In [5]:
```
# importing required libraries
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
import keras
from tensorflow.keras.optimizers import Adam
from keras.layers import Input, Embedding, Flatten
from keras.layers import dot
from pylab import rcParams
```

In [6]:
```
# reading the data files
movies = pd.read_fwf(r"C:\Users\suraj\Downloads\zee-movies.dat", encoding='ISO-8859-1')
ratings = pd.read_fwf(r"C:\Users\suraj\Downloads\zee-ratings.dat", encoding='ISO-8859-1')
users = pd.read_fwf(r"C:\Users\suraj\Downloads\zee-users.dat", encoding='ISO-8859-1')
```

Data Formatting

Movies

In [7]:
```
movies.head()
```

Out[7]:

	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 [8]:

```
# removing the columns with NaN
movies.drop(columns = ['Unnamed: 1', 'Unnamed: 2'], axis = 1, inplace = True)
movies.head(2)
```

Out[8]:

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

In [9]:

```
# Now lets make columns separating based on ::
delimiter = '::'
movies = movies['Movie ID::Title::Genres'].str.split(delimiter, expand = True)
movies.columns = ['Movie ID', 'Title', 'Genres']
movies.head(2)
```

Out[9]:

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

In [10]:

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

In [11]:

```
movies.head(2)
```

Out[11]:

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

Ratings

In [12]:

```
ratings.head(2)
```

Out[12]:

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

In [13]:

```
# lets split and make columns for the ratings also as we did it for the movies
delimiter = '::'
ratings = ratings['UserID::MovieID::Rating::Timestamp'].str.split(delimiter, expand = True)
ratings.columns = ['UserID', 'MovieID', 'Rating', 'Timestamp']
ratings.head(2)
```

Out[13]:

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

Users

In [14]:

```
users.head(3)
```

Out[14]:

	UserID::Gender::Age::Occupation::Zip-code
0	1::F::1::10::48067
1	2::M::56::16::70072
2	3::M::25::15::55117

In [15]:
```
users = users['UserID::Gender::Age::Occupation::Zip-code'].str.split(delimiter, expand=True)
users.columns = ['UserID', 'Gender', 'Age', 'Occupation', 'Zip-code']
users.head(3)
```

Out[15]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117

In [16]:
```
users['Age'].value_counts()
# users['Occupation'].value_counts()
```

Out[16]:
```
Age
25    2096
35    1193
18    1103
45     550
50     496
56     380
1      222
Name: count, dtype: int64
```

In [17]:
```
# lets replace with age and occupation as given from users
users.replace({'Age' : {
    '1' : "Under 18",
    '18':  "18-24",
    '35':  "35-44",
    '25':  "25-34",
    '45':  "45-49",
    '50':  "50-55",
    '56':  "56 Above"

}}, inplace = True)

users.replace({'Occupation':{'0': "other",
                             '1': "academic/educator",
```

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

In [18]:

```
users.head(5)
```

Out[18]:

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

Merging the dataframes

In [19]:

```
df_1 = pd.merge(movies, ratings, how='inner', on='MovieID')
df_1.head()
```

Out[19]:

	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 [20]:

```
df_2 = pd.merge(df_1, users, how='inner', on='UserID')
df_2.head()
```

Out[20]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008	F	50-55	homemaker	55117
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496	M	25-34	programmer	11413
3	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952	M	25-34	technician/engineer	61614
4	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474	F	35-44	academic/educator	95370

In [21]:

```
data = df_2.copy(deep=True)
data
```

Out[21]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008	F	50-55	homemaker	55117
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496	M	25-34	programmer	11413
3	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952	M	25-34	technician/engineer	61614
4	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474	F	35-44	academic/educator	95370
...	...	...	...	...	...	...	...	...	...	...
1000204	3952	Contender, The (2000)	Drama|Thriller	5812	4	992072099	F	25-34	executive/managerial	92120
1000205	3952	Contender, The (2000)	Drama|Thriller	5831	3	986223125	M	25-34	academic/educator	92120
1000206	3952	Contender, The (2000)	Drama|Thriller	5837	4	1011902656	M	25-34	executive/managerial	60607
1000207	3952	Contender, The (2000)	Drama|Thriller	5927	1	979852537	M	35-44	sales/marketing	10003
1000208	3952	Contender, The (2000)	Drama|Thriller	5998	4	1001781044	M	18-24	college/grad student	61820

1000209 rows × 10 columns

EDA

In [22]:

```
data.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
```

Feature Engineering

In [23]:
```
data['Rating'].unique()
```

Out[23]:
```
array(['5', '4', '3', '2', '1'], dtype=object)
```

As it is in categorical lets convert it into integer

In [24]:
```
data['Rating'] = data['Rating'].astype('int32')
```

In [25]:
```
data['Datetime'] = pd.to_datetime(data['Timestamp'],
                                  unit='s')
```

```
C:\Users\suraj\AppData\Local\Temp\ipykernel_2240\606865118.py:1: FutureWarning: The behavior of 'to_datetime' with 'unit' when p
arsing 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 numeric type before calling to_datetime.
  data['Datetime'] = pd.to_datetime(data['Timestamp'],
```

In [26]:
```
data.head()
```

Out[26]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Datetime
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067	2001-01-06 23:37:48
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008	F	50-55	homemaker	55117	2000-12-31 04:30:08
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496	M	25-34	programmer	11413	2000-12-31 03:31:36
3	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952	M	25-34	technician/engineer	61614	2000-12-31 01:25:52
4	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474	F	35-44	academic/educator	95370	2000-12-31 01:34:34

In [27]:
```
# pip install --upgrade pandas
```

In [28]:
```
data['Datetime'] = pd.to_datetime(data['Timestamp'], unit='s')
data.info()
```

```
C:\Users\suraj\AppData\Local\Temp\ipykernel_2240\1440960711.py:1: 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 numeric type before calling to_datetime.
  data['Datetime'] = pd.to_datetime(data['Timestamp'], unit='s')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 11 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  int32
 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
 10  Datetime    1000209 non-null  datetime64[ns]
dtypes: datetime64[ns](1), int32(1), object(9)
memory usage: 80.1+ MB
```

In [29]:
```
data.head()
```

Out[29]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Datetime
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067	2001-01-06 23:37:48
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008	F	50-55	homemaker	55117	2000-12-31 04:30:08
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496	M	25-34	programmer	11413	2000-12-31 03:31:36
3	1	Toy Story (1995)	Animation|Children's|Comedy	9	5	978225952	M	25-34	technician/engineer	61614	2000-12-31 01:25:52
4	1	Toy Story (1995)	Animation|Children's|Comedy	10	5	978226474	F	35-44	academic/educator	95370	2000-12-31 01:34:34

In [30]:
```
data['ReleaseYear'] = data['Title'].str.extract(r'\((\d{4})\)')
# data['ReleaseYear'] = data['ReleaseYear'].str.lstrip("(").str.rstrip(")")
```

In [31]:
```
data = data.dropna(subset=['ReleaseYear'])
```

In [32]:
```
data['ReleaseYear'].unique()
```

Out[32]:
```
array(['1995', '1994', '1996', '1976', '1993', '1992', '1988', '1967',
       '1964', '1977', '1965', '1982', '1962', '1990', '1991', '1989',
       '1937', '1940', '1969', '1981', '1973', '1970', '1960', '1955',
       '1956', '1959', '1968', '1980', '1975', '1948', '1943', '1950',
       '1987', '1997', '1974', '1958', '1972', '1998', '1952', '1951',
       '1957', '1961', '1954', '1934', '1944', '1963', '1942', '1941',
       '1953', '1939', '1947', '1946', '1945', '1938', '1935', '1936',
       '1926', '1949', '1932', '1930', '1971', '1979', '1986', '1966',
       '1978', '1985', '1983', '1984', '1933', '1931', '1922', '1927',
       '1929', '1928', '1999', '1925', '1919', '1923', '2000', '1920',
       '1921'], dtype=object)
```

In [33]:
```
data['ReleaseYear'] = data['ReleaseYear'].astype(int)
```

```
C:\Users\suraj\AppData\Local\Temp\ipykernel_2240\2010661776.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-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy
  data['ReleaseYear'] = data['ReleaseYear'].astype(int)
```

In [34]:
```
data.head(3)
```

Out[34]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Datetime	ReleaseYear
0	1	Toy Story (1995)	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067	2001-01-06 23:37:48	1995
1	1	Toy Story (1995)	Animation|Children's|Comedy	6	4	978237008	F	50-55	homemaker	55117	2000-12-31 04:30:08	1995
2	1	Toy Story (1995)	Animation|Children's|Comedy	8	4	978233496	M	25-34	programmer	11413	2000-12-31 03:31:36	1995

In [35]:

```
data['Title'] = data['Title'].str.replace(r'\s*\(\d{4}\)$', '', regex = True)
```

```
C:\Users\suraj\AppData\Local\Temp\ipykernel_2240\3862611213.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-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy
  data['Title'] = data['Title'].str.replace(r'\s*\(\d{4}\)$', '', regex = True)
```

In [36]:

```
data.head(2)
```

Out[36]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Datetime	ReleaseYear
0	1	Toy Story	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067	2001-01-06 23:37:48	1995
1	1	Toy Story	Animation|Children's|Comedy	6	4	978237008	F	50-55	homemaker	55117	2000-12-31 04:30:08	1995

In [37]:

```
bins = [1919, 1929, 1939, 1949, 1959, 1969, 1979, 1989, 2000]
labels = ['20s', '30s', '40s', '50s', '60s', '70s', '80s', '90s']
data['ReleaseDec'] = pd.cut(data['ReleaseYear'], bins = bins, labels = labels)
```

```
C:\Users\suraj\AppData\Local\Temp\ipykernel_2240\3505609566.py:3: 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-ver
sus-a-copy
  data['ReleaseDec'] = pd.cut(data['ReleaseYear'], bins = bins, labels = labels)
```

In [38]:
```
data.head(1)
```

Out[38]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Datetime	ReleaseYear	ReleaseDec
0	1	Toy Story	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067	2001-01-06 23:37:48	1995	90s

Checking for null values

In [39]:
```
data.isna().sum()
```

Out[39]:
```
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
ReleaseDec      45
dtype: int64
```

Checking for duplicate rows

In [40]:
```
duplicate_rows = data[data.duplicated()]
print("No. of duplicate rows: ", duplicate_rows.shape[0])
```

```
No. of duplicate rows:  0
```

Data Visualization

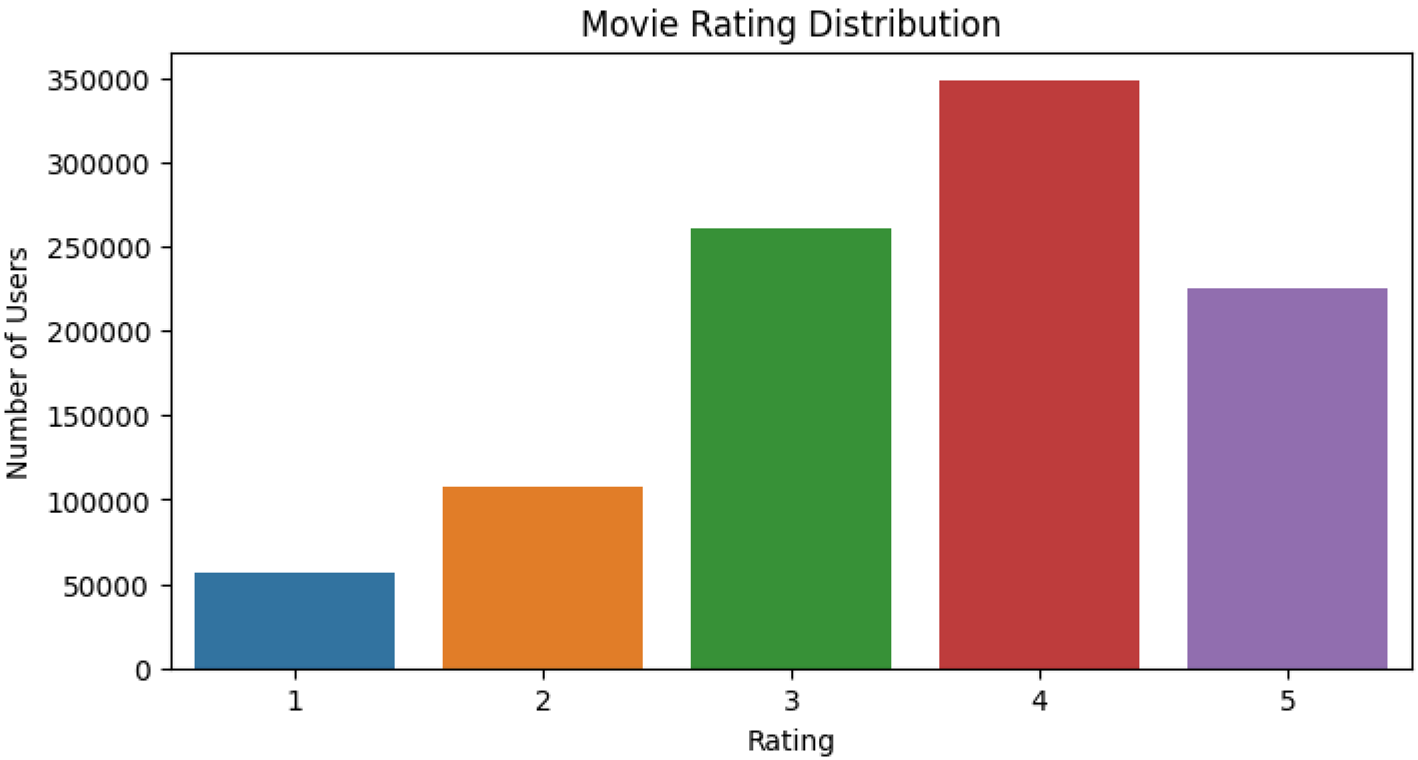
Distribution of Movie Ratings

In [41]:
```
data.head(2)
```

Out[41]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Datetime	ReleaseYear	ReleaseDec
0	1	Toy Story	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067	2001-01-06 23:37:48	1995	90s
1	1	Toy Story	Animation|Children's|Comedy	6	4	978237008	F	50-55	homemaker	55117	2000-12-31 04:30:08	1995	90s

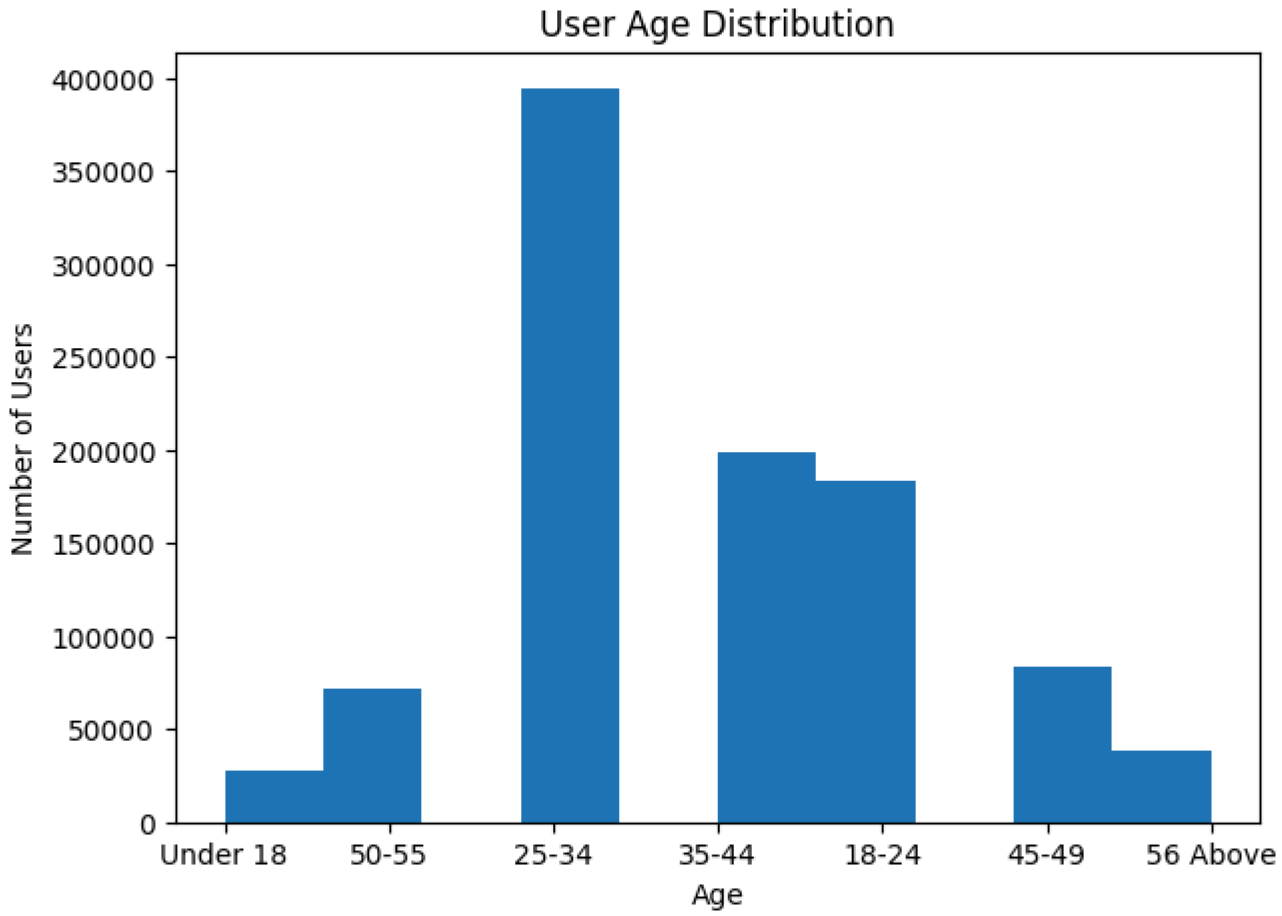
In [42]:
```
plt.figure(figsize = (8, 4))
sns.countplot(x='Rating', data=data)
plt.title("Movie Rating Distribution")
plt.xlabel("Rating")
plt.ylabel("Number of Users")
plt.show()
```



We can observe that the rating 4 has the highest number of count

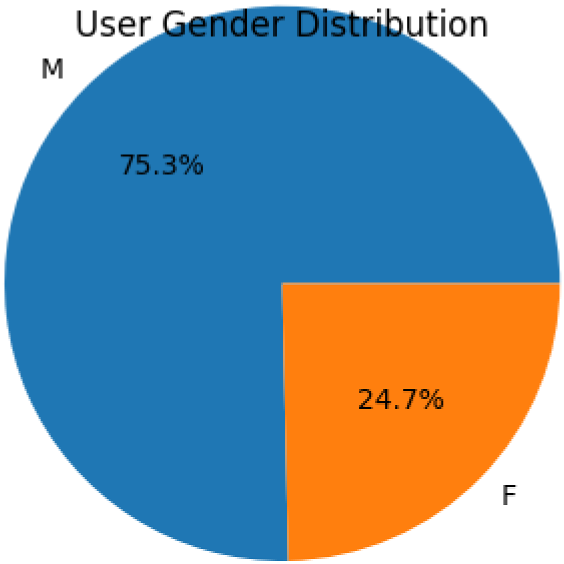
Distribution by Age

In [43]:
```
data['Age'].hist(figsize=(7, 5))
plt.title('User Age Distribution')
plt.xlabel('Age')
plt.ylabel('Number of Users')
plt.grid(False)
plt.show()
```



Distribution By gender

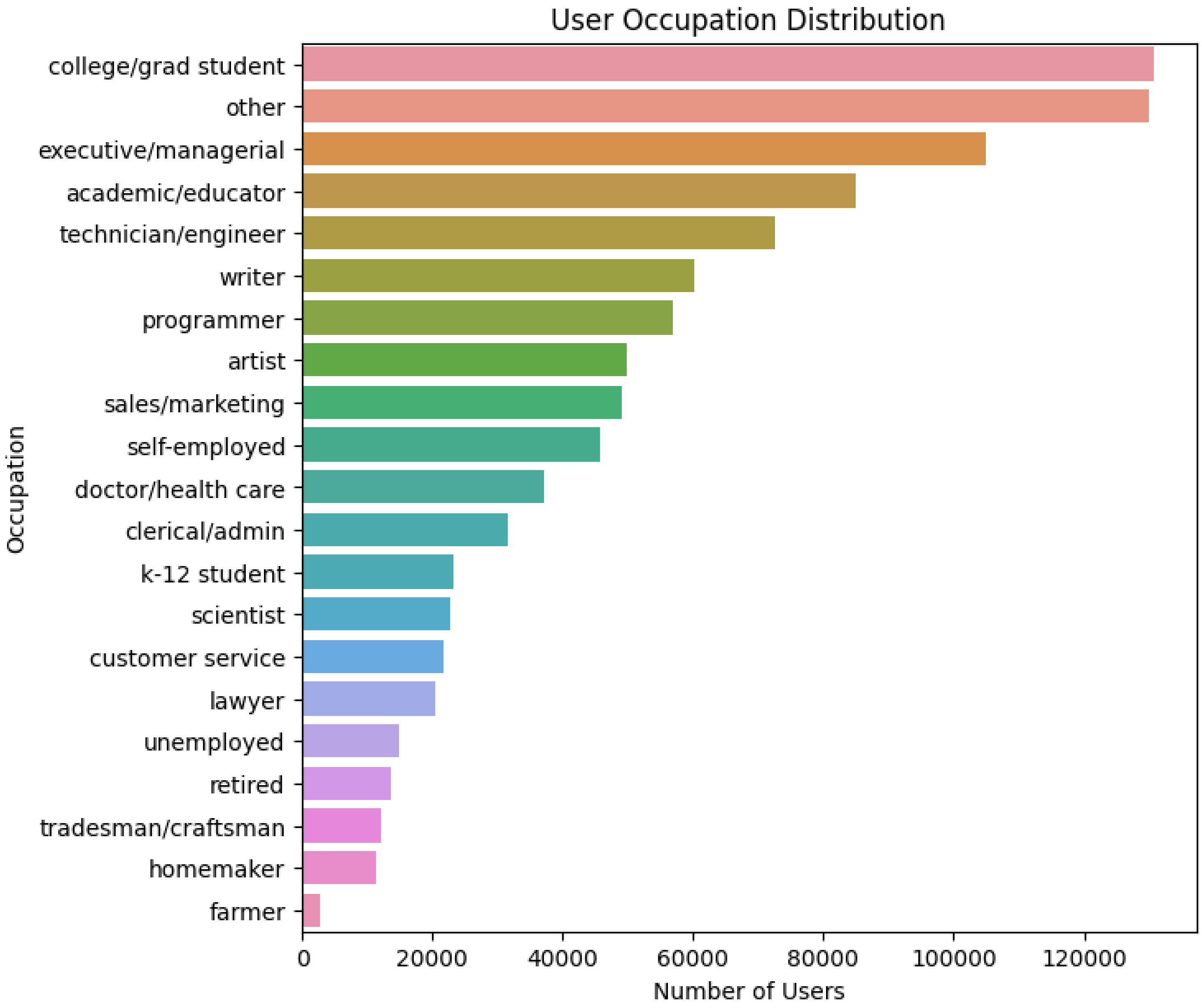
In [44]:
```
x = data['Gender'].value_counts().values
plt.figure(figsize=(6, 3))
plt.pie(x, center = (0, 0), radius = 1.5, labels = ['M', 'F'], autopct='%1.1f%%')
plt.title('User Gender Distribution')
# plt.axis('equal')
plt.show()
data['Gender'].value_counts()
```



Out[44]:
```
Gender
M    750941
F    245724
Name: count, dtype: int64
```

Distribution by Occupation

In [45]:
```
plt.figure(figsize=(7, 7))
sns.countplot(y='Occupation', data=data, order=data['Occupation'].value_counts().index)
plt.title('User Occupation Distribution')
plt.xlabel('Number of Users')
plt.ylabel('Occupation')
plt.show()
```



Distribution by Release Year

In [46]:
```
data.head(2)
```

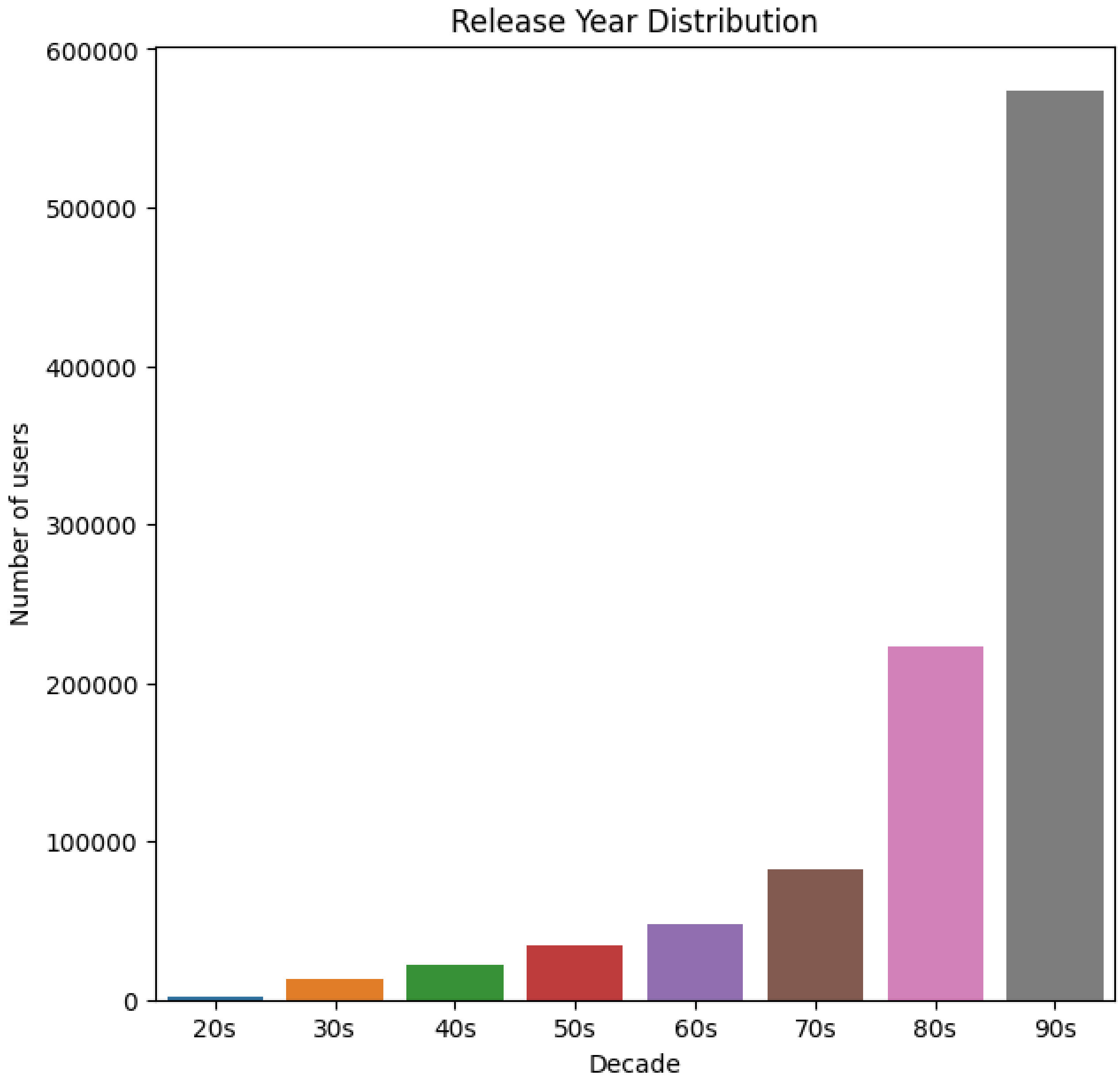
Out[46]:

	MovieID	Title	Genres	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Datetime	ReleaseYear	ReleaseDec
0	1	Toy Story	Animation|Children's|Comedy	1	5	978824268	F	Under 18	k-12 student	48067	2001-01-06 23:37:48	1995	90s
1	1	Toy Story	Animation|Children's|Comedy	6	4	978237008	F	50-55	homemaker	55117	2000-12-31 04:30:08	1995	90s

In [47]:

```
plt.figure(figsize=(7, 7))
sns.countplot(x = 'ReleaseDec', data = data)
plt.title("Release Year Distribution")
plt.xlabel('Decade')
plt.ylabel("Number of users")
plt.show()
```

```
c:\Users\suraj\AppData\Local\Programs\Python\Python311\Lib\site-packages\seaborn\categorical.py:641: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.
  grouped_vals = vals.groupby(grouper)
```



Grouping the data

Average Rate

In [48]:
```
data.groupby('Title')['Rating'].mean().sort_values(ascending = False).head(5)
```

Out[48]:
```
Title
Lured                          5.0
Smashing Time                  5.0
Gate of Heavenly Peace, The    5.0
One Little Indian              5.0
Follow the Bitch               5.0
Name: Rating, dtype: float64
```

No of ratings

In [49]:
```
data.groupby('Title')['Rating'].count().sort_values(ascending = False).head(5)
```

Out[49]:
```
Title
American Beauty                                  3428
Star Wars: Episode IV - A New Hope               2991
Star Wars: Episode V - The Empire Strikes Back   2990
Star Wars: Episode VI - Return of the Jedi       2883
Jurassic Park                                    2672
Name: Rating, dtype: int64
```

In [50]:
```
df = pd.DataFrame(data.groupby('Title')['Rating'].agg([('Avg rating', 'mean')]))
df['No. of ratings'] = pd.DataFrame(data.groupby('Title')['Rating'].count())
df.head(3)
```

Out[50]:

Title	Avg rating	No. of ratings
$1,000,000 Duck	3.027027	37
'Night Mother	3.371429	70
'Til There Was You	2.692308	52

In our case, we will be working on a Collaborative Filtering Recommender System. Collaborative filtering methods are classified as memory-based and model-based. Also there are two approaches to this method. A user-based approach and an item-based approach

Pivot Table

Creating a pivot table of movie title and user_id

In [51]:
```
matrix = pd.pivot_table(data, index = 'UserID', columns = 'Title', values = 'Rating', aggfunc = 'mean')
matrix.head()
```

Out[51]:

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	...	Young Poisoner's Handbook, The	Young Sherlock Holmes	Young and Innocent	Your Friends and Neighbors	Zachari
UserID																
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	Na
10	NaN	NaN	NaN	4.0	NaN	NaN	NaN	NaN	3.0	4.0	...	NaN	NaN	NaN	NaN	Na
100	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	Na
1000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4.0	NaN	NaN	...	NaN	NaN	NaN	NaN	Na
1001	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.0	NaN	NaN	...	NaN	NaN	NaN	4.0	Na

5 rows × 3646 columns

Imputing 'NaN' values with Zero rating

In [52]:
```
matrix.fillna(0, inplace = True)
matrix.head(3)
```

Out[52]:

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	...	Young Poisoner's Handbook, The	Young Sherlock Holmes	Young and Innocent	Your Friends and Neighbors	Zacharia
UserID																
1	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	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	3.0	4.0	...	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

3 rows × 3646 columns

In [53]:

```
matrix.shape
```

Out[53]:

```
(6040, 3646)
```

Pearson Correlation

Correlation is a measure that tells how closely two variables move in the same or opposite direction. A positive value indicates that they move in the same direction (i.e. if one increases other increases), where as negative value indicates the opposite

The most popular correlation measure for numerical data is Pearson's Correlatio. This measures the degree of linear relationship between two numeric variables and lies between -1 to +1. It is represented by 'r'

```
r=1 means perfect positive correlation
r=-1 means perfect negative correlation
r=0 means no linear correlation (note, it does not mean no correlation)
```

Item Based Approach

We will take a movie name as an input from the user and see which other five movies have maximum correlation with it

In [54]:
```
movie_name = 'Liar Liar'
```

In [ ]:
```
movie_rating = matrix[movie_name]
```

```
UserID
1       0.0
10      0.0
100     0.0
1000    0.0
1001    0.0
       ...
995     0.0
996     0.0
997     0.0
998     0.0
999     0.0
Name: Liar Liar, Length: 6040, dtype: float64
```

In [57]:
```
similar_movies = matrix.corrwith(movie_rating)
```

In [59]:
```
sim_df = pd.DataFrame(similar_movies, columns = ['Correlation'])
sim_df.sort_values('Correlation', ascending = False, inplace = True)
```

In [60]:
```
sim_df.iloc[1:, :].head()
```

Out[60]:

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

Cosine Similarity

Cosine similarity is a measure of similarity between two sequences of numbers. Those sequences are viewed as vectors in a higher dimensional space, and the cosine similarity defined as the cosine of the angle between them, i.e. the dot product of the vectors divided by the product of their lengths.

The cosine similarity always belongs to the interval [-1, 1]. For example, two proportional vectors have a cosine similarity of 1, two orthogonal vectors have a similarity of 0, and two opposite vectors have a similarity of -1

In [61]:
```
item_sim = cosine_similarity(matrix.T)
item_sim
```

Out[61]:
```
array([[1.        , 0.07235746, 0.03701053, ..., 0.        , 0.12024178,
        0.02700277],
       [0.07235746, 1.        , 0.11528952, ..., 0.        , 0.        ,
        0.07780705],
       [0.03701053, 0.11528952, 1.        , ..., 0.        , 0.04752635,
        0.0632837 ],
       ...,
       [0.        , 0.        , 0.        , ..., 1.        , 0.        ,
        0.04564448],
       [0.12024178, 0.        , 0.04752635, ..., 0.        , 1.        ,
        0.04433508],
       [0.02700277, 0.07780705, 0.0632837 , ..., 0.04564448, 0.04433508,
        1.        ]])
```

Item similarity matrix

In [62]:
```
item_sim_mat = pd.DataFrame(item_sim, index = matrix.columns, columns = matrix.columns)
item_sim_mat.head()
```

Out[62]:

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	...	Young Poisoner's Handbook, The	Young Sherlock Holmes	Young and Innocent
Title														
$1,000,000 Duck	1.000000	0.072357	0.037011	0.079291	0.060838	0.00000	0.058619	0.189843	0.094785	0.058418	...	0.038725	0.076474	0.000000
'Night Mother	0.072357	1.000000	0.115290	0.115545	0.159526	0.00000	0.076798	0.137135	0.111413	0.046135	...	0.053010	0.087828	0.063758
'Til There Was You	0.037011	0.115290	1.000000	0.098756	0.066301	0.08025	0.127895	0.128523	0.079115	0.066598	...	0.029200	0.062893	0.000000
'burbs, The	0.079291	0.115545	0.098756	1.000000	0.143620	0.00000	0.192191	0.250140	0.170719	0.197808	...	0.113386	0.207897	0.019962
...And Justice for All	0.060838	0.159526	0.066301	0.143620	1.000000	0.00000	0.075093	0.178928	0.205486	0.122431	...	0.089998	0.153006	0.067009

5 rows × 3646 columns

In [63]:

```
user_sim = cosine_similarity(matrix)
user_sim
```

Out[63]:
```
array([[1.        , 0.25531859, 0.12396703, ..., 0.15926709, 0.11935626,
        0.12239079],
       [0.25531859, 1.        , 0.25964457, ..., 0.16569953, 0.13332665,
        0.24845029],
       [0.12396703, 0.25964457, 1.        , ..., 0.20430203, 0.11352239,
        0.30693676],
       ...,
       [0.15926709, 0.16569953, 0.20430203, ..., 1.        , 0.18657496,
        0.18563871],
       [0.11935626, 0.13332665, 0.11352239, ..., 0.18657496, 1.        ,
        0.10827118],
       [0.12239079, 0.24845029, 0.30693676, ..., 0.18563871, 0.10827118,
        1.        ]])
```

User similarity matrix

In [87]:
```python
user_sim_mat = pd.DataFrame(user_sim, index=matrix.index, columns=matrix.index)
user_sim_mat.head()
```

Out[87]:

UserID	**1**	**10**	**100**	**1000**	**1001**	**1002**	**1003**	**1004**	**1005**	**1006**	**...**	**990**	**991**	**992**	**993**	
UserID																
1	1.000000	0.255319	0.123967	0.207800	0.139317	0.110320	0.121384	0.180226	0.103896	0.052816	...	0.079367	0.038048	0.032136	0.067631	0.
10	0.255319	1.000000	0.259645	0.280479	0.158703	0.112917	0.141985	0.432536	0.194915	0.102487	...	0.154412	0.186234	0.083739	0.125894	0.
100	0.123967	0.259645	1.000000	0.306067	0.075736	0.110450	0.358686	0.237492	0.172872	0.099147	...	0.098235	0.097953	0.065152	0.178664	0.
1000	0.207800	0.280479	0.306067	1.000000	0.099117	0.047677	0.201722	0.355920	0.325966	0.130702	...	0.170100	0.076779	0.000000	0.200343	0.
1001	0.139317	0.158703	0.075736	0.099117	1.000000	0.164854	0.053887	0.150196	0.138602	0.134710	...	0.146270	0.026891	0.097011	0.119609	0.

5 rows × 6040 columns

Nearest Neighbours

In [88]:
```python
csr_mat = sparse.csr_matrix(matrix.T.values)
csr_mat
```

Out[88]:
```
<3646x6040 sparse matrix of type '<class 'numpy.float64'>'
	with 993541 stored elements in Compressed Sparse Row format>
```

A sparse matrix or sparse array is a matrix in which most of the elements are zero. A compressed sparse row (csr) matrix 'M' is representes by three (one-dimensional) array that respectively contain nonzero values, the extents of rows, and column indices. The CSR format stores a sparse m x n matrix M in row form using three (one-dimensional) arrays (COL_INDEX, ROW_INDEX)

For Example

Dense matrix representation:

[[1 0 0 0 0 0]

[0 0 2 0 0 1]

[0 0 0 2 0 0]]

Sparse 'row' matrix:

(0, 0) 1

(1, 2) 2

(1, 5) 1

(2, 3) 2

Fitting the model with 'cosine similarity' as the distance metric and 5 (five) as the no. of nearest neighbors

In [94]:
```
knn  = NearestNeighbors(n_neighbors=5, metric = 'cosine', n_jobs=1)
knn.fit(csr_mat)
```

Out[94]:
```
NearestNeighbors
NearestNeighbors(metric='cosine', n_jobs=1)
```

Lets make recommendations for a movie of the user's choice

In [95]:
```
movie_name = 'Liar Liar'
movie_index = matrix.columns.get_loc(movie_name)
```

In [96]:
```
distances, indices = knn.kneighbors(matrix[movie_name].values.reshape(1, -1), n_neighbors = 11)
```

In [97]:
```
for i in range(0, len(distances.flatten())):
    if i == 0:
        print("Recommendations for the movie: {0}\n".format(movie_name))
    else:
        print('{0}: {1}, with distance of {2}'.format(i, matrix.columns[indices.flatten()[i]],
round(distances.flatten()[i], 3)))
```

```
Recommendations for the movie: Liar Liar

1: Mrs. Doubtfire, with distance of 0.443
2: Ace Ventura: Pet Detective, with distance of 0.483
3: Dumb & Dumber, with distance of 0.487
4: Home Alone, with distance of 0.489
5: Wayne's World, with distance of 0.501
6: Wedding Singer, The, with distance of 0.503
7: Austin Powers: International Man of Mystery, with distance of 0.511
8: There's Something About Mary, with distance of 0.517
9: League of Their Own, A, with distance of 0.518
10: Mask, The, with distance of 0.531
```

Matrix Factorizarion

First we need to create embeddings for both the user as well as the item or movie. For this we have used the Embedding layer from keras

In [98]:
```
# Creating embeddings for both users and movies
users = data.UserID.unique()
movies = data.MovieID.unique()

userid2idx = {o:i for i, o in enumerate(users)}
movieid2idx = {o:i for i, o in enumerate(movies)}
```

The number of dimensions (Latent Factors) in the embeddings is a hyperparameter to deal with in this implementation of collaborative filtering

In [99]:

```
data['UserID'] = data['UserID'].apply(lambda x: userid2idx[x])
data['MovieID'] = data['MovieID'].apply(lambda x: movieid2idx[x])
split = np.random.rand(len(data))<0.8
train = data[split]
valid = data[~split]
print(train.shape, valid.shape)
```

```
C:\Users\suraj\AppData\Local\Temp\ipykernel_2240\1502675303.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-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy
  data['UserID'] = data['UserID'].apply(lambda x: userid2idx[x])
C:\Users\suraj\AppData\Local\Temp\ipykernel_2240\1502675303.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-ver
sus-a-copy
  data['MovieID'] = data['MovieID'].apply(lambda x: movieid2idx[x])
(797877, 13) (198788, 13)
```

In [111…

```
n_movies = len(data['MovieID'].unique())
n_users = len(data['UserID'].unique())

n_latent_factors = 64
```

Specify the input expected to be embedded (Both in user and item embedding). Then user Embedding layer which expects the number of latents factors in the resulting embedding also the number of users or items

In [113…

```
user_input = Input(shape = (1, ), name = 'user_input', dtype = 'int64')
user_embedding = Embedding(input_dim=n_users, output_dim=n_latent_factors, name='user_embedding')
(user_input)
user_vec = Flatten(name = 'FlattenUsers')(user_embedding)
```

In [114…

```
movie_input = Input(shape = (1, ), name = 'movie_input', dtype = 'int64')
movie_embedding = Embedding(n_movies, output_dim=n_latent_factors, name = 'movie_embedding')(movie_input)
movie_vec = Flatten(name = 'FlattenMovies')(movie_embedding)
```

Then we take the 'Dot-Product' of both the embeddings using the 'merge' layer. Note that 'dot-product' is just a measure of simalrity and we can use any other mode like 'mulitply' or 'cosine simalarity' or 'concatenate' etc.

In [115…

```
sim = dot([user_vec, movie_vec], name = 'Similarity-Dot-Product', axes = 1)
model = keras.models.Model([user_input, movie_input], sim)
```

Lastly we make a Keras model from the specified details

In [116…

```
model.compile(optimizer = Adam(learning_rate = 1e-4), loss = 'mse')
```

Let's see the model's summary

In [117…

```
model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
user_input (InputLayer)	(None, 1)	0	-
movie_input (InputLayer)	(None, 1)	0	-
user_embedding (Embedding)	(None, 1, 64)	386,560	user_input[0][0]
movie_embedding (Embedding)	(None, 1, 64)	236,032	movie_input[0][0]
FlattenUsers (Flatten)	(None, 64)	0	user_embedding[0…
FlattenMovies (Flatten)	(None, 64)	0	movie_embedding[…
Similarity-Dot-Pro… (Dot)	(None, 1)	0	FlattenUsers[0][… FlattenMovies[0]…

Total params: 622,592 (2.38 MB)

Trainable params: 622,592 (2.38 MB)

Non-trainable params: 0 (0.00 B)

Note that the metrics used is 'Mean squared Error'. Our aim is to minimize the mse on the training set i.e. over the values which the user has rated.

Model Training

In [118…

```
model_hist = model.fit([train.UserID, train.MovieID], train.Rating, batch_size = 128,
                        epochs = 20, validation_data = ([valid.UserID, valid.MovieID], valid.Rating),
                        verbose = 1)
```

```
Epoch 1/20
```

```
c:\Users\suraj\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\models\functional.py:225: UserWarning: The st
ructure of `inputs` doesn't match the expected structure: ['user_input', 'movie_input']. Received: the structure of inputs=('*',
'*')
  warnings.warn(
```

```
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 14.0512 - val_loss: 13.3742
Epoch 2/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - loss: 11.6506 - val_loss: 5.1640
Epoch 3/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - loss: 3.9460 - val_loss: 2.0418
Epoch 4/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - loss: 1.7546 - val_loss: 1.2909
Epoch 5/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - loss: 1.1772 - val_loss: 1.0350
Epoch 6/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - loss: 0.9759 - val_loss: 0.9297
Epoch 7/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - loss: 0.8898 - val_loss: 0.8802
Epoch 8/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - loss: 0.8483 - val_loss: 0.8542
Epoch 9/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.8262 - val_loss: 0.8391
Epoch 10/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.8121 - val_loss: 0.8292
Epoch 11/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.8037 - val_loss: 0.8218
Epoch 12/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.7971 - val_loss: 0.8157
Epoch 13/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 25s 4ms/step - loss: 0.7894 - val_loss: 0.8107
Epoch 14/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 24s 4ms/step - loss: 0.7834 - val_loss: 0.8060
Epoch 15/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.7777 - val_loss: 0.8020
Epoch 16/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.7707 - val_loss: 0.7978
Epoch 17/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.7653 - val_loss: 0.7943
Epoch 18/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.7568 - val_loss: 0.7908
Epoch 19/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.7533 - val_loss: 0.7871
```

```
Epoch 20/20
6234/6234 ━━━━━━━━━━━━━━━━━━━━ 23s 4ms/step - loss: 0.7493 - val_loss: 0.7836
```

Model Evaluation

In [119…

```
y_pred = model.predict([valid.UserID, valid.MovieID], verbose=0)
y_pred_class = np.argmax(y_pred, axis = 1)
```

calculating the rmse

In [120…

```
from sklearn.metrics import mean_squared_error
rmse = mean_squared_error(valid.Rating, y_pred, squared = False)
print("Root Mean Squared Error : {:.3f}".format(rmse))
```

```
Root Mean Squared Error : 0.885
```

```
c:\Users\suraj\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\metrics\_regression.py:483: FutureWarning: 'squared' is deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

Calculation the MAPE

In [121…

```
from sklearn.metrics import mean_absolute_percentage_error
mape =  mean_absolute_percentage_error(valid.Rating, y_pred)
print('Mean Absolute Percentage Error: {:.3f}'.format(mape))
```

```
Mean Absolute Percentage Error: 0.271
```

Plotting the Model Loss

In [122…

```
rcParams['figure.figsize'] = 10, 5
plt.plot(model_hist.history['loss'], 'g')
plt.plot(model_hist.history['val_loss'], 'b')
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epochs')
plt.legend(['train', 'test'], loc = 'upper right')
```

```
plt.grid(True)
plt.show()
```