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.

We will be using collaborative filtering

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import sparse
from scipy.stats import pearsonr
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.neighbors import NearestNeighbors
import warnings
```

```
C:\Users\Sharat\AppData\Roaming\Python\Python311\site-packages\pandas\core\arrays
\masked.py:60: UserWarning: Pandas requires version '1.3.6' or newer of 'bottlenec
k' (version '1.3.5' currently installed).
  from pandas.core import (
```

Reading dat files

In [10]:
```
movies = pd.read_fwf('zee-movies.dat', encoding='ISO-8859-1')
ratings = pd.read_fwf('zee-ratings.dat', encoding='ISO-8859-1')
users = pd.read_fwf('zee-users.dat', encoding='ISO-8859-1')
```

In [11]:
```
movies.head()
```

Out[11]:

	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 [12]:
```
ratings.head()
```

Out[12]:

	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 [13]:
```
users.head()
```

Out[13]:

	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

Formatting Data Files

In [14]:
```
movies.drop(columns=['Unnamed: 1', 'Unnamed: 2'], inplace=True)
```

In [15]:
```
# Split the existing column into three separate columns
movies[['Movie ID', 'Title', 'Genres']] = movies['Movie ID::Title::Genres'].str.spl

# Drop the original column
movies.drop(columns=['Movie ID::Title::Genres'], inplace=True)

# Display the modified datafr
movies.head()
```

Out[15]:

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

In [16]:
```
# Split the existing column into four separate columns
ratings[['UserID', 'MovieID', 'Rating', 'Timestamp']] = ratings['UserID::MovieID::R

# Drop the original column
ratings.drop(columns=['UserID::MovieID::Rating::Timestamp'], inplace=True)
```

In [18]:
```
ratings.head()
```

Out[18]:

	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 [19]:

```python
# Split the existing column into five separate columns
users[['UserID', 'Gender', 'Age', 'Occupation', 'Zip-code']] = users['UserID::Gende

# Drop the original column
users.drop(columns=['UserID::Gender::Age::Occupation::Zip-code'], inplace=True)
```

In [21]:

```python
users.head()
```

Out[21]:

	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 [22]:

```python
# Replace numerical codes with categorical values for Gender
users['Gender'] = users['Gender'].replace({'M': 'Male', 'F': 'Female'})

# Replace numerical codes with categorical values for Age
age_mapping = {
    '1': 'Under 18',
    '18': '18-24',
    '25': '25-34',
    '35': '35-44',
    '45': '45-49',
    '50': '50-55',
    '56': '56+'
}
users['Age'] = users['Age'].replace(age_mapping)

# Replace numerical codes with categorical values for Occupation
occupation_mapping = {
    '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'
}
users['Occupation'] = users['Occupation'].replace(occupation_mapping)
```

In [23]:
```
users.head()
```

Out[23]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	Female	Under 18	K-12 Student	48067
1	2	Male	56+	Self-Employed	70072
2	3	Male	25-34	Scientist	55117
3	4	Male	45-49	Executive/Managerial	02460
4	5	Male	25-34	Writer	55455

In [24]:
```
# Check the shape of the dataframe
print("Movies dataframe shape:", movies.shape)

# Check the information of the dataframe
print("\nMovies dataframe information:")
print(movies.info())
```

```
Movies dataframe shape: (3883, 3)

Movies dataframe information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   Movie ID  3883 non-null   object
 1   Title     3883 non-null   object
 2   Genres    3858 non-null   object
dtypes: object(3)
memory usage: 91.1+ KB
None
```

In [25]:
```
# Check the shape of the dataframe
print("Ratings dataframe shape:", ratings.shape)

# Check the information of the dataframe
print("\nRatings dataframe information:")
print(ratings.info())
```

```
Ratings dataframe shape: (1000209, 4)

Ratings dataframe information:
<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
None
```

In [26]:

```
# Check the shape of the dataframe
print("Users dataframe shape:", users.shape)

# Check the information of the dataframe
print("\nUsers dataframe information:")
print(users.info())
```

```
Users dataframe shape: (6040, 5)

Users dataframe information:
<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
None
```

In [27]:

```
# Merge the ratings and movies dataframes on the common column 'MovieID' using an i
#merged_df = pd.merge(movies, ratings, on='MovieID', how='inner')

# Display the merged dataframe
#(merged_df.head())
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
Cell In[27], line 2
      1 # Merge the ratings and movies dataframes on the common column 'MovieID' u
sing an inner join
----> 2 merged_df = pd.merge(movies, ratings, on='MovieID', how='inner')
      4 # Display the merged dataframe
      5 (merged_df.head())

File ~\AppData\Roaming\Python\Python311\site-packages\pandas\core\reshape\merge.p
y:170, in merge(left, right, how, on, left_on, right_on, left_index, right_index,
sort, suffixes, copy, indicator, validate)
    155     return _cross_merge(
    156         left_df,
    157         right_df,
   (...)
    167         copy=copy,
    168     )
    169 else:
--> 170     op = _MergeOperation(
    171         left_df,
    172         right_df,
    173         how=how,
    174         on=on,
    175         left_on=left_on,
    176         right_on=right_on,
    177         left_index=left_index,
    178         right_index=right_index,
    179         sort=sort,
    180         suffixes=suffixes,
    181         indicator=indicator,
    182         validate=validate,
    183     )
    184     return op.get_result(copy=copy)

File ~\AppData\Roaming\Python\Python311\site-packages\pandas\core\reshape\merge.p
y:794, in _MergeOperation.__init__(self, left, right, how, on, left_on, right_on,
left_index, right_index, sort, suffixes, indicator, validate)
    784     raise MergeError(msg)
    786 self.left_on, self.right_on = self._validate_left_right_on(left_on, right_
on)
    788 (
    789     self.left_join_keys,
    790     self.right_join_keys,
    791     self.join_names,
    792     left_drop,
    793     right_drop,
--> 794 ) = self._get_merge_keys()
    796 if left_drop:
    797     self.left = self.left._drop_labels_or_levels(left_drop)

File ~\AppData\Roaming\Python\Python311\site-packages\pandas\core\reshape\merge.p
y:1310, in _MergeOperation._get_merge_keys(self)
   1306 if lk is not None:
   1307     # Then we're either Hashable or a wrong-length arraylike,
   1308     #  the latter of which will raise
   1309     lk = cast(Hashable, lk)
-> 1310     left_keys.append(left._get_label_or_level_values(lk))
   1311     join_names.append(lk)
   1312 else:
   1313     # work-around for merge_asof(left_index=True)

File ~\AppData\Roaming\Python\Python311\site-packages\pandas\core\generic.py:1910,
in NDFrame._get_label_or_level_values(self, key, axis)
```

```
   1908         values = self.axes[axis].get_level_values(key)._values
   1909     else:
-> 1910         raise KeyError(key)
   1912     # Check for duplicates
   1913     if values.ndim > 1:

KeyError: 'MovieID'
```

In [28]:
```
# Rename the 'Movie ID' column to 'MovieID' without spaces in the movies dataframe
movies.rename(columns={'Movie ID': 'MovieID'}, inplace=True)
```

Merging data files into single Dataframe

In [29]:
```
# Merge the ratings and movies dataframes on the common column 'MovieID' using an i
merged_df = pd.merge(movies, ratings, on='MovieID', how='inner')

# Display the merged dataframe
(merged_df.head())
```

Out[29]:

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

In [30]:
```
# Merge the merged_df and users dataframes on the common column 'UserID' using an i
final_df = pd.merge(merged_df, users, on='UserID', how='inner')

# Display the final merged dataframe
(final_df.head())
```

Out[30]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	Female	Under 18	
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008	Female	50-55	
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496	Male	25-34	
3	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952	Male	25-34	Techr
4	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474	Female	35-44	Acad

Reviewing shape and structure

In [31]:
```
final_df.shape
```

Out[31]:
```
(1000209, 10)
```

In [32]:
```
# Make a copy of the merged dataframe
final_df_copy = final_df.copy()
```

In [33]:
```
final_df_copy.sample(10)
```

Out[33]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age
289409	1177	Enchanted April (1991)	Drama	3611	4	966614836	Male	25-34
420689	1429	Jackie Chan's First Strike (1996)	Action	3684	5	966350143	Male	25-34
774420	2879	Operation Condor (Feiying gaiwak) (1990)	Action|Adventure|Comedy	4489	4	983304003	Male	18-24
56443	208	Waterworld (1995)	Action|Adventure	4156	3	965342068	Male	56+
502884	1873	Misérables, Les (1998)	Drama	2692	5	973318362	Female	18-24
396994	1370	Die Hard 2 (1990)	Action|Thriller	668	3	975635187	Female	25-34
697980	2596	SLC Punk! (1998)	Comedy|Drama	3834	5	966396625	Male	18-24
120533	446	Farewell My Concubine (1993)	Drama|Romance	1052	4	974956663	Female	35-44
615169	2282	Pecker (1998)	Comedy|Drama	4447	4	965175344	Male	45-49
695529	2574	Out-of-Towners, The (1999)	Comedy	2116	4	974650867	Male	18-24

In [34]:
```
final_df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 10 columns):
 #   Column      Non-Null Count    Dtype 
---  ------      --------------    ----- 
 0   MovieID     1000209 non-null  object
 1   Title       1000209 non-null  object
 2   Genres      996144 non-null   object
 3   UserID      1000209 non-null  object
 4   Rating      1000209 non-null  object
 5   Timestamp   1000209 non-null  object
 6   Gender      1000209 non-null  object
 7   Age         1000209 non-null  object
 8   Occupation  1000209 non-null  object
 9   Zip-code    1000209 non-null  object
dtypes: object(10)
memory usage: 76.3+ MB
```

Performing necessary type conversion and deriving new features

In [35]:
```
final_df_copy['Rating'] = final_df_copy['Rating'].astype('int32')
```

In [36]:
```
# Convert the 'Timestamp' column to datetime format
final_df_copy['Datetime'] = pd.to_datetime(final_df_copy['Timestamp'], unit='s')
```

```
C:\Users\Sharat\AppData\Local\Temp\ipykernel_45892\3752505912.py:2: FutureWarning:
The behavior of 'to_datetime' with 'unit' when parsing strings is deprecated. In a
future version, strings will be parsed as datetime strings, matching the behavior
without a 'unit'. To retain the old behavior, explicitly cast ints or floats to nu
meric type before calling to_datetime.
  final_df_copy['Datetime'] = pd.to_datetime(final_df_copy['Timestamp'], unit='s')
```

In [37]:
```
warnings.simplefilter('ignore')
```

In [38]:
```
# Extract the release year from the 'Title' column and create a new 'ReleaseYear' c
final_df_copy['ReleaseYear'] = final_df_copy['Title'].str.extract(r'\((\d{4})\)')
```

In [40]:
```
final_df_copy['ReleaseYear'].unique().sort_values()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[40], line 1
----> 1 final_df_copy['ReleaseYear'].unique().sort_values()

AttributeError: 'numpy.ndarray' object has no attribute 'sort_values'
```

In [41]:
```
# Print unique values in the 'ReleaseYear' column in ascending order
print("Unique Release Years (Ascending Order):", sorted(final_df_copy['ReleaseYear'
```

```
Unique Release Years (Ascending Order): [1919, 1920, 1921, 1922, 1923, 1925, 1926,
1927, 1928, 1929, 1930, 1931, 1932, 1933, 1934, 1935, 1936, 1937, 1938, 1939, 194
0, 1941, 1942, 1943, 1944, 1945, 1946, 1947, 1948, 1949, 1950, 1951, 1952, 1953, 1
954, 1955, 1956, 1957, 1958, 1959, 1960, 1961, 1962, 1963, 1964, 1965, 1966, 1967,
1968, 1969, 1970, 1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 198
1, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993, 1994, 1
995, 1996, 1997, 1998, 1999, 2000]
```

In [42]:
```
final_df_copy
```

Out[42]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	Female
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008	Female
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496	Male
3	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952	Male
4	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474	Female
...	...	...	...	...	...	...	...
1000204	3952	Contender, The (2000)	Drama|Thriller	5812	4	992072099	Female
1000205	3952	Contender, The (2000)	Drama|Thriller	5831	3	986223125	Male
1000206	3952	Contender, The (2000)	Drama|Thriller	5837	4	1011902656	Male
1000207	3952	Contender, The (2000)	Drama|Thriller	5927	1	979852537	Male
1000208	3952	Contender, The (2000)	Drama|Thriller	5998	4	1001781044	Male

1000209 rows × 12 columns

In [43]:

```
# Drop rows where 'ReleaseYear' is NaN
final_df_copy.dropna(subset=['ReleaseYear'], inplace=True)
```

In [44]:

```
# Change the data type of 'ReleaseYear' column to int32
final_df_copy['ReleaseYear'] = final_df_copy['ReleaseYear'].astype('int32')
```

In [45]:

```
# Extract the titles of the movies from the 'Title' column
final_df_copy['Title'] = final_df_copy['Title'].str.split(' \(', n=1, expand=True)[
```

In [48]:

```
# Define a function to map release years to decades
def map_to_decade(year):
    if year > 1920 and year <= 1930:
        return '20s'
    elif year > 1930 and year <= 1940:
        return '30s'
    elif year > 1940 and year <= 1950:
```

```python
        return '40s'
    elif year > 1950 and year <= 1960:
        return '50s'
    elif year > 1960 and year <= 1970:
        return '60s'
    elif year > 1970 and year <= 1980:
        return '70s'
    elif year > 1980 and year <= 1990:
        return '80s'
    elif year > 1990 and year <= 2000:
        return '90s'
    elif year > 2000 and year <= 2010:
        return '2000s'
    elif year > 2010 and year <= 2020:
        return '2010s'
    else:
        return 'Unknown'

# Apply the function to create the 'Decade' column
final_df_copy['Decade'] = final_df_copy['ReleaseYear'].apply(map_to_decade)
```

In [49]:

```python
final_df_copy
```

Out[49]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender
0	1	Toy Story	Animation|Children's|Comedy	1	5	978824268	Female
1	1	Toy Story	Animation|Children's|Comedy	6	4	978237008	Female
2	1	Toy Story	Animation|Children's|Comedy	8	4	978233496	Male
3	1	Toy Story	Animation|Children's|Comedy	9	5	978225952	Male
4	1	Toy Story	Animation|Children's|Comedy	10	5	978226474	Female
...	...	...	...	...	...	...	...
1000204	3952	Contender, The	Drama|Thriller	5812	4	992072099	Female
1000205	3952	Contender, The	Drama|Thriller	5831	3	986223125	Male
1000206	3952	Contender, The	Drama|Thriller	5837	4	1011902656	Male
1000207	3952	Contender, The	Drama|Thriller	5927	1	979852537	Male
1000208	3952	Contender, The	Drama|Thriller	5998	4	1001781044	Male

996665 rows × 13 columns

In [50]:
```
final_df_copy.isna().sum()
```

Out[50]:
```
MovieID          0
Title            0
Genres         521
UserID           0
Rating           0
Timestamp        0
Gender           0
Age              0
Occupation       0
Zip-code         0
Datetime         0
ReleaseYear      0
Decade           0
dtype: int64
```

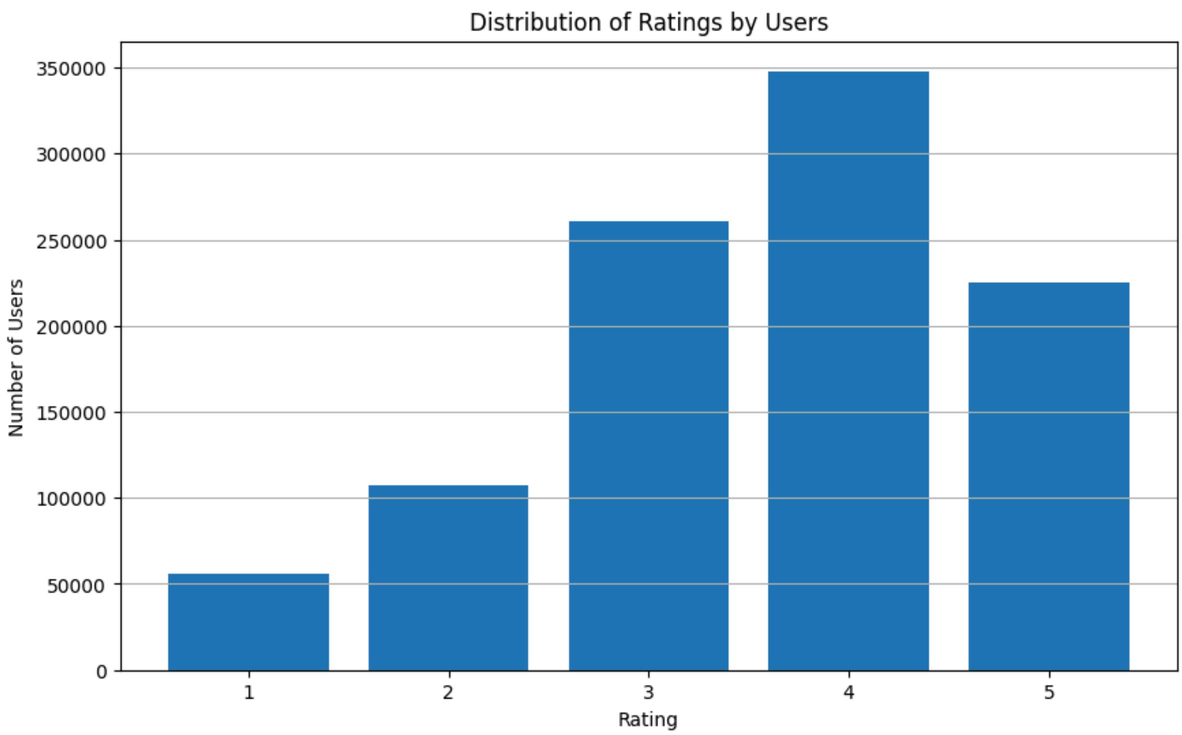
In [51]:

```python
# Check for duplicate rows
duplicate_rows = final_df_copy.duplicated()
num_duplicate_rows = duplicate_rows.sum()

# Display the number of duplicate rows
print("Number of Duplicate Rows:", num_duplicate_rows)
```

```
Number of Duplicate Rows: 0
```

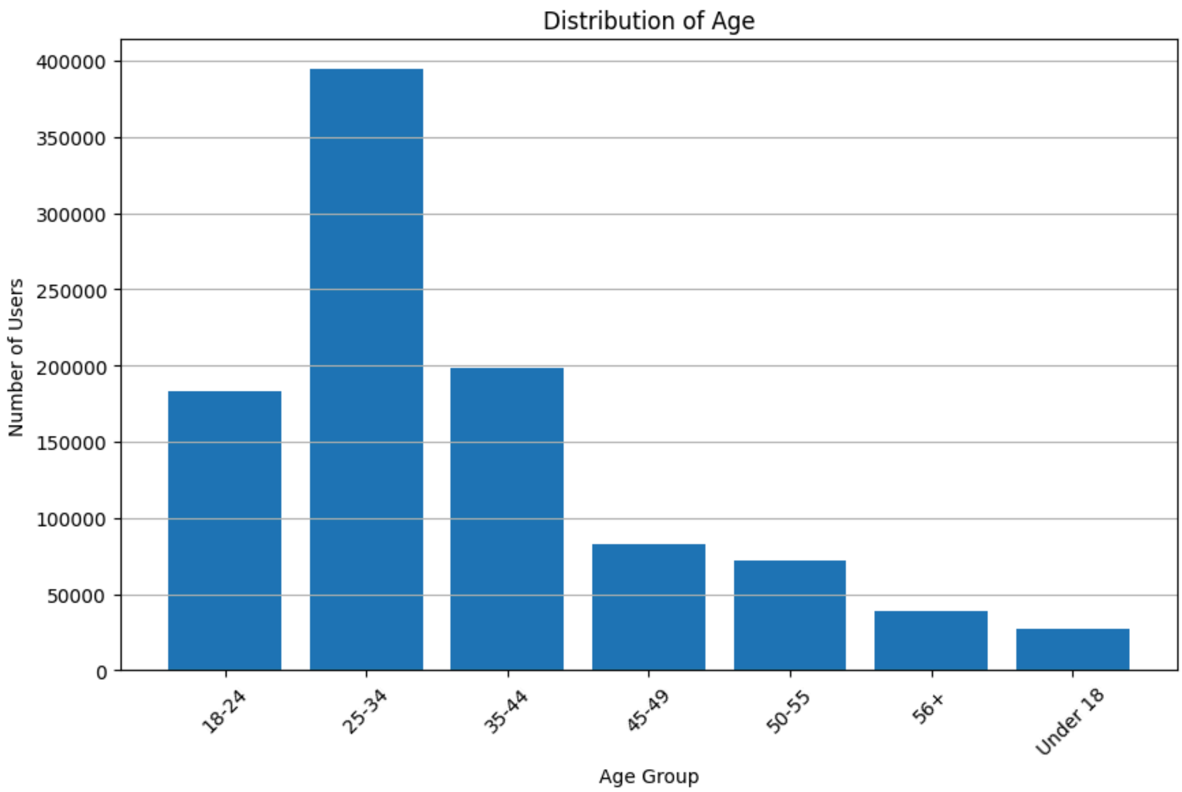
In [53]:

```python
# Count the number of occurrences of each rating
rating_counts = final_df_copy['Rating'].value_counts().sort_index()

# Plotting the graph
plt.figure(figsize=(10, 6))
plt.bar(rating_counts.index, rating_counts.values)
plt.title('Distribution of Ratings by Users')
plt.xlabel('Rating')
plt.ylabel('Number of Users')
plt.xticks(range(1, 6))  # Set x-axis ticks from 1 to 5
plt.grid(axis='y')  # Show grid lines on the y-axis
plt.show()
```



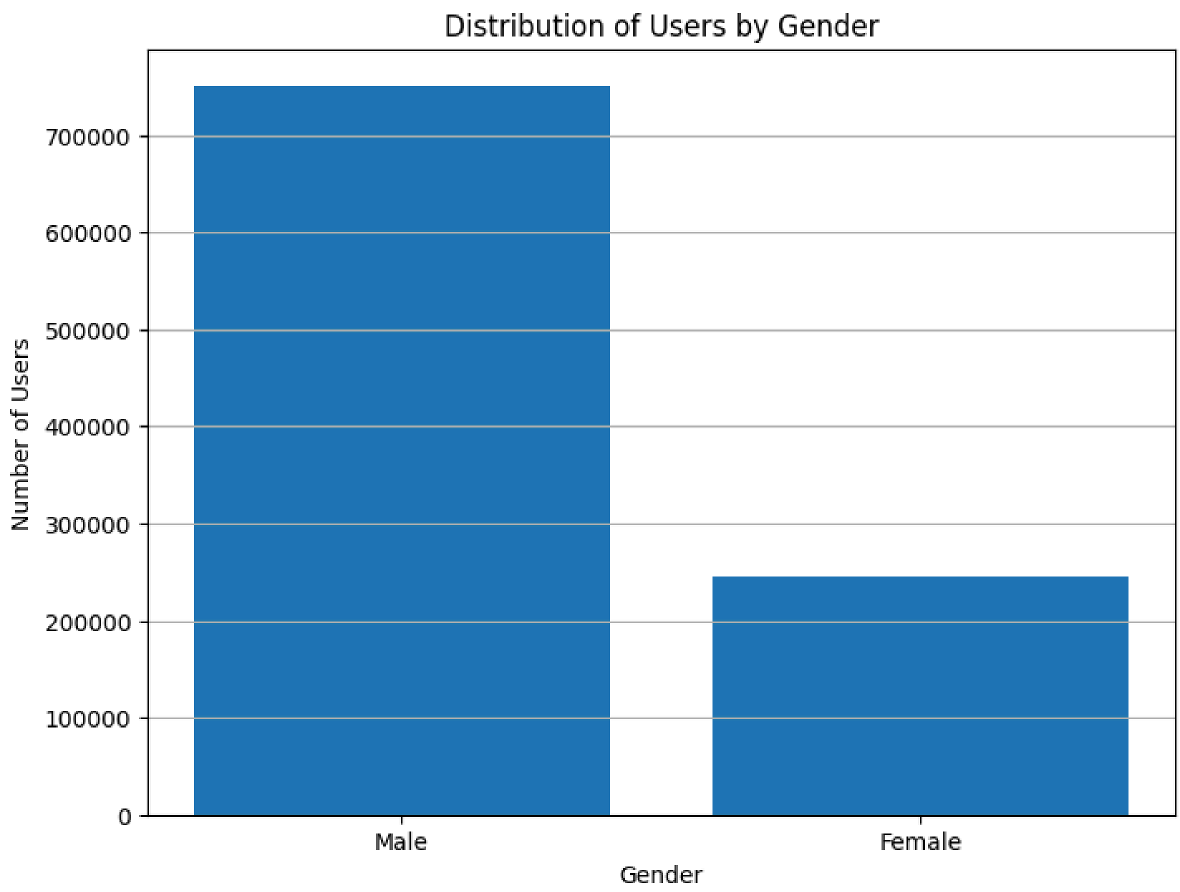
In [54]:

```python
# Count the number of occurrences of each age group
age_counts = final_df_copy['Age'].value_counts().sort_index()

# Plotting the graph
plt.figure(figsize=(10, 6))
plt.bar(age_counts.index, age_counts.values)
plt.title('Distribution of Age')
plt.xlabel('Age Group')
plt.ylabel('Number of Users')
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.grid(axis='y')  # Show grid lines on the y-axis
plt.show()
```



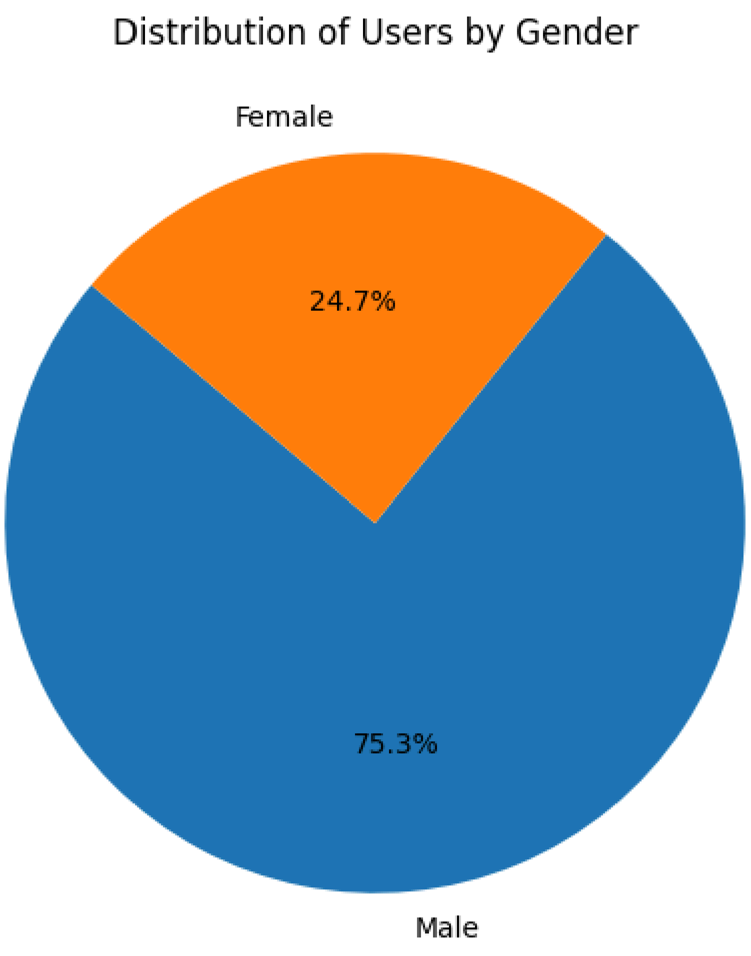
In [55]:

```
# Count the number of occurrences of each gender
gender_counts = final_df_copy['Gender'].value_counts()

# Plotting the graph
plt.figure(figsize=(8, 6))
plt.bar(gender_counts.index, gender_counts.values)
plt.title('Distribution of Users by Gender')
plt.xlabel('Gender')
plt.ylabel('Number of Users')
plt.grid(axis='y')  # Show grid lines on the y-axis
plt.show()
```



In [56]:

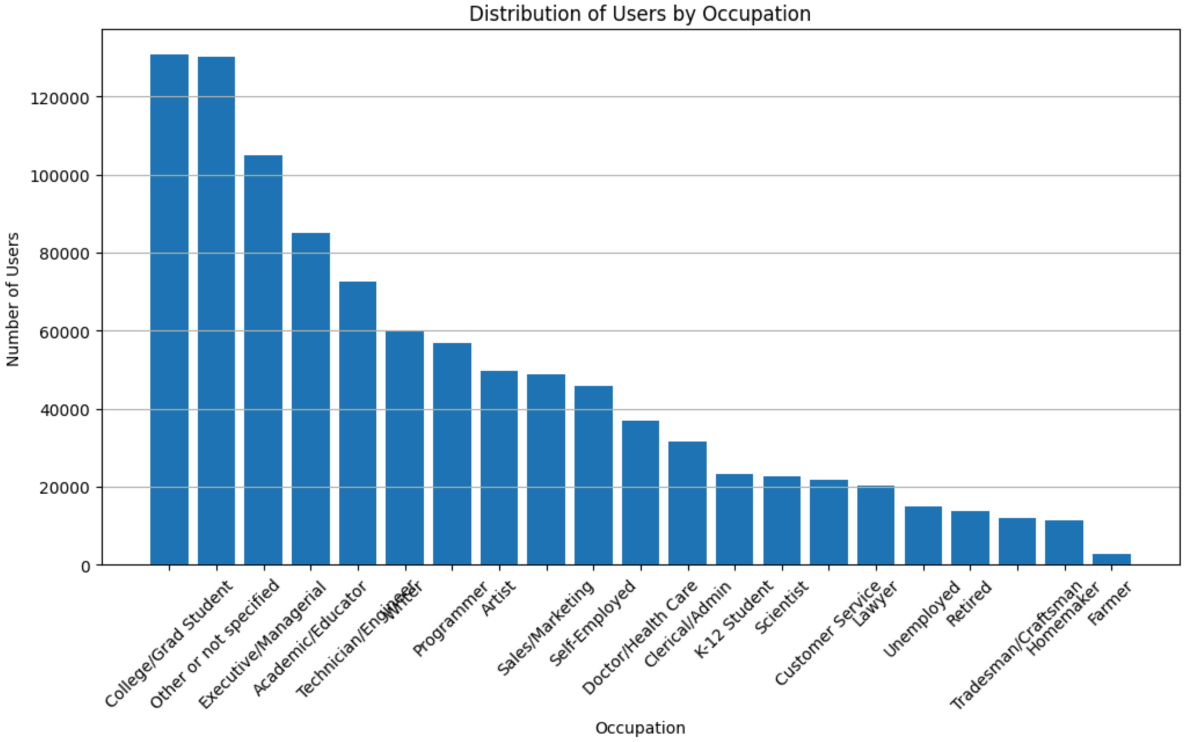
```
# Count the number of occurrences of each gender
gender_counts = final_df_copy['Gender'].value_counts()

# Plotting the pie chart
plt.figure(figsize=(8, 6))
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%', startangle=14
plt.title('Distribution of Users by Gender')
plt.show()
```



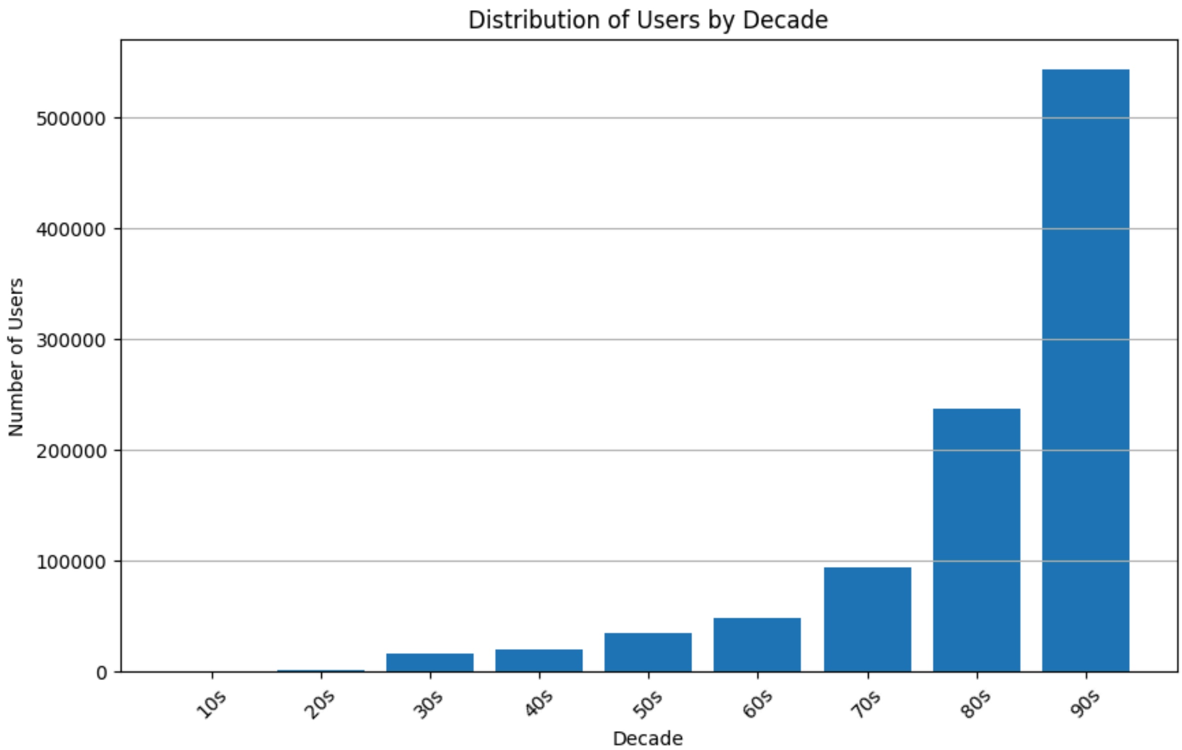
In [59]:
```
users.Gender.value_counts()
```

Out[59]:
```
Gender
Male      4331
Female    1709
Name: count, dtype: int64
```

In [60]:
```
# Count the number of occurrences of each occupation
occupation_counts = final_df_copy['Occupation'].value_counts()

# Plotting the graph
plt.figure(figsize=(12, 6))
plt.bar(occupation_counts.index, occupation_counts.values)
plt.title('Distribution of Users by Occupation')
plt.xlabel('Occupation')
plt.ylabel('Number of Users')
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.grid(axis='y')  # Show grid lines on the y-axis
plt.show()
```



In [65]:
```
# Count the number of occurrences of each decade
decade_counts = final_df_copy['Decade'].value_counts().sort_index()

# Plotting the graph
plt.figure(figsize=(10, 6))
plt.bar(decade_counts.index, decade_counts.values)
plt.title('Distribution of Users by Decade')
plt.xlabel('Decade')
plt.ylabel('Number of Users')
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.grid(axis='y')  # Show grid lines on the y-axis
plt.show()
```



In [62]:
```
final_df_copy['Decade'].value_counts()
```

Out[62]:
```
Decade
90s        542930
80s        237476
70s         94218
60s         48005
50s         35556
40s         19660
30s         16697
20s          2054
Unknown        69
Name: count, dtype: int64
```

In [63]:
```
# Define a function to map release years to decades
def map_to_decade(year):
    if year > 1910 and year <= 1920:
        return '10s'
    elif year > 1920 and year <= 1930:
        return '20s'
    elif year > 1930 and year <= 1940:
        return '30s'
    elif year > 1940 and year <= 1950:
        return '40s'
    elif year > 1950 and year <= 1960:
        return '50s'
    elif year > 1960 and year <= 1970:
        return '60s'
    elif year > 1970 and year <= 1980:
        return '70s'
    elif year > 1980 and year <= 1990:
        return '80s'
    elif year > 1990 and year <= 2000:
        return '90s'
    elif year > 2000 and year <= 2010:
        return '2000s'
    else:
        return 'Unknown'

# Apply the function to create the 'Decade' column
final_df_copy['Decade'] = final_df_copy['ReleaseYear'].apply(map_to_decade)
```

In [64]:
```
final_df_copy['Decade'].value_counts()
```

Out[64]:
```
Decade
90s    542930
80s    237476
70s     94218
60s     48005
50s     35556
40s     19660
30s     16697
20s      2054
10s        69
Name: count, dtype: int64
```

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

In [74]:
```
# Group by 'Title' and calculate aggregate statistics
title_stats = final_df_copy.groupby('Title').agg({'Rating': 'mean', 'Rating': 'cour
title_stats['Avg rating'] = final_df_copy.groupby('Title')['Rating'].mean().round(2
```

```
# Display the new dataframe
(title_stats.head(10))  # Show the first 10 rows for demonstration
```

Out[74]:

	Title	No. of ratings	Avg rating
0	$1,000,000 Duck	37	3.03
1	'Night Mother	70	3.37
2	'Til There Was You	52	2.69
3	'burbs, The	303	2.91
4	...And Justice for All	199	3.71
5	1-900	2	2.50
6	10 Things I Hate About You	700	3.42
7	101 Dalmatians	929	3.38
8	12 Angry Men	616	4.30
9	13th Warrior, The	750	3.16

In [75]:
```
title_stats[title_stats['Title']=='Judgment Night']
```

Out[75]:

	Title	No. of ratings	Avg rating
1746	Judgment Night	133	2.8

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

In [76]:
```
# Create a pivot table of UserID as index, titles as columns, and values as ratings
pivot_table = pd.pivot_table(final_df_copy, values='Rating', index='UserID', columr

# Display the pivot tab
(pivot_table.head())
```

Out[76]:

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	..
UserID											
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	..
10	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	3.0	4.0	..
100	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	..
1000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	..
1001	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	..

5 rows × 3639 columns

In [77]:
```
pivot_table.shape
```

Out[77]:
```
(6040, 3639)
```

In [81]:
```
movie_name = input("Enter a movie name: ")
movie_rating = pivot_table[movie_name]
```

```
Enter a movie name: Liar Liar
```

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

In [83]:
```
similar_movies = pivot_table.corrwith(movie_rating)
```

In [84]:
```
sim_df = pd.DataFrame(similar_movies, columns=['Correlation'])
sim_df.sort_values('Correlation', ascending=False, inplace=True)
```

In [85]:
```
sim_df.iloc[1: , :].head()
```

Out[85]:

Title	Correlation
Mrs. Doubtfire	0.499927
Dumb & Dumber	0.459601
Ace Ventura: Pet Detective	0.458654
Home Alone	0.455967
Wedding Singer, The	0.429222

Print the user similarity matrix and item similarity matrix

In [86]:
```
# Create a pivot table of movies and user ratings
pivot_table_cos = pd.pivot_table(final_df_copy, values='Rating', index='UserID', co

# Calculate cosine similarity for item-item similarity based on movie titles
item_similarity = cosine_similarity(pivot_table_cos.T)

# Create a dataframe of item-item similarity
item_similarity_df = pd.DataFrame(item_similarity, index=pivot_table_cos.columns, c

# Display the item-item similarity dataframe
(item_similarity_df.head())
```

Out[86]:

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	
Title									
$1,000,000 Duck	1.000000	0.072357	0.037011	0.079291	0.060838	0.00000	0.058619	0.189843	0.0
'Night Mother	0.072357	1.000000	0.115290	0.115545	0.159526	0.00000	0.076798	0.137135	0.1
'Til There Was You	0.037011	0.115290	1.000000	0.098756	0.066301	0.08025	0.127895	0.128523	0.0
'burbs, The	0.079291	0.115545	0.098756	1.000000	0.143620	0.00000	0.192191	0.250140	0.1
...And Justice for All	0.060838	0.159526	0.066301	0.143620	1.000000	0.00000	0.075093	0.178928	0.2

5 rows × 3639 columns

In [87]:

```
# Calculate cosine similarity for user-user similarity based on user ratings
user_similarity = cosine_similarity(pivot_table_cos)

# Create a dataframe of user-user similarity
user_similarity_df = pd.DataFrame(user_similarity, index=pivot_table_cos.index, col

# Display the user-user similarity dataframe
(user_similarity_df.head())
```

Out[87]:

UserID	1	10	100	1000	1001	1002	1003	1004	1005
UserID									
1	1.000000	0.255319	0.123967	0.207800	0.139317	0.110320	0.121384	0.180226	0.103896
10	0.255319	1.000000	0.259645	0.280479	0.158703	0.112917	0.141985	0.432536	0.194915
100	0.123967	0.259645	1.000000	0.306067	0.075736	0.110450	0.358686	0.237492	0.172872
1000	0.207800	0.280479	0.306067	1.000000	0.099117	0.047677	0.201722	0.355920	0.325966
1001	0.139317	0.158703	0.075736	0.099117	1.000000	0.164854	0.053887	0.152057	0.138602

5 rows × 6040 columns

Use the Item-based approach to create a recommender system that uses Nearest Neighbors algorithm and Cosine Similarity

In [91]:

```
from sklearn.neighbors import NearestNeighbors
from scipy.sparse import csr_matrix

# Create a sparse matrix using the CSR format
```

```
sparse_matrix = csr_matrix(pivot_table_cos.T.values)

# Fit the Nearest Neighbors model using Cosine Similarity
model = NearestNeighbors(metric='cosine', algorithm='brute')
model.fit(sparse_matrix)

# Get input movie name from the user
movie_name = input("Enter the name of a movie: ")

# Find the index of the input movie in the pivot table
movie_index = pivot_table_cos.columns.get_loc(movie_name)

# Find the 6 nearest neighbors (including the input movie itself)
distances, indices = model.kneighbors(sparse_matrix[movie_index], n_neighbors=6)

# Get the indices of the recommended movies (excluding the input movie itself)
recommended_indices = indices.flatten()[1:]

# Get the titles of the recommended movies
recommended_movies = pivot_table_cos.columns[recommended_indices]

# Display the top 5 recommended movies
print("Top 5 recommended movies similar to", movie_name)
for i, movie in enumerate(recommended_movies[:5], 1):
    print(i, "-", movie)
```

```
Enter the name of a movie: Liar Liar
Top 5 recommended movies similar to Liar Liar
1 - Mrs. Doubtfire
2 - Ace Ventura: Pet Detective
3 - Dumb & Dumber
4 - Home Alone
5 - Wayne's World
```

Create a Recommender System using the Matrix Factorization method

In [95]:

```
!pip install cmfrec
```

```
Collecting cmfrec
  Using cached cmfrec-3.5.1.post8.tar.gz (268 kB)
  Installing build dependencies: started
  Installing build dependencies: finished with status 'done'
  Getting requirements to build wheel: started
  Getting requirements to build wheel: finished with status 'done'
  Preparing metadata (pyproject.toml): started
  Preparing metadata (pyproject.toml): finished with status 'done'
Requirement already satisfied: cython in c:\users\sharat\appdata\roaming\python\py
thon311\site-packages (from cmfrec) (3.0.9)
Requirement already satisfied: numpy>=1.25 in c:\users\sharat\appdata\roaming\pyth
on\python311\site-packages (from cmfrec) (1.26.4)
Requirement already satisfied: scipy in c:\users\sharat\appdata\roaming\python\pyt
hon311\site-packages (from cmfrec) (1.11.4)
Requirement already satisfied: pandas in c:\users\sharat\appdata\roaming\python\py
thon311\site-packages (from cmfrec) (2.2.1)
Collecting findblas (from cmfrec)
  Using cached findblas-0.1.23-py3-none-any.whl
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\sharat\appdata\r
oaming\python\python311\site-packages (from pandas->cmfrec) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\sharat\appdata\roaming\pyt
hon\python311\site-packages (from pandas->cmfrec) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in c:\users\sharat\appdata\roaming\p
ython\python311\site-packages (from pandas->cmfrec) (2024.1)
Requirement already satisfied: six>=1.5 in c:\users\sharat\appdata\roaming\python
\python311\site-packages (from python-dateutil>=2.8.2->pandas->cmfrec) (1.16.0)
Building wheels for collected packages: cmfrec
  Building wheel for cmfrec (pyproject.toml): started
  Building wheel for cmfrec (pyproject.toml): finished with status 'done'
  Created wheel for cmfrec: filename=cmfrec-3.5.1.post8-cp311-cp311-win_amd64.whl
size=1068419 sha256=0ed70e0deaae88950d08c7182bd748f512160e912917783c2d89bfe95af805
a7
  Stored in directory: c:\users\sharat\appdata\local\pip\cache\wheels\54\37\84\f76
8850e8861afeedd63dacbfc9eedd23c62310a6852d53a2c
Successfully built cmfrec
Installing collected packages: findblas, cmfrec
Successfully installed cmfrec-3.5.1.post8 findblas-0.1.23
```

In [101…

```python
from sklearn.model_selection import train_test_split
from cmfrec import CMF

# Step 2: Load and preprocess the data
# Assuming you have a DataFrame named final_df_copy with columns UserID, MovieID, a
data = final_df_copy[['UserID', 'MovieID', 'Rating']]

# Step 3: Rename columns to match the expected format by CMF model
data.rename(columns={'UserID': 'UserId', 'MovieID': 'ItemId'}, inplace=True)

# Step 4: Split the data into training and testing sets for Matrix Factorization
train_data, test_data = train_test_split(data, test_size=0.2, random_state=42)

# Step 5: Train the Matrix Factorization model with d=4 embeddings
model = CMF(k=4, random_state=42, niter=100)
model.fit(train_data)

# Step 6: Evaluate the model's performance using RMSE and MAPE
predictions = []
for _, row in test_data.iterrows():
    user_id, item_id = row['UserId'], row['ItemId']
    pred_rating = model.predict(user=user_id, item=item_id)
    predictions.append(pred_rating)

predictions = np.array(predictions)
rmse = np.sqrt(np.mean((test_data['Rating'] - predictions)**2))
```

```python
mape = np.mean(np.abs(test_data['Rating'] - predictions) / test_data['Rating']) * 1

print("RMSE:", rmse)
print("MAPE:", mape)

# Step 7: Use the learned embeddings for visualization and similarity-based models
user_embeddings = model.U_
item_embeddings = model.V_

# Step 8: Redesign item-item and user-user similarity functions using MF embeddings
# For example, to compute cosine similarity between item embeddings
def item_item_similarity(item_id_1, item_id_2):
    emb_1 = item_embeddings[item_id_1]
    emb_2 = item_embeddings[item_id_2]
    similarity = np.dot(emb_1, emb_2) / (np.linalg.norm(emb_1) * np.linalg.norm(emb
    return similarity

# Similarly, compute user-user similarity using MF embeddings
def user_user_similarity(user_id_1, user_id_2):
    emb_1 = user_embeddings[user_id_1]
    emb_2 = user_embeddings[user_id_2]
    similarity = np.dot(emb_1, emb_2) / (np.linalg.norm(emb_1) * np.linalg.norm(emb
    return similarity

# Bonus: Get d=2 embeddings and plot the results
import matplotlib.pyplot as plt

model_2d = CMF(k=2, random_state=42, niter=100)
model_2d.fit(train_data)
item_embeddings_2d = model_2d.V_

plt.scatter(item_embeddings_2d[:, 0], item_embeddings_2d[:, 1])
plt.xlabel('Embedding Dimension 1')
plt.ylabel('Embedding Dimension 2')
plt.title('2D Embeddings Visualization')
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[101], line 25
     22     pred_rating = model.predict(user=user_id, item=item_id)
     23     predictions.append(pred_rating)
---> 25 predictions = np.array(predictions)
     26 rmse = np.sqrt(np.mean((test_data['Rating'] - predictions)**2))
     27 mape = np.mean(np.abs(test_data['Rating'] - predictions) / test_data['Rati
ng']) * 100

ValueError: setting an array element with a sequence. The requested array has an i
nhomogeneous shape after 1 dimensions. The detected shape was (199333,) + inhomoge
neous part.
```

In [102…

```python
# Step 1: Install Surprise library
!pip install scikit-surprise
```

```
Collecting scikit-surprise
  Downloading scikit-surprise-1.1.3.tar.gz (771 kB)
     ---------------------------------------- 0.0/772.0 kB ? eta -:--:--
     ------------ ------------------------- 256.0/772.0 kB 5.2 MB/s eta 0:00:01
     -------------------------------------  768.0/772.0 kB 9.7 MB/s eta 0:00:01
     -------------------------------------- 772.0/772.0 kB 8.1 MB/s eta 0:00:00
  Preparing metadata (setup.py): started
  Preparing metadata (setup.py): finished with status 'done'
Requirement already satisfied: joblib>=1.0.0 in c:\users\sharat\appdata\roaming\py
thon\python311\site-packages (from scikit-surprise) (1.3.2)
Requirement already satisfied: numpy>=1.17.3 in c:\users\sharat\appdata\roaming\py
thon\python311\site-packages (from scikit-surprise) (1.26.4)
Requirement already satisfied: scipy>=1.3.2 in c:\users\sharat\appdata\roaming\pyt
hon\python311\site-packages (from scikit-surprise) (1.11.4)
Building wheels for collected packages: scikit-surprise
  Building wheel for scikit-surprise (setup.py): started
  Building wheel for scikit-surprise (setup.py): finished with status 'done'
  Created wheel for scikit-surprise: filename=scikit_surprise-1.1.3-cp311-cp311-wi
n_amd64.whl size=1295298 sha256=9729a909c940bc53859aac3b348556b89e537cf5cbef9055cc
55ee27b0d4ce81
  Stored in directory: c:\users\sharat\appdata\local\pip\cache\wheels\f4\2b\26\e2a
5eae55d3b7688995e66abe7f40473aac6c95ddd8ee174a8
Successfully built scikit-surprise
Installing collected packages: scikit-surprise
Successfully installed scikit-surprise-1.1.3
```

Evaluate the model in terms of the Root Mean Squared Error and Mean Absolute Percentage Error

In [103…

```python
# Step 2: Import necessary modules from Surprise
from surprise import Dataset, Reader
from surprise.model_selection import train_test_split
from surprise import SVD
from surprise import accuracy

# Step 3: Load your dataset into Surprise
# Assuming you have a DataFrame named final_df_copy with columns UserID, MovieID, c
reader = Reader(rating_scale=(1, 5))
data = Dataset.load_from_df(final_df_copy[['UserID', 'MovieID', 'Rating']], reader)

# Step 4: Split the data into training and testing sets
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)

# Step 5: Train the Matrix Factorization model (SVD) on the training set
model = SVD(n_factors=4, random_state=42)
model.fit(trainset)

# Step 6: Make predictions on the test set
predictions = model.test(testset)

# Step 7: Evaluate the model's performance using RMSE
rmse = accuracy.rmse(predictions)
print("RMSE:", rmse)
```

```
RMSE: 0.8842
RMSE: 0.8842343257986099
```

In [107…

```python
# Step 12: Make predictions using the trained SVD model
predictions = [model.predict(uid, iid, r_ui_trans) for (uid, iid, r_ui_trans) in te

# Step 13: Compute absolute percentage error for each prediction
absolute_percentage_errors = []
```

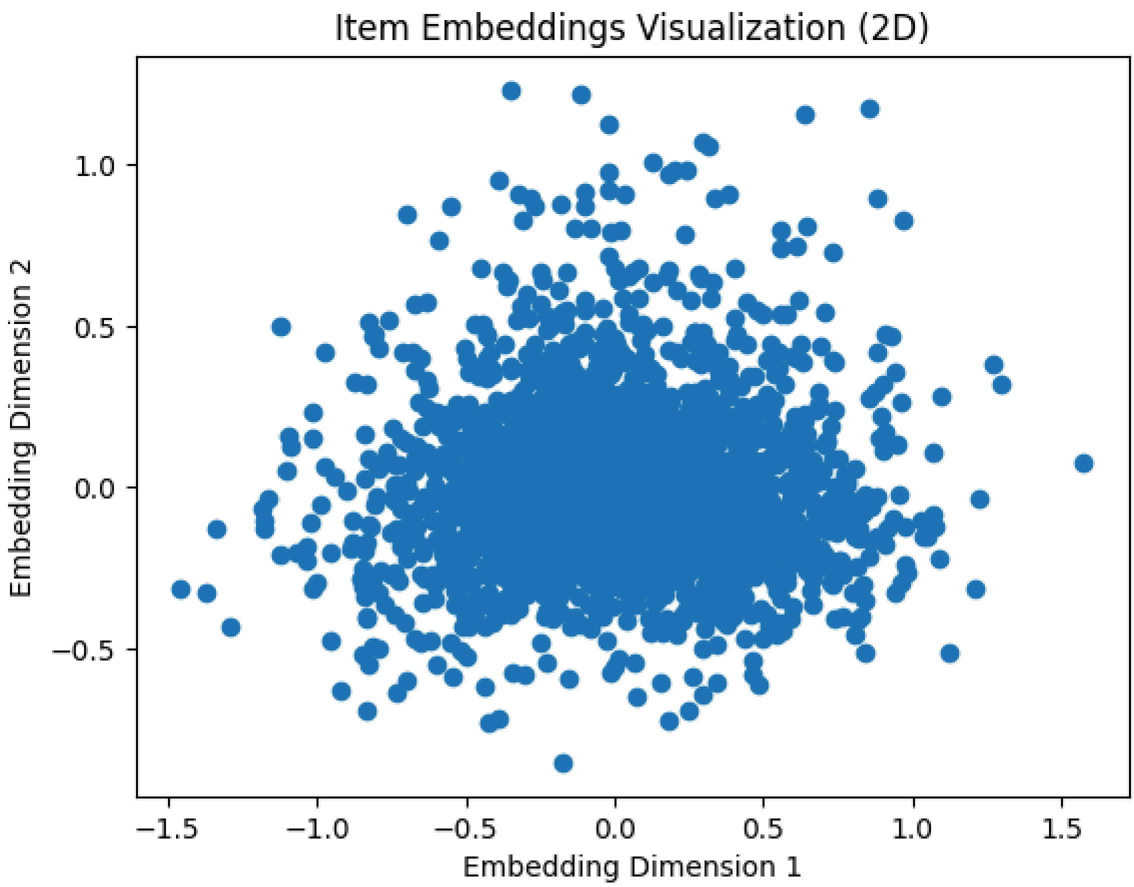
```
for prediction in predictions:
    actual_rating = prediction.r_ui
    predicted_rating = prediction.est
    absolute_percentage_error = abs((actual_rating - predicted_rating) / actual_rat
    absolute_percentage_errors.append(absolute_percentage_error)

# Step 14: Calculate MAPE
mape = np.mean(absolute_percentage_errors)

print("MAPE:", mape)
```

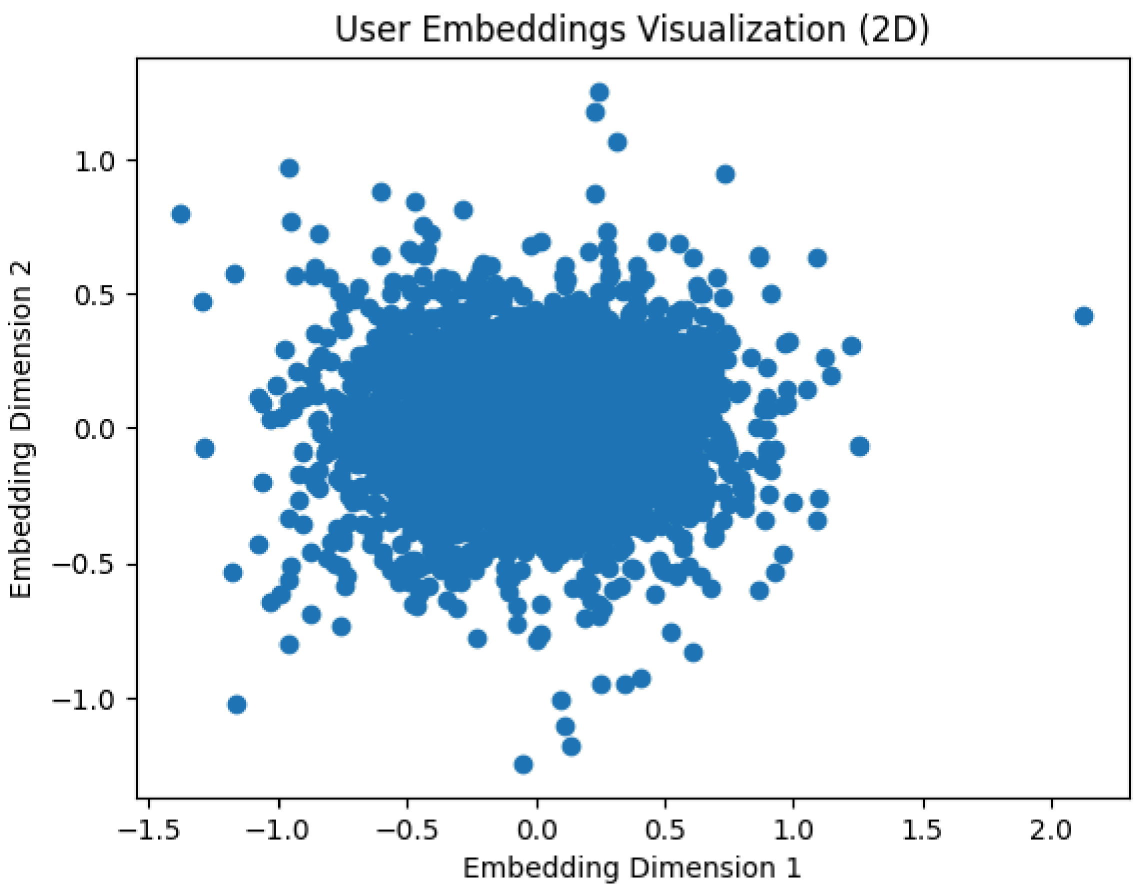
```
MAPE: 0.2612327752643904
```

Use embeddings for visualization and similarity-based models.

In [104…

```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# Step 8: Extract item and user embeddings from the trained SVD model
item_embeddings = model.qi
user_embeddings = model.pu

# Step 9: Redesign item-item similarity function using MF embeddings
def item_item_similarity(item_id_1, item_id_2):
    emb_1 = item_embeddings[item_id_1]
    emb_2 = item_embeddings[item_id_2]
    similarity = np.dot(emb_1, emb_2) / (np.linalg.norm(emb_1) * np.linalg.norm(emb
    return similarity

# Step 10: Redesign user-user similarity function using MF embeddings
def user_user_similarity(user_id_1, user_id_2):
    emb_1 = user_embeddings[user_id_1]
    emb_2 = user_embeddings[user_id_2]
    similarity = np.dot(emb_1, emb_2) / (np.linalg.norm(emb_1) * np.linalg.norm(emb
    return similarity

# Step 11: Bonus - Get d=2 embeddings and plot the results
pca = PCA(n_components=2)
item_embeddings_2d = pca.fit_transform(item_embeddings)
user_embeddings_2d = pca.fit_transform(user_embeddings)

# Plot item embeddings in 2D
plt.scatter(item_embeddings_2d[:, 0], item_embeddings_2d[:, 1])
plt.xlabel('Embedding Dimension 1')
plt.ylabel('Embedding Dimension 2')
plt.title('Item Embeddings Visualization (2D)')
plt.show()

# Plot user embeddings in 2D
plt.scatter(user_embeddings_2d[:, 0], user_embeddings_2d[:, 1])
plt.xlabel('Embedding Dimension 1')
plt.ylabel('Embedding Dimension 2')
plt.title('User Embeddings Visualization (2D)')
plt.show()
```





In [108…

```
# Assuming your old dataframe is named final_df_copy
max_rated_movie = final_df_copy.groupby('Title')['Rating'].count().idxmax()
max_rating_count = final_df_copy.groupby('Title')['Rating'].count().max()

print("Movie with maximum ratings:")
print("Title:", max_rated_movie)
print("Number of Ratings:", max_rating_count)
```

```
Movie with maximum ratings:
Title: American Beauty
Number of Ratings: 3428
```

In [ ]: