547
Bug's Life, A (1998)                       0.402679
Beauty and the Beast (1991)                0.395510
Babe (1995)                                0.378794
Wayne's World (1992)                       0.370424
There's Something About Mary (1998)        0.357726
Name: Toy Story (1995), dtype: float64
```

Build a Recommender System based on Cosine Similarity. (20 Points)

In [31]:
```
## User Similarity Matrix
us=df.copy()
us=us.pivot_table(index='UserID', columns='title', values='Rating')
us=us.fillna(0)
us
```

Out[31]:

title	$1,000,000 Duck (1971)	'Night Mother (1986)	'Til There Was You (1997)	'burbs, The (1989)	...And Justice for All (1979)	1-900 (1994)	10 Things I Hate About You (1999)	101 Dalmatians (1961)	1 Dalmatia (199
UserID									
1	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	(
3	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	(
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
...	...	...	...	...	...	...	...	...	
6036	0.0	3.0	0.0	0.0	0.0	0.0	2.0	4.0	(
6037	0.0	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	(
6039	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
6040	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(

6040 rows × 3682 columns

In [32]:
```
## Item Similarity Matrix
it=df.copy()
it['genres'] = it['genres'].str.split('|')
it = it.explode('genres')
it=it[it['genres'].isin(['Animation', 'Comedy', 'Adventure', 'Fantasy',
       'Romance', 'Drama', 'Action', 'Crime', 'Thriller', 'Horror',
       'Sci-Fi', 'Documentary', 'War', 'Musical', 'Mystery', 'Film-Noir',
        'Western', 'Children'])]
```

In [33]:
```
it=it.pivot_table(index='title', columns='genres', values='Rating')
it= ~it.isna()
it = it.astype(int)
it
```

Out[33]:

genres title	Action	Adventure	Animation	Children	Comedy	Crime	Documentary	Drar
$1,000,000 Duck (1971)	0	0	0	0	1	0	0	
'Night Mother (1986)	0	0	0	0	0	0	0	
'Til There Was You (1997)	0	0	0	0	0	0	0	
'burbs, The (1989)	0	0	0	0	1	0	0	
...And Justice for All (1979)	0	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	
Zachariah (1971)	0	0	0	0	0	0	0	
Zed & Two Noughts, A (1985)	0	0	0	0	0	0	0	
Zero Effect (1998)	0	0	0	0	1	0	0	
Zero Kelvin (Kjærlighetens kjøtere) (1995)	1	0	0	0	0	0	0	
eXistenZ (1999)	1	0	0	0	0	0	0	

3657 rows × 18 columns

In [34]:
```
from sklearn.neighbors import NearestNeighbors
```

In [35]:
```
neigh = NearestNeighbors(n_neighbors=11,metric='cosine')
neigh.fit(it)
```

Out[35]:
```
NearestNeighbors(metric='cosine', n_neighbors=11)
```

In [36]:
```
movies.MovieID=movies.MovieID.apply(lambda x: int(x))
```

In [37]:
```
b=input('Enter the name of the movie: ')
n=neigh.kneighbors(it.loc[b].values.reshape(1,-1),11,return_distance=False)
movies[movies.MovieID.isin(n[0])]
```

```
Enter the name of the movie: Toy Story (1995)
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:450: UserWarning:
X does not have valid feature names, but NearestNeighbors was fitted with fe
ature names
  warnings.warn(
```

Out[37]:

	MovieID	title	genres
137	139	Target (1995)	Action|Drama
319	322	Swimming with Sharks (1995)	Comedy|Drama
548	552	Three Musketeers, The (1993)	Action|Adventure|Comedy
640	645	Nelly & Monsieur Arnaud (1995)	Drama
766	776	Babyfever (1994)	Comedy|Drama
2747	2816	Iron Eagle II (1988)	Action|War
2776	2845	White Boys (1999)	Drama
2992	3061	Holiday Inn (1942)	Comedy|Musical
3297	3366	Where Eagles Dare (1969)	Action|Adventure|War
3298	3367	Devil's Brigade, The (1968)	War
3558	3627	Carnival of Souls (1962)	Horror|Thriller

Build a Recommender System based on Matrix Factorization. (30 Points)

In [38]:

```
rm_raw = ratings[['UserID', 'MovieID', 'Rating']].copy()
rm_raw.columns = ['UserId', 'ItemId', 'Rating']
rm_raw.head()
```

Out[38]:

	UserId	ItemId	Rating
0	1	1193	5
1	1	661	3
2	1	914	3
3	1	3408	4
4	1	2355	5

In [39]:

```
from cmfrec import CMF
model = CMF(k=7,lambda_=0.1, user_bias=False, item_bias=False, verbose=False
model.fit(rm_raw)
```

```
/opt/anaconda3/lib/python3.9/site-packages/cmfrec/__init__.py:132: UserWarni
ng: Attempting to use more than 1 thread, but package was built without mult
i-threading support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
```

Out[39]:

```
Collective matrix factorization model
(explicit-feedback variant)
```

In [40]:

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

Out[40]:

MovieID	1	10	100	1000	1002	1003	1004	1005	1006	1007	...	99	990	991	992
UserID															
1	5	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
100	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
1001	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0

5 rows × 3706 columns

In [41]:

```
from sklearn.metrics import mean_squared_error as mse
from sklearn.metrics import mean_absolute_percentage_error as mape
rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_
mse(rm.values[rm > 0], rm__[rm > 0])**0.5
```

Out[41]: 1.509118434433985

In [42]:

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

Out[42]: 0.4277082530313631

In [43]:

```
top_items = model.topN(user=5, n=10)
top_items=pd.Series(top_items)
top_items=top_items.apply(lambda x: int(x)).values
movies.loc[movies.MovieID.isin(top_items)]
```

Out[43]:

	MovieID	title	genres
52	53	Lamerica (1994)	Drama
910	922	Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)	Film-Noir
911	923	Citizen Kane (1941)	Drama
989	1002	Ed's Next Move (1996)	Comedy
1194	1212	Third Man, The (1949)	Mystery|Thriller
1997	2066	Out of the Past (1947)	Film-Noir
2770	2839	West Beirut (West Beyrouth) (1998)	Drama
3065	3134	Grand Illusion (Grande illusion, La) (1937)	Drama|War
3074	3143	Hell in the Pacific (1968)	Drama|War
3739	3808	Two Women (La Ciociara) (1961)	Drama|War

In [44]:

```
model2=model.swap_users_and_items(precompute=True)
```

```
/opt/anaconda3/lib/python3.9/site-packages/cmfrec/__init__.py:132: UserWarni
ng: Attempting to use more than 1 thread, but package was built without mult
i-threading support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
```

In [45]:

```
top_items1 = model2.topN(user=8, n=20)
top_items1=pd.Series(top_items1)
top_items1=top_items1.apply(lambda x: int(x)).values
movies.loc[movies.MovieID.isin(top_items1)]
```

Out[45]:

	MovieID	title	genres
138	140	Up Close and Personal (1996)	Drama|Romance
659	665	Underground (1995)	War
960	972	Last Time I Saw Paris, The (1954)	Drama
1195	1213	GoodFellas (1990)	Crime|Drama
1312	1332	Believers, The (1987)	Horror|Thriller
1414	1439	Meet Wally Sparks (1997)	Comedy
1420	1445	McHale's Navy (1997)	Comedy|War
1795	1864	Sour Grapes (1998)	Comedy
1838	1907	Mulan (1998)	Animation|Children's
1858	1927	All Quiet on the Western Front (1930)	War
2039	2108	L.A. Story (1991)	Comedy|Romance
2444	2513	Pet Sematary (1989)	Horror
2513	2582	Twin Dragons (Shuang long hui) (1992)	Action|Comedy
3009	3078	Liberty Heights (1999)	Drama
3386	3455	Buddy Boy (1999)	Drama|Thriller
3501	3570	Last September, The (1999)	Drama

In [46]:
```
movies.loc[movies.MovieID==5]
```

Out[46]:

	MovieID	title	genres
4	5	Father of the Bride Part II (1995)	Comedy

In [47]:
```
users.UserID=users.UserID.apply(lambda x: int(x))
```

In [48]:
```
top_items1
```

Out[48]:
```
array([1213,  665, 4811, 3570, 2108, 3078, 5693, 3455, 2582, 5380, 1864,
       1332, 2513, 1445,  972,  140, 1439, 1907, 5145, 1927])
```

Visualization of embeddings for Item-Item Similarity matrix

In [49]:
```
from cmfrec import CMF
model1 = CMF(k=2, user_bias=False, item_bias=False, verbose=False)
model1.fit(rm_raw)
```

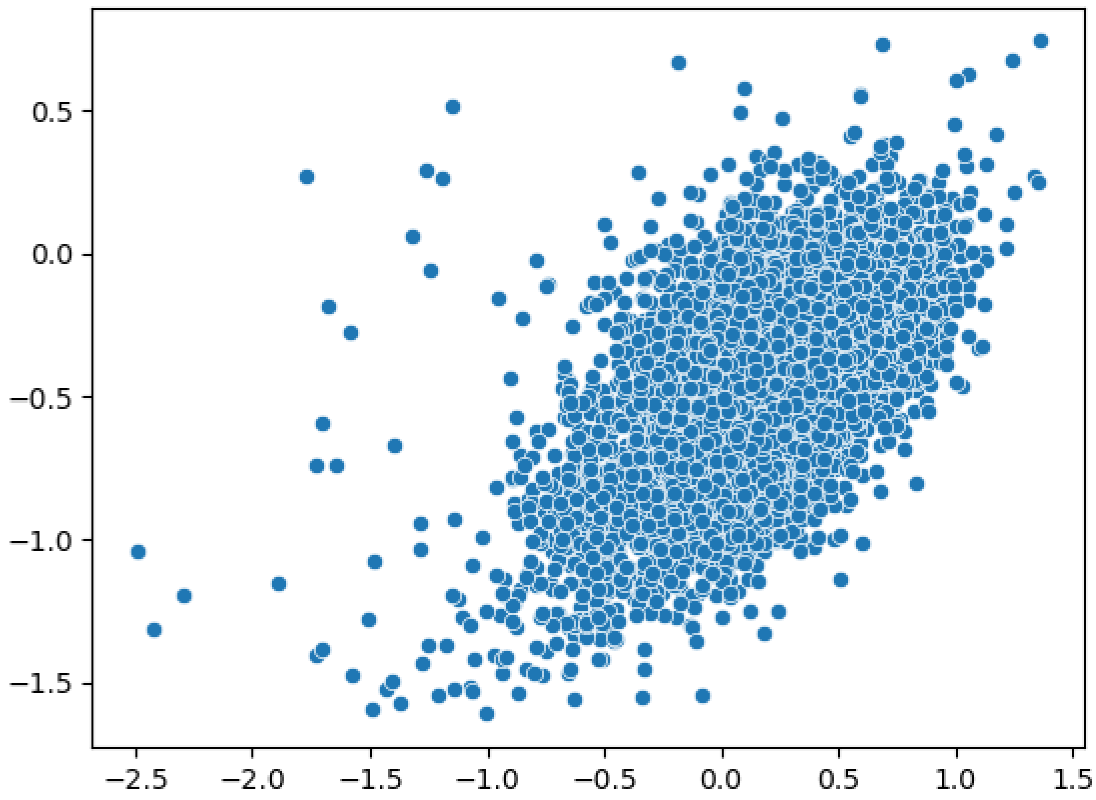
```
/opt/anaconda3/lib/python3.9/site-packages/cmfrec/__init__.py:132: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
```

Out[49]:
```
Collective matrix factorization model
(explicit-feedback variant)
```

In [50]:
```
sns.scatterplot(model1.A_.T[0],model1.A_.T[1])
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: Future
Warning: Pass the following variables as keyword args: x, y. From version 0.
12, the only valid positional argument will be `data`, and passing other arg
uments without an explicit keyword will result in an error or misinterpretat
ion.
  warnings.warn(
```

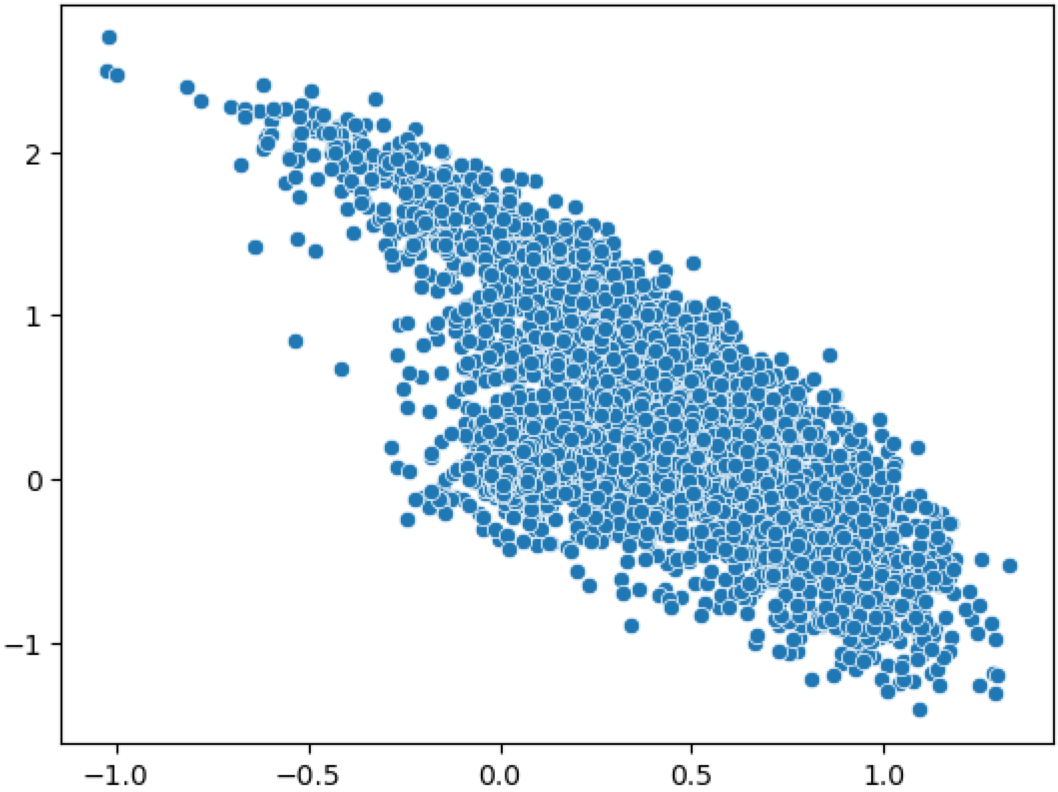
Out[50]: <AxesSubplot:>



In [51]:
```
sns.scatterplot(model1.B_.T[0],model1.B_.T[1])
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: Future
Warning: Pass the following variables as keyword args: x, y. From version 0.
12, the only valid positional argument will be `data`, and passing other arg
uments without an explicit keyword will result in an error or misinterpretat
ion.
  warnings.warn(
```

Out[51]: <AxesSubplot:>



Questionnaire:

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

=>User in the age group of 25 watched and rated the most number of movies

In [52]:
```
df.groupby('Age')['Rating'].count().reset_index().sort_values(by=['Rating'],
```

Out[52]:

	Age	Rating
2	25	394105
3	35	198084
1	18	183047
4	45	83161
5	50	72071
6	56	38544
0	1	27132

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

=> Users belonging to Occupation 4 watched and rated the most movies

In [53]:
```
df.groupby('Occupation')['Rating'].count().reset_index().sort_values(by=['Ra
```

Out[53]:

	Occupation	Rating
4	4	130626
0	0	130001
7	7	105013
1	1	84936
17	17	72534
20	20	60098
12	12	56931
2	2	49823
14	14	48952
16	16	45815
6	6	37040
3	3	31520
10	10	23238
15	15	22821
5	5	21781
11	11	20462
19	19	14841
13	13	13658
18	18	12050
9	9	11312
8	8	2692

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

==> True

In [54]:
```
df.groupby('Gender')['Rating'].count().reset_index().sort_values(by=['Rating
```

Out[54]:

	Gender	Rating
1	M	750590
0	F	245554

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

==> Most of the movies in the dataset were released in 90s

In [55]:
```
df1=df[['title','year']]
df1.year=df1.year.apply(lambda x: int(x))
bins = [1919,1930,1940,1950,1960,1970,1980,1990,2000]
```

```
df1['year'] = pd.cut(df1['year'], bins)
df1.groupby('year')['title'].count().reset_index().sort_values(by=['title'],
```

```
/var/folders/qb/r0jcfxtj39g77g5j7nzw__tm0000gn/T/ipykernel_11670/3313309839.
py:2: 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-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df1.year=df1.year.apply(lambda x: int(x))
/var/folders/qb/r0jcfxtj39g77g5j7nzw__tm0000gn/T/ipykernel_11670/3313309839.
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-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df1['year'] = pd.cut(df1['year'], bins)
```

Out[55]:

	year	title
7	(1990, 2000]	542798
6	(1980, 1990]	237204
5	(1970, 1980]	94218
4	(1960, 1970]	47888
3	(1950, 1960]	35556
2	(1940, 1950]	19660
1	(1930, 1940]	16697
0	(1919, 1930]	2078

5. The movie with maximum no. of ratings is American Beauty (1999) with 3428 ratings.

In [56]:
```
df.groupby('title')['Rating'].count().reset_index().sort_values(by=['Rating'
```

Out[56]:

	title	Rating
126	American Beauty (1999)	3428

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

1.Shaggy Dog, The (1959)

2.That Darn Cat! (1965)

3.Robin Hood: Prince of Thieves (1991)

In [57]:
```
b=input('Enter the name of the movie: ')
n=neigh.kneighbors(it.loc[b].values.reshape(1,-1),11,return_distance=False)
movies[movies.MovieID.isin(n[0])][:3]
```

```
Enter the name of the movie: Toy Story (1995)
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:450: UserWarning:
X does not have valid feature names, but NearestNeighbors was fitted with fe
ature names
  warnings.warn(
```

Out[57]:

	MovieID	title	genres
137	139	Target (1995)	Action|Drama
319	322	Swimming with Sharks (1995)	Comedy|Drama
548	552	Three Musketeers, The (1993)	Action|Adventure|Comedy

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

8. Pearson Correlation ranges between -1 to 1 whereas, Cosine Similarity belongs to the interval between 0 to 1

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

1.509118434433985 for RMSE and 0.4277082530313631 for mape

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

[[1 0] [3 7]]

In [58]:
```
mat=np.array([[1,0],[3,7]])
```

In [59]:
```
from scipy import sparse

b=sparse.csr_matrix(mat)
print(b)
```

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

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [136…
```
df
```

Out[136]:

	MovieID	title	genres	UserID	Rating	Gende
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	F
1	48	Pocahontas (1995)	Animation|Children's|Musical|Romance	1	5	F
2	150	Apollo 13 (1995)	Drama	1	5	F
3	260	Star Wars: Episode IV - A New Hope (1977)	Action|Adventure|Fantas	1	4	F
4	527	Schindler's List (1993)	Drama|War	1	5	F
...	...	...	...	...	...	..
1000204	3513	Rules of Engagement (2000)	Drama|Thriller	5727	4	M
1000205	3535	American Psycho (2000)	Comedy|Horror|Thriller	5727	2	M
1000206	3536	Keeping the Faith (2000)	Comedy|Romance	5727	5	M
1000207	3555	U-571 (2000)	Action|Thriller	5727	3	M
1000208	3578	Gladiator (2000)	Action|Drama	5727	5	M

996144 rows × 11 columns

In [137…

```
df.columns
```

Out[137]:

```
Index(['MovieID', 'title', 'genres', 'UserID', 'Rating', 'Gender', 'Age',
       'Occupation', 'Zip-code', 'year', 'hour'],
      dtype='object')
```

In [138…

```
df1=df.groupby(['MovieID','title'])['Rating','Age','Occupation','year','hour
```

```
/var/folders/qb/r0jcfxtj39g77g5j7nzw__tm0000gn/T/ipykernel_11670/672764214.p
y:1: FutureWarning: Indexing with multiple keys (implicitly converted to a t
uple of keys) will be deprecated, use a list instead.
  df1=df.groupby(['MovieID','title'])['Rating','Age','Occupation','year','ho
ur','Zip-code'].mean().reset_index()
```

In [139…

```
df1
```

Out[139]:

	MovieID	title	Rating	Age	Occupation	hour
0	1	Toy Story (1995)	4.146846	27.700530	8.067886	9.673568
1	2	Jumanji (1995)	3.201141	27.800285	7.680456	9.366619
2	3	Grumpier Old Men (1995)	3.016736	29.276151	7.826360	10.292887
3	4	Waiting to Exhale (1995)	2.729412	27.788235	6.752941	10.829412
4	5	Father of the Bride Part II (1995)	3.006757	27.425676	7.506757	9.611486
...	...	...	...	...	...	...
3677	3948	Meet the Parents (2000)	3.635731	27.737819	8.305104	9.534803
3678	3949	Requiem for a Dream (2000)	4.115132	26.203947	7.578947	9.911184
3679	3950	Tigerland (2000)	3.666667	27.851852	7.407407	8.240741
3680	3951	Two Family House (2000)	3.900000	35.100000	7.800000	9.525000
3681	3952	Contender, The (2000)	3.780928	31.188144	8.378866	8.976804

3682 rows × 6 columns

In [140…
```
df1
X=df1.drop(['MovieID','title'],axis=1)
```

In [141…
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
Xsc=sc.fit_transform(X)
```

In [155…
```
nn = NearestNeighbors(n_neighbors=7,metric='cosine')
nn.fit(Xsc)
```

Out[155]:
```
NearestNeighbors(metric='cosine', n_neighbors=7)
```

In [176…
```
n=nn.kneighbors(Xsc[0:1],11,return_distance=False)
```

In [177…
```
n=n.flatten()
```

In [178…
```
df1.iloc[n]
```

Out[178]:

	MovieID	title	Rating	Age	Occupation	hour
0	1	Toy Story (1995)	4.146846	27.700530	8.067886	9.673568
2694	2918	Ferris Bueller's Day Off (1986)	4.117447	27.949762	8.107264	9.704005
2576	2797	Big (1988)	3.855801	28.833669	7.975184	9.752515
2186	2391	Simple Plan, A (1998)	3.751678	28.612081	7.979866	9.759732
3229	3481	High Fidelity (2000)	3.928623	28.171886	7.925710	9.771304
2473	2692	Run Lola Run (Lola rennt) (1998)	4.224813	27.567164	8.123134	9.430037
1583	1747	Wag the Dog (1997)	3.489526	29.797133	7.938258	9.769570
1526	1673	Boogie Nights (1997)	3.769504	28.913121	8.039894	9.563830
1615	1794	Love and Death on Long Island (1997)	3.430464	29.953642	7.986755	9.688742
2543	2763	Thomas Crown Affair, The (1999)	3.641873	29.285583	8.075298	9.781451
355	368	Maverick (1994)	3.523691	29.822943	7.956359	9.695761

In [162…

Out[162]:

	MovieID	title	Rating	Age	Occupation	hour
0	1	Toy Story (1995)	4.146846	27.700530	8.067886	9.673568
1	2	Jumanji (1995)	3.201141	27.800285	7.680456	9.366619
2	3	Grumpier Old Men (1995)	3.016736	29.276151	7.826360	10.292887
3	4	Waiting to Exhale (1995)	2.729412	27.788235	6.752941	10.829412
4	5	Father of the Bride Part II (1995)	3.006757	27.425676	7.506757	9.611486
...	...	...	...	...	...	...
3677	3948	Meet the Parents (2000)	3.635731	27.737819	8.305104	9.534803
3678	3949	Requiem for a Dream (2000)	4.115132	26.203947	7.578947	9.911184
3679	3950	Tigerland (2000)	3.666667	27.851852	7.407407	8.240741
3680	3951	Two Family House (2000)	3.900000	35.100000	7.800000	9.525000
3681	3952	Contender, The (2000)	3.780928	31.188144	8.378866	8.976804

3682 rows × 6 columns

In [134…

```
movies[movies.MovieID==3146]
```

Out[134]:

	MovieID	title	genres
3077	3146	Deuce Bigalow: Male Gigolo (1999)	Comedy

In [117…

```
df.iloc[0]
```

Out[117]:
```
MovieID                                 1
title                    Toy Story (1995)
genres        Animation|Children's|Comedy
UserID                                  1
Rating                                  5
Gender                                  F
Age                                     1
Occupation                             10
Zip-code                            48067
year                                 1995
hour                                    5
Name: 0, dtype: object
```

In [ ]: