In [1]:

```
# from google.colab import drive
# drive.mount('/content/drive')
```

In [145]:

```
# !pip install skimpy
```

In [146]:

```
# pip install cmfrec
```

In [4]:

```
import cmfrec
```

In [5]:

```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")
```

In [6]:

```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [7]:

```
# datasets

ratings = pd.read_csv('/content/drive/MyDrive/Scaler/datasets/zee rat.csv')
users = pd.read_csv('/content/drive/MyDrive/Scaler/datasets/zee user.csv')
movies = pd.read_csv('/content/drive/MyDrive/Scaler/datasets/zee movie.csv',encoding='ISO
-8859-1')
```

In [8]:

```
# cleaning column names

from skimpy import clean_columns

movies = clean_columns(movies, case = 'snake')
ratings = clean_columns(ratings, case = 'snake')
users = clean_columns(users, case = 'snake')
```

**3** column names have been cleaned

**4** column names have been cleaned

**5** column names have been cleaned

In [9]:

```
# finding shapes

ratings.shape,movies.shape,users.shape
```

Out[9]:

```
((1000209, 4), (3883, 3), (6040, 5))
```

In [10]:

```
ratings.dropna(inplace=True)
```

```
ratings.isnull().sum()
```

Out[10]:

```
user_id      0
movie_id     0
rating       0
timestamp    0
dtype: int64
```

In [11]:

```
# converting timestamps to datetime format

from datetime import datetime

ratings['date'] = [datetime.fromtimestamp(i).strftime('%d-%m-%Y') for i in ratings.times
tamp]


ratings['hours'] = ratings['timestamp'].apply(lambda x: datetime.fromtimestamp(x).hour)
```

In [12]:

```
ratings['date'] = ratings['date'].astype(np.datetime64)
```

In [13]:

```
# finding nuniques()

print('_'*40)
print('RATINGS NUNIQUES','\n')
for i in ratings:
    print(i ,':',ratings[i].nunique())


print('_'*40)

print('MOVIES NUNIQUES','\n')
for i in movies:
    print(i ,':',movies[i].nunique())



print('_'*40)

print('USERS NUNIQUES','\n')
for i in users:
    print(i ,':',users[i].nunique())
print('_'*40)
```

```
________________________________________
RATINGS NUNIQUES

user_id : 6040
movie_id : 3706
rating : 5
timestamp : 458455
date : 1040
hours : 24
________________________________________
MOVIES NUNIQUES

movie_id : 3883
title : 3883
genres : 301
________________________________________
USERS NUNIQUES

user_id : 6040
gender : 2
```

```
age : 7
occupation : 21
zip_code : 3439
________________________________________
```

In [14]:

```python
# finding missing values

ratings.isnull().sum(), movies.isnull().sum(), users.isnull().sum()
```

Out[14]:

```
(user_id      0
 movie_id     0
 rating       0
 timestamp    0
 date         0
 hours        0
 dtype: int64,
 movie_id    0
 title       0
 genres      0
 dtype: int64,
 user_id       0
 gender        0
 age           0
 occupation    0
 zip_code      0
 dtype: int64)
```

***No missing values found in all three datasets***

In [15]:

```python
# finding duplicates

ratings.duplicated().sum(),movies.duplicated().sum(),users.duplicated().sum()
```

Out[15]:

```
(0, 0, 0)
```

***ratings dataset has 24 duplicate rows***

In [16]:

```python
# removing duplicates

ratings.drop_duplicates(inplace=True)
ratings.duplicated().sum()
```

Out[16]:

```
0
```

---

***DESCRIBE AND INFO***

In [17]:

```python
print('RATINGS INFO AND DESCRIBE','\n')
pd.options.display.float_format='{:.2f}'.format
ratings.describe(),ratings.info()
```

```
RATINGS INFO AND DESCRIBE

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns (total 6 columns):
```

```
 #   Column     Non-Null Count    Dtype
---  ------     --------------    -----
 0   user_id    1000209 non-null  int64
 1   movie_id   1000209 non-null  int64
 2   rating     1000209 non-null  int64
 3   timestamp  1000209 non-null  int64
 4   date       1000209 non-null  datetime64[ns]
 5   hours      1000209 non-null  int64
dtypes: datetime64[ns](1), int64(5)
memory usage: 53.4 MB
```

Out[17]:

```
(          user_id   movie_id      rating      timestamp       hours
 count 1000209.00 1000209.00 1000209.00     1000209.00 1000209.00
 mean     3024.51    1865.54        3.58   972243695.40       11.92
 std      1728.41    1096.04        1.12    12152558.94        7.89
 min         1.00       1.00        1.00   956703932.00        0.00
 25%      1506.00    1030.00        3.00   965302637.00        4.00
 50%      3070.00    1835.00        4.00   973018006.00       14.00
 75%      4476.00    2770.00        4.00   975220939.00       19.00
 max      6040.00    3952.00        5.00  1046454590.00       23.00,
 None)
```

In [18]:

```
ratings.describe(include = np.number, percentiles=[.10,.25,.75,.90,.95, .99]).round(2).T
.astype(int)
```

Out[18]:

| | count | mean | std | min | 10% | 25% | 50% | 75% | 90% | 95% |
|---|---|---|---|---|---|---|---|---|---|---|
| **user_id** | 1000209 | 3024 | 1728 | 1 | 669 | 1506 | 3070 | 4476 | 5443 | 5740 |
| **movie_id** | 1000209 | 1865 | 1096 | 1 | 357 | 1030 | 1835 | 2770 | 3430 | 3675 |
| **rating** | 1000209 | 3 | 1 | 1 | 2 | 3 | 4 | 4 | 5 | 5 |
| **timestamp** | 1000209 | 972243695 | 12152558 | 956703932 | 960681570 | 965302637 | 973018006 | 975220939 | 978133376 | 993074152 |
| **hours** | 1000209 | 11 | 7 | 0 | 1 | 4 | 14 | 19 | 22 | 23 |

In [19]:

```
print('MOVIES INFO AND DESCRIBE','\n')
pd.options.display.float_format='{:.2f}'.format
movies.describe(),movies.info()
```

```
MOVIES INFO AND DESCRIBE

<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   int64
 1   title     3883 non-null   object
 2   genres    3883 non-null   object
dtypes: int64(1), object(2)
memory usage: 91.1+ KB
```

Out[19]:

```
(        movie_id
 count   3883.00
 mean    1986.05
 std     1146.78
 min        1.00
 25%      982.50
```

```
 25%      982.50
 50%     2010.00
 75%     2980.50
 max     3952.00,
 None)
```

In [20]:

```
movies.describe(include=object)
```

Out[20]:

| | title | genres |
|---|---|---|
| **count** | 3883 | 3883 |
| **unique** | 3883 | 301 |
| **top** | Toy Story (1995) | Drama |
| **freq** | 1 | 843 |

In [21]:

```
movies.describe(include = np.number, percentiles=[.10,.25,.75,.90,.95, .99]).round(2).T.
astype(int)
```

Out[21]:

| | count | mean | std | min | 10% | 25% | 50% | 75% | 90% | 95% | 99% | max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **movie_id** | 3883 | 1986 | 1146 | 1 | 392 | 982 | 2010 | 2980 | 3562 | 3756 | 3913 | 3952 |

---

In [22]:

```
print('USERS INFO AND DESCRIBE','\n')
pd.options.display.float_format='{:.2f}'.format
users.describe(),users.info()
```

```
USERS INFO AND DESCRIBE

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6040 entries, 0 to 6039
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   user_id     6040 non-null   int64 
 1   gender      6040 non-null   object
 2   age         6040 non-null   int64 
 3   occupation  6040 non-null   int64 
 4   zip_code    6040 non-null   object
dtypes: int64(3), object(2)
memory usage: 236.1+ KB
```

Out[22]:

```
(        user_id     age  occupation
 count  6040.00 6040.00     6040.00
 mean   3020.50   30.64        8.15
 std    1743.74   12.90        6.33
 min       1.00    1.00        0.00
 25%    1510.75   25.00        3.00
 50%    3020.50   25.00        7.00
 75%    4530.25   35.00       14.00
 max    6040.00   56.00       20.00,
 None)
```

In [23]:

```
users.describe(include=object)
```

Out[23]:

| | gender | zip_code |
|---|---|---|
| **count** | 6040 | 6040 |
| **unique** | 2 | 3439 |
| **top** | M | 48104 |
| **freq** | 4331 | 19 |

In [24]:

```
users.describe(include = np.number, percentiles=[.10,.25,.75,.90,.95, .99]).round(2).T.astype(int)
```

Out[24]:

| | count | mean | std | min | 10% | 25% | 50% | 75% | 90% | 95% | 99% | max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **user_id** | 6040 | 3020 | 1743 | 1 | 604 | 1510 | 3020 | 4530 | 5436 | 5738 | 5979 | 6040 |
| **age** | 6040 | 30 | 12 | 1 | 18 | 25 | 25 | 35 | 50 | 56 | 56 | 56 |
| **occupation** | 6040 | 8 | 6 | 0 | 0 | 3 | 7 | 14 | 17 | 19 | 20 | 20 |

***DESCRIBE AND INFO ENDS***

---

In [25]:

```
ratings.head()
```

Out[25]:

| | user_id | movie_id | rating | timestamp | date | hours |
|---|---|---|---|---|---|---|
| **0** | 1 | 1193 | 5 | 978300760 | 2000-12-31 | 22 |
| **1** | 1 | 661 | 3 | 978302109 | 2000-12-31 | 22 |
| **2** | 1 | 914 | 3 | 978301968 | 2000-12-31 | 22 |
| **3** | 1 | 3408 | 4 | 978300275 | 2000-12-31 | 22 |
| **4** | 1 | 2355 | 5 | 978824291 | 2001-06-01 | 23 |

In [26]:

```
movies.head()
```

Out[26]:

| | 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 [27]:

```
users.head()
```

Out[27]:

| | user_id | 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 | 2460 |
| 4 | 5 | M | 25 | 20 | 55455 |

In [28]:

```
# merging all three datasets

df = ratings.merge(users,on='user_id', how='inner')
df = df.merge(movies,on='movie_id', how='inner')
```

In [29]:

```
# creating new feature release year


df['release_year']  = df['title'].str.extract(r'([\d]+)')
df['title'] = df['title'].replace('[0-9]','',regex=True).str.strip('()')
```

In [30]:

```
df['release_year'] = df['release_year'].astype(int)
```

In [31]:

```
df = df[df['release_year'].between(df['release_year'].quantile(.04),
                                    df['release_year'].quantile(.999),
                                    inclusive=True)]
```

In [32]:

```
df['title'] = df['title'].str.lstrip('(')
df['title'] = df['title'].str.lstrip(')')
```

In [33]:

```
df.shape
```

Out[33]:

```
(959268, 13)
```

In [34]:

```
df.head()
```

Out[34]:

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | genres | release_year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1193 | 5 | 978300760 | 2000-12-31 | 22 | F | 1 | 10 | 48067 | One Flew Over the Cuckoo's Nest | Drama | 1975 |
| 1 | 2 | 1193 | 5 | 978298413 | 2000-12-31 | 21 | M | 56 | 16 | 70072 | One Flew Over the Cuckoo's Nest | Drama | 1975 |
| 2 | 12 | 1193 | 4 | 978220179 | 2000-12-30 | 23 | M | 25 | 12 | 32793 | One Flew Over the Cuckoo's Nest | Drama | 1975 |

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | genres | release_year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 15 | 1193 | 4 | 978199279 | 2000-12-30 | 18 | M | 25 | 7 | 22903 | One Flew Over the Cuckoo's Nest | Drama | 1975 |
| 4 | 17 | 1193 | 5 | 978158471 | 2000-12-30 | 6 | M | 50 | 1 | 95350 | One Flew Over the Cuckoo's Nest | Drama | 1975 |

In [35]:

```
df = df[df['age'].between(df['age'].quantile(.03),
                          df['age'].quantile(1),
                          inclusive=True)]
```

In [36]:

```
df.head()
```

Out[36]:

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | genres | release_year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 1193 | 5 | 978298413 | 2000-12-31 | 21 | M | 56 | 16 | 70072 | One Flew Over the Cuckoo's Nest | Drama | 1975 |
| 2 | 12 | 1193 | 4 | 978220179 | 2000-12-30 | 23 | M | 25 | 12 | 32793 | One Flew Over the Cuckoo's Nest | Drama | 1975 |
| 3 | 15 | 1193 | 4 | 978199279 | 2000-12-30 | 18 | M | 25 | 7 | 22903 | One Flew Over the Cuckoo's Nest | Drama | 1975 |
| 4 | 17 | 1193 | 5 | 978158471 | 2000-12-30 | 6 | M | 50 | 1 | 95350 | One Flew Over the Cuckoo's Nest | Drama | 1975 |
| 5 | 18 | 1193 | 4 | 978156168 | 2000-12-30 | 6 | F | 18 | 3 | 95825 | One Flew Over the Cuckoo's Nest | Drama | 1975 |

## *Apriori Algorithm*

### *Recommendations according to movie title*

In [37]:

```
df
```

Out[37]:

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 1193 | 5 | 978298413 | 2000-12-31 | 21 | M | 56 | 16 | 70072 | One Flew Over the Cuckoo's Nest |
| 2 | 12 | 1193 | 4 | 978220179 | 2000-12-30 | 23 | M | 25 | 12 | 32793 | One Flew Over the Cuckoo's Nest |
| 3 | 15 | 1193 | 4 | 978199279 | 2000- | 18 | M | 25 | 7 | 22903 | One Flew Over the |

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 17 | 1193 | 5 | 978158471 | 2000-12-30 | 6 | M | 50 | 1 | 95350 | One Flew Over the Cuckoo's Nest | |
| 5 | 18 | 1193 | 4 | 978156168 | 2000-12-30 | 6 | F | 18 | 3 | 95825 | One Flew Over the Cuckoo's Nest | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 1000204 | 5949 | 2198 | 5 | 958846401 | 2000-05-20 | 18 | M | 18 | 17 | 47901 | Modulations | Doc |
| 1000205 | 5675 | 2703 | 3 | 976029116 | 2000-05-12 | 15 | M | 35 | 14 | 30030 | Broken Vessels | |
| 1000206 | 5780 | 2845 | 1 | 958153068 | 2000-12-05 | 17 | M | 18 | 17 | 92886 | White Boys | |
| 1000207 | 5851 | 3607 | 5 | 957756608 | 2000-08-05 | 3 | F | 18 | 20 | 55410 | One Little Indian | Comedy\|Drama |
| 1000208 | 5938 | 2909 | 4 | 957273353 | 2000-02-05 | 13 | M | 25 | 1 | 35401 | Five Wives, Three Secretaries and Me | Doc |

933429 rows × 13 columns

In [38]:

```
df1 = df.sample(700000)
```

In [39]:

```
df1['user_id'] = df1.user_id.astype(object)
df1['movie_id'] = df1.movie_id.astype(object)

df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 700000 entries, 450840 to 829031
Data columns (total 13 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   user_id       700000 non-null  object
 1   movie_id      700000 non-null  object
 2   rating        700000 non-null  int64
 3   timestamp     700000 non-null  int64
 4   date          700000 non-null  datetime64[ns]
 5   hours         700000 non-null  int64
 6   gender        700000 non-null  object
 7   age           700000 non-null  int64
 8   occupation    700000 non-null  int64
 9   zip_code      700000 non-null  object
 10  title         700000 non-null  object
 11  genres        700000 non-null  object
 12  release_year  700000 non-null  int64
dtypes: datetime64[ns](1), int64(6), object(6)
memory usage: 74.8+ MB
```

In [40]:

```
data = df1.groupby(['user_id','title'])['movie_id'].sum().unstack().reset_index().fillna
(0).set_index('user_id')
```

In [41]:

```
data[data.index == 6036].sum(axis=1)
```

Out[41]:

```
user_id
6036    1186000
dtype: int64
```

In [42]:

```
data = (data>0).astype(int)
```

In [43]:

```
data[data.index == 6036].sum(axis=1)
```

Out[43]:

```
user_id
6036    635
dtype: int64
```

In [44]:

```
data.head()
```

Out[44]:

| title | 'Night Mother | 'Til There Was You | 'burbs, The | ...And Justice for All | : A Space Odyssey | A Chef in Love | Abbott and Costello Meet Frankenstein | Abominable Snowman, The | About Adam | About Last Night... | ... | Young Poisoner's Handbook, The | Young Sherlock Holmes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **user_id** | | | | | | | | | | | | | |
| **2** | 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 |
| **4** | 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 |
| **6** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 |

5 rows × 3466 columns

In [45]:

```
from mlxtend.frequent_patterns import apriori
```

In [46]:

```
itemset = apriori(data,min_support=.12,use_colnames=True).sort_values('support',ascendin
g=False).reset_index()
```

In [47]:

```
itemset.shape
```

Out[47]:

```
(578, 3)
```

In [48]:

```
itemset.loc[itemset['itemsets'].apply(lambda x: len(x)) >= 2]
```

Out[48]:

| | index | support | itemsets |
|---|---|---|---|
| **39** | 558 | 0.22 | (Star Wars: Episode V - The Empire Strikes Bac... |
| **56** | 565 | 0.20 | (Star Wars: Episode V - The Empire Strikes Bac... |

| | index | support | itemsets |
|---|---|---|---|
| 62 | 559 | 0.20 | (Star Wars: Episode IV - A New Hope , Star War... |
| 65 | 513 | 0.19 | (Star Wars: Episode V - The Empire Strikes Bac... |
| 75 | 430 | 0.18 | (Men in Black , Jurassic Park ) |
| ... | ... | ... | ... |
| 573 | 507 | 0.12 | (Shakespeare in Love , Raiders of the Lost Ark ) |
| 574 | 449 | 0.12 | (L.A. Confidential , Shakespeare in Love ) |
| 575 | 528 | 0.12 | (Saving Private Ryan , Toy Story ) |
| 576 | 467 | 0.12 | (Matrix, The , Speed ) |
| 577 | 491 | 0.12 | (Star Wars: Episode I - The Phantom Menace , P... |

361 rows × 3 columns

In [49]:

```
from mlxtend.frequent_patterns import association_rules


rules = association_rules(itemset,metric='lift',min_threshold=1)
```

In [50]:

```
rules
```

Out[50]:

| | antecedents | consequents | antecedent support | consequent support | support | confidence | lift | leverage | conviction |
|---|---|---|---|---|---|---|---|---|---|
| 0 | (Star Wars: Episode V - The Empire Strikes Back ) | (Star Wars: Episode IV - A New Hope ) | 0.37 | 0.38 | 0.22 | 0.59 | 1.58 | 0.08 | 1.53 |
| 1 | (Star Wars: Episode IV - A New Hope ) | (Star Wars: Episode V - The Empire Strikes Back ) | 0.38 | 0.37 | 0.22 | 0.58 | 1.58 | 0.08 | 1.51 |
| 2 | (Star Wars: Episode V - The Empire Strikes Back ) | (Star Wars: Episode VI - Return of the Jedi ) | 0.37 | 0.36 | 0.20 | 0.55 | 1.52 | 0.07 | 1.42 |
| 3 | (Star Wars: Episode VI - Return of the Jedi ) | (Star Wars: Episode V - The Empire Strikes Back ) | 0.36 | 0.37 | 0.20 | 0.56 | 1.52 | 0.07 | 1.44 |
| 4 | (Star Wars: Episode IV - A New Hope ) | (Star Wars: Episode VI - Return of the Jedi ) | 0.38 | 0.36 | 0.20 | 0.52 | 1.44 | 0.06 | 1.33 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 725 | (Toy Story ) | (Saving Private Ryan ) | 0.26 | 0.33 | 0.12 | 0.47 | 1.40 | 0.03 | 1.25 |
| 726 | (Matrix, The ) | (Speed ) | 0.32 | 0.21 | 0.12 | 0.37 | 1.81 | 0.05 | 1.27 |
| 727 | (Speed ) | (Matrix, The ) | 0.21 | 0.32 | 0.12 | 0.58 | 1.81 | 0.05 | 1.63 |
| 728 | (Star Wars: Episode I - The Phantom Menace ) | (Princess Bride, The ) | 0.28 | 0.29 | 0.12 | 0.43 | 1.46 | 0.04 | 1.24 |
| 729 | (Princess Bride, The ) | (Star Wars: Episode I - The Phantom Menace ) | 0.29 | 0.28 | 0.12 | 0.41 | 1.46 | 0.04 | 1.22 |

730 rows × 9 columns

In [51]:

```
rules.antecedents.value_counts()
```

Out[51]:

```
(Star Wars: Episode V - The Empire Strikes Back )
44
(Star Wars: Episode IV - A New Hope )
42
(Star Wars: Episode VI - Return of the Jedi )
37
(American Beauty )
36
(Raiders of the Lost Ark )
32
(Matrix, The )
32
(Silence of the Lambs, The )
28
(Back to the Future )
27
(Saving Private Ryan )
27
(Fargo )
25
(Men in Black )
24
(Jurassic Park )
24
(Braveheart )
21
(Princess Bride, The )
19
(Groundhog Day )
19
(Terminator, The )
19
(Sixth Sense, The )
19
(Pulp Fiction )
18
(Shawshank Redemption, The )
17
(L.A. Confidential )
16
(E.T. the Extra-Terrestrial )
15
(Shakespeare in Love )
15
(Total Recall )
14
(Star Wars: Episode I - The Phantom Menace )
14
(Fugitive, The )
13
(Forrest Gump )
12
(Alien )
11
(Schindler's List )
11
(Ghostbusters )
9
(Godfather, The )
9
(Toy Story )
9
(Aliens )
8
(Being John Malkovich )
8
(Blade Runner )
7
(Die Hard )
6
(GoodFellas )
```

```
5
(Usual Suspects, The )
5
(Indiana Jones and the Last Crusade )
4
(Who Framed Roger Rabbit? )
3
(Abyss, The )
3
(Jaws )
2
(Star Wars: Episode V - The Empire Strikes Back , Star Wars: Episode IV - A New Hope )
2
(Stand by Me )
2
(Wizard of Oz, The )
2
(Hunt for Red October, The )
2
(: A Space Odyssey )
2
(Election )
1
(Lethal Weapon )
1
(Mission: Impossible )
1
(Babe )
1
(Star Wars: Episode IV - A New Hope , Star Wars: Episode VI - Return of the Jedi )
1
(Star Wars: Episode IV - A New Hope , Raiders of the Lost Ark )
1
(Star Wars: Episode V - The Empire Strikes Back , Raiders of the Lost Ark )
1
(Star Wars: Episode V - The Empire Strikes Back , Star Wars: Episode VI - Return of the J
edi )      1
(Godfather: Part II, The )
1
(Gladiator )
1
(Speed )
1
Name: antecedents, dtype: int64
```

In [52]:

```
rules.loc[rules.antecedents == rules.antecedents.iloc[15]].sort_values(by='lift',ascendi
ng=False)
```

Out[52]:

| | antecedents | consequents | antecedent support | consequent support | support | confidence | lift | leverage | conviction |
|---|---|---|---|---|---|---|---|---|---|
| 627 | (Back to the Future ) | (Aliens ) | 0.32 | 0.23 | 0.12 | 0.38 | 1.67 | 0.05 | 1.24 |
| 589 | (Back to the Future ) | (Blade Runner ) | 0.32 | 0.23 | 0.12 | 0.38 | 1.64 | 0.05 | 1.24 |
| 249 | (Back to the Future ) | (Terminator, The ) | 0.32 | 0.27 | 0.14 | 0.43 | 1.63 | 0.05 | 1.29 |
| 177 | (Back to the Future ) | (E.T. the Extra-Terrestrial ) | 0.32 | 0.28 | 0.15 | 0.46 | 1.62 | 0.06 | 1.32 |
| 241 | (Back to the Future ) | (Ghostbusters ) | 0.32 | 0.27 | 0.14 | 0.43 | 1.62 | 0.05 | 1.29 |
| 492 | (Back to the Future ) | (Alien ) | 0.32 | 0.25 | 0.13 | 0.39 | 1.56 | 0.05 | 1.23 |
| 193 | (Back to the Future ) | (Princess Bride, The ) | 0.32 | 0.29 | 0.15 | 0.45 | 1.54 | 0.05 | 1.29 |

| | antecedents | consequents | antecedent support | consequent support | support | confidence | lift | leverage | conviction |
|---|---|---|---|---|---|---|---|---|---|
| 15 | (Back to the Future ) | (Star Wars: Episode V - The Empire Strikes Back ) | 0.32 | 0.37 | 0.18 | 0.55 | 1.50 | 0.06 | 1.41 |
| 656 | (Back to the Future ) | (Total Recall ) | 0.32 | 0.25 | 0.12 | 0.38 | 1.48 | 0.04 | 1.20 |
| 595 | (Back to the Future ) | (Toy Story ) | 0.32 | 0.26 | 0.12 | 0.38 | 1.48 | 0.04 | 1.20 |
| 147 | (Back to the Future ) | (Raiders of the Lost Ark ) | 0.32 | 0.32 | 0.15 | 0.47 | 1.47 | 0.05 | 1.28 |
| 155 | (Back to the Future ) | (Men in Black ) | 0.32 | 0.32 | 0.15 | 0.46 | 1.46 | 0.05 | 1.27 |
| 39 | (Back to the Future ) | (Star Wars: Episode VI - Return of the Jedi ) | 0.32 | 0.36 | 0.17 | 0.53 | 1.46 | 0.05 | 1.35 |
| 363 | (Back to the Future ) | (Groundhog Day ) | 0.32 | 0.29 | 0.13 | 0.41 | 1.45 | 0.04 | 1.22 |
| 27 | (Back to the Future ) | (Star Wars: Episode IV - A New Hope ) | 0.32 | 0.38 | 0.18 | 0.54 | 1.44 | 0.05 | 1.36 |
| 529 | (Back to the Future ) | (Forrest Gump ) | 0.32 | 0.27 | 0.13 | 0.39 | 1.42 | 0.04 | 1.19 |
| 489 | (Back to the Future ) | (Star Wars: Episode I - The Phantom Menace ) | 0.32 | 0.28 | 0.13 | 0.39 | 1.41 | 0.04 | 1.19 |
| 195 | (Back to the Future ) | (Matrix, The ) | 0.32 | 0.32 | 0.15 | 0.45 | 1.40 | 0.04 | 1.24 |
| 182 | (Back to the Future ) | (Jurassic Park ) | 0.32 | 0.34 | 0.15 | 0.46 | 1.36 | 0.04 | 1.22 |
| 692 | (Back to the Future ) | (Shawshank Redemption, The ) | 0.32 | 0.29 | 0.12 | 0.37 | 1.31 | 0.03 | 1.14 |
| 279 | (Back to the Future ) | (Silence of the Lambs, The ) | 0.32 | 0.33 | 0.14 | 0.43 | 1.30 | 0.03 | 1.17 |
| 615 | (Back to the Future ) | (Shakespeare in Love ) | 0.32 | 0.30 | 0.12 | 0.38 | 1.28 | 0.03 | 1.13 |
| 451 | (Back to the Future ) | (Fargo ) | 0.32 | 0.32 | 0.13 | 0.40 | 1.26 | 0.03 | 1.14 |
| 355 | (Back to the Future ) | (Saving Private Ryan ) | 0.32 | 0.33 | 0.13 | 0.42 | 1.25 | 0.03 | 1.14 |
| 637 | (Back to the Future ) | (Sixth Sense, The ) | 0.32 | 0.30 | 0.12 | 0.38 | 1.25 | 0.02 | 1.12 |
| 557 | (Back to the Future ) | (Braveheart ) | 0.32 | 0.31 | 0.12 | 0.39 | 1.23 | 0.02 | 1.12 |
| 129 | (Back to the Future ) | (American Beauty ) | 0.32 | 0.43 | 0.15 | 0.47 | 1.09 | 0.01 | 1.07 |

## *Recommendations according to movie genres*

In [53]:

```
# Exploding feature genres


df2 = df.copy()
df2['genres'] = df2['genres'].str.split('|')

df2 = df2.explode('genres')
df2
```

Out[53]:

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | genres |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | One Flew | |

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | genres |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 1193 | 5 | 978298413 | 2000-12-31 | 21 | M | 56 | 16 | 70072 | Over the Cuckoo's Nest | Drama |
| 2 | 12 | 1193 | 4 | 978220179 | 2000-12-30 | 23 | M | 25 | 12 | 32793 | One Flew Over the Cuckoo's Nest | Drama |
| 3 | 15 | 1193 | 4 | 978199279 | 2000-12-30 | 18 | M | 25 | 7 | 22903 | One Flew Over the Cuckoo's Nest | Drama |
| 4 | 17 | 1193 | 5 | 978158471 | 2000-12-30 | 6 | M | 50 | 1 | 95350 | One Flew Over the Cuckoo's Nest | Drama |
| 5 | 18 | 1193 | 4 | 978156168 | 2000-12-30 | 6 | F | 18 | 3 | 95825 | One Flew Over the Cuckoo's Nest | Drama |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 1000206 | 5780 | 2845 | 1 | 958153068 | 2000-12-05 | 17 | M | 18 | 17 | 92886 | White Boys | Drama |
| 1000207 | 5851 | 3607 | 5 | 957756608 | 2000-08-05 | 3 | F | 18 | 20 | 55410 | One Little Indian | Comedy |
| 1000207 | 5851 | 3607 | 5 | 957756608 | 2000-08-05 | 3 | F | 18 | 20 | 55410 | One Little Indian | Drama |
| 1000207 | 5851 | 3607 | 5 | 957756608 | 2000-08-05 | 3 | F | 18 | 20 | 55410 | One Little Indian | Western |
| 1000208 | 5938 | 2909 | 4 | 957273353 | 2000-02-05 | 13 | M | 25 | 1 | 35401 | Five Wives, Three Secretaries and Me | Documentary |

1958837 rows × 13 columns

In [54]:

```
df3 = df2.copy().sample(1000000)
```

In [55]:

```
df2
```

Out[55]:

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | genres |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 1193 | 5 | 978298413 | 2000-12-31 | 21 | M | 56 | 16 | 70072 | One Flew Over the Cuckoo's Nest | Drama |
| 2 | 12 | 1193 | 4 | 978220179 | 2000-12-30 | 23 | M | 25 | 12 | 32793 | One Flew Over the Cuckoo's Nest | Drama |
| 3 | 15 | 1193 | 4 | 978199279 | 2000-12-30 | 18 | M | 25 | 7 | 22903 | One Flew Over the Cuckoo's Nest | Drama |
| 4 | 17 | 1193 | 5 | 978158471 | 2000-12-30 | 6 | M | 50 | 1 | 95350 | One Flew Over the Cuckoo's Nest | Drama |
| | | | | | | | | | | | One Flew | |

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | genres |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 18 | 1193 | 4 | 978156168 | 2000-12-30 | 6 | F | 18 | 3 | 95825 | Over the Cuckoo's Nest | Drama |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **1000206** | 5780 | 2845 | 1 | 958153068 | 2000-12-05 | 17 | M | 18 | 17 | 92886 | White Boys | Drama |
| **1000207** | 5851 | 3607 | 5 | 957756608 | 2000-08-05 | 3 | F | 18 | 20 | 55410 | One Little Indian | Comedy |
| **1000207** | 5851 | 3607 | 5 | 957756608 | 2000-08-05 | 3 | F | 18 | 20 | 55410 | One Little Indian | Drama |
| **1000207** | 5851 | 3607 | 5 | 957756608 | 2000-08-05 | 3 | F | 18 | 20 | 55410 | One Little Indian | Western |
| **1000208** | 5938 | 2909 | 4 | 957273353 | 2000-02-05 | 13 | M | 25 | 1 | 35401 | Five Wives, Three Secretaries and Me | Documentary |

1958837 rows × 13 columns

In [56]:

```
df2 = df2.sample(700000)
```

In [57]:

```
# from tensorflow.keras import backend as K
# K.clear_session()
```

In [58]:

```
data = df2.groupby(['user_id','genres'])['movie_id'].sum().unstack().reset_index().filln
a(0).set_index('user_id')
data = (data>0).astype(int)
```

In [59]:

```
data.head()
```

Out[59]:

| genres | Action | Adventure | Animation | Children's | Comedy | Crime | Documentary | Drama | Fantasy | Film-Noir | Horror | Musical | My |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **user_id** | | | | | | | | | | | | | |
| **2** | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | |
| **3** | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | |
| **4** | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| **5** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | |
| **6** | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | |

In [60]:

```
from mlxtend.frequent_patterns import apriori

itemset = apriori(data,min_support=.5,use_colnames=True).sort_values('support',ascending
=False).reset_index()
```

In [61]:

```
itemset.shape
```

Out[61]:

```
(2253, 3)
```

In [62]:

```
itemset.loc[itemset['itemsets'].apply(lambda x: len(x)) >= 2]
```

Out[62]:

| | index | support | itemsets |
|---|---|---|---|
| **2** | 59 | 0.97 | (Comedy, Drama) |
| **4** | 20 | 0.94 | (Drama, Action) |
| **5** | 18 | 0.93 | (Comedy, Action) |
| **7** | 137 | 0.92 | (Comedy, Drama, Action) |
| **8** | 83 | 0.92 | (Thriller, Drama) |
| **...** | ... | ... | ... |
| **2248** | 1539 | 0.50 | (Horror, Sci-Fi, Crime, War, Romance) |
| **2249** | 1999 | 0.50 | (Horror, Sci-Fi, Drama, Crime, War, Romance) |
| **2250** | 1985 | 0.50 | (Comedy, Sci-Fi, Drama, War, Thriller, Fantasy) |
| **2251** | 1383 | 0.50 | (Sci-Fi, Drama, War, Adventure, Fantasy) |
| **2252** | 1478 | 0.50 | (Comedy, Crime, War, Mystery, Romance) |

**2238 rows × 3 columns**

In [63]:

```
from mlxtend.frequent_patterns import association_rules
rules = association_rules(itemset,metric='lift',min_threshold=1)

rules.head()
```

Out[63]:

| | antecedents | consequents | antecedent support | consequent support | support | confidence | lift | leverage | conviction |
|---|---|---|---|---|---|---|---|---|---|
| **0** | (Comedy) | (Drama) | 0.98 | 0.99 | 0.97 | 0.99 | 1.00 | 0.00 | 1.06 |
| **1** | (Drama) | (Comedy) | 0.99 | 0.98 | 0.97 | 0.98 | 1.00 | 0.00 | 1.03 |
| **2** | (Drama) | (Action) | 0.99 | 0.95 | 0.94 | 0.95 | 1.00 | 0.00 | 1.04 |
| **3** | (Action) | (Drama) | 0.95 | 0.99 | 0.94 | 0.99 | 1.00 | 0.00 | 1.21 |
| **4** | (Comedy) | (Action) | 0.98 | 0.95 | 0.93 | 0.95 | 1.00 | 0.00 | 1.05 |

In [64]:

```
rules.antecedents.value_counts()
```

Out[64]:

```
(Drama)                                                     1120
(Comedy)                                                    1110
(Action)                                                    1096
(Thriller)                                                  1064
(Romance)                                                   1006
                                                            ...
(Action, Comedy, Drama, Musical, Adventure, Thriller)          1
(Action, Comedy, Drama, Musical, Romance, Thriller)            1
(Action, Comedy, Drama, Musical, Adventure, Romance)           1
(Action, Comedy, Musical, Adventure, Romance, Thriller)        1
(Sci-Fi, War, Fantasy, Adventure)                              1
Name: antecedents, Length: 2173, dtype: int64
```

In [65]:

```
rules.loc[rules.antecedents == rules.antecedents.iloc[15]].sort_values(by='lift',ascendi
```

```
ng=False)
```

Out[65]:

| | antecedents | consequents | antecedent support | consequent support | support | confidence | lift | leverage | conviction |
|---|---|---|---|---|---|---|---|---|---|
| **82419** | (Thriller) | (Horror, Action, Comedy, Sci-Fi, Drama, Crime,... | 0.93 | 0.51 | 0.51 | 0.55 | 1.07 | 0.03 | 1.08 |
| **75457** | (Thriller) | (Horror, Action, Sci-Fi, Drama, Crime, War) | 0.93 | 0.51 | 0.51 | 0.55 | 1.07 | 0.03 | 1.08 |
| **81919** | (Thriller) | (Horror, Action, Comedy, Sci-Fi, Crime, War) | 0.93 | 0.51 | 0.51 | 0.55 | 1.07 | 0.03 | 1.08 |
| **88373** | (Thriller) | (Horror, Action, Comedy, Drama, Crime, War, Ad... | 0.93 | 0.51 | 0.50 | 0.54 | 1.07 | 0.03 | 1.08 |
| **74621** | (Thriller) | (Horror, Action, Sci-Fi, Crime, War) | 0.93 | 0.51 | 0.51 | 0.55 | 1.07 | 0.03 | 1.08 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **151** | (Thriller) | (Comedy, Romance) | 0.93 | 0.89 | 0.83 | 0.89 | 1.01 | 0.01 | 1.06 |
| **99** | (Thriller) | (Romance) | 0.93 | 0.90 | 0.84 | 0.91 | 1.01 | 0.01 | 1.07 |
| **20** | (Thriller) | (Comedy, Drama) | 0.93 | 0.97 | 0.90 | 0.97 | 1.00 | 0.00 | 1.09 |
| **12** | (Thriller) | (Drama) | 0.93 | 0.99 | 0.92 | 0.99 | 1.00 | 0.00 | 1.19 |
| **15** | (Thriller) | (Comedy) | 0.93 | 0.98 | 0.91 | 0.98 | 1.00 | 0.00 | 1.05 |

1064 rows × 9 columns

## *Apriori Algorithm Ends*

In [66]:

```
df2.head()
```

Out[66]:

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | genres | releas |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **735006** | 4683 | 2642 | 1 | 963676881 | 2000-07-15 | 16 | M | 25 | 0 | 22101 | Superman III | Action | |
| **740271** | 5734 | 11 | 5 | 976312039 | 2000-08-12 | 21 | F | 25 | 14 | 10022 | American President, The | Comedy | |
| **579188** | 117 | 10 | 4 | 977501371 | 2000-12-22 | 16 | M | 25 | 17 | 33314 | GoldenEye | Thriller | |
| **996457** | 5795 | 888 | 2 | 958146185 | 2000-12-05 | 15 | M | 25 | 1 | 92688 | Land Before Time III: The Time of the Great Gi... | Children's | |
| **384904** | 3017 | 25 | 4 | 970507008 | 2000-02-10 | 17 | F | 35 | 9 | 85255 | Leaving Las Vegas | Romance | |

---

***Several similaity mesuring functions and similarity based recommender system function***

---

In [67]:

```
def hamming_distance(x,y):
  return sum(abs(x-y))


def euclidian_distance(x,y):
  return np.sqrt(np.sum((x-y)**2))


def cosine_similarity(v1, v2):
    dot_prod = np.dot(v1, v2)
    norm_v1 = np.linalg.norm(v1)
    norm_v2 = np.linalg.norm(v2)
    return dot_prod / (norm_v1 * norm_v2)

def pearson_sim(x,y):


    # Calculate the mean of x and y
    x_mean = np.mean(x)
    y_mean = np.mean(y)

    # Calculate the numerator
    num = np.sum((x - x_mean) * (y - y_mean))

    # Calculate the denominator
    x_denom = np.sqrt(np.sum((x - x_mean)**2))
    y_denom = np.sqrt(np.sum((y - y_mean)**2))
    denom = x_denom * y_denom

    # Calculate the Pearson correlation coefficient
    r = num / denom

    return r



def similarity_based_recsys(m,movies,movie_id,hamming_distance):
  ranks = []

  for query in m.index[:10]:
      for candidate in m.index:
          if candidate == query:
              continue
          ranks.append([query, candidate, hamming_distance(m.loc[query], m.loc[candidate
])])

  ranks = pd.DataFrame(ranks, columns=['query', 'candidate', 'distance'])
  ranks = ranks.merge(movies[['movie_id', 'title']], left_on='query', right_on='movie_id
').rename(columns={'title': 'query_tittle'}).drop(columns=['movie_id'])
  ranks = ranks.merge(movies[['movie_id', 'title']], left_on='candidate', right_on='movi
e_id').rename(columns={'title': 'recommendation_title'}).drop(columns=['movie_id'])
  ranks = ranks.sort_values(by=['query', 'distance'])
  return ranks
```

***Pivot table for item item based recommender system***

In [68]:

```
m = df2.groupby(['movie_id','genres'])['title'].unique().str[0].unstack().reset_index().
set_index('movie_id')
m = ~m.isna()
m = m.astype(int)
m.head()
```

Out[68]:

| genres<br>movie_id | Action | Adventure | Animation | Children's | Comedy | Crime | Documentary | Drama | Fantasy | Film-Noir | Horror | Musical |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### *Item item based recommender system using cosine similarity*

In [69]:

```
similarity_based_recsys(m,movies[['movie_id', 'title']],movies.movie_id,cosine_similarity
)
```

Out[69]:

| | query | candidate | distance | query_tittle | recommendation_title |
|---|---|---|---|---|---|
| 36 | 1 | 6 | 0.00 | Toy Story (1995) | Heat (1995) |
| 63 | 1 | 9 | 0.00 | Toy Story (1995) | Sudden Death (1995) |
| 72 | 1 | 10 | 0.00 | Toy Story (1995) | GoldenEye (1995) |
| 111 | 1 | 14 | 0.00 | Toy Story (1995) | Nixon (1995) |
| 121 | 1 | 15 | 0.00 | Toy Story (1995) | Cutthroat Island (1995) |
| ... | ... | ... | ... | ... | ... |
| 8540 | 10 | 990 | 1.00 | GoldenEye (1995) | Maximum Risk (1996) |
| 12820 | 10 | 1499 | 1.00 | GoldenEye (1995) | Anaconda (1997) |
| 13250 | 10 | 1552 | 1.00 | GoldenEye (1995) | Con Air (1997) |
| 14750 | 10 | 1744 | 1.00 | GoldenEye (1995) | Firestorm (1998) |
| 32450 | 10 | 3755 | 1.00 | GoldenEye (1995) | Perfect Storm, The (2000) |

34270 rows × 5 columns

### *Item item based recommender system using pearson correlation similarity*

In [70]:

```
similarity_based_recsys(m,movies[['movie_id', 'title']],movies.movie_id,pearson_sim)
```

Out[70]:

| | query | candidate | distance | query_tittle | recommendation_title |
|---|---|---|---|---|---|
| 10201 | 1 | 1196 | -0.28 | Toy Story (1995) | Star Wars: Episode V - The Empire Strikes Back... |
| 10331 | 1 | 1210 | -0.28 | Toy Story (1995) | Star Wars: Episode VI - Return of the Jedi (1983) |
| 10841 | 1 | 1264 | -0.28 | Toy Story (1995) | Diva (1981) |

| | query | candidate | distance | query_tittle | recommendation_title |
|---|---|---|---|---|---|
| 19681 | 1 | 2322 | -0.28 | Toy Story (1995) | Soldier (1998) |
| 1451 | 1 | 160 | -0.24 | Toy Story (1995) | Congo (1995) |
| ... | ... | ... | ... | ... | ... |
| 8540 | 10 | 990 | 1.00 | GoldenEye (1995) | Maximum Risk (1996) |
| 12820 | 10 | 1499 | 1.00 | GoldenEye (1995) | Anaconda (1997) |
| 13250 | 10 | 1552 | 1.00 | GoldenEye (1995) | Con Air (1997) |
| 14750 | 10 | 1744 | 1.00 | GoldenEye (1995) | Firestorm (1998) |
| 32450 | 10 | 3755 | 1.00 | GoldenEye (1995) | Perfect Storm, The (2000) |

34270 rows × 5 columns

---

***CSR Matrix***

---

In [71]:

```
cmfrec.csr_matrix(np.array(m)).toarray()
```

Out[71]:

```
array([[0, 0, 1, ..., 0, 0, 0],
       [0, 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, ..., 1, 0, 0]])
```

In [72]:

```
cmfrec.csr_matrix(np.array(m))
```

Out[72]:

```
<3428x18 sparse matrix of type '<class 'numpy.int64'>'
 with 5752 stored elements in Compressed Sparse Row format>
```

---

***CSR Matrix Ends***

---

---

***Collaborative Filtering (Item-based & User-based Approach)***

---

In [73]:

```
ratings.head()
```

Out[73]:

| | user_id | movie_id | rating | timestamp | date | hours |
|---|---|---|---|---|---|---|
| 0 | 1 | 1193 | 5 | 978300760 | 2000-12-31 | 22 |
| 1 | 1 | 661 | 3 | 978302109 | 2000-12-31 | 22 |
| 2 | 1 | 914 | 3 | 978301968 | 2000-12-31 | 22 |

| | user_id | movie_id | rating | timestamp | date | hours |
|---|---|---|---|---|---|---|
| **3** | 1 | 3408 | 4 | 978300275 | 2000-12-31 | 22 |
| **4** | 1 | 2355 | 5 | 978824291 | 2001-06-01 | 23 |

In [74]:

```
rm = ratings.pivot(index = 'user_id', columns ='movie_id', values = 'rating').fillna(0)
rm.astype(int).head()
```

Out[74]:

| movie_id | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | ... | 3943 | 3944 | 3945 | 3946 | 3947 | 3948 | 3949 | 3950 | 3951 | 3952 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **user_id** | | | | | | | | | | | | | | | | | | | | | |
| **1** | 5 | 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 |
| **3** | 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 |
| **5** | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**5 rows × 3706 columns**

In [75]:

```
rm_raw = ratings[['user_id', 'movie_id', 'rating']].copy()
rm_raw.columns = ['UserId', 'ItemId', 'Rating']  # Lib requires specific column names
rm_raw.head(2)
```

Out[75]:

| | UserId | ItemId | Rating |
|---|---|---|---|
| **0** | 1 | 1193 | 5 |
| **1** | 1 | 661 | 3 |

In [76]:

```
from cmfrec import CMF
```

In [77]:

```
# from cmfrec import CMF

model = CMF(k=3, lambda_=0.1, user_bias=False, item_bias=False, verbose=False)
model.fit(rm_raw)
```

Out[77]:

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

In [78]:

```
model.A_.shape
```

Out[78]:

```
(6040, 3)
```

In [79]:

```
model.B_.shape
```

Out[79]:

```
(3706, 3)
```

In [80]:

```
model.A_
```

Out[80]:

```
array([[-0.00958391, -0.17743202,  0.16195586],
       [-0.16286132, -0.3025382 , -0.37213776],
       [-0.08792485, -0.22111896, -0.04388591],
       ...,
       [-0.14682147, -0.21881038, -0.24433388],
       [-0.17056152, -0.09411836, -0.11553887],
       [-0.3991945 ,  0.24622837, -0.16886806]], dtype=float32)
```

In [81]:

```
cmfrec.csr_matrix(model.A_)
```

Out[81]:

```
<6040x3 sparse matrix of type '<class 'numpy.float32'>'
 with 18120 stored elements in Compressed Sparse Row format>
```

In [82]:

```
model.B_
```

Out[82]:

```
array([[-4.013367  , -1.4335079 ,  1.2978806 ],
       [ 0.27379817, -0.48399982,  2.3520467 ],
       [-1.7438495 , -3.3851151 ,  0.4928088 ],
       ...,
       [ 0.9760184 ,  1.8206757 , -1.9986285 ],
       [-0.37541583, -1.8747995 , -1.0537992 ],
       [-0.6224832 ,  0.10011666,  0.19826597]], dtype=float32)
```

In [83]:

```
cmfrec.csr_matrix(model.B_)
```

Out[83]:

```
<3706x3 sparse matrix of type '<class 'numpy.float32'>'
 with 11118 stored elements in Compressed Sparse Row format>
```

In [84]:

```
top_items = model.topN(user=4, n=10)
movies.loc[movies.movie_id.isin(top_items)]
```

Out[84]:

| | movie_id | title | genres |
|---|---|---|---|
| 49 | 50 | Usual Suspects, The (1995) | Crime\|Thriller |
| 52 | 53 | Lamerica (1994) | Drama |
| 735 | 745 | Close Shave, A (1995) | Animation\|Comedy\|Thriller |
| 740 | 750 | Dr. Strangelove or: How I Learned to Stop Worr... | Sci-Fi\|War |
| 847 | 858 | Godfather, The (1972) | Action\|Crime\|Drama |
| 910 | 922 | Sunset Blvd. (a.k.a. Sunset Boulevard) (1950) | Film-Noir |
| 911 | 923 | Citizen Kane (1941) | Drama |
| 1950 | 2019 | Seven Samurai (The Magnificent Seven) (Shichin... | Action\|Drama |
| 2836 | 2905 | Sanjuro (1962) | Action\|Adventure |
| 3269 | 3338 | For All Mankind (1989) | Documentary |

### *Evaluation of model using mse and rmse*

In [85]:

```
from sklearn.metrics import mean_squared_error as mse
from sklearn.metrics import mean_absolute_percentage_error as mape
```

In [86]:

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

Out[86]:

```
1.3321351755683746
```

In [129]:

```
np.sqrt(mse(rm.values[rm > 0], rm__[rm > 0]))
```

Out[129]:

```
1.3321351755683746
```

In [130]:

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

Out[130]:

```
0.3796718211689346
```

### *Movie Recommendations on the basis of pearson correlation*

In [89]:

```
m1 = df2.groupby(['movie_id','genres'])['rating'].mean().unstack().reset_index().set_ind
ex('movie_id').T.fillna(0)
correlated_movie_matrix = m1.corr()
correlated_movie_matrix
```

Out[89]:

| movie_id | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | ... | 3943 | 3944 | 3945 | 3946 | 3947 | 3948 | 3949 | 3950 | 3951 | 3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **movie_id** | | | | | | | | | | | | | | | | | | | | | |
| **1** | 1.00 | 0.20 | 0.31 | 0.33 | 0.54 | -0.20 | 0.30 | 0.29 | -0.11 | -0.20 | ... | 0.54 | 0.22 | 0.63 | -0.20 | -0.11 | 0.54 | -0.11 | -0.11 | -0.11 | ( |
| **2** | 0.20 | 1.00 | -0.16 | -0.16 | -0.11 | -0.20 | -0.16 | 0.79 | -0.11 | 0.20 | ... | -0.11 | -0.15 | 0.60 | -0.20 | -0.11 | -0.11 | -0.11 | -0.11 | -0.11 | ( |
| **3** | 0.31 | -0.16 | 1.00 | 0.44 | 0.67 | -0.16 | 1.00 | -0.12 | -0.09 | -0.16 | ... | 0.67 | 0.31 | -0.16 | -0.16 | -0.09 | 0.67 | -0.09 | -0.09 | -0.09 | ( |
| **4** | 0.33 | -0.16 | 0.44 | 1.00 | 0.71 | -0.16 | 0.44 | -0.12 | -0.09 | -0.16 | ... | 0.71 | 0.97 | -0.16 | 0.33 | -0.09 | 0.71 | 0.66 | 0.66 | 0.66 | ( |
| **5** | 0.54 | -0.11 | 0.67 | 0.71 | 1.00 | -0.11 | 0.67 | -0.09 | -0.06 | -0.11 | ... | 1.00 | 0.52 | -0.11 | -0.11 | -0.06 | 1.00 | -0.06 | -0.06 | -0.06 | ( |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **3948** | 0.54 | -0.11 | 0.67 | 0.71 | 1.00 | -0.11 | 0.67 | -0.09 | -0.06 | -0.11 | ... | 1.00 | 0.52 | -0.11 | -0.11 | -0.06 | 1.00 | -0.06 | -0.06 | -0.06 | ( |

| movie_id | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | ... | 3943 | 3944 | 3945 | 3946 | 3947 | 3948 | 3949 | 3950 | 3951 | 3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3949 | 0.11 | 0.12 | 0.09 | 0.66 | 0.06 | 0.16 | 0.09 | 0.08 | 0.06 | 0.10 | ... | [illegible] | 0.82 | [illegible] | 0.58 | [illegible] | [illegible] | 1.00 | 1.00 | 1.00 | 0 |
| 3950 | -0.11 | -0.11 | -0.09 | 0.66 | -0.06 | -0.11 | -0.09 | -0.09 | -0.06 | -0.11 | ... | -0.06 | 0.82 | -0.11 | 0.58 | -0.06 | -0.06 | 1.00 | 1.00 | 1.00 | 0 |
| 3951 | -0.11 | -0.11 | -0.09 | 0.66 | -0.06 | -0.11 | -0.09 | -0.09 | -0.06 | -0.11 | ... | -0.06 | 0.82 | -0.11 | 0.58 | -0.06 | -0.06 | 1.00 | 1.00 | 1.00 | 0 |
| 3952 | -0.16 | -0.16 | -0.12 | 0.42 | -0.09 | 0.32 | -0.12 | -0.12 | -0.09 | 0.32 | ... | -0.09 | 0.54 | -0.16 | 0.81 | 0.69 | -0.09 | 0.69 | 0.69 | 0.69 | 1 |

**3428 rows × 3428 columns**

In [90]:

```
# correlated_movie_matrix.to_dict()
```

In [91]:

```
def recommend_movie_based_on_correlation(movie):
    TITLE = movies[movies.title.str.contains(movie)].iloc[0]["title"]

    INDEX = movies[movies.title.str.contains(movie)].iloc[0].movie_id

    print(TITLE)
    print(INDEX)
    # r = []
    # r.append((movies[movies.movie_id.isin(correlated_movie_matrix[INDEX].sort_values(as
cending=False).head(10).index.to_list())]["title"]))
    return movies[movies.movie_id.isin(correlated_movie_matrix[INDEX].sort_values(ascend
ing=False).head(10).index.to_list())]["title"]
    # return r
```

In [92]:

```
d = recommend_movie_based_on_correlation('Braveheart')
```

```
Braveheart (1995)
110
```

In [93]:

```
d
```

Out[93]:

```
108                  Braveheart (1995)
1204          Full Metal Jacket (1987)
1214      Boat, The (Das Boot) (1981)
1222                      Glory (1989)
1545                  G.I. Jane (1997)
1959         Saving Private Ryan (1998)
2358          Thin Red Line, The (1998)
3559              Flying Tigers (1942)
3585     Guns of Navarone, The (1961)
3684               Patriot, The (2000)
Name: title, dtype: object
```

In [94]:

```
type(recommend_movie_based_on_correlation('Toy Story'))
```

```
Toy Story (1995)
1
```

Out[94]:

```
pandas.core.series.Series
```

In [95]:

```
recommend_movie_based_on_correlation('Toy Story')
```

```
Toy Story (1995)
1
```

Out[95]:

```
0                                   Toy Story (1995)
1050          Aladdin and the King of Thieves (1996)
2033                         Steamboat Willie (1940)
2072                        American Tail, An (1986)
2073        American Tail: Fievel Goes West, An (1991)
2285                       Rugrats Movie, The (1998)
2286                            Bug's Life, A (1998)
3542                           Saludos Amigos (1943)
3682                              Chicken Run (2000)
3685    Adventures of Rocky and Bullwinkle, The (2000)
Name: title, dtype: object
```

In [96]:

```python
# recommend_movie_based_on_correlation('Gladiator')
```

In [97]:

```python
import pickle
```

In [98]:

```python
pickle.dump(movies,open('movie.pkl','wb'))
```

In [99]:

```python
!cp ./movie.pkl /content/drive/MyDrive/Scaler/datasets
```

In [100]:

```python
movies.head()
```

Out[100]:

| | 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 [101]:

```python
pickle.dump(movies.to_dict(),open('movie_dict.pkl','wb'))
!cp ./movie_dict.pkl /content/drive/MyDrive/Scaler/datasets
```

In [102]:

```python
pickle.dump(correlated_movie_matrix.to_dict(),open('correlated_movie_matrix.pkl','wb'))
!cp ./correlated_movie_matrix.pkl /content/drive/MyDrive/Scaler/datasets
```

In [103]:

```python
pickle.dump(df2[['title']].to_dict(),open('titles_.pkl','wb'))
!cp ./titles_.pkl /content/drive/MyDrive/Scaler/datasets
```

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

In [104]:

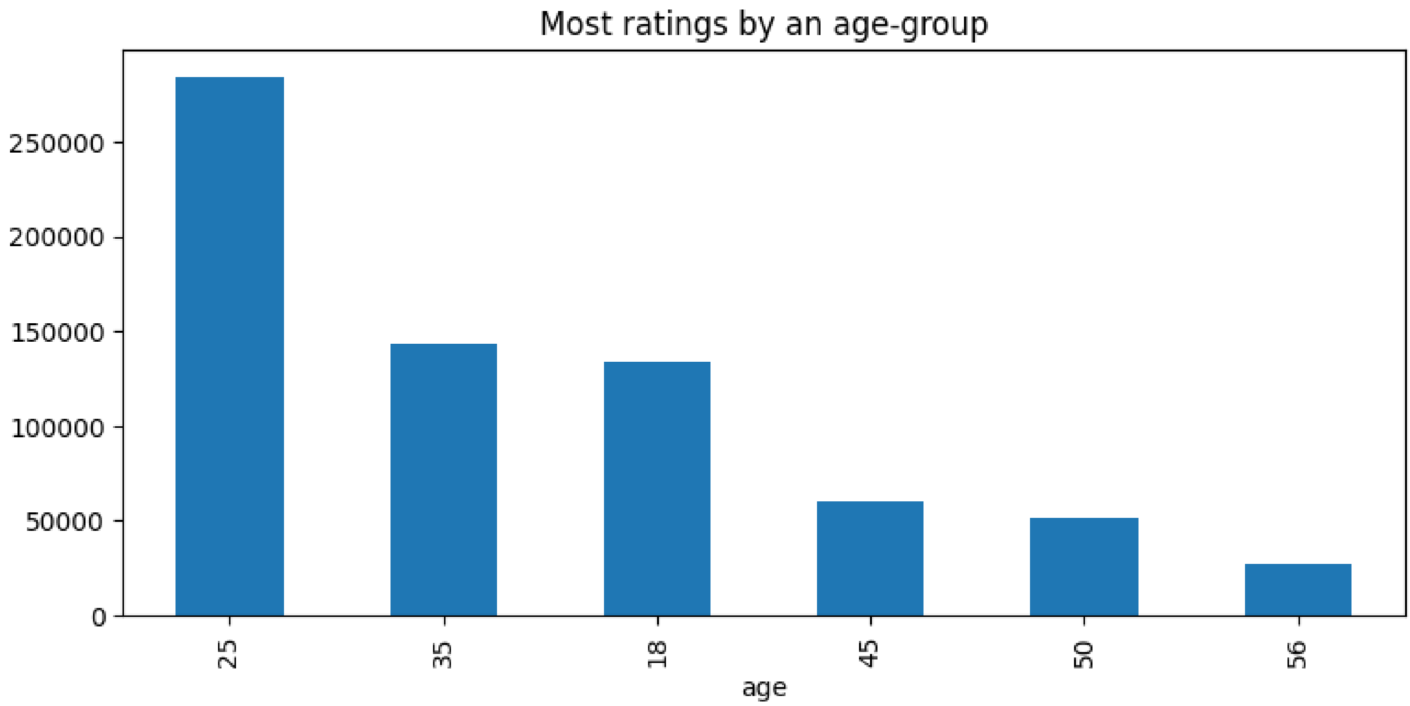
```
Q1 = df2[['user_id','age','rating','movie_id']].reset_index().drop(['index'],axis=1)
```

In [105]:

```
# Most ratings by an agegroup
plt.figure(figsize=(9,4))

Q1.groupby(['age'])['rating'].count().sort_values(ascending=False).plot(kind='bar')
plt.title('Most ratings by an age-group',fontsize=12,fontname='Comic Sans MS')
plt.show()
```

```
WARNING:matplotlib.font_manager:findfont: Font family ['Comic Sans MS'] not found. Fallin
g back to DejaVu Sans.
```

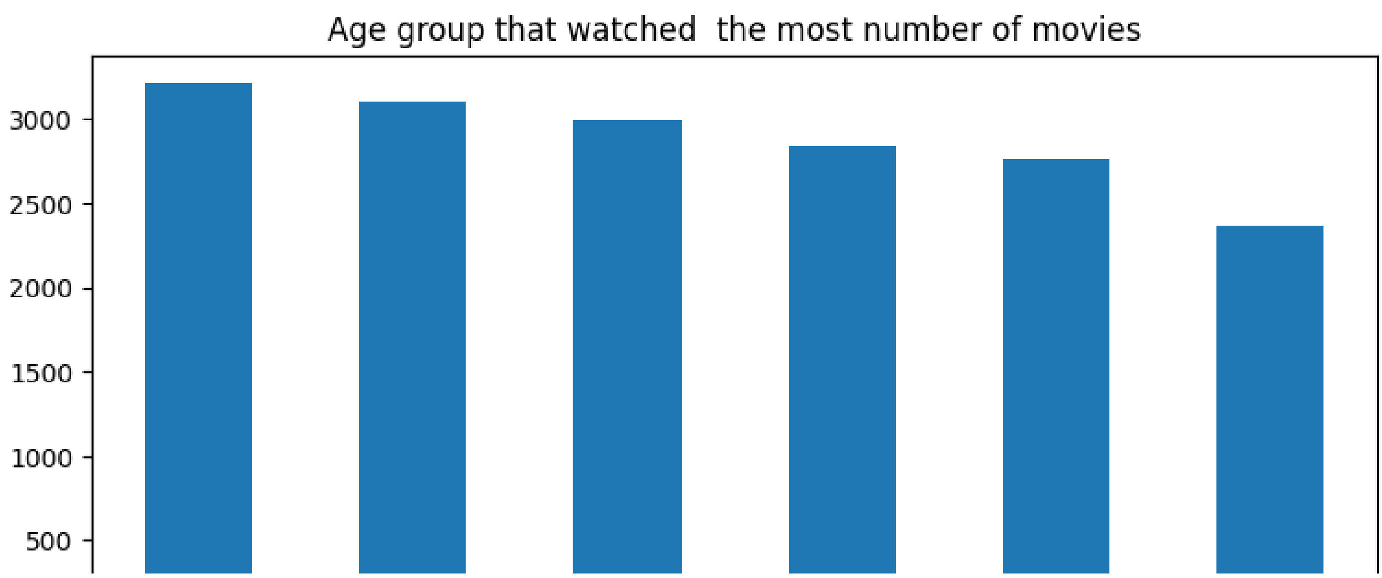


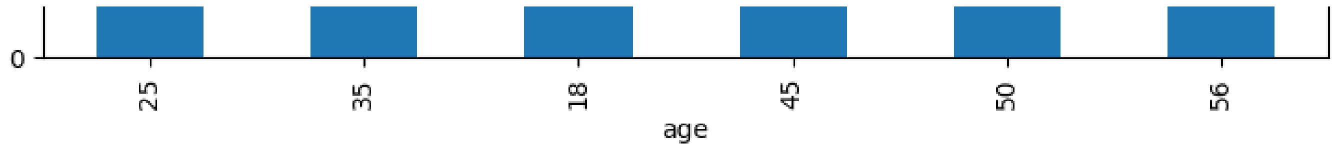

In [106]:

```
# Age group that watched  the most number of movies
plt.figure(figsize=(9,4))

Q1.groupby(['age'])['movie_id'].nunique().sort_values(ascending=False).plot(kind='bar')
plt.title('Age group that watched  the most number of movies',fontsize=12,fontname='Comic
Sans MS')

plt.show()
```






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

In [107]:

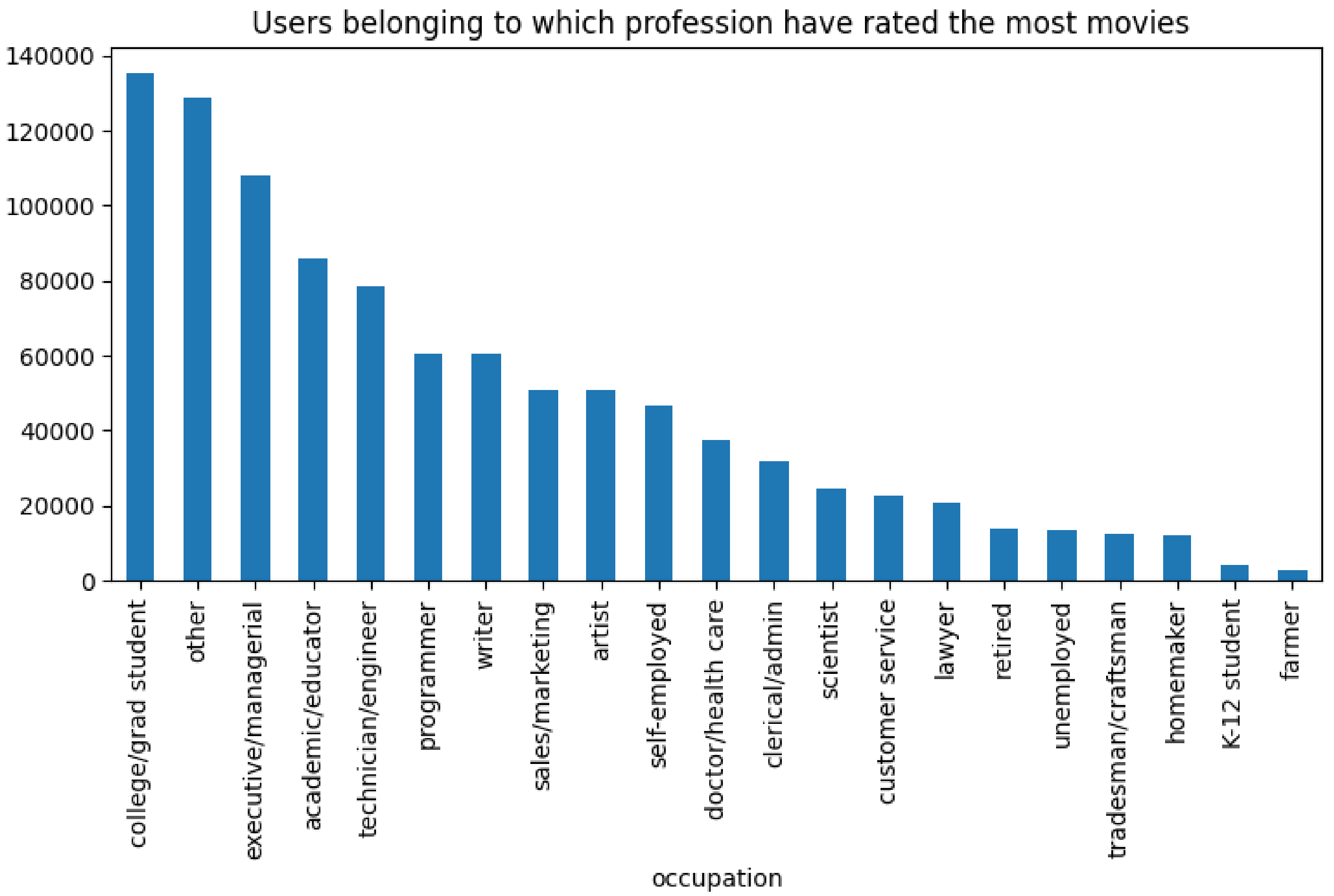
```
mapit = {0: "other", 1: "academic/educator" ,2: "artist" ,3: "clerical/admin" ,4: "colle
ge/grad student" ,5: "customer service" ,6: "doctor/health care" ,7: "executive/manageri
al" ,8: "farmer" ,9: "homemaker" ,10: "K-12 student" ,11: "lawyer" ,12: "programmer" ,13
: "retired" ,14: "sales/marketing" ,15: "scientist" ,16: "self-employed" ,17: "technicia
n/engineer" ,18: "tradesman/craftsman" ,19: "unemployed", 20: "writer"}

df3['occupation'] = df3['occupation'].map(mapit)
```

In [108]:

```
# Most ratings by an agegroup
plt.figure(figsize=(9,4))

df3.groupby(['occupation'])['rating'].count().sort_values(ascending=False).plot(kind='ba
r')
plt.title(' Users belonging to which profession have rated the most movies',fontsize=12,f
ontname='Comic Sans MS')
plt.show()
```




In [109]:

```
df3
```

Out[109]:

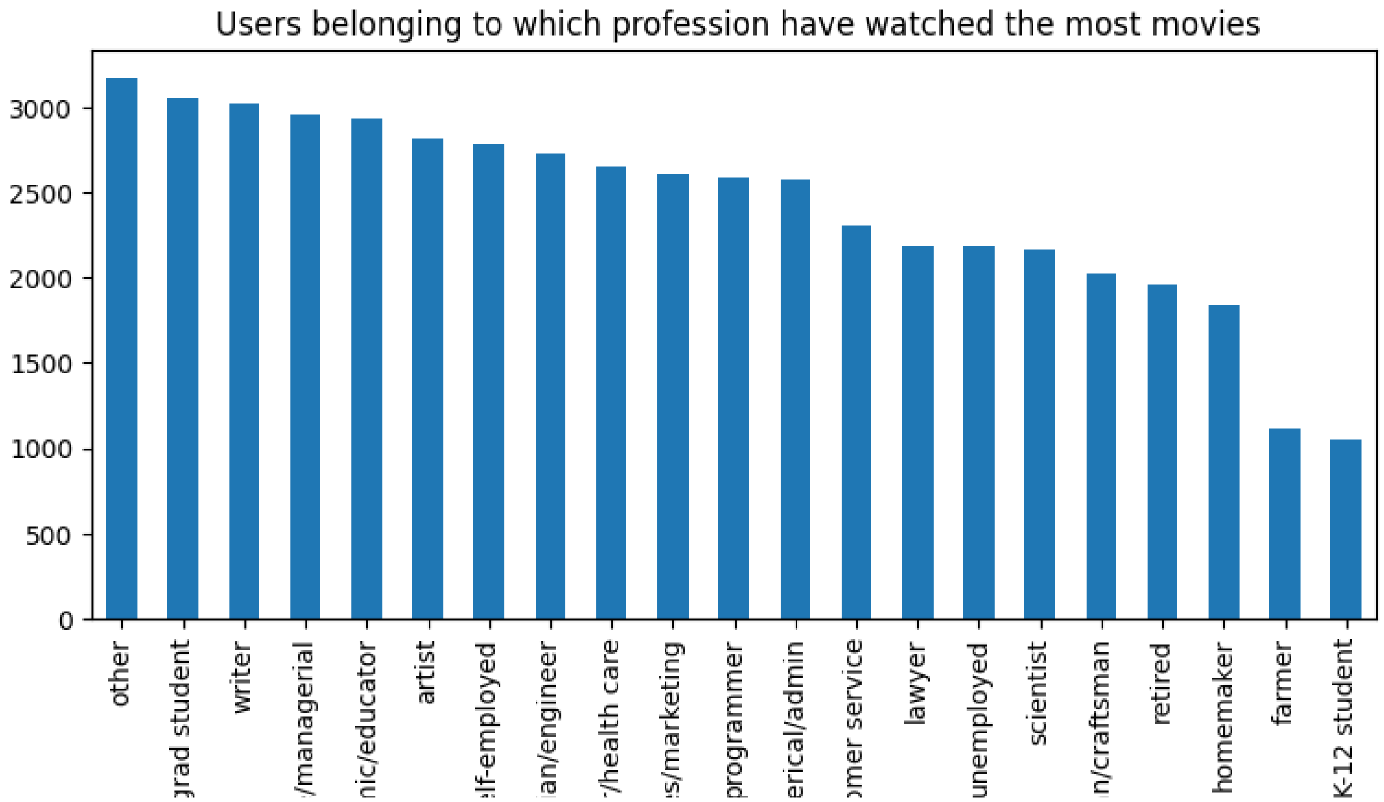
| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | ge |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **115541** | 4956 | 1084 | 4 | 962638726 | 2000-03-07 | 15 | M | 35 | scientist | 77007 | Bonnie and Clyde | Di |
| **361393** | 1873 | 3155 | 4 | 974740115 | 2000-11-20 | 17 | M | 35 | executive/managerial | 2127 | Anna and the King | Rom |
| **6098** | 502 | 1197 | 5 | 976210655 | 2000-07-12 | 17 | M | 35 | doctor/health care | 55126 | Princess Bride, The | Adver |
| **792171** | 3441 | 122 | 2 | 967308615 | 2000-08-26 | 16 | F | 25 | sales/marketing | 94109 | Boomerang | Cor |
| **473069** | 193 | 1374 | 3 | 1035342850 | 2002-10-23 | 3 | F | 45 | scientist | 44106 | Star Trek: The Wrath of Khan | S |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **263553** | 1944 | 1127 | 5 | 974692037 | 2000-11-20 | 3 | F | 18 | college/grad student | 93107 | Abyss, The | Adver |
| **865084** | 2106 | 2491 | 2 | 975439895 | 2000-11-28 | 19 | F | 18 | writer | 495321 | Simply Irresistible | Cor |
| **274216** | 2581 | 3744 | 3 | 974065088 | 2000-12-11 | 21 | M | 25 | lawyer | 60611 | Shaft | C |
| **869660** | 1755 | 2443 | 3 | 1037947827 | 2002-11-22 | 6 | F | 18 | college/grad student | 77005 | Playing by Heart | Rom |
| **669903** | 2567 | 3635 | 3 | 973958742 | 2000-11-11 | 16 | M | 25 | other | 6451 | Spy Who Loved Me, The | A |

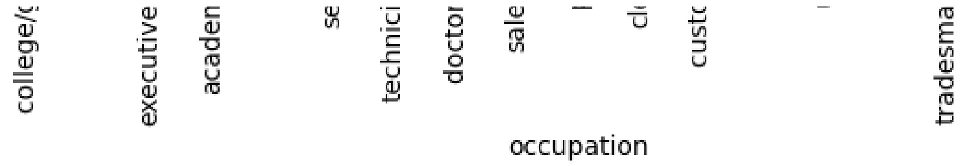
1000000 rows × 13 columns

In [110]:

```
# Age group that watched  the most number of movies
plt.figure(figsize=(9,4))
df3.groupby(['occupation'])['movie_id'].nunique().sort_values(ascending=False).plot(kind
='bar')
plt.title(' Users belonging to which profession have watched the most movies',fontsize=12
,fontname='Comic Sans MS')

plt.show()
```






In [111]:

```
df3.head()
```

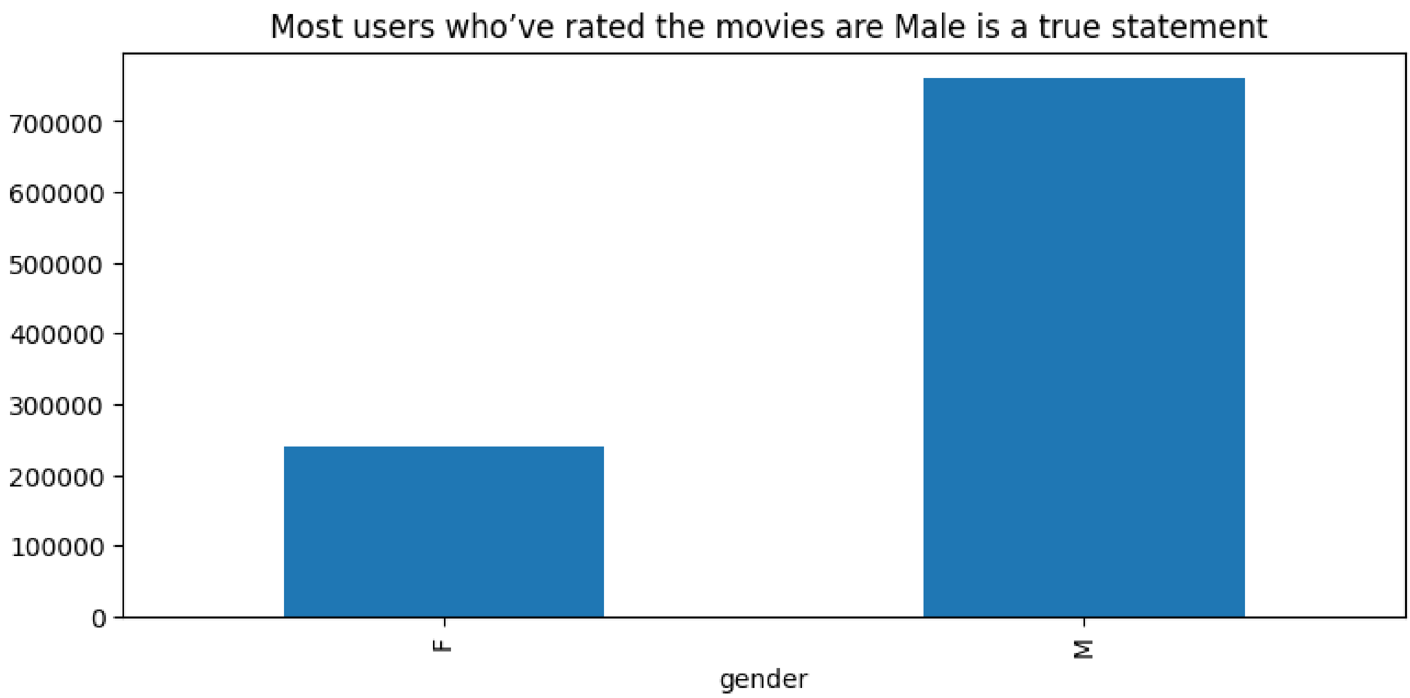
Out[111]:

| | user_id | movie_id | rating | timestamp | date | hours | gender | age | occupation | zip_code | title | ge |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **115541** | 4956 | 1084 | 4 | 962638726 | 2000-03-07 | 15 | M | 35 | scientist | 77007 | Bonnie and Clyde | D |
| **361393** | 1873 | 3155 | 4 | 974740115 | 2000-11-20 | 17 | M | 35 | executive/managerial | 2127 | Anna and the King | Rom |
| **6098** | 502 | 1197 | 5 | 976210655 | 2000-07-12 | 17 | M | 35 | doctor/health care | 55126 | Princess Bride, The | Adve |
| **792171** | 3441 | 122 | 2 | 967308615 | 2000-08-26 | 16 | F | 25 | sales/marketing | 94109 | Boomerang | Co |
| **473069** | 193 | 1374 | 3 | 1035342850 | 2002-10-23 | 3 | F | 45 | scientist | 44106 | Star Trek: The Wrath of Khan | S |

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

In [112]:

```
plt.figure(figsize=(9,4))
df3.groupby(['gender'])['rating'].count().plot(kind='bar')
plt.title(' Most users who've rated the movies are Male is a true statement',fontsize=12,
fontname='Comic Sans MS')
plt.show()
```



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

`70s b. 90s c. 50s d.80s`

In [113]:

```
n = df3.groupby(['release_year'])['movie_id'].nunique().sort_values(ascending=False).res
et_index()
```

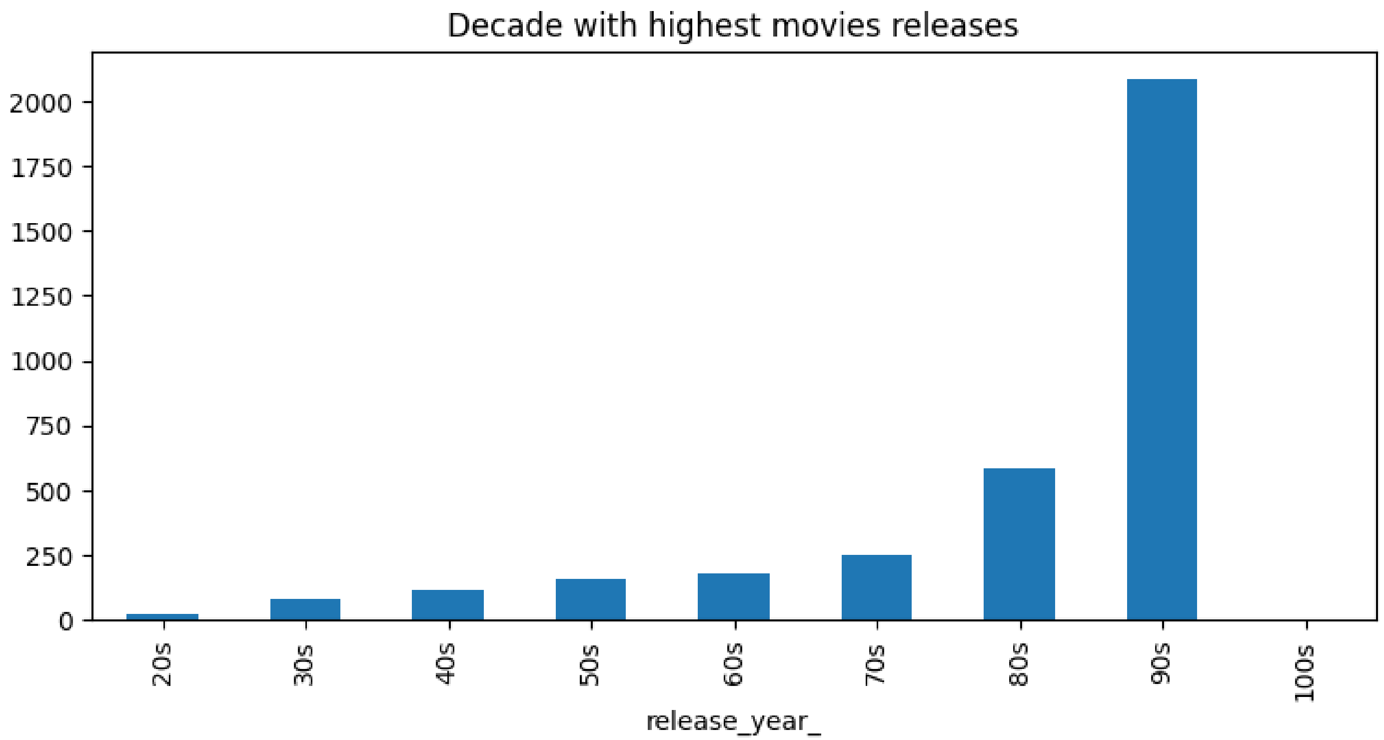
In [114]:

```
bins = [1920,1930,1940,1950,1960,1970,1980,1990,2000,2010]

label = ['20s','30s','40s','50s','60s','70s','80s','90s','100s']
n['release_year_'] = pd.cut(n['release_year'],bins,labels=label)
```

In [115]:

```
plt.figure(figsize=(9,4))
n.groupby('release_year_')['movie_id'].sum().plot(kind='bar')
plt.title('Decade with highest movies releases',fontsize=12,fontname='Comic Sans MS')
plt.show()
```

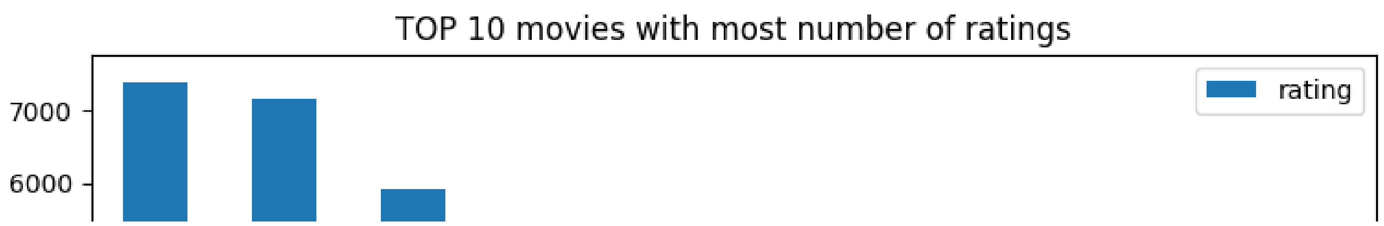


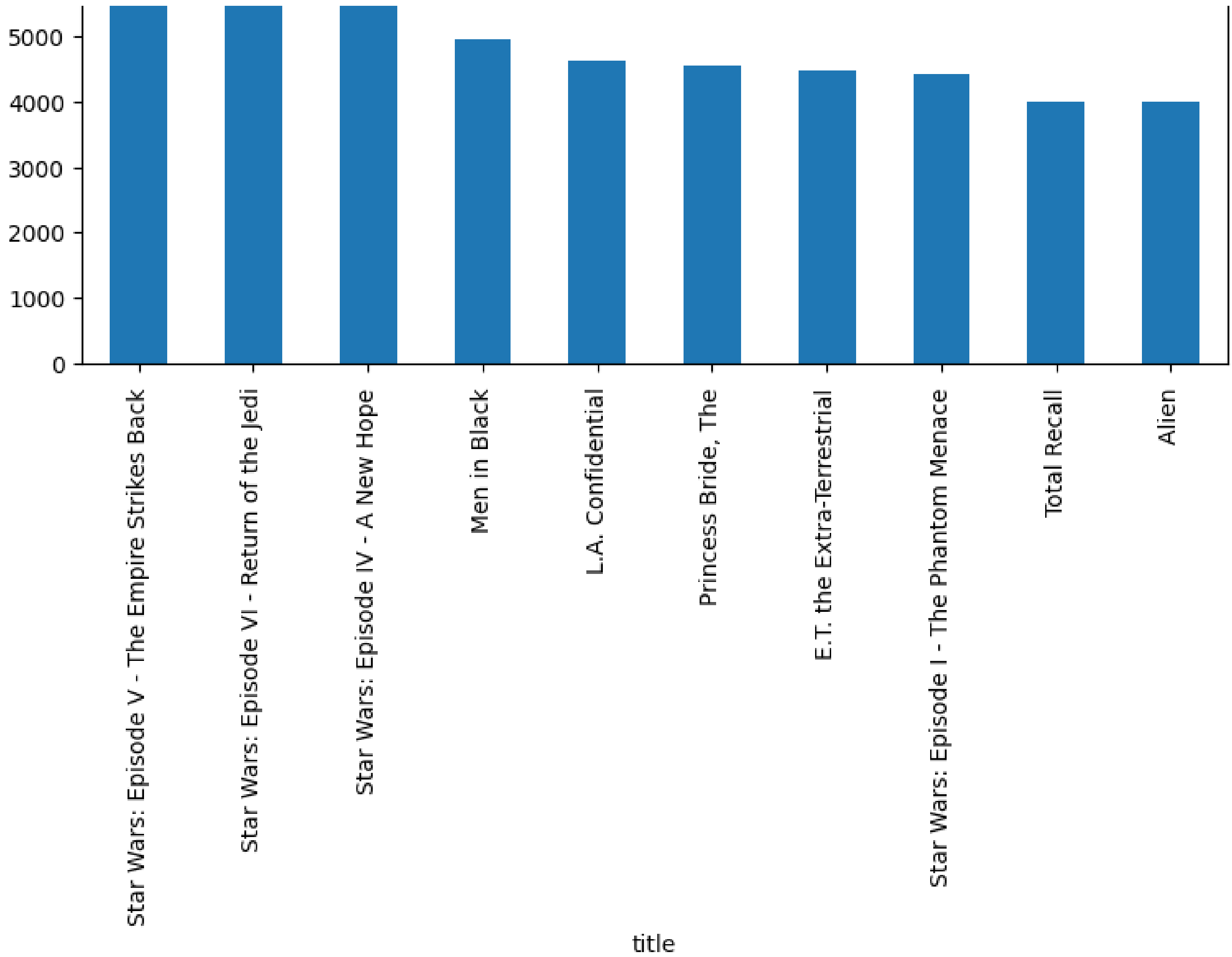

---

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

In [125]:

```
df3.groupby("title")["rating"].count().reset_index().sort_values(by="rating",ascending=F
alse).set_index('title').head(10).plot(kind='bar',figsize=(9,4))
plt.title('TOP 10 movies with most number of ratings',fontsize=12,fontname='Comic Sans MS
')
plt.show()
```






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

In [128]:

```
recommend_movie_based_on_correlation('Liar Liar')[:3]
```

```
Liar Liar (1997)
1485
```

Out[128]:

```
117     Steal Big, Steal Little (1995)
407                  You So Crazy (1994)
658                     Faithful (1996)
Name: title, dtype: object
```

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

***ITEM-ITEM BASED AND USER-USER BASED***

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

**between *to* .**

***Pearson Correlation ranges from -1 to 1, whereas Cosine Similarity ranges from 0 to 1.***

---

---

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

In [131]:

```
print('MAPE : ',mape(rm.values[rm > 0], rm__[rm > 0]),'\n')
print('RMSE :',np.sqrt(mse(rm.values[rm > 0], rm__[rm > 0])))
```

```
MAPE :  0.3796718211689346

RMSE : 1.3321351755683746
```

---

---

### Give the sparse 'row' matrix representation for the following dense matrix -

**[[1 0] [3 7]]**

In [132]:

```
import numpy as np
from scipy.sparse import coo_matrix

dense_matrix = np.array([[1, 0], [3, 7]])
sparse_matrix = coo_matrix(dense_matrix)
print(sparse_matrix)
```

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

In [ ]:

```

```

---

---

### 5 Top rated Recommended Movies as per age :

In [142]:

```
age_groups = df3.age.unique()
```

In [143]:

```
for age_ in age_groups:
  print(age_)
  print("------")
  print(df3[df3.age == age_].groupby("title")["rating"].count().sort_values(ascending=Fa
lse).head())
  print()
  print()
  print()
```

```
35
------
title
Star Wars: Episode V - The Empire Strikes Back      1539
```

```
Star Wars: Episode V - The Empire Strikes Back     1559
Star Wars: Episode VI - Return of the Jedi         1381
Star Wars: Episode IV - A New Hope                 1269
Men in Black                                       1008
E.T. the Extra-Terrestrial                          967
Name: rating, dtype: int64



25
------
title
Star Wars: Episode V - The Empire Strikes Back     2975
Star Wars: Episode VI - Return of the Jedi         2932
Star Wars: Episode IV - A New Hope                 2318
Princess Bride, The                                2008
Men in Black                                       1972
Name: rating, dtype: int64



45
------
title
Star Wars: Episode V - The Empire Strikes Back     568
Star Wars: Episode VI - Return of the Jedi         545
Star Wars: Episode IV - A New Hope                 485
E.T. the Extra-Terrestrial                         406
L.A. Confidential                                  399
Name: rating, dtype: int64



18
------
title
Star Wars: Episode VI - Return of the Jedi         1513
Star Wars: Episode V - The Empire Strikes Back     1468
Star Wars: Episode IV - A New Hope                 1171
Star Wars: Episode I - The Phantom Menace          1065
Men in Black                                       1005
Name: rating, dtype: int64



56
------
title
Star Wars: Episode V - The Empire Strikes Back     289
Star Wars: Episode VI - Return of the Jedi         259
L.A. Confidential                                  258
Star Wars: Episode IV - A New Hope                 237
African Queen, The                                 202
Name: rating, dtype: int64



50
------
title
Star Wars: Episode V - The Empire Strikes Back     543
Star Wars: Episode VI - Return of the Jedi         516
Star Wars: Episode IV - A New Hope                 440
Men in Black                                       391
L.A. Confidential                                  382
Name: rating, dtype: int64
```

In [ ]:

# Questions and Answers :

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

- **age group 25-35**

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

- **College Graduate Students and Other category**

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

- **Male(True)**

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

- **90s**

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

- **Star Wars: Episode V - The Empire Strikes Back**

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

**- Steal Big, Steal Little (1995)**

**- You So Crazy (1994)**

**- Faithful (1996)**

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

- **item and User**

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

**- Pearson Correlation ranges between -1 to +1**

**- Cosine Similarity belongs to the interval between 0 to 1**

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

**User-based Model :**

- MAPE : 0.3796718211689346

- RMSE : 1.3321351755683746

**10) Give the sparse 'row' matrix representation for the following dense matrix -**

**[[1 0],[3 7]]**

- ans : (0, 0) 1 (1, 0) 3 (1, 1) 7