ZEE RECOMMENDER SYSTEMS

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1. Defining the Problem and Exploratory Data Analysis (EDA)

1.1 Definition of Problem

We are asked to 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.

MOVIES FILE DESCRIPTION

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Movie information is in the file "movies.dat" and is in the following format:

MovieID::Title::Genres

- Titles are identical to titles provided by the IMDB (including year of release)

- Genres are pipe-separated and are selected from the following genres:

    - Action
    - Adventure
    - Animation
    - Children's
    - Comedy
    - Crime
    - Documentary
    - Drama
    - Fantasy
    - Film-Noir
    - Horror
    - Musical
    - Mystery
    - Romance
    - Sci-Fi
    - Thriller
    - War
    - Western

RATINGS FILE DESCRIPTION

==

All ratings are contained in the file "ratings.dat" and are in the following format:

UserID::MovieID::Rating::Timestamp

- UserIDs range between 1 and 6040
- MovieIDs range between 1 and 3952
- Ratings are made on a 5-star scale (whole-star ratings only)
- Timestamp is represented in seconds
- Each user has at least 20 ratings

USERS FILE DESCRIPTION

==

User information is in the file "users.dat" and is in the following format:

UserID::Gender::Age::Occupation::Zip-code

All demographic information is provided voluntarily by the users and is not checked for accuracy.
Only users who have provided some demographic information are included in this data set.

- Gender is denoted by a "M" for male and "F" for female

- Age is chosen from the following ranges:

    - 1: "Under 18"
    - 18: "18-24"
    - 25: "25-34"
    - 35: "35-44"
    - 45: "45-49"
    - 50: "50-55"
    - 56: "56+"
- Occupation is chosen from the following choices:

    - 0: "other" or not specified
    - 1: "academic/educator"
    - 2: "artist"
    - 3: "clerical/admin"
    - 4: "college/grad student"
    - 5: "customer service"
    - 6: "doctor/health care"
    - 7: "executive/managerial"
    - 8: "farmer"
    - 9: "homemaker"
    - 10: "K-12 student"
    - 11: "lawyer"
    - 12: "programmer"
    - 13: "retired"
    - 14: "sales/marketing"
    - 15: "scientist"
    - 16: "self-employed"

- 17: "technician/engineer"
- 18: "tradesman/craftsman"
- 19: "unemployed"
- 20: "writer"

In [1]:
```
!pip install -r requirements.txt
```

```
Requirement already satisfied: numpy in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from -r requirements.txt (line 1)) (2.3.4)
Requirement already satisfied: pandas in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from -r requirements.txt (line 2)) (2.3.1)
Requirement already satisfied: matplotlib in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from -r requirements.txt (line 3)) (3.10.5)
Requirement already satisfied: datetime in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from -r requirements.txt (line 4)) (5.5)
Requirement already satisfied: scikit-learn in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from -r requirements.txt (line 5)) (1.6.1)
Requirement already satisfied: scipy in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from -r requirements.txt (line 6)) (1.16.1)
Requirement already satisfied: cmfrec in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from -r requirements.txt (line 7)) (3.5.1.post13)
Requirement already satisfied: joblib in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from -r requirements.txt (line 8)) (1.5.1)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\dell\appdata\roaming\python\python313\site-packages (from pandas->-r requirements.txt (line 2)) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from pandas->-r requirements.txt (line 2)) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from pandas->-r requirements.txt (line 2)) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from matplotlib->-r requirements.txt (line 3)) (1.3.3)
Requirement already satisfied: cycler>=0.10 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from matplotlib->-r requirements.txt (line 3)) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from matplotlib->-r requirements.txt (line 3)) (4.59.0)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from matplotlib->-r requirements.txt (line 3)) (1.4.9)
Requirement already satisfied: packaging>=20.0 in c:\users\dell\appdata\roaming\python\python313\site-packages (from matplotlib->-r requirements.txt (line 3)) (25.0)
Requirement already satisfied: pillow>=8 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from matplotlib->-r requirements.txt (line 3)) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from matplotlib->-r requirements.txt (line 3)) (3.2.3)
Requirement already satisfied: zope.interface in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from datetime->-r requirements.txt (line 4)) (8.0.1)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn->-r requirements.txt (line 5)) (3.6.0)
Requirement already satisfied: cython in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from cmfrec->-r requirements.txt (line 7)) (3.1.6)
Requirement already satisfied: findblas in c:\users\dell\appdata\local\programs\python\python313\lib\site-packages (from cmfrec->-r requirements.txt (line 7)) (0.1.26.post1)
Requirement already satisfied: six>=1.5 in c:\users\dell\appdata\roaming\python\python313\site-packages (from python-dateutil>=2.8.2->pandas->-r requirements.txt (line 2)) (1.17.0)
```

Let us import the required libraries.

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from sklearn.metrics.pairwise import cosine_similarity
from scipy import sparse
from sklearn.neighbors import NearestNeighbors
from sklearn.model_selection import GroupShuffleSplit
from sklearn.metrics import root_mean_squared_error, mean_absolute_percentage_error
from sklearn.model_selection import train_test_split
from sklearn.model_selection import ParameterGrid
from cmfrec import CMF
from tqdm.notebook import tqdm
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import umap.umap_ as umap

import warnings
warnings.filterwarnings('ignore')
```

1.2 Exploratory Data Analysis (EDA)

1.2.1 Movies

In [3]:
```python
movies = pd.read_csv('zee-movies.dat',sep='::',engine='python', encoding='latin1')
movies.head()
```

Out[3]:

	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 [4]:
```python
# Getting the year of release from the title
movies['Year'] = movies['Title'].str.extract(r'\((\d{4})\)').astype(float)
movies.head()
```

Out[4]:

	Movie ID	Title	Genres	Year
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0
1	2	Jumanji (1995)	Adventure|Children's|Fantasy	1995.0
2	3	Grumpier Old Men (1995)	Comedy|Romance	1995.0
3	4	Waiting to Exhale (1995)	Comedy|Drama	1995.0
4	5	Father of the Bride Part II (1995)	Comedy	1995.0

In [5]:
```python
movies.info()
```

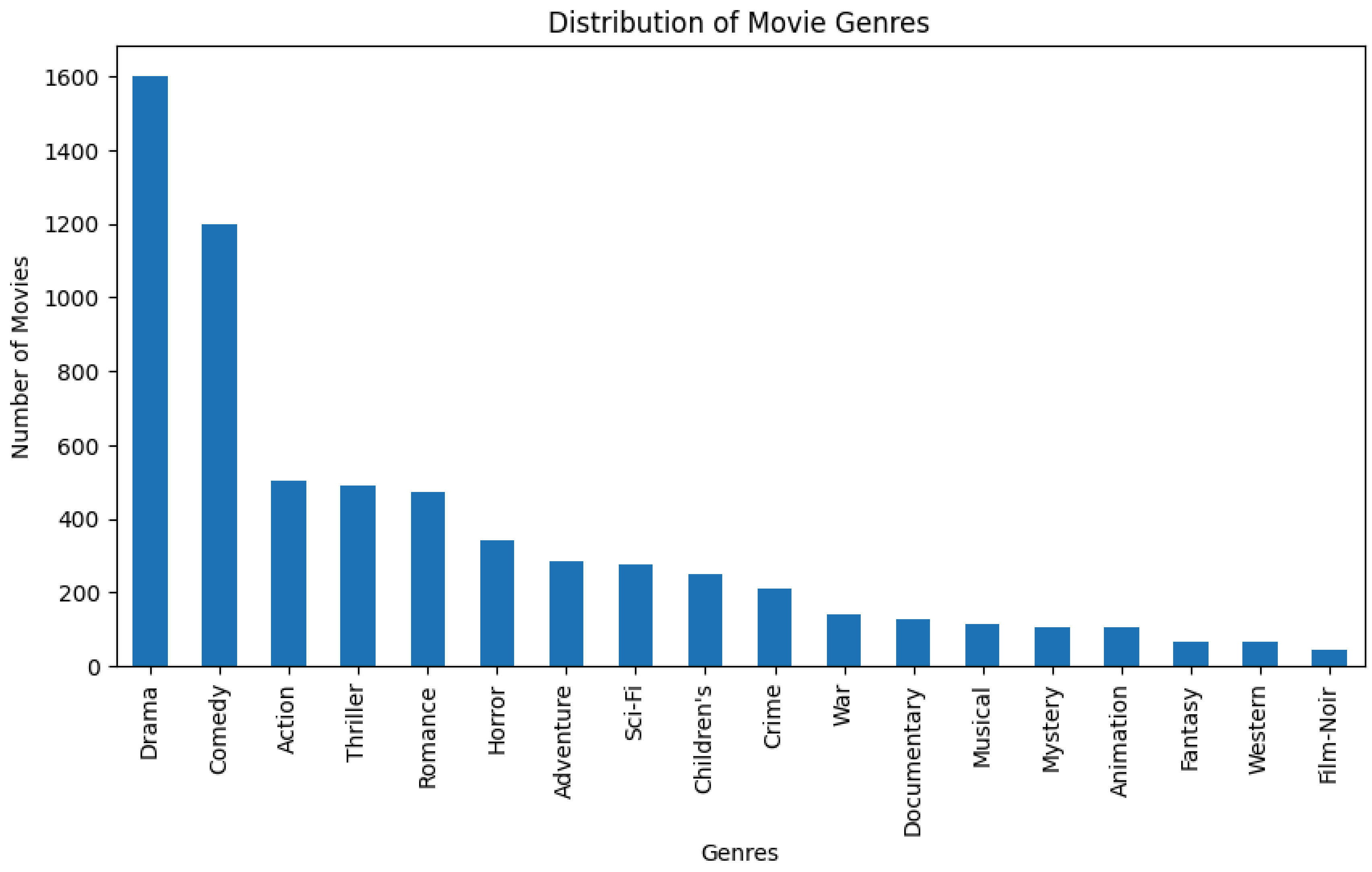
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Movie ID  3883 non-null   int64  
 1   Title     3883 non-null   object 
 2   Genres    3883 non-null   object 
 3   Year      3883 non-null   float64
dtypes: float64(1), int64(1), object(2)
memory usage: 121.5+ KB
```

In [6]:
```python
movies.describe(include='all').T
```

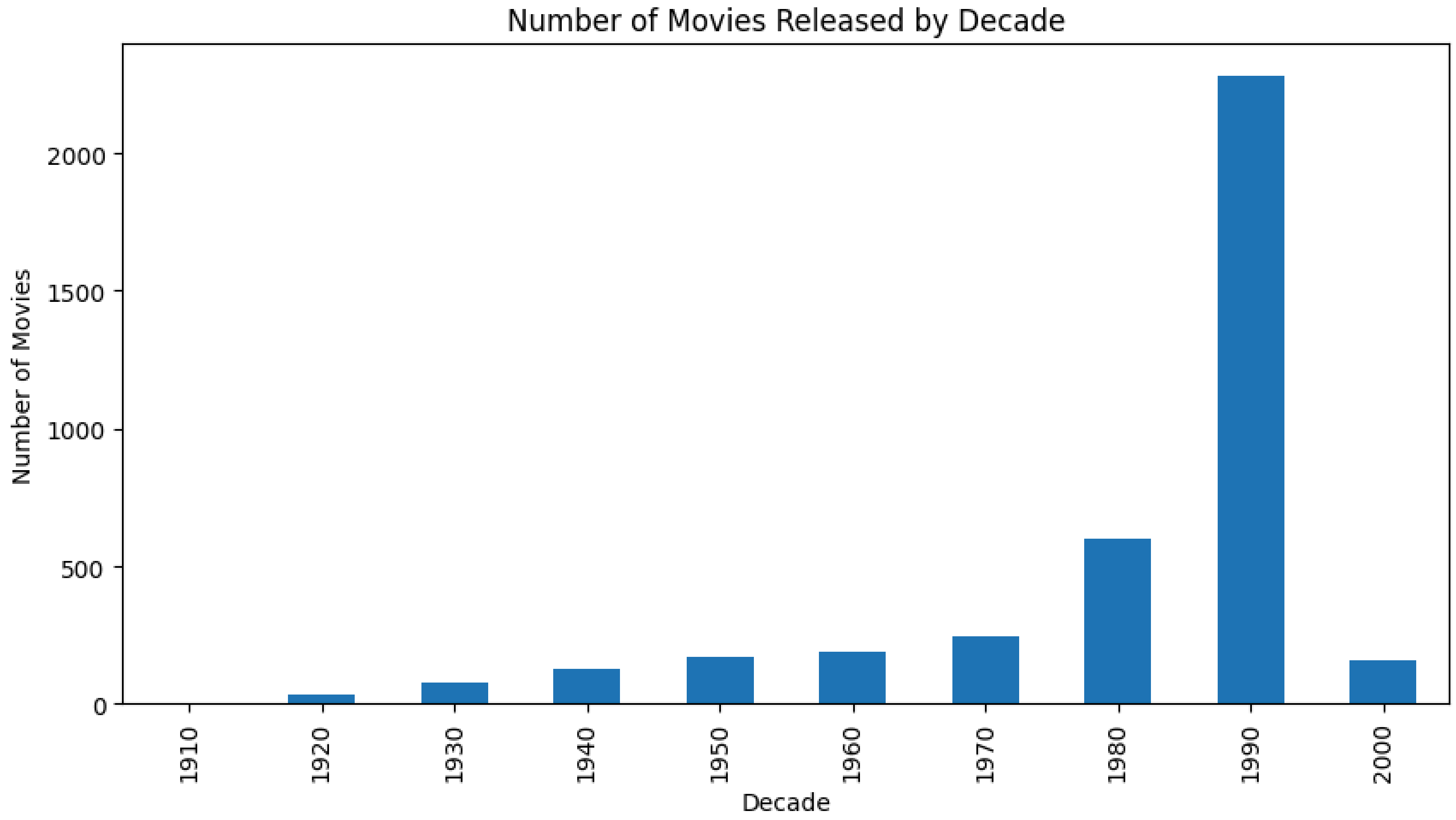
Out[6]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
Movie ID	3883.0	NaN	NaN	NaN	1986.049446	1146.778349	1.0	982.5	2010.0	2980.5	3952.0
Title	3883	3883	Toy Story (1995)	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Genres	3883	301	Drama	843	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Year	3883.0	NaN	NaN	NaN	1986.066959	16.89569	1919.0	1982.0	1994.0	1997.0	2000.0

In [7]:
```
# Analyzing the distribution of movie genres
movies['Genres'].str.split('|').explode().value_counts().plot(kind='bar', figsize=(10,5))
plt.title('Distribution of Movie Genres')
plt.xlabel('Genres')
plt.ylabel('Number of Movies')
plt.show()
```



In [8]:
```
# Analyzing the year of movie releases by decade
movies['Decade'] = ((movies['Year'] // 10) * 10).astype(int)
movies['Decade'].value_counts().sort_index().plot(kind='bar', figsize=(10,5))
plt.title('Number of Movies Released by Decade')
plt.xlabel('Decade')
plt.ylabel('Number of Movies')
plt.show()
```



1.2.2 Ratings

In [9]:
```
ratings = pd.read_csv('zee-ratings.dat',sep='::',engine='python', encoding='latin1')
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]:
```
# Converting Timestamp to Datetime
ratings['Timestamp'] = ratings['Timestamp'].apply(lambda x: datetime.fromtimestamp(x))
```

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

Out[11]:

	UserID	MovieID	Rating	Timestamp
0	1	1193	5	2001-01-01 03:42:40
1	1	661	3	2001-01-01 04:05:09
2	1	914	3	2001-01-01 04:02:48
3	1	3408	4	2001-01-01 03:34:35
4	1	2355	5	2001-01-07 05:08:11

In [12]:

```
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  int64
 1   MovieID    1000209 non-null  int64
 2   Rating     1000209 non-null  int64
 3   Timestamp  1000209 non-null  datetime64[ns]
dtypes: datetime64[ns](1), int64(3)
memory usage: 30.5 MB
```

In [13]:

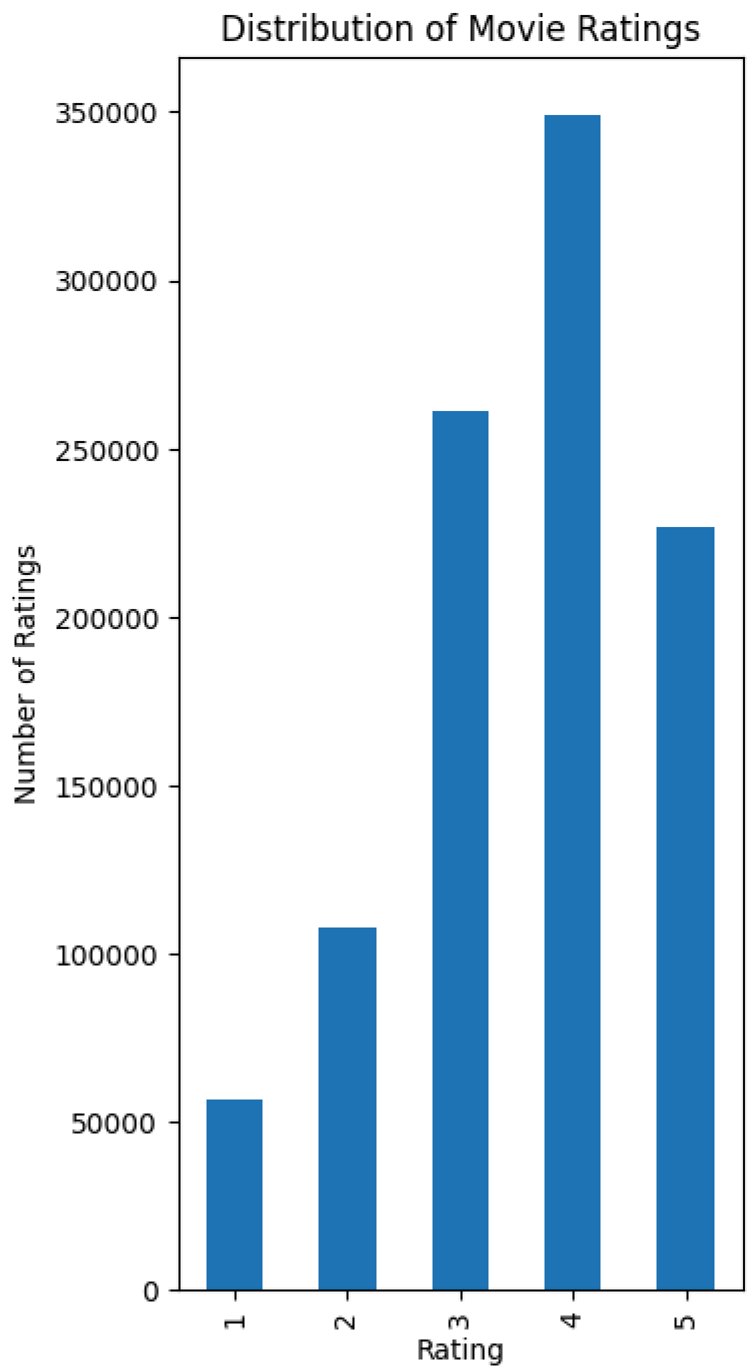
```
ratings.describe(include='all').T
```

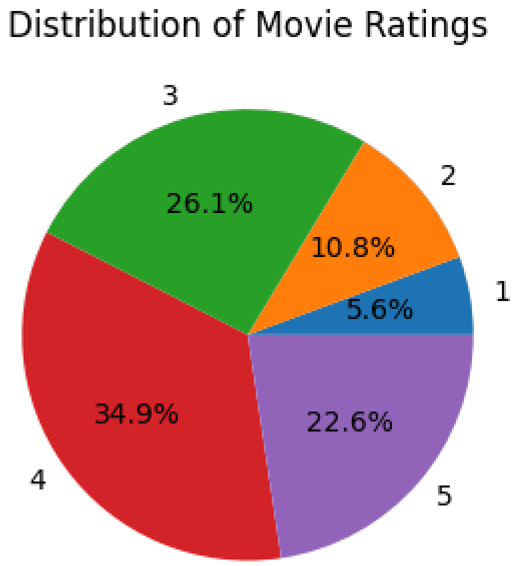
Out[13]:

	count	mean	min	25%	50%	75%	max	std
UserID	1000209.0	3024.512348	1.0	1506.0	3070.0	4476.0	6040.0	1728.412695
MovieID	1000209.0	1865.539898	1.0	1030.0	1835.0	2770.0	3952.0	1096.040689
Rating	1000209.0	3.581564	1.0	3.0	4.0	4.0	5.0	1.117102
Timestamp	1000209	2000-10-23 01:11:35.404665344	2000-04-26 04:35:32	2000-08-03 17:07:17	2000-11-01 00:16:46	2000-11-26 12:12:19	2003-02-28 23:19:50	NaN

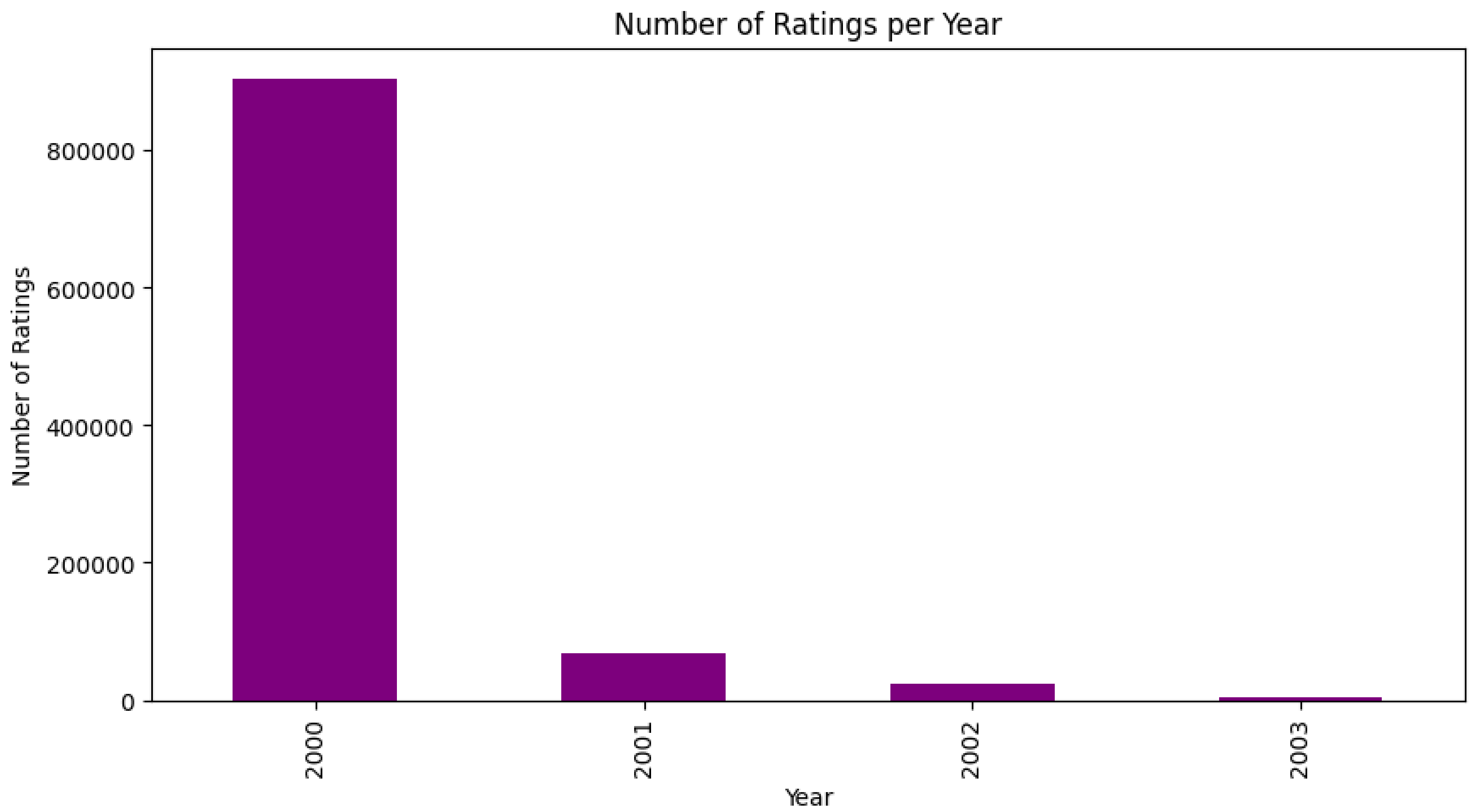
In [14]:

```
# Analyzing the ratings distribution using bar and pie charts
plt.subplot(1, 2, 1)
ratings['Rating'].value_counts().sort_index().plot(kind='bar', figsize=(10,5))
plt.title('Distribution of Movie Ratings')
plt.xlabel('Rating')
plt.ylabel('Number of Ratings')
plt.subplot(1, 2, 2)
ratings['Rating'].value_counts().sort_index().plot(kind='pie', autopct='%1.1f%%', figsize=(8,8))
plt.title('Distribution of Movie Ratings')
plt.ylabel('')
plt.show()
```

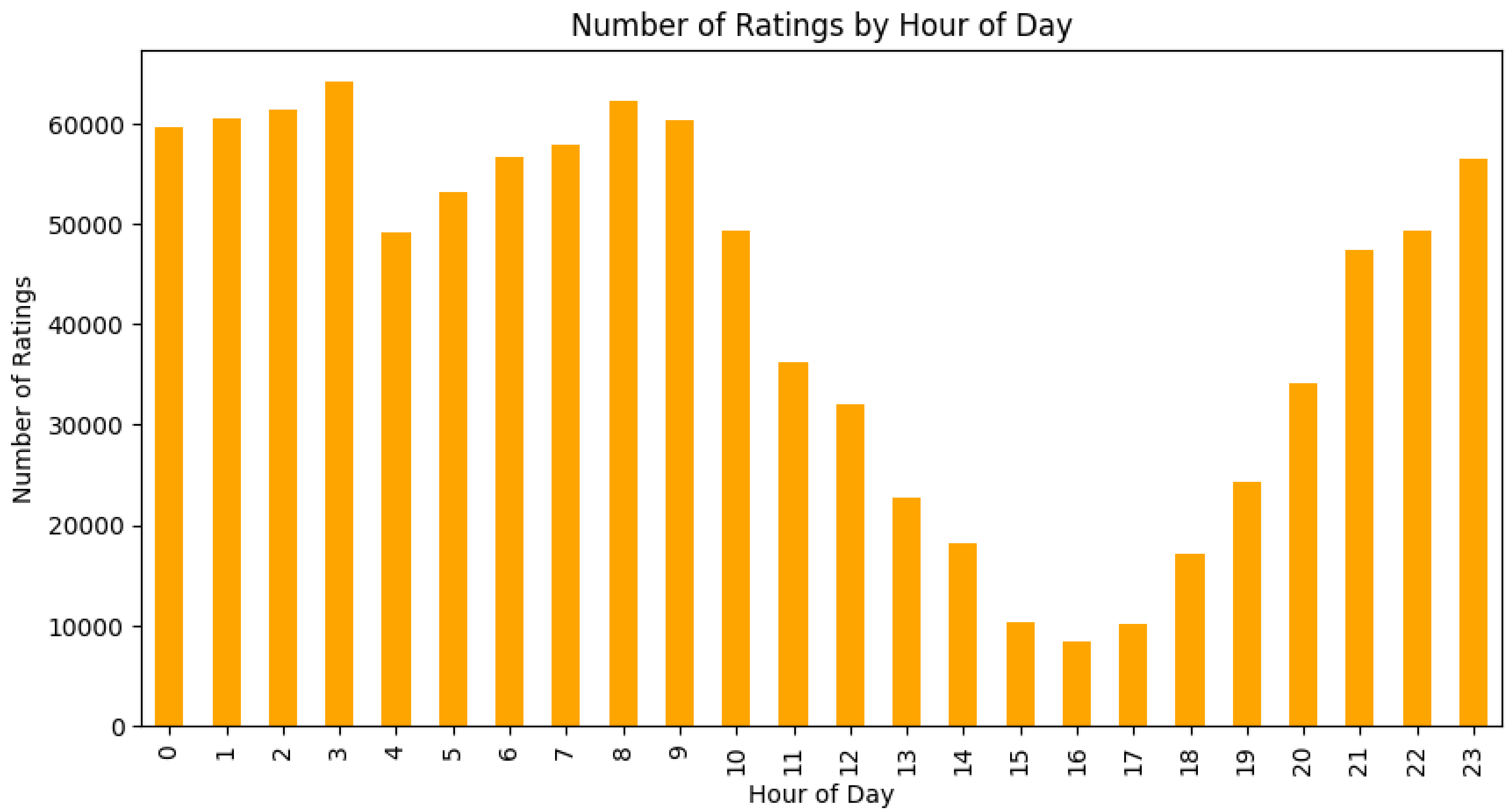




In [15]:
```
# Analyzing the Timestamp distribution
ratings['Timestamp'].dt.year.value_counts().sort_index().plot(kind='bar', figsize=(10,5), color='purple')
plt.title('Number of Ratings per Year')
plt.xlabel('Year')
plt.ylabel('Number of Ratings')
plt.show()
```



In [16]:
```
# Analyzing the time of ratings
ratings['Timestamp'].dt.hour.value_counts().sort_index().plot(kind='bar', figsize=(10,5), color='orange')
plt.title('Number of Ratings by Hour of Day')
plt.xlabel('Hour of Day')
plt.ylabel('Number of Ratings')
plt.show()
```

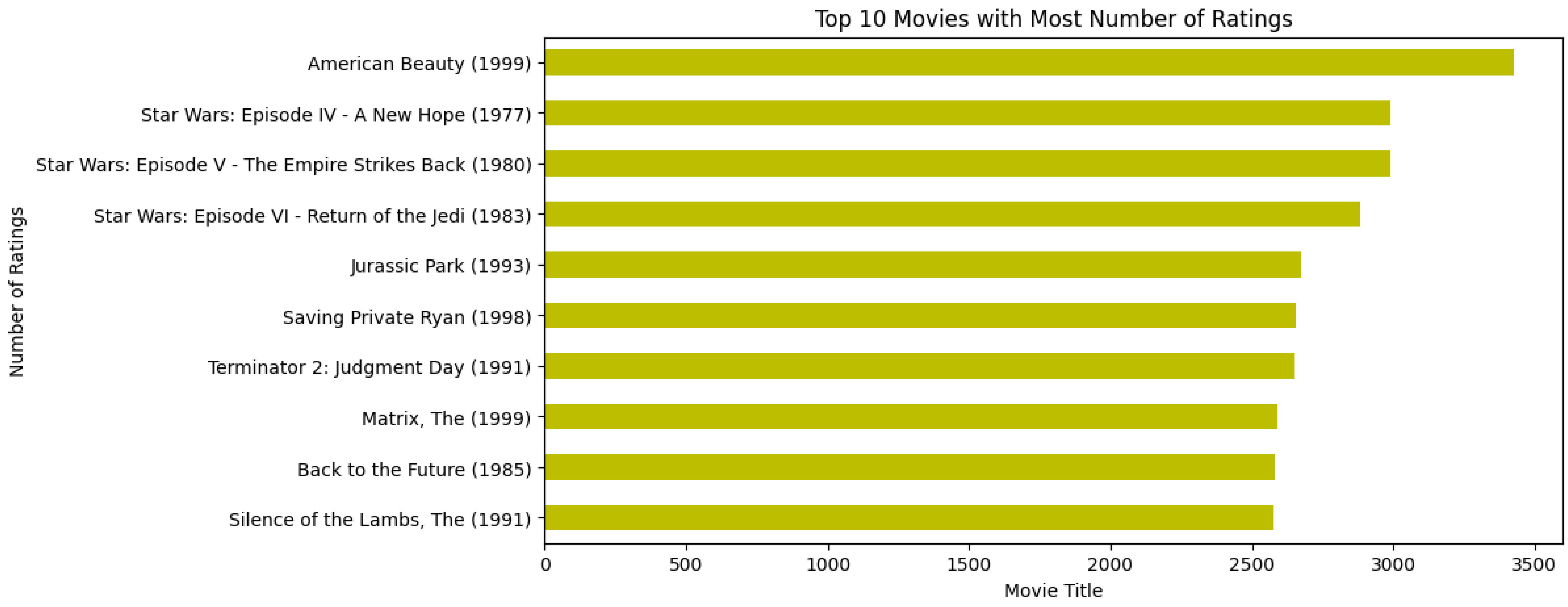


In [17]:
```
movies_ratings = pd.merge(movies, ratings, left_on='Movie ID', right_on='MovieID', how='inner')
movies_ratings.head()
```

Out[17]:

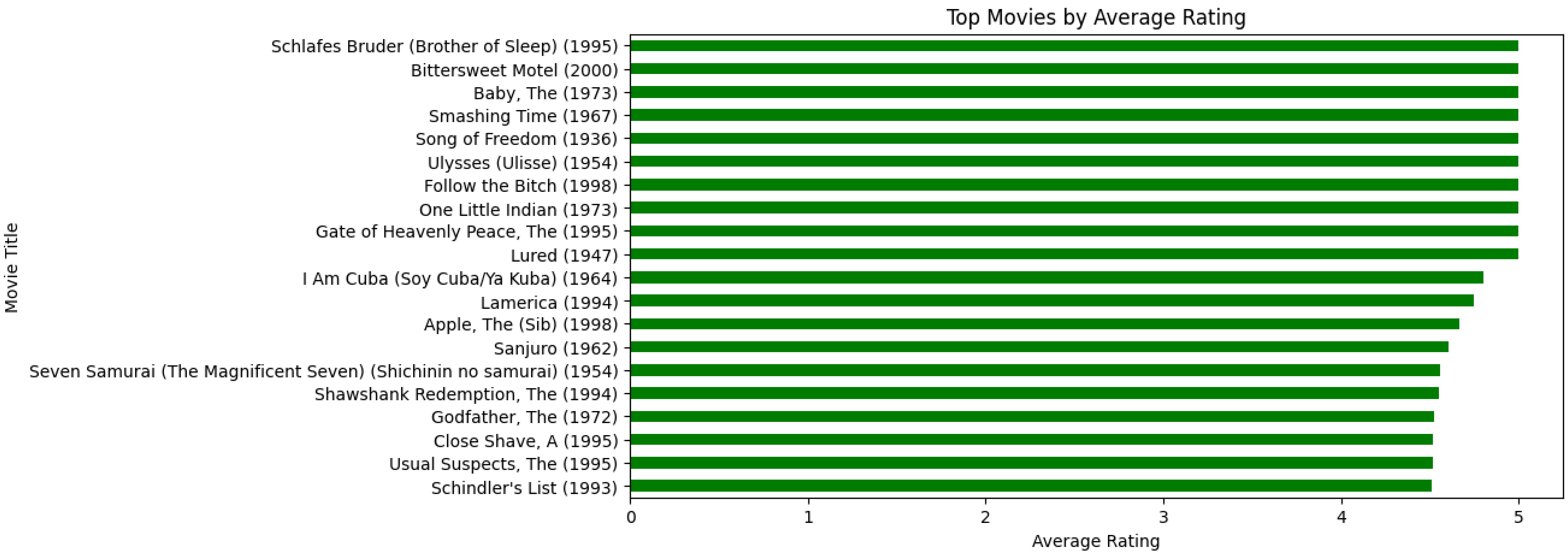
	Movie ID	Title	Genres	Year	Decade	UserID	MovieID	Rating	Timestamp
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	1	1	5	2001-01-07 05:07:48
1	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	6	1	4	2000-12-31 10:00:08
2	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	8	1	4	2000-12-31 09:01:36
3	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	9	1	5	2000-12-31 06:55:52
4	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	10	1	5	2000-12-31 07:04:34

In [18]:
```
# Getting top 10 titles with most number of ratings
top_10_rated_movies = movies_ratings['Title'].value_counts().head(10).sort_values(ascending=True)
top_10_rated_movies.plot(kind='barh', figsize=(10,5), color='y')
plt.title('Top 10 Movies with Most Number of Ratings')
plt.xlabel('Movie Title')
plt.ylabel('Number of Ratings')
plt.show()
```



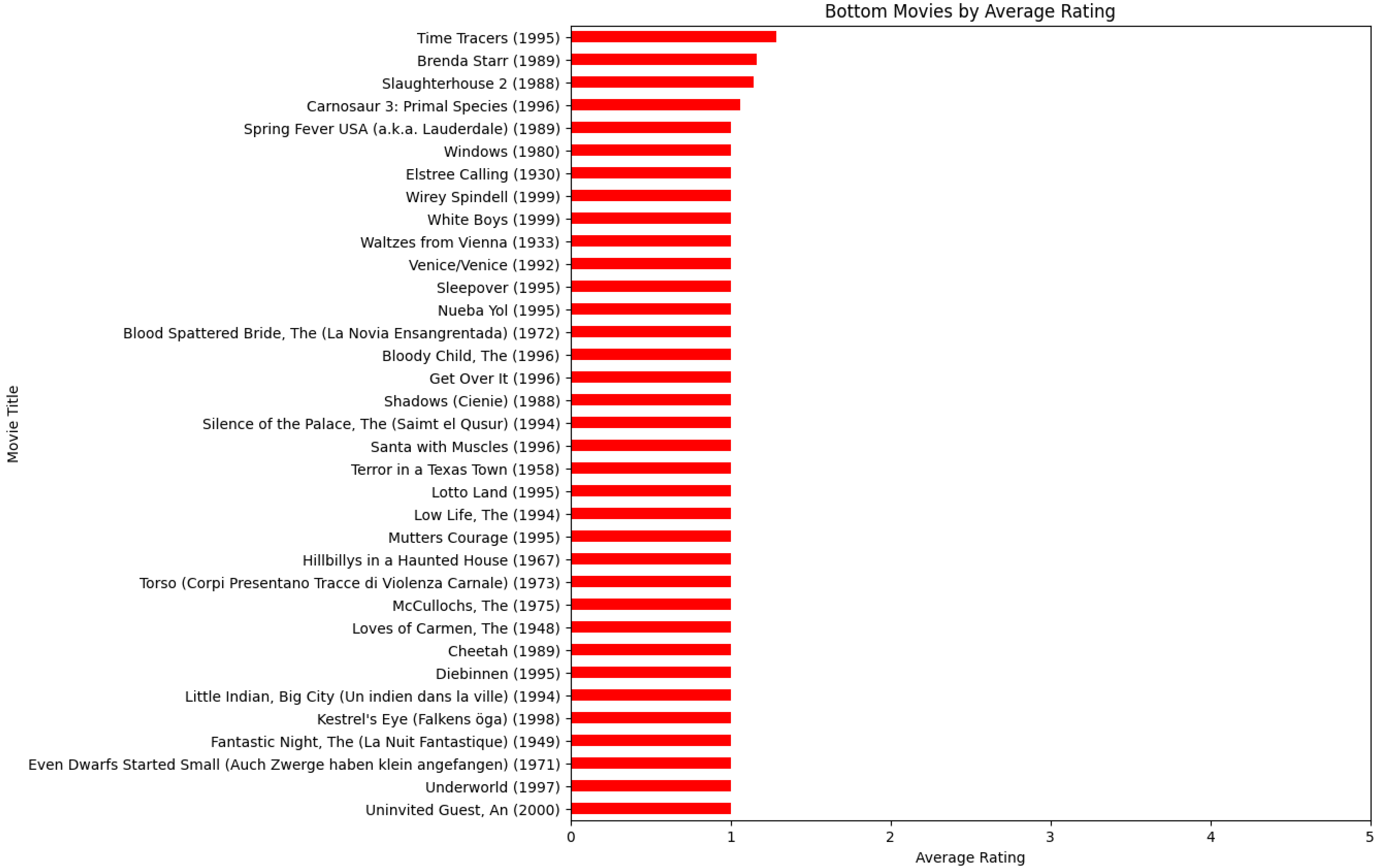
In [19]:

```
# Getting top 10 movies by average rating
top_movies = movies_ratings.groupby('Title')['Rating'].mean().sort_values(ascending=True).tail(20)
top_movies.plot(kind='barh', figsize=(10,5), color='g')
plt.title('Top Movies by Average Rating')
plt.xlabel('Average Rating')
plt.ylabel('Movie Title')
plt.show()
```



In [20]:

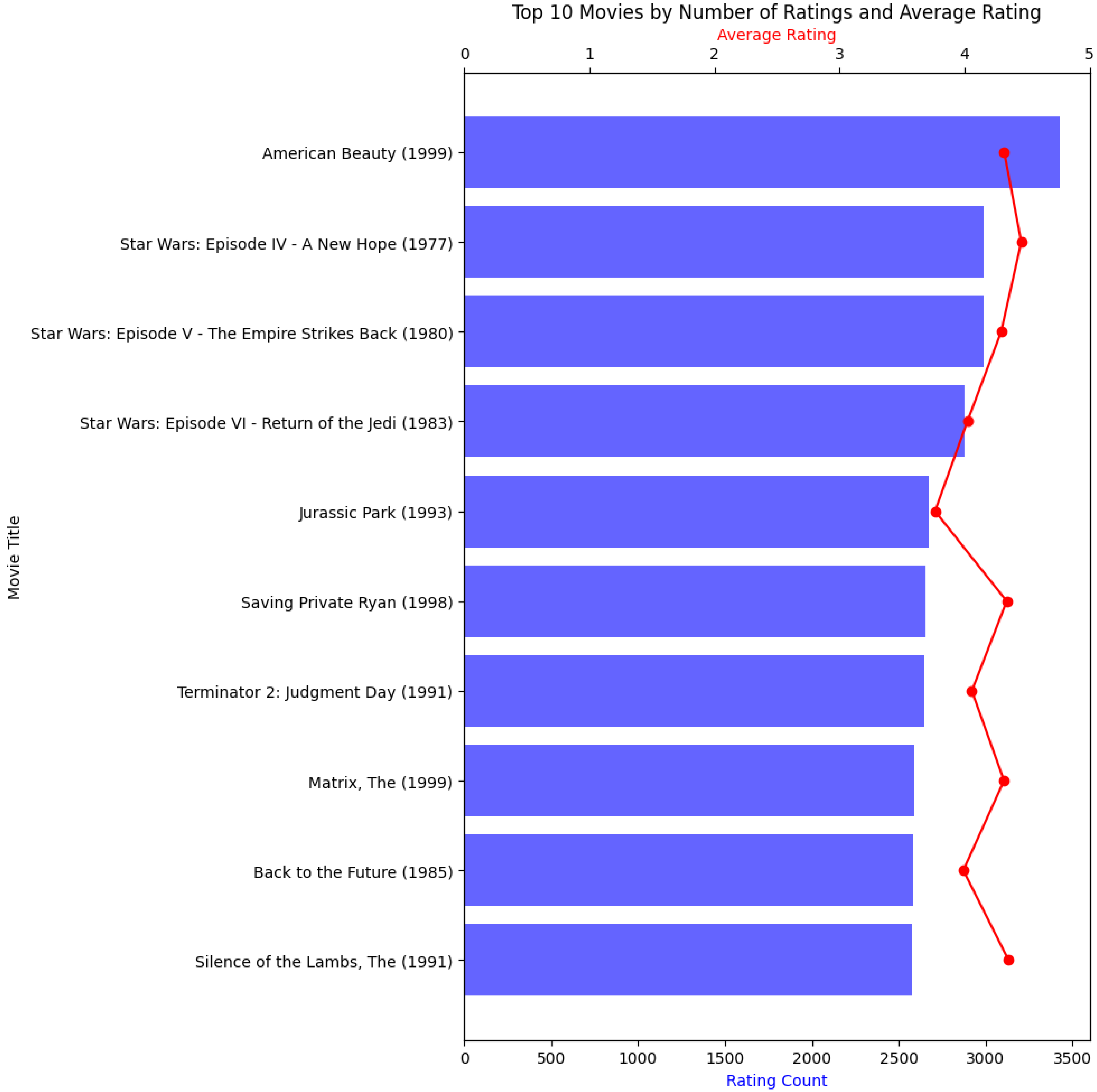
```
# Getting bottom 10 movies by average rating
bottom_movies = movies_ratings.groupby('Title')['Rating'].mean().sort_values(ascending=True).head(35)
bottom_movies.plot(kind='barh', figsize=(10,10), color='r')
plt.title('Bottom Movies by Average Rating')
plt.xlabel('Average Rating')
plt.ylabel('Movie Title')
plt.xlim(0,5)
plt.show()
```



In [21]:

```
# Getting top 10 movies sorted first by number of ratings then by average rating
top_10_movies = movies_ratings.groupby('Title').agg({'Rating': ['count', 'mean']})
top_10_movies.columns = ['Rating Count', 'Average Rating']
top_10_movies = top_10_movies.sort_values(by='Rating Count', ascending=True).tail(10)
fig, ax1 = plt.subplots(figsize=(10,10))
ax1.barh(top_10_movies.index, top_10_movies['Rating Count'], color='b', alpha=0.6, label='Rating Count')
ax1.set_ylabel('Movie Title')
ax1.set_yticks(range(len(top_10_movies.index)))
```

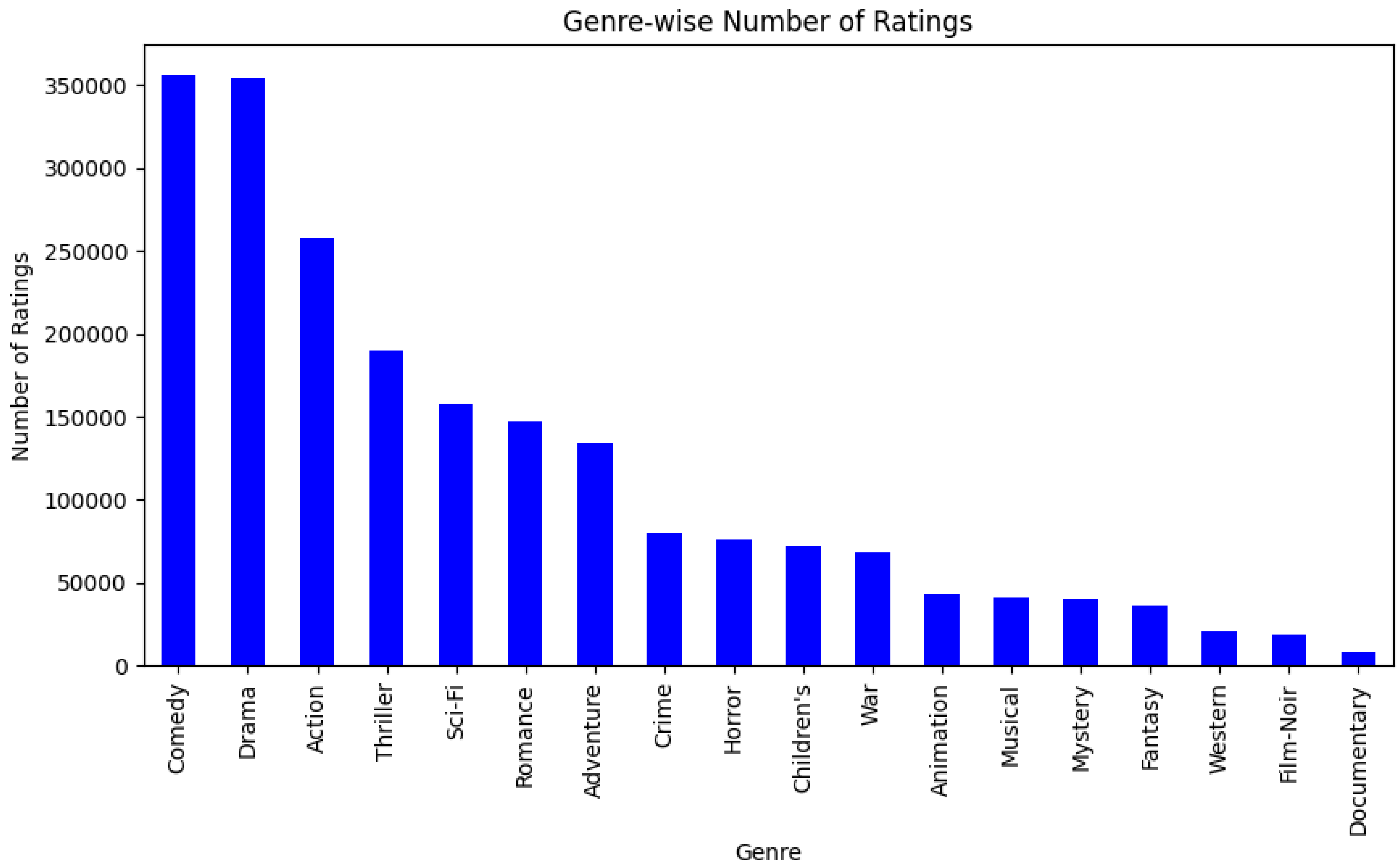
```
ax1.set_yticklabels(top_10_movies.index)
ax1.set_xlabel('Rating Count', color='b')
ax2 = ax1.twiny()
ax2.plot(top_10_movies['Average Rating'], top_10_movies.index, color='r', marker='o', label='Average Rating')
ax2.set_xlabel('Average Rating', color='r')
ax2.set_xlim(0,5)
plt.title('Top 10 Movies by Number of Ratings and Average Rating')
fig.tight_layout()
plt.show()
```



Top 10 Movies by Number of Ratings and Average Rating
Average Rating
0
1
2
3
4
5
American Beauty (1999)
Star Wars: Episode IV - A New Hope (1977)
Star Wars: Episode V - The Empire Strikes Back (1980)
Star Wars: Episode VI - Return of the Jedi (1983)
Jurassic Park (1993)
Saving Private Ryan (1998)
Terminator 2: Judgment Day (1991)
Matrix, The (1999)
Back to the Future (1985)
Silence of the Lambs, The (1991)
Movie Title
0
500
1000
1500
2000
2500
3000
3500
Rating Count

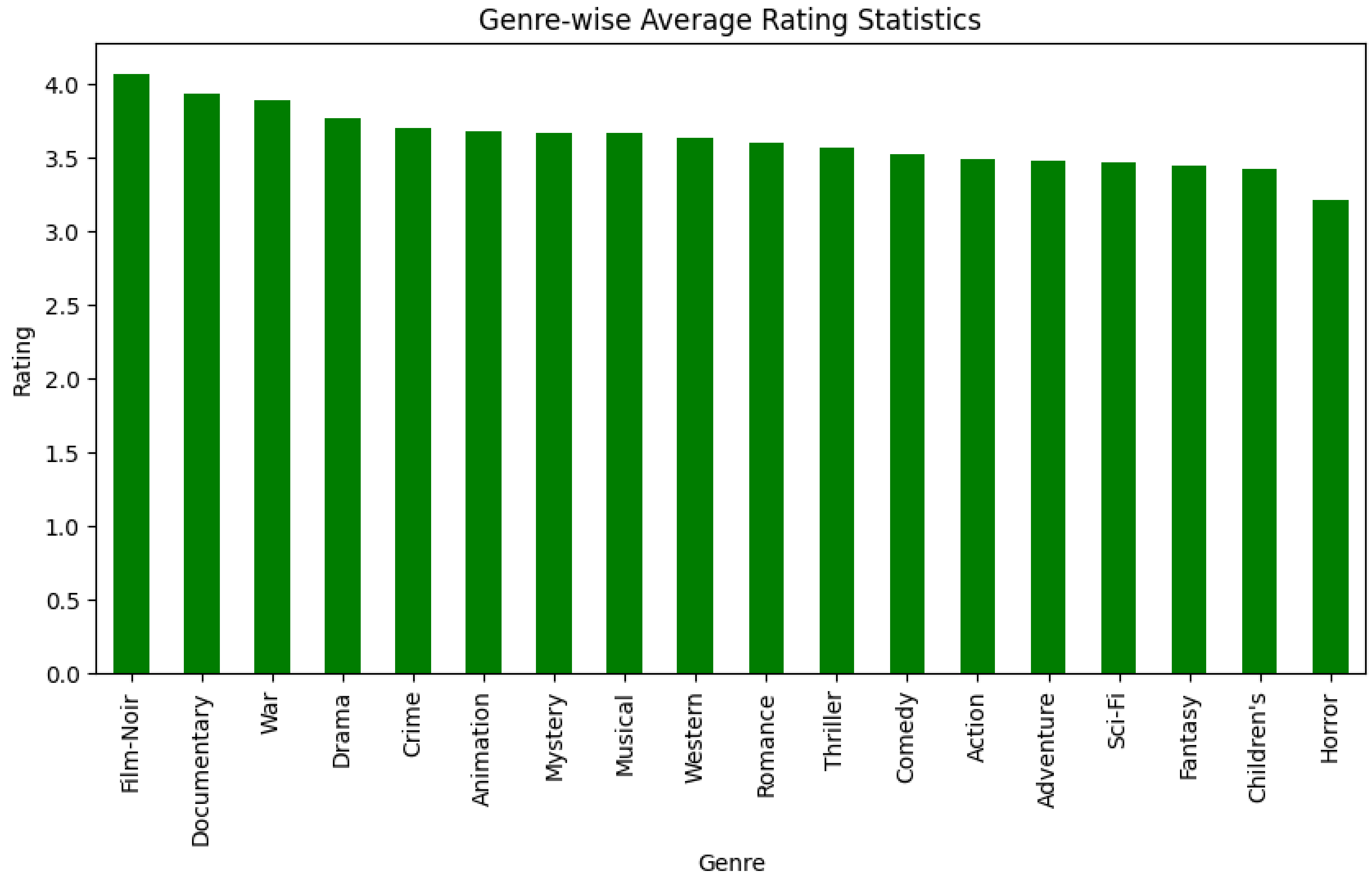
In [22]:

```
# Getting genre-wise number of ratings plot
genre_ratings = movies_ratings.copy()
genre_ratings = genre_ratings.assign(Genre=genre_ratings['Genres'].str.split('|')).explode('Genre')
genre_counts = genre_ratings['Genre'].value_counts().sort_values(ascending=False)
genre_counts.plot(kind='bar', figsize=(10,5), color='b', legend=False)
plt.title('Genre-wise Number of Ratings')
plt.xlabel('Genre')
plt.ylabel('Number of Ratings')
plt.show()
```



In [23]:

```
# Getting genre wise average rating plot, sorted by average rating
genre_ratings = movies_ratings.copy()
genre_ratings = genre_ratings.assign(Genre=genre_ratings['Genres'].str.split('|')).explode('Genre')
genre_stats = genre_ratings.groupby('Genre')['Rating'].agg(['mean']).sort_values(by='mean', ascending=False)
genre_stats.plot(kind='bar', figsize=(10,5), color='g', legend=False)
plt.title('Genre-wise Average Rating Statistics')
plt.xlabel('Genre')
plt.ylabel('Rating')
plt.show()
```



1.2.3 Users

In [24]:
```
users = pd.read_csv('zee-users.dat',sep='::',engine='python', encoding='latin1')
users.head()
```

Out[24]:

	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 [25]:
```
# Encoding Occupation column with actual occupation names
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"
}
# use .loc for mapping
users['Occupation'] = users['Occupation'].astype(object)
users.loc[:, 'Occupation'] = users['Occupation'].map(occupation_mapping)
users.head()
```

Out[25]:

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

In [26]:

```
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'].astype(object)
users['Age'] = users['Age'].map(age_mapping)

users['Age'] = pd.Categorical(users['Age'], categories=[
    "Under 18", "18-24", "25-34", "35-44", "45-49", "50-55", "56+"], ordered=True)
users.head()
```

Out[26]:

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

In [27]:
```
users.info()
```

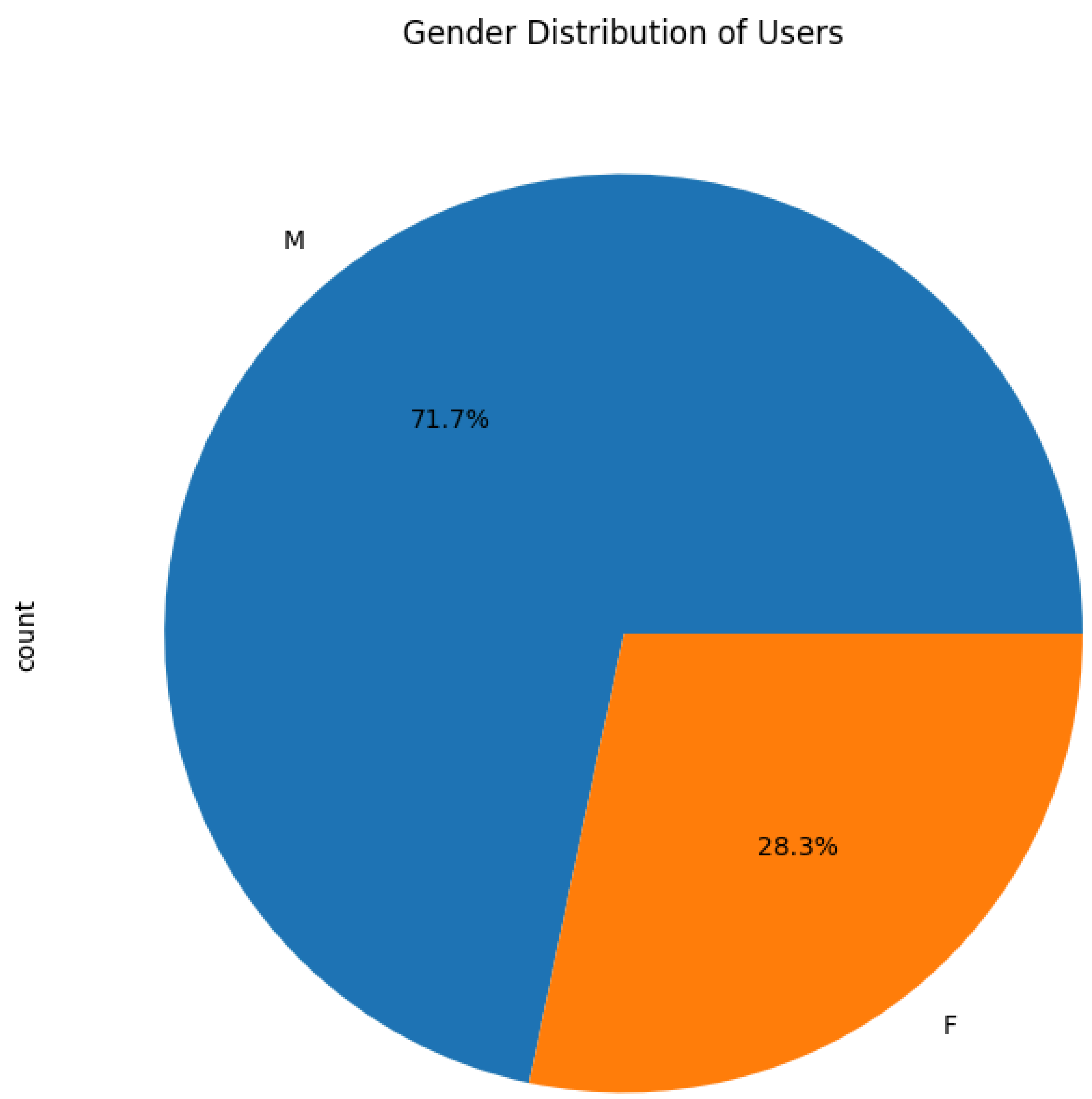
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6040 entries, 0 to 6039
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   UserID      6040 non-null   int64
 1   Gender      6040 non-null   object
 2   Age         6040 non-null   category
 3   Occupation  6040 non-null   object
 4   Zip-code    6040 non-null   object
dtypes: category(1), int64(1), object(3)
memory usage: 195.1+ KB
```

In [28]:
```
users.describe(include='all').T
```

Out[28]:

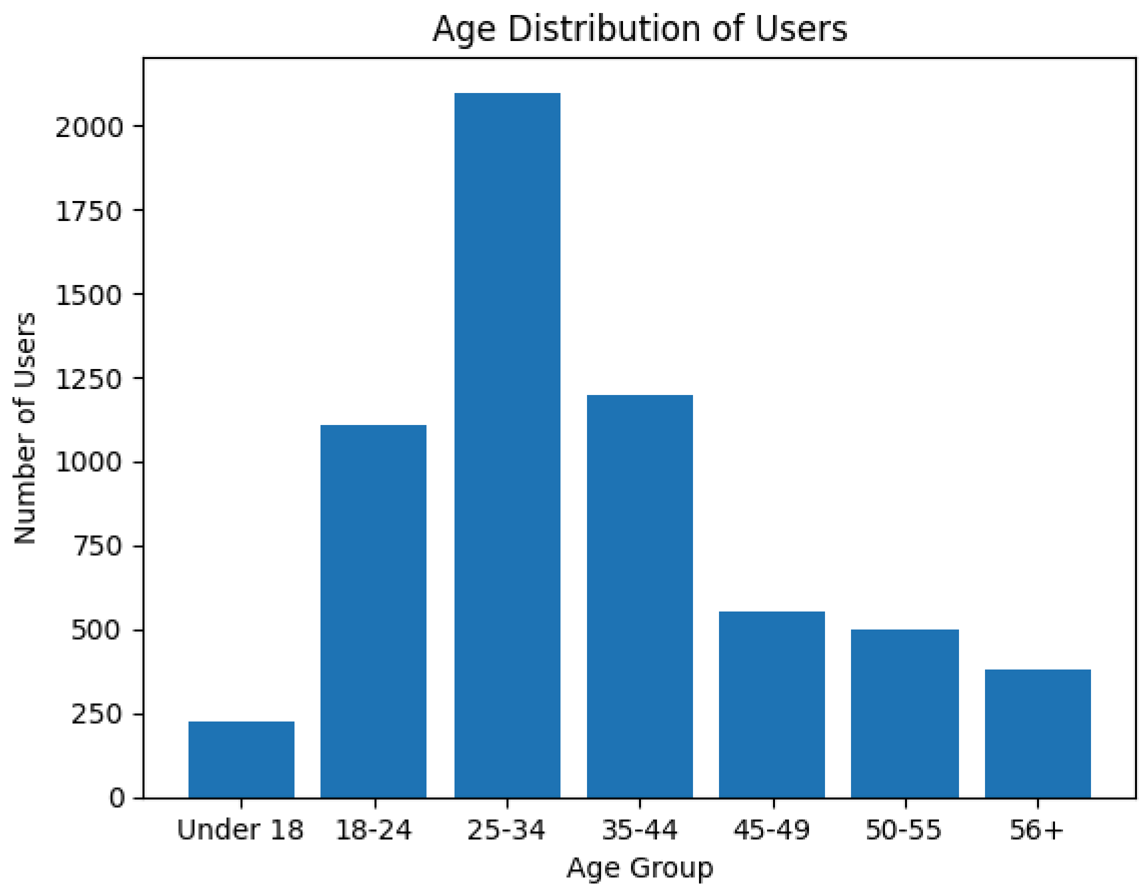
	count	unique	top	freq	mean	std	min	25%	50%	75%	max
UserID	6040.0	NaN	NaN	NaN	3020.5	1743.742145	1.0	1510.75	3020.5	4530.25	6040.0
Gender	6040	2	M	4331	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Age	6040	7	25-34	2096	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Occupation	6040	21	college/grad student	759	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Zip-code	6040	3439	48104	19	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [29]:
```
# Gender distribution of users (pie chart)
users['Gender'].value_counts().plot(kind='pie', autopct='%1.1f%%', figsize=(8,8))
plt.title('Gender Distribution of Users')
plt.show()
```



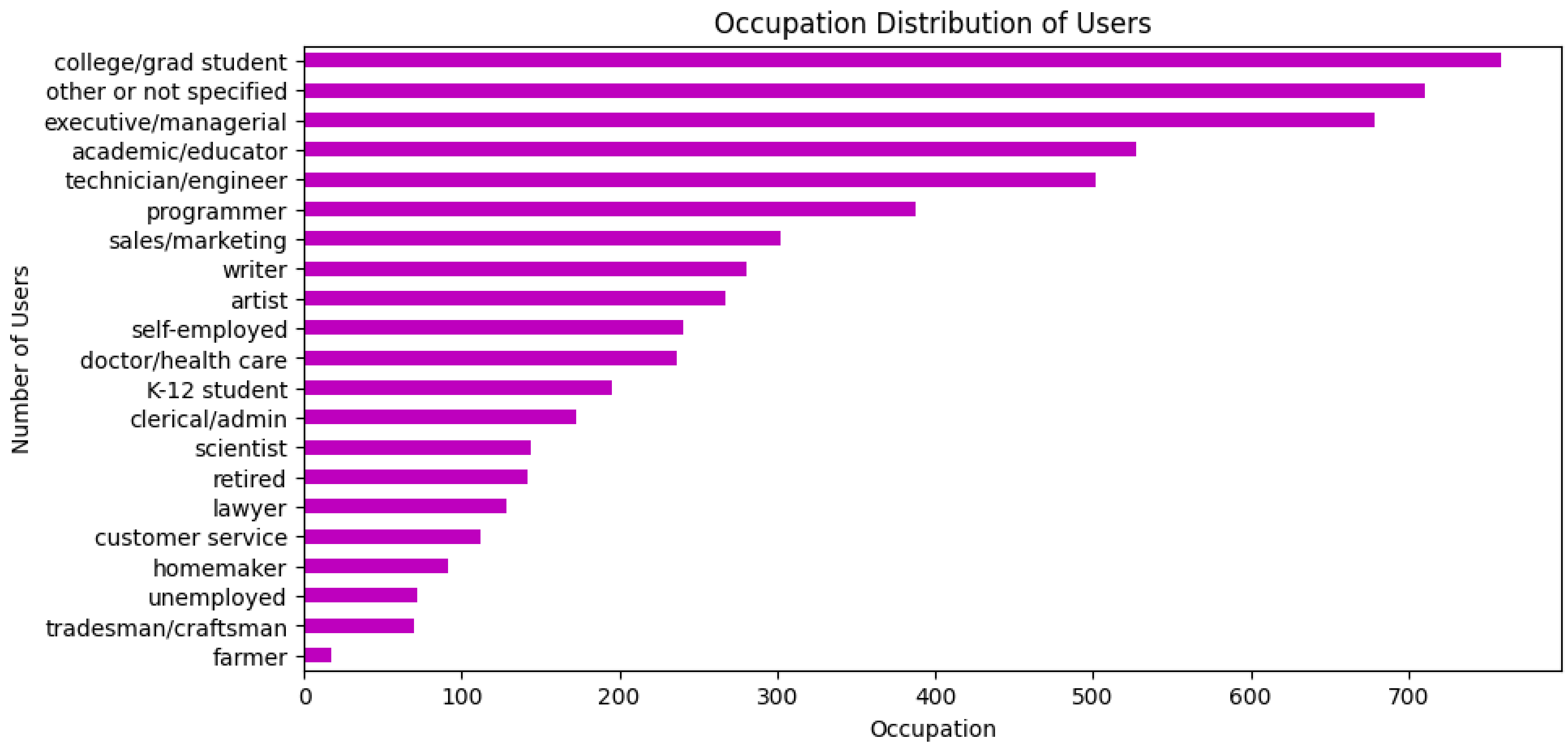
In [30]:

```
# Age distribution of users (age is now categorical after mapping)
plt.bar(users['Age'].value_counts().sort_index().index, users['Age'].value_counts().sort_index().values)
plt.title('Age Distribution of Users')
plt.xlabel('Age Group')
plt.ylabel('Number of Users')
plt.show()
```



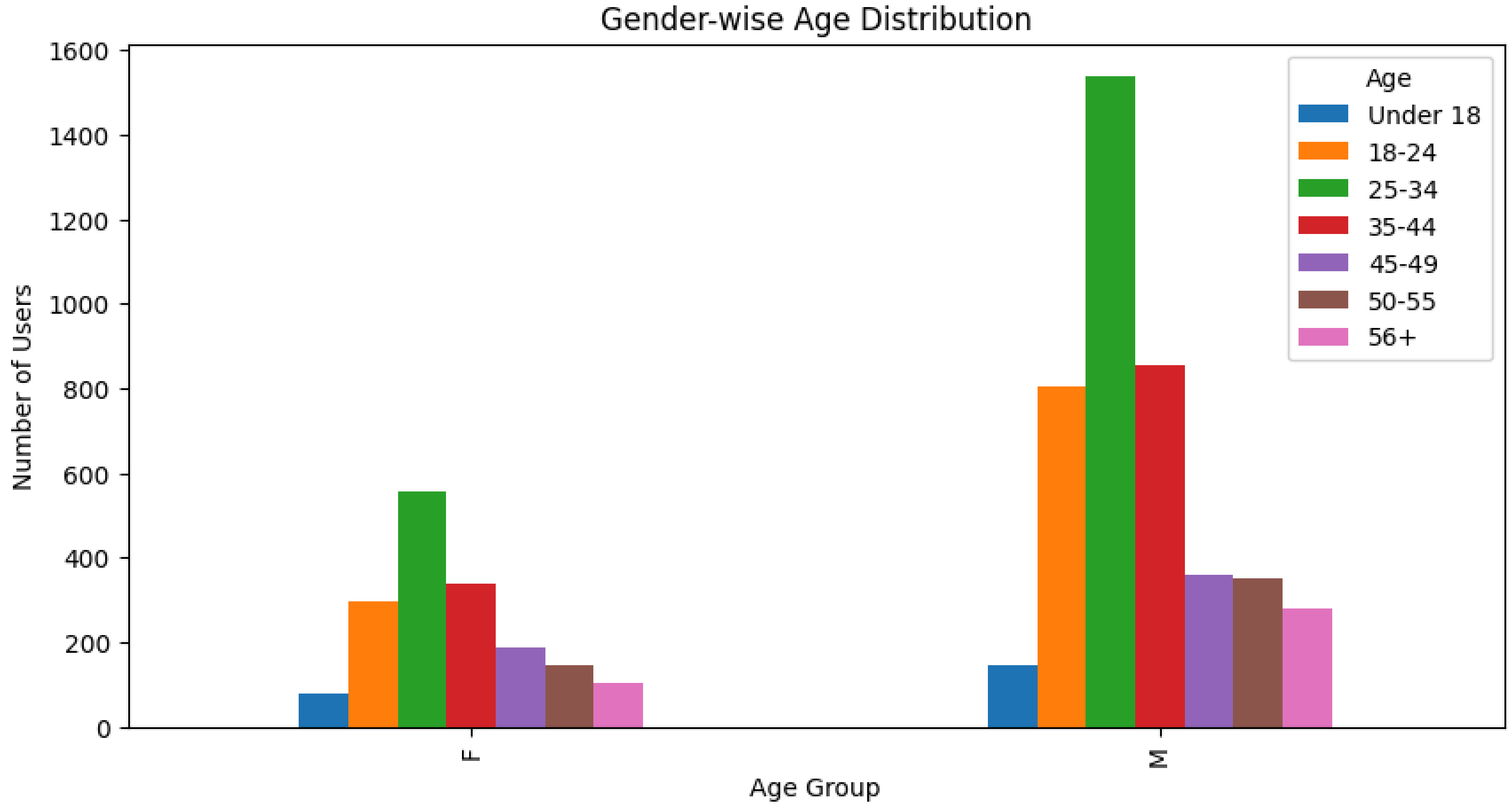
In [31]:

```
# Occupation distribution of users
users['Occupation'].value_counts().sort_values(ascending=True).plot(kind='barh', figsize=(10,5), color='m')
plt.title('Occupation Distribution of Users')
plt.xlabel('Occupation')
plt.ylabel('Number of Users')
plt.show()
```

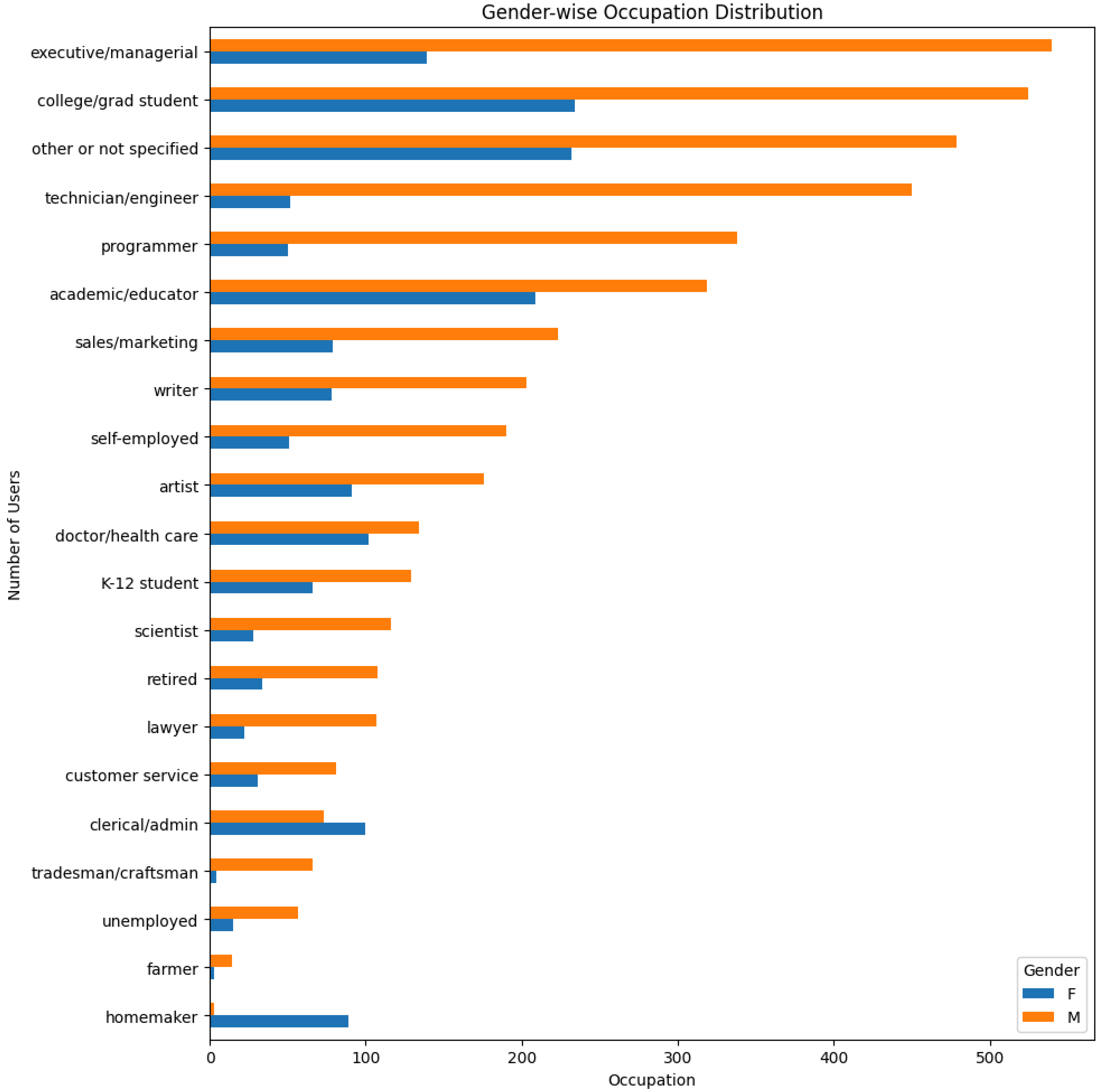


In [32]:

```
# Gender-wise age distribution
gender_age_dist = users.groupby(['Gender', 'Age'], observed=True).size().unstack().fillna(0)
gender_age_dist.plot(kind='bar', figsize=(10,5))
plt.title('Gender-wise Age Distribution')
plt.xlabel('Age Group')
plt.ylabel('Number of Users')
plt.show()
```



In [33]:
```
# Gender-wise occupation distribution
gender_occupation_dist = users.groupby(['Occupation', 'Gender'], observed=True).size().unstack().fillna(0).sort_values(by='M')
gender_occupation_dist.plot(kind='barh', figsize=(10,10))
plt.title('Gender-wise Occupation Distribution')
plt.xlabel('Occupation')
plt.ylabel('Number of Users')
plt.tight_layout()
plt.show()
```



Gender-wise Occupation Distribution
executive/managerial
college/grad student
other or not specified
technician/engineer
programmer
academic/educator
sales/marketing
writer
self-employed
artist
doctor/health care
K-12 student
scientist
retired
lawyer
customer service
clerical/admin
tradesman/craftsman
unemployed
farmer
homemaker
Number of Users
0
100
200
300
400
500
Occupation
Gender
F
M

In [34]:
```python
# merging everything together
df = pd.merge(movies_ratings, users, left_on='UserID', right_on='UserID', how='inner')
# Dropping unnecessary columns
df = df.drop(columns=['MovieID'])
df.head()
```

Out[34]:

	Movie ID	Title	Genres	Year	Decade	UserID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	1	5	2001-01-07 05:07:48	F	Under 18	K-12 student	48067
1	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	6	4	2000-12-31 10:00:08	F	50-55	homemaker	55117
2	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	8	4	2000-12-31 09:01:36	M	25-34	programmer	11413
3	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	9	5	2000-12-31 06:55:52	M	25-34	technician/engineer	61614
4	1	Toy Story (1995)	Animation|Children's|Comedy	1995.0	1990	10	5	2000-12-31 07:04:34	F	35-44	academic/educator	95370

2. Data Proprocessing

2.1 Data Cleaning and Formatting

In [59]:
```python
df.duplicated().sum()
```

Out[59]:
```
np.int64(0)
```

2.2 Data Transformation

In [35]:
```python
df.columns
```

Out[35]:
```
Index(['Movie ID', 'Title', 'Genres', 'Year', 'Decade', 'UserID', 'Rating',
       'Timestamp', 'Gender', 'Age', 'Occupation', 'Zip-code'],
      dtype='object')
```

In [36]:
```python
matrix = pd.pivot_table(df, index='UserID', columns='Title', values='Rating', aggfunc='mean', fill_value=0)
matrix
```

Out[36]:

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)	101 Dalmatians (1996)	12 Angry Men (1957)	...	Young Poisoner's Handbook, The (1995)	Young Sherlock Holmes (1985)	Young and Innocent (1937)	Your Friends and Neighbors (1998)	Zachariah (1971)	Zed & Two Noughts, A (1985)	Zero Effect (1998)	Zero Kelvin (Kjærlighetens kjøtere) (1995)	Zeus and Roxanne (1997)	e)
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	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	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	0.0	0.0	...	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6037	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6038	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6039	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6040	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

6040 rows × 3706 columns

2.3 Analyzing Sparsity

In [60]:

```
# sparsity

sparsity = 1.0 - (np.count_nonzero(matrix.values) / float(matrix.size))
print(f"Sparsity of the user-item matrix: {sparsity:.4f}")
```

```
Sparsity of the user-item matrix: 0.9553
```

3. Model Building

3.1 Collaborative Filtering with Pearson Correlation

In [58]:

```
# For a given movie, calculate the Pearson Correlation with other movies to find the most similar ones.
def recommend_movies_by_pearson_corr(df, movie_title, top_n=10):
    for col in df.columns:
        if movie_title in col:
            movie_title = col
            break
    movie_rating = df[movie_title]
    similar_movies = df.corrwith(movie_rating)
    sim_df = pd.DataFrame(similar_movies, columns=['Pearson Correlation'])
    sim_df.sort_values(by='Pearson Correlation', ascending=False, inplace=True)
    print(f"Top {top_n} movies similar to '{movie_title}':")
```

```python
    return sim_df.iloc[1:,:].head(top_n)

recommend_movies_by_pearson_corr(matrix, 'Liar Liar', 3)
```

```
Top 3 movies similar to 'Liar Liar (1997)':
```

Out[58]:

	Pearson Correlation
Title	
Mrs. Doubtfire (1993)	0.499927
Dumb & Dumber (1994)	0.459601
Ace Ventura: Pet Detective (1994)	0.458654

3.2 Collaborative Filtering with Cosine Similarity

In [39]:
```python
item_sim = cosine_similarity(matrix.T)
item_sim  = pd.DataFrame(item_sim, index=matrix.columns, columns=matrix.columns)
item_sim.head()
```

Out[39]:

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)	101 Dalmatians (1996)	12 Angry Men (1957)	...	Young Poisoner's Handbook, The (1995)	Young Sherlock Holmes (1985)	Young and Innocent (1937)	Your Friends and Neighbors (1998)	Zachariah (1971)	Zed & Two Noughts, A (1985)	Zero Effect (1998)	Zero Kel (Kjærlighete kjøte (19
Title																			
$1,000,000 Duck (1971)	1.000000	0.072357	0.037011	0.079291	0.060838	0.00000	0.058619	0.189965	0.172254	0.094785	...	0.038725	0.076474	0.000000	0.044074	0.0	0.045280	0.039395	0.0000
'Night Mother (1986)	0.072357	1.000000	0.115290	0.115545	0.159526	0.00000	0.076798	0.147437	0.095922	0.111413	...	0.053010	0.087828	0.063758	0.135962	0.0	0.091150	0.074787	0.0000
'Til There Was You (1997)	0.037011	0.115290	1.000000	0.098756	0.066301	0.08025	0.127895	0.112654	0.125670	0.079115	...	0.029200	0.062893	0.000000	0.079187	0.0	0.022594	0.079261	0.0000
'burbs, The (1989)	0.079291	0.115545	0.098756	1.000000	0.143620	0.00000	0.192191	0.246927	0.175885	0.170719	...	0.113386	0.207897	0.019962	0.138064	0.0	0.055704	0.161174	0.0000
...And Justice for All (1979)	0.060838	0.159526	0.066301	0.143620	1.000000	0.00000	0.075093	0.194154	0.116379	0.205486	...	0.089998	0.153006	0.067009	0.109029	0.0	0.086080	0.110867	0.0743

5 rows × 3706 columns

In [40]:
```python
user_sim = cosine_similarity(matrix)
user_sim = pd.DataFrame(user_sim, index=matrix.index, columns=matrix.index)
user_sim.head()
```

Out[40]:

UserID	1	2	3	4	5	6	7	8	9	10	...	6031	6032	6033	6034	6035	6036	6037	6038	6039	6040
UserID																					
1	1.000000	0.096382	0.120610	0.132455	0.090158	0.179222	0.059678	0.138241	0.226148	0.255288	...	0.170588	0.082006	0.069807	0.033663	0.114877	0.186329	0.135979	0.000000	0.174604	0.133590
2	0.096382	1.000000	0.151479	0.171176	0.114394	0.100865	0.305787	0.203337	0.190198	0.226861	...	0.112503	0.091222	0.268565	0.014286	0.183384	0.228241	0.206274	0.066118	0.066457	0.218276
3	0.120610	0.151479	1.000000	0.151227	0.062907	0.074603	0.138332	0.077656	0.126457	0.213655	...	0.092960	0.125864	0.161507	0.000000	0.097308	0.143264	0.107744	0.120234	0.094675	0.133144
4	0.132455	0.171176	0.151227	1.000000	0.045094	0.013529	0.130339	0.100856	0.093651	0.120738	...	0.163629	0.093041	0.382803	0.000000	0.082097	0.170583	0.127464	0.062907	0.064634	0.137968
5	0.090158	0.114394	0.062907	0.045094	1.000000	0.047449	0.126257	0.220817	0.261330	0.117052	...	0.100652	0.035732	0.061806	0.054151	0.179083	0.293365	0.172686	0.020459	0.027689	0.241437

5 rows × 6040 columns

In [41]:

```
csr_matrix = sparse.csr_matrix(matrix.T.values)
csr_matrix
```

Out[41]:

```
<Compressed Sparse Row sparse matrix of dtype 'float64'
	with 1000209 stored elements and shape (3706, 6040)>
```

In [42]:

```
def recommend_movies_by_knn(df, movie_title, top_n=10):
    for col in df.columns:
        if movie_title in col:
            movie_title = col
            break
    knn = NearestNeighbors(n_neighbors=top_n+1,
                           metric='cosine',
                           n_jobs=-1)
    knn.fit(csr_matrix)
    distances, indices = knn.kneighbors(
        df[movie_title].values.reshape(1,-1),
        n_neighbors=top_n+1
        )
    for i in range(0, len(distances.flatten())):
        if i == 0:
            print('Recommendations for the movie: {0}\n'.format(movie_title))
        else:
            print(f'{i}: {df.columns[indices.flatten()[i]]}, with distance of {round(distances.flatten()[i], 3)}')

recommend_movies_by_knn(matrix, 'Liar Liar', 10)
```

```
Recommendations for the movie: Liar Liar (1997)

1: Mrs. Doubtfire (1993), with distance of 0.443
2: Ace Ventura: Pet Detective (1994), with distance of 0.483
3: Dumb & Dumber (1994), with distance of 0.487
4: Home Alone (1990), with distance of 0.489
5: Wayne's World (1992), with distance of 0.501
6: Wedding Singer, The (1998), with distance of 0.503
7: Austin Powers: International Man of Mystery (1997), with distance of 0.511
8: There's Something About Mary (1998), with distance of 0.517
9: League of Their Own, A (1992), with distance of 0.518
10: Mask, The (1994), with distance of 0.531
```

3.3 Matrix Factorization

- **Concept:** Decomposes a large user–item rating matrix into the product of two lower-dimensional matrices representing user and item latent factors.
- **Goal:** Predict missing ratings by learning hidden patterns linking users and items.
- **Mathematical Form:**

  Given rating matrix R (m×n), approximate as $R \approx P \times Q^T$,

  where P is (m×k) user-feature matrix and Q is (n×k) item-feature matrix, and $k \ll m,n$.

- **Optimization Objective:**

  Minimize the error between observed ratings and predictions:

  $\min \Sigma_{(u,i)\in K}(R_{ui} - P_u \cdot Q_i^T)^2 + \lambda(||P||^2 + ||Q||^2)$

  where λ controls regularization to prevent overfitting.

- **Algorithms Used:**
  - Stochastic Gradient Descent (SGD)
  - Alternating Least Squares (ALS)
- **Variants:**
  - **Bias-aware MF:** Adds user and item bias terms.
  - **SVD++:** Incorporates implicit feedback.
  - **Non-negative MF:** Forces latent features to be non-negative for interpretability.
- **Advantages:**
  - Captures complex user–item relationships in fewer dimensions.
  - Scales well with large sparse datasets.
  - Supports personalization and latent pattern discovery.
- **Limitations:**
  - Cold-start problem for new users or items.
  - Assumes linear interactions between latent factors.
  - Needs sufficient data for stable factor estimation.
- **Use Cases:**
  - Movie, product, and content recommendations.
  - Personalized ranking and rating prediction tasks.

We will use `cmfrec` library for Collective Matrix Factorization (CMF).

3.4 Model Evaluation and Tuning

In [43]:
```
df1 = df[['UserID', 'Movie ID', 'Rating']].copy()
df1.columns = ['UserId', 'ItemId', 'Rating']
df1.head()
```

Out[43]:

	UserId	ItemId	Rating
0	1	1	5
1	6	1	4
2	8	1	4
3	9	1	5
4	10	1	5

In [44]:
```
df1['UserId'] = df1['UserId'].astype('category').cat.codes
df1['ItemId'] = df1['ItemId'].astype('category').cat.codes
df1.head()
```

Out[44]:

	UserId	ItemId	Rating
0	0	0	5
1	5	0	4
2	7	0	4
3	8	0	5
4	9	0	5

In [45]:
```
genres_decoded = pd.DataFrame(columns=movies['Genres'].str.split('|').explode().unique())

for i, row in movies.iterrows():
    genres = row['Genres'].split('|')
    for genre in genres:
        genres_decoded.at[i, genre] = 1
    for genre in genres_decoded.columns:
        if genre not in genres:
            genres_decoded.at[i, genre] = 0

decade_encoded = pd.get_dummies(movies["Decade"].astype(str), prefix="Decade").astype(int)

movie_features = pd.concat([genres_decoded, decade_encoded], axis=1)

movie_features.index = movies['Movie ID'].astype('category').cat.codes
movie_features['ItemId'] = movie_features.index
movie_features.head()
```

Out[45]:

	Animation	Children's	Comedy	Adventure	Fantasy	Romance	Drama	Action	Crime	Thriller	...	Decade_1920	Decade_1930	Decade_1940	Decade_1950	Decade_1960	Decade_1970	Decade_1980	Decad
0	1	1	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
1	0	1	0	1	1	0	0	0	0	0	...	0	0	0	0	0	0	0	
2	0	0	1	0	0	1	0	0	0	0	...	0	0	0	0	0	0	0	
3	0	0	1	0	0	0	1	0	0	0	...	0	0	0	0	0	0	0	
4	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	

5 rows × 29 columns

In [46]:

```python
users_age_encoded = pd.get_dummies(users["Age"].astype(str), prefix="Age").astype(int)
users_age_encoded.index = users['UserID'].astype('category').cat.codes

users_occupation_encoded = pd.get_dummies(users["Occupation"], prefix="Occupation").astype(int)
users_occupation_encoded.index = users['UserID'].astype('category').cat.codes

users_gender_encoded = pd.get_dummies(users["Gender"], prefix="Gender").astype(int)
users_gender_encoded.index = users['UserID'].astype('category').cat.codes

user_features = pd.concat([users_age_encoded, users_occupation_encoded, users_gender_encoded], axis=1)
user_features.index = users['UserID'].astype('category').cat.codes

user_features['UserId'] = user_features.index
user_features.head()
```

Out[46]:

	Age_18-24	Age_25-34	Age_35-44	Age_45-49	Age_50-55	Age_56+	Age_Under 18	Occupation_K-12 student	Occupation_academic/educator	Occupation_artist	...	Occupation_sales/marketing	Occupation_scientist	Occupation_self-employed
0	0	0	0	0	0	0	1	1	0	0	...	0	0	0
1	0	0	0	0	0	1	0	0	0	0	...	0	0	1
2	0	1	0	0	0	0	0	0	0	0	...	0	1	0
3	0	0	0	1	0	0	0	0	0	0	...	0	0	0
4	0	1	0	0	0	0	0	0	0	0	...	0	0	0

5 rows × 31 columns

In [47]:

```python
train_df, test_df = train_test_split(df1, test_size=0.3, random_state=42)

param_grid = {
    "k": [4, 8, 16, 32],
    "lambda_": [0.01, 0.1, 1, 10, 100],
    "method": ['als'],
    "user_bias": [True],
    "item_bias": [True],
    "use_cg": [True, False],
    "scale_lam": [True]
}

grid = ParameterGrid(param_grid)
```

```
best_rmse = float("inf")
best_params = None
```

In [48]:
```
results = []
for params in tqdm(grid, desc="Hyperparameter Tuning"):
    model = CMF(**params, niter=50)
    model.fit(X=train_df,
              U=user_features,
              I=movie_features)
    train_pred = model.predict(train_df['UserId'], train_df['ItemId'])
    test_pred = model.predict(test_df['UserId'], test_df['ItemId'])

    train_rmse = root_mean_squared_error(train_df['Rating'], train_pred)
    test_rmse = root_mean_squared_error(test_df['Rating'], test_pred)

    train_mape = mean_absolute_percentage_error(train_df['Rating'], train_pred)
    test_mape = mean_absolute_percentage_error(test_df['Rating'], test_pred)

    rmse_diff = abs(train_rmse - test_rmse)
    mape_diff = abs(train_mape - test_mape)

    results.append({
        'params': params,
        'train_rmse': train_rmse,
        'test_rmse': test_rmse,
        'train_mape': train_mape,
        'test_mape': test_mape,
        'rmse_diff': rmse_diff,
        'mape_diff': mape_diff
    })

res_df = pd.DataFrame(results)
res_df = res_df.sort_values(by=['test_rmse']).reset_index(drop=True)
```

```
Hyperparameter Tuning:   0%|          | 0/40 [00:00<?, ?it/s]
```

In [49]:
```
res_df
```

Out[49]:

	params	train_rmse	test_rmse	train_mape	test_mape	rmse_diff	mape_diff
0	{'item_bias': True, 'k': 32, 'lambda_': 0.1, '...	0.818183	0.869115	0.253690	0.271318	0.050932	0.017628
1	{'item_bias': True, 'k': 32, 'lambda_': 0.1, '...	0.818350	0.869152	0.253739	0.271333	0.050801	0.017594
2	{'item_bias': True, 'k': 16, 'lambda_': 0.1, '...	0.822102	0.869251	0.254896	0.271283	0.047149	0.016386
3	{'item_bias': True, 'k': 16, 'lambda_': 0.1, '...	0.822186	0.869302	0.254919	0.271303	0.047116	0.016384
4	{'item_bias': True, 'k': 8, 'lambda_': 0.1, 'm...	0.831152	0.870472	0.257743	0.271517	0.039320	0.013774
5	{'item_bias': True, 'k': 8, 'lambda_': 0.1, 'm...	0.831231	0.870533	0.257764	0.271536	0.039302	0.013772
6	{'item_bias': True, 'k': 4, 'lambda_': 0.01, '...	0.800404	0.873474	0.238043	0.261271	0.073070	0.023229
7	{'item_bias': True, 'k': 4, 'lambda_': 0.01, '...	0.800439	0.873483	0.238037	0.261287	0.073044	0.023250
8	{'item_bias': True, 'k': 4, 'lambda_': 0.1, 'm...	0.844672	0.875330	0.261973	0.273007	0.030659	0.011034
9	{'item_bias': True, 'k': 4, 'lambda_': 0.1, 'm...	0.844668	0.875331	0.261970	0.273006	0.030662	0.011035
10	{'item_bias': True, 'k': 8, 'lambda_': 0.01, '...	0.747943	0.882498	0.218887	0.260112	0.134555	0.041225
11	{'item_bias': True, 'k': 8, 'lambda_': 0.01, '...	0.748376	0.882973	0.219014	0.260420	0.134597	0.041406
12	{'item_bias': True, 'k': 16, 'lambda_': 0.01, ...	0.670311	0.930032	0.191209	0.269764	0.259722	0.078555
13	{'item_bias': True, 'k': 16, 'lambda_': 0.01, ...	0.671742	0.930162	0.191652	0.270398	0.258420	0.078746
14	{'item_bias': True, 'k': 8, 'lambda_': 1, 'met...	0.964683	0.971630	0.318397	0.322117	0.006947	0.003720
15	{'item_bias': True, 'k': 8, 'lambda_': 1, 'met...	0.964683	0.971630	0.318397	0.322117	0.006947	0.003720
16	{'item_bias': True, 'k': 16, 'lambda_': 1, 'me...	0.964683	0.971630	0.318397	0.322117	0.006947	0.003720
17	{'item_bias': True, 'k': 16, 'lambda_': 1, 'me...	0.964683	0.971630	0.318397	0.322117	0.006947	0.003720
18	{'item_bias': True, 'k': 4, 'lambda_': 1, 'met...	0.964683	0.971630	0.318397	0.322117	0.006947	0.003720
19	{'item_bias': True, 'k': 4, 'lambda_': 1, 'met...	0.964683	0.971630	0.318397	0.322117	0.006947	0.003720
20	{'item_bias': True, 'k': 32, 'lambda_': 1, 'me...	0.964683	0.971630	0.318397	0.322117	0.006947	0.003720
21	{'item_bias': True, 'k': 32, 'lambda_': 1, 'me...	0.964683	0.971630	0.318397	0.322117	0.006947	0.003720
22	{'item_bias': True, 'k': 32, 'lambda_': 0.01, ...	0.553929	1.000079	0.151700	0.287670	0.446150	0.135970
23	{'item_bias': True, 'k': 32, 'lambda_': 0.01, ...	0.550433	1.000673	0.150505	0.286964	0.450239	0.136459
24	{'item_bias': True, 'k': 8, 'lambda_': 10, 'me...	1.083850	1.086465	0.369184	0.371790	0.002615	0.002606
25	{'item_bias': True, 'k': 8, 'lambda_': 10, 'me...	1.083850	1.086465	0.369184	0.371790	0.002615	0.002606
26	{'item_bias': True, 'k': 32, 'lambda_': 10, 'm...	1.083850	1.086465	0.369184	0.371790	0.002615	0.002606
27	{'item_bias': True, 'k': 32, 'lambda_': 10, 'm...	1.083850	1.086465	0.369184	0.371790	0.002615	0.002606
28	{'item_bias': True, 'k': 16, 'lambda_': 10, 'm...	1.083850	1.086465	0.369184	0.371790	0.002615	0.002606
29	{'item_bias': True, 'k': 16, 'lambda_': 10, 'm...	1.083850	1.086465	0.369184	0.371790	0.002615	0.002606
30	{'item_bias': True, 'k': 4, 'lambda_': 10, 'me...	1.083850	1.086465	0.369184	0.371790	0.002615	0.002606
31	{'item_bias': True, 'k': 4, 'lambda_': 10, 'me...	1.083850	1.086465	0.369184	0.371790	0.002615	0.002606
32	{'item_bias': True, 'k': 16, 'lambda_': 100, '...	1.112898	1.114758	0.379476	0.381895	0.001861	0.002419

	params	train_rmse	test_rmse	train_mape	test_mape	rmse_diff	mape_diff
33	{'item_bias': True, 'k': 16, 'lambda_': 100, '...	1.112898	1.114758	0.379476	0.381895	0.001861	0.002419
34	{'item_bias': True, 'k': 8, 'lambda_': 100, 'm...	1.112898	1.114758	0.379476	0.381895	0.001861	0.002419
35	{'item_bias': True, 'k': 8, 'lambda_': 100, 'm...	1.112898	1.114758	0.379476	0.381895	0.001861	0.002419
36	{'item_bias': True, 'k': 4, 'lambda_': 100, 'm...	1.112898	1.114758	0.379476	0.381895	0.001861	0.002419
37	{'item_bias': True, 'k': 4, 'lambda_': 100, 'm...	1.112898	1.114758	0.379476	0.381895	0.001861	0.002419
38	{'item_bias': True, 'k': 32, 'lambda_': 100, '...	1.112898	1.114758	0.379476	0.381895	0.001861	0.002419
39	{'item_bias': True, 'k': 32, 'lambda_': 100, '...	1.112898	1.114758	0.379476	0.381895	0.001861	0.002419

In [50]:
```
best_params = res_df.head(1)['params'].values[0]
best_params
```

Out[50]:
```
{'item_bias': True,
 'k': 32,
 'lambda_': 0.1,
 'method': 'als',
 'scale_lam': True,
 'use_cg': False,
 'user_bias': True}
```

In [51]:
```
best_model = CMF(**best_params, niter=50)
best_model.fit(X=train_df,
              U=user_features,
              I=movie_features)
predictions = best_model.predict(test_df['UserId'], test_df['ItemId'])
predictions
```

Out[51]:
```
array([2.3640647, 2.9073412, 3.4502718, ..., 3.8852334, 3.0963821,
       2.6603909], shape=(300063,), dtype=float32)
```

3.5 Advanced Collaborative Filtering Techniques

In [61]:
```
movies['Main Genre'] = movies['Genres'].str.split('|').str[0]
```

3.5.1 PCA

Visualizing Item Embeddings

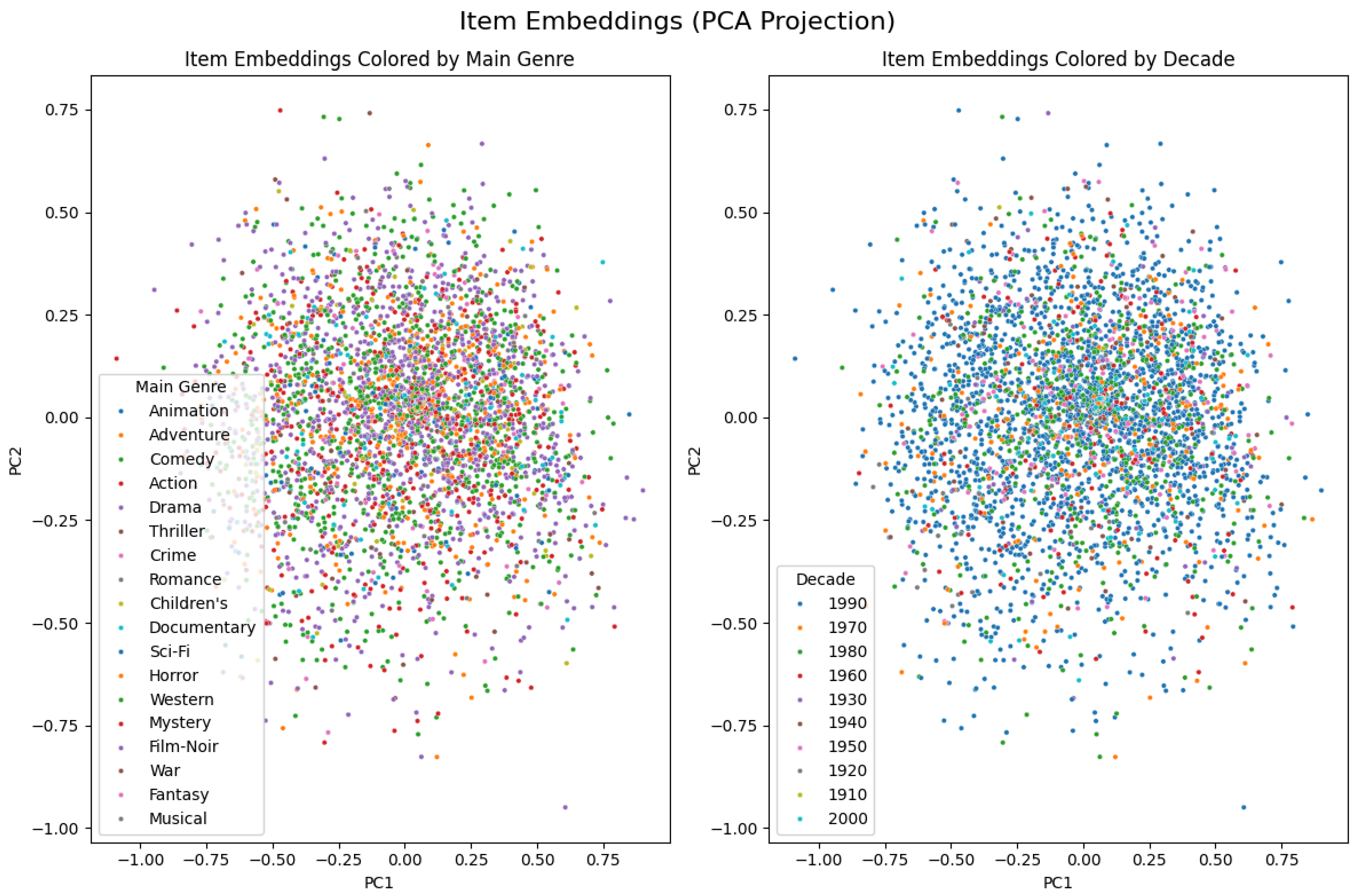
In [63]:
```
# latent factors
user_emb = best_model.A_     # shape (n_users, n_factors)
item_emb = best_model.B_     # shape (n_items, n_factors)

# example: item-item similarity matrix
item_sim = cosine_similarity(item_emb)

# example: user-user similarity matrix
user_sim = cosine_similarity(user_emb)

pca = PCA(n_components=2)
item_2d = pca.fit_transform(item_emb)
```

```python
plt.figure(figsize=(12,8)).suptitle("Item Embeddings (PCA Projection)", fontsize=16)
plt.subplot(1, 2, 1)
sns.scatterplot(
    x=item_2d[:,0],
    y=item_2d[:,1],
    hue=movies['Main Genre'],
    palette='tab10',
    s=10,
    legend=True  # Show legend only if few categories
)
plt.title("Item Embeddings Colored by Main Genre")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.subplot(1, 2, 2)
sns.scatterplot(
    x=item_2d[:,0],
    y=item_2d[:,1],
    hue=movies['Decade'].astype(str),
    palette='tab10',
    s=10,
    legend=True   # Show legend only if few categories
)
plt.title("Item Embeddings Colored by Decade")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.tight_layout()
plt.show()
```

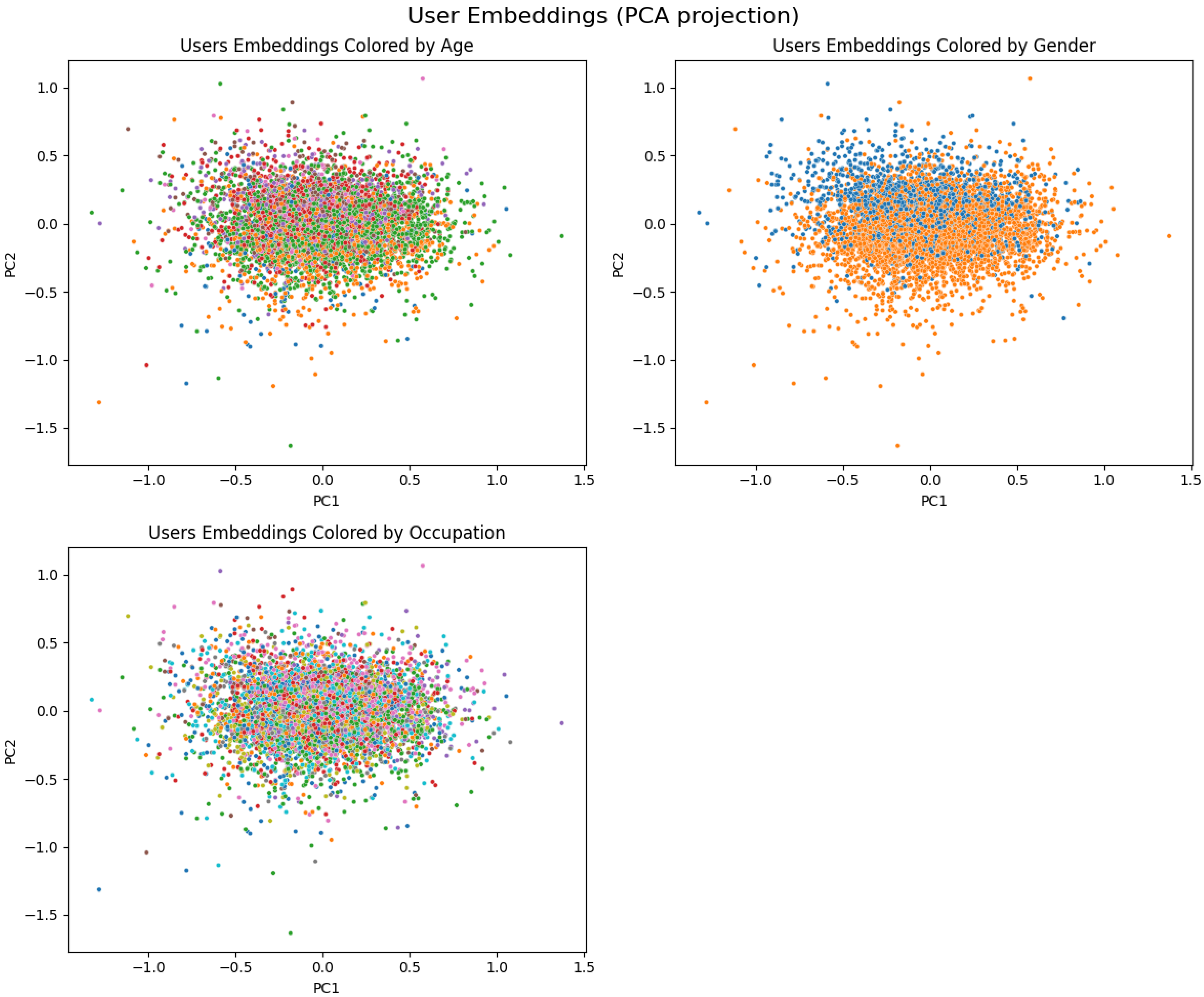


Visualizing User Embeddings

```
In [64]: pca = PCA(n_components=2)
user_2d = pca.fit_transform(user_emb)

plt.figure(figsize=(12,10)).suptitle("User Embeddings (PCA projection)", fontsize=16)
plt.subplot(2,2,1)
sns.scatterplot(
    x=user_2d[:,0],
    y=user_2d[:,1],
    hue=users['Age'],  # or any categorical column
    palette='tab10',
```

```
    s=10,
    legend=False
)
plt.title("Users Embeddings Colored by Age")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.subplot(2,2,2)
sns.scatterplot(
    x=user_2d[:,0],
    y=user_2d[:,1],
    hue=users['Gender'],  # or any categorical column
    palette='tab10',
    s=10,
    legend=False
)
plt.title("Users Embeddings Colored by Gender")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.subplot(2,2,3)
sns.scatterplot(
    x=user_2d[:,0],
    y=user_2d[:,1],
    hue=users['Occupation'],  # or any categorical column
    palette='tab10',
    s=10,
    legend=False
)
plt.title("Users Embeddings Colored by Occupation")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.tight_layout()
plt.show()
```

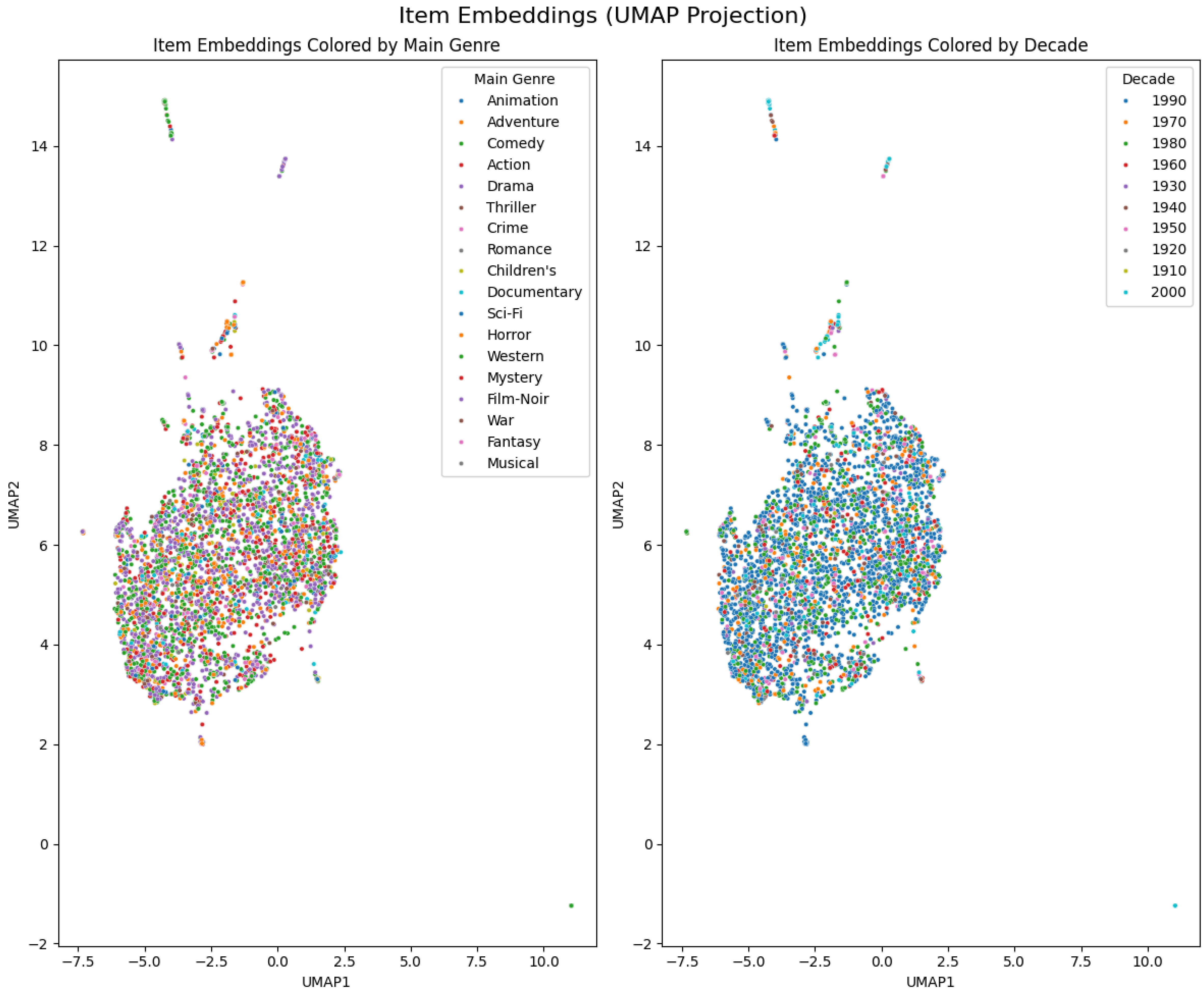

User Embeddings (PCA projection)
Users Embeddings Colored by Age
Users Embeddings Colored by Gender
Users Embeddings Colored by Occupation
PC1
PC2
1.0
0.5
0.0
−0.5
−1.0
−1.5
1.5

3.5.2 UMAP

Visualizing Item Embeddings

```
In [ ]: # reduce item embeddings to 2D
reducer = umap.UMAP(n_components=2,
                    random_state=42,
                    n_neighbors=10,
                    verbose=False)
item_2d = reducer.fit_transform(item_emb)


plt.figure(figsize=(12,10)).suptitle("Item Embeddings (UMAP Projection)", fontsize=16)
plt.subplot(1, 2, 1)
sns.scatterplot(
    x=item_2d[:,0],
    y=item_2d[:,1],
    hue=movies['Main Genre'],
    palette='tab10',
    s=10,
    legend=True  # Show legend only if few categories
)
plt.title("Item Embeddings Colored by Main Genre")
plt.xlabel("UMAP1")
plt.ylabel("UMAP2")
plt.subplot(1, 2, 2)
sns.scatterplot(
    x=item_2d[:,0],
    y=item_2d[:,1],
    hue=movies['Decade'].astype(str),
    palette='tab10',
    s=10,
    legend=True   # Show legend only if few categories
)
plt.title("Item Embeddings Colored by Decade")
plt.xlabel("UMAP1")
plt.ylabel("UMAP2")
plt.tight_layout()
plt.show()
```


Item Embeddings (UMAP Projection)
Item Embeddings Colored by Main Genre
Main Genre
Animation
Adventure
Comedy
Action
Drama
Thriller
Crime
Romance
Children's
Documentary
Sci-Fi
Horror
Western
Mystery
Film-Noir
War
Fantasy
Musical
UMAP2
UMAP1
Item Embeddings Colored by Decade
Decade
1990
1970
1980
1960
1930
1940
1950
1920
1910
2000
UMAP2
UMAP1

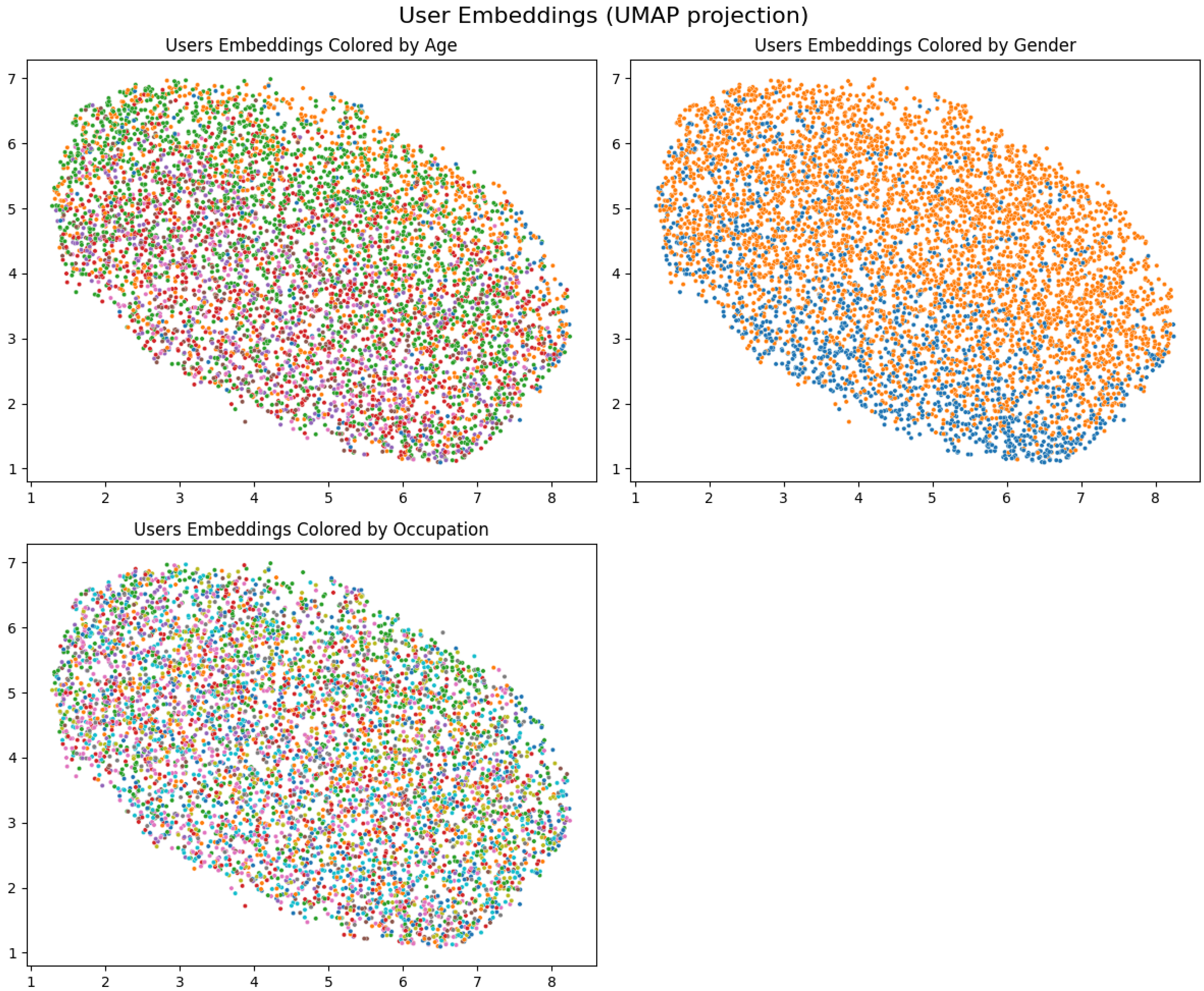
Visualizing User Embeddings

In [ ]:
```python
# reduce user embeddings to 2D
reducer = umap.UMAP(n_components=2,
                    random_state=42,
                    n_neighbors=50,
                    verbose=True)
user_2d = reducer.fit_transform(user_emb)

plt.figure(figsize=(12,10)).suptitle("User Embeddings (UMAP projection)", fontsize=16)
plt.subplot(2,2,1)
sns.scatterplot(
    x=user_2d[:,0],
    y=user_2d[:,1],
    hue=users['Age'],  # or any categorical column
    palette='tab10',
    s=10,
    legend=False
)
plt.title("Users Embeddings Colored by Age")
plt.subplot(2,2,2)
sns.scatterplot(
    x=user_2d[:,0],
    y=user_2d[:,1],
    hue=users['Gender'],  # or any categorical column
    palette='tab10',
    s=10,
    legend=False
)
plt.title("Users Embeddings Colored by Gender")
plt.subplot(2,2,3)
sns.scatterplot(
    x=user_2d[:,0],
    y=user_2d[:,1],
    hue=users['Occupation'],  # or any categorical column
    palette='tab10',
    s=10,
    legend=False
)
plt.title("Users Embeddings Colored by Occupation")
plt.tight_layout()
plt.show()
```

```
UMAP(n_jobs=1, n_neighbors=50, random_state=42, verbose=True)
Fri Oct 31 12:58:26 2025 Construct fuzzy simplicial set
Fri Oct 31 12:58:26 2025 Finding Nearest Neighbors
Fri Oct 31 12:58:26 2025 Building RP forest with 9 trees
Fri Oct 31 12:58:31 2025 NN descent for 13 iterations
         1  /  13
         2  /  13
         3  /  13
        Stopping threshold met -- exiting after 3 iterations
Fri Oct 31 12:58:41 2025 Finished Nearest Neighbor Search
Fri Oct 31 12:58:42 2025 Construct embedding
Epochs completed:   0%|            0/500 [00:00]
```

```
        completed  0  /  500 epochs
        completed  50  /  500 epochs
        completed  100  /  500 epochs
        completed  150  /  500 epochs
        completed  200  /  500 epochs
        completed  250  /  500 epochs
        completed  300  /  500 epochs
        completed  350  /  500 epochs
        completed  400  /  500 epochs
        completed  450  /  500 epochs
Fri Oct 31 12:58:56 2025 Finished embedding
```



User Embeddings (UMAP projection)
Users Embeddings Colored by Age
Users Embeddings Colored by Gender
Users Embeddings Colored by Occupation
1
2
3
4
5
6
7
8

4. Insights and Recommendations

- Users aged between **25 to 34** have watched and rated the most number of movies.
- Users who are **college/grad students** or who are at some **executive/managerial** position have watched and rated the most movies.
- **71.7%** of the users in our dataset who've rated the movies are Male.
- Most of the movies present in our dataset were released in the **90s** decade.
- The movie with the maximum no. of ratings is **American Beauty (1999)**.
- Top 3 movies similar to 'Liar Liar' on the item-based approach are **Mrs. Doubtfire (1993), Dumb & Dumber (1994)** and **Ace Ventura: Pet Detective (1994)**.
- On the basis of approach, Collaborative Filtering methods can be classified into **user-based** and **item-based** methods.
- Pearson Correlation ranges between **-1 to +1**, whereas Cosine Similarity belongs to the interval between **0 to 1**.
- From Matrix factorization (for the best model): Training RMSE = 0.8182 Testing RMSE = 0.8691 Training MAPE = 0.2537 Testing MAPE = 0.2713
    - RMSE < 1 indicates small average prediction errors on a typical rating scale (usually 1–5).
    - The testing RMSE (0.8691) is close to the training RMSE (0.8182), showing low overfitting.
    - MAPE ≈ 0.25–0.27 means average prediction error is about 25–27%, which is acceptable for recommender systems.
    - In summary: the model generalizes well and performs at a solid accuracy level.
- Given the following dense matrix:

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

Compressed Sparse Row (CSR) representation is given as below:

```
shape  = (2, 2)

data   = [1, 3, 7]
indices= [0, 0, 1]
indptr = [0, 1, 3]
```

Strategies to refine the recommender system

- Collect more explicit feedback: ask for ratings, thumbs up/down, and short reviews to reduce reliance on implicit signals.
- Leverage implicit feedback: incorporate clicks, views, dwell time, purchases and session sequences as additional signals.
- Use temporal dynamics: include timestamps and time-decay to model changing user preferences.
- Incorporate side information: add user demographics, item metadata (category, tags), and context (device, location, time of day).
- Apply hybrid models: combine collaborative filtering with content-based methods to reduce cold-start problems.
- Try advanced matrix factorization variants: add biases, temporal factors, and regularization (SVD++, FunkSVD extensions).
- Experiment with factorization machines and LightFM: handle sparse features and mix of numeric/categorical side data efficiently.
- Explore neural models: autoencoders, neural collaborative filtering, and sequence models (RNN/Transformer) for session or sequence-aware recommendations.
- Use graph-based methods: build user-item interaction graphs and apply graph neural networks or PageRank-like propagation for richer relations.
- Optimize for business metrics: add objectives for diversity, novelty, serendipity, and revenue, not just RMSE/accuracy.

- Ensemble models: blend multiple models (CF, content, neural) to improve robustness and lift performance.
- Tune hyperparameters and regularization: run systematic searches and use validation curves to prevent overfitting.
- Improve evaluation: use holdout, time-split evaluation, precision/recall, NDCG, and online A/B tests to measure real impact.
- Address cold-start explicitly: use onboarding questionnaires, popularity priors, and content similarity for new users/items.
- Scale and latency engineering: use approximate nearest neighbors, model quantization, and caching for low-latency serving.
- Add explainability: provide short reasons or attributable signals to increase user trust and corrective feedback.
- Collect corrective feedback loops: let users mark “not relevant” and use that signal to retrain quickly.
- Monitor fairness and privacy: audit for bias, limit sensitive features, and apply differential privacy or federated learning if needed.
- Instrument and monitor production: track offline vs online drift, data quality, and model health metrics continuously.