movie-recommender-system

January 22, 2024

[1]:
```python
# from google.colab import drive
# drive.mount('/content/drive')
```

[145]:
```python
# !pip install skimpy
```

[146]:
```python
# pip install cmfrec
```

[4]:
```python
import cmfrec
```

[5]:
```python
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")
```

[6]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
```

[7]:
```python
# 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')
```

[8]:
```python
# 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
```

[9]:
```python
# finding shapes

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

[9]:
```
((1000209, 4), (3883, 3), (6040, 5))
```

[10]:
```python
ratings.dropna(inplace=True)

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

[10]:
```
user_id      0
movie_id     0
rating       0
timestamp    0
dtype: int64
```

[11]:
```python
# converting timestamps to datetime format

from datetime import datetime

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


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

[12]:
```python
ratings['date'] = ratings['date'].astype(np.datetime64)
```

[13]:
```python
# 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())
```

```python
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
________________________________________
```

[14]:

```python
# finding missing values

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

[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

[15]:
```
# finding duplicates

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

[15]:
```
(0, 0, 0)
```

ratings dataset has 24 duplicate rows

[16]:
```
# removing duplicates

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

[16]:
```
0
```

DESCRIBE AND INFO

[17]:
```
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
```

[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)
```

[18]:
```
ratings.describe(include = np.number, percentiles=[.10,.25,.75,.90,.95, .99]).
↪round(2).T.astype(int)
```

[18]:
```
             count       mean       std        min        10%        25%  \
user_id    1000209       3024      1728          1        669       1506
movie_id   1000209       1865      1096          1        357       1030
rating     1000209          3         1          1          2          3
timestamp  1000209  972243695  12152558  956703932  960681570  965302637
hours      1000209         11         7          0          1          4

                 50%        75%        90%        95%         99%         max
user_id         3070       4476       5443       5740        5978        6040
movie_id        1835       2770       3430       3675        3871        3952
rating             4          4          5          5           5           5
timestamp  973018006  975220939  978133376  993074152  1029360403  1046454590
hours             14         19         22         23          23          23
```

---

[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
```

[19]:
```
(         movie_id
 count    3883.00
 mean     1986.05
 std      1146.78
 min         1.00
 25%       982.50
 50%      2010.00
 75%      2980.50
 max      3952.00,
 None)
```

[20]:
```
movies.describe(include=object)
```

[20]:

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

[21]:
```
movies.describe(include = np.number, percentiles=[.10,.25,.75,.90,.95, .99]).
↪round(2).T.astype(int)
```

[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

---

[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
```

[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)
```

[23]:
```
users.describe(include=object)
```

[23]:
```
       gender zip_code
count    6040     6040
unique      2     3439
top         M    48104
freq     4331       19
```

[24]:
```
users.describe(include = np.number, percentiles=[.10,.25,.75,.90,.95, .99]).
 ↪round(2).T.astype(int)
```

[24]:
```
            count  mean   std  min  10%   25%   50%   75%   90%   95%   99%  \
user_id      6040  3020  1743    1  604  1510  3020  4530  5436  5738  5979
age          6040    30    12    1   18    25    25    35    50    56    56
occupation   6040     8     6    0    0     3     7    14    17    19    20

             max
user_id     6040
age           56
occupation    20
```

DESCRIBE AND INFO ENDS

---

[25]:
```
ratings.head()
```

[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
```

[26]:
```
movies.head()
```

[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
```

[27]:
```
users.head()
```

[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
```

[28]:
```
# merging all three datasets

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

[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('()')
```

[30]:
```
df['release_year'] = df['release_year'].astype(int)
```

[31]:
```
df = df[df['release_year'].between(df['release_year'].quantile(.04),
                                   df['release_year'].quantile(.999),
                                   inclusive=True)]
```

[32]:
```
df['title'] = df['title'].str.lstrip('(')
df['title'] = df['title'].str.lstrip(')')
```

[33]:
```
df.shape
```

[33]:
```
(959268, 13)
```

[34]:
```
df.head()
```

[34]:
```
   user_id  movie_id  rating  timestamp        date  hours gender  age  \
0        1      1193       5  978300760  2000-12-31     22      F    1
1        2      1193       5  978298413  2000-12-31     21      M   56
2       12      1193       4  978220179  2000-12-30     23      M   25
3       15      1193       4  978199279  2000-12-30     18      M   25
4       17      1193       5  978158471  2000-12-30      6      M   50

   occupation zip_code                            title genres  release_year
```

```
0           10    48067  One Flew Over the Cuckoo's Nest   Drama           1975
1           16    70072  One Flew Over the Cuckoo's Nest   Drama           1975
2           12    32793  One Flew Over the Cuckoo's Nest   Drama           1975
3            7    22903  One Flew Over the Cuckoo's Nest   Drama           1975
4            1    95350  One Flew Over the Cuckoo's Nest   Drama           1975
```

[35]:
```
df = df[df['age'].between(df['age'].quantile(.03),
                                   df['age'].quantile(1),
                                   inclusive=True)]
```

[36]:
```
df.head()
```

[36]:
```
   user_id  movie_id  rating  timestamp       date  hours gender  age  \
1        2      1193       5  978298413 2000-12-31     21      M   56
2       12      1193       4  978220179 2000-12-30     23      M   25
3       15      1193       4  978199279 2000-12-30     18      M   25
4       17      1193       5  978158471 2000-12-30      6      M   50
5       18      1193       4  978156168 2000-12-30      6      F   18

   occupation zip_code                            title genres  release_year
1          16    70072  One Flew Over the Cuckoo's Nest   Drama           1975
2          12    32793  One Flew Over the Cuckoo's Nest   Drama           1975
3           7    22903  One Flew Over the Cuckoo's Nest   Drama           1975
4           1    95350  One Flew Over the Cuckoo's Nest   Drama           1975
5           3    95825  One Flew Over the Cuckoo's Nest   Drama           1975
```

0.0.1 *Apriori Algorithm*

Recommendations according to movie title

[37]:
```
df
```

[37]:
```
         user_id  movie_id  rating  timestamp       date  hours gender  age  \
1              2      1193       5  978298413 2000-12-31     21      M   56
2             12      1193       4  978220179 2000-12-30     23      M   25
3             15      1193       4  978199279 2000-12-30     18      M   25
4             17      1193       5  978158471 2000-12-30      6      M   50
5             18      1193       4  978156168 2000-12-30      6      F   18
…             …        …       …         …          …      …     …    …
1000204     5949      2198       5  958846401 2000-05-20     18      M   18
1000205     5675      2703       3  976029116 2000-05-12     15      M   35
1000206     5780      2845       1  958153068 2000-12-05     17      M   18
1000207     5851      3607       5  957756608 2000-08-05      3      F   18
1000208     5938      2909       4  957273353 2000-02-05     13      M   25

         occupation zip_code                            title  \
1                16    70072        One Flew Over the Cuckoo's Nest
2                12    32793        One Flew Over the Cuckoo's Nest
```

```
3                  7    22903       One Flew Over the Cuckoo's Nest
4                  1    95350       One Flew Over the Cuckoo's Nest
5                  3    95825       One Flew Over the Cuckoo's Nest
…             …    …                                              …
1000204           17    47901                            Modulations
1000205           14    30030                        Broken Vessels
1000206           17    92886                            White Boys
1000207           20    55410                     One Little Indian
1000208            1    35401  Five Wives, Three Secretaries and Me

                       genres  release_year
1                       Drama          1975
2                       Drama          1975
3                       Drama          1975
4                       Drama          1975
5                       Drama          1975
…                         …            …
1000204           Documentary          1998
1000205                 Drama          1998
1000206                 Drama          1999
1000207  Comedy|Drama|Western          1973
1000208           Documentary          1998

[933429 rows x 13 columns]
```

[38]:
```python
df1 = df.sample(700000)
```

[39]:
```python
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
```

[40]:
```python
data = df1.groupby(['user_id','title'])['movie_id'].sum().unstack().
 ↪reset_index().fillna(0).set_index('user_id')
```

[41]:
```python
data[data.index == 6036].sum(axis=1)
```

[41]:
```
user_id
6036    1186000
dtype: int64
```

[42]:
```python
data = (data>0).astype(int)
```

[43]:
```python
data[data.index == 6036].sum(axis=1)
```

[43]:
```
user_id
6036    635
dtype: int64
```

[44]:
```python
data.head()
```

[44]:
```
title    'Night Mother   'Til There Was You   'burbs, The   \
user_id
2                    0                    0             0
3                    0                    0             0
4                    0                    0             0
5                    0                    0             0
6                    0                    0             0

title    …And Justice for All   : A Space Odyssey   A Chef in Love   \
user_id
2                           0                   0                0
3                           0                   0                0
4                           0                   0                0
5                           0                   0                0
6                           0                   0                0

title    Abbott and Costello Meet Frankenstein   Abominable Snowman, The   \
user_id
2                                            0                         0
3                                            0                         0
4                                            0                         0
5                                            0                         0
```

```
6                                            0                         0

title    About Adam   About Last Night…   …  \
user_id                                     …
2                 0                     0   …
3                 0                     0   …
4                 0                     0   …
5                 0                     0   …
6                 0                     0   …

title    Young Poisoner's Handbook, The   Young Sherlock Holmes   \
user_id
2                                     0                       0
3                                     0                       0
4                                     0                       0
5                                     0                       0
6                                     0                       0

title    Young and Innocent   Your Friends and Neighbors   Zachariah   \
user_id
2                         0                            0           0
3                         0                            0           0
4                         0                            0           0
5                         0                            0           0
6                         0                            0           0

title    Zed & Two Noughts, A   Zero Effect   \
user_id
2                           0             0
3                           0             0
4                           0             0
5                           0             0
6                           0             0

title    Zero Kelvin (Kjærlighetens kjøtere)   Zeus and Roxanne   eXistenZ
user_id
2                                          0                  0          0
3                                          0                  0          0
4                                          0                  0          0
5                                          0                  0          0
6                                          0                  0          0

[5 rows x 3466 columns]
```

[45]:
```
from mlxtend.frequent_patterns import apriori
```

[46]:
```
itemset = apriori(data,min_support=.12,use_colnames=True).
  ↪sort_values('support',ascending=False).reset_index()
```

[47]:
```
itemset.shape
```

[47]:
```
(578, 3)
```

[48]:
```
itemset.loc[itemset['itemsets'].apply(lambda x: len(x)) >= 2]
```

[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…
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 x 3 columns]
```

[49]:
```
from mlxtend.frequent_patterns import association_rules


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

[50]:
```
rules
```

[50]:
```
                                        antecedents  \
0    (Star Wars: Episode V - The Empire Strikes Back )
1                (Star Wars: Episode IV - A New Hope )
2    (Star Wars: Episode V - The Empire Strikes Back )
3        (Star Wars: Episode VI - Return of the Jedi )
4                (Star Wars: Episode IV - A New Hope )
..                                                 …
725                                       (Toy Story )
726                                     (Matrix, The )
727                                           (Speed )
728       (Star Wars: Episode I - The Phantom Menace )
729                             (Princess Bride, The )

                                        consequents  antecedent support  \
0                (Star Wars: Episode IV - A New Hope )                0.37
1    (Star Wars: Episode V - The Empire Strikes Back )                0.38
```

```
2        (Star Wars: Episode VI - Return of the Jedi )                0.37
3    (Star Wars: Episode V - The Empire Strikes Back )                0.36
4        (Star Wars: Episode VI - Return of the Jedi )                0.38
..                                                 …                    …
725                            (Saving Private Ryan )                 0.26
726                                          (Speed )                 0.32
727                                   (Matrix, The )                  0.21
728                            (Princess Bride, The )                 0.28
729       (Star Wars: Episode I - The Phantom Menace )                0.29

     consequent support  support  confidence  lift  leverage  conviction
0                  0.38     0.22        0.59  1.58      0.08        1.53
1                  0.37     0.22        0.58  1.58      0.08        1.51
2                  0.36     0.20        0.55  1.52      0.07        1.42
3                  0.37     0.20        0.56  1.52      0.07        1.44
4                  0.36     0.20        0.52  1.44      0.06        1.33
..                    …        …          …     …         …           …
725                0.33     0.12        0.47  1.40      0.03        1.25
726                0.21     0.12        0.37  1.81      0.05        1.27
727                0.32     0.12        0.58  1.81      0.05        1.63
728                0.29     0.12        0.43  1.46      0.04        1.24
729                0.28     0.12        0.41  1.46      0.04        1.22

[730 rows x 9 columns]
```

[51]:

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

[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 Jedi) 1
(Godfather: Part II, The)
1
(Gladiator)
1
(Speed)
1

```
Name: antecedents, dtype: int64
```

[52]:

```python
rules.loc[rules.antecedents == rules.antecedents.iloc[15]].
    ↪sort_values(by='lift',ascending=False)
```

[52]:

```
                antecedents                                          consequents  \
627  (Back to the Future )                                            (Aliens )
589  (Back to the Future )                                      (Blade Runner )
249  (Back to the Future )                                   (Terminator, The )
177  (Back to the Future )                        (E.T. the Extra-Terrestrial )
241  (Back to the Future )                                      (Ghostbusters )
492  (Back to the Future )                                             (Alien )
193  (Back to the Future )                                (Princess Bride, The )
15   (Back to the Future )  (Star Wars: Episode V - The Empire Strikes Back )
656  (Back to the Future )                                      (Total Recall )
595  (Back to the Future )                                         (Toy Story )
147  (Back to the Future )                           (Raiders of the Lost Ark )
155  (Back to the Future )                                      (Men in Black )
39   (Back to the Future )      (Star Wars: Episode VI - Return of the Jedi )
363  (Back to the Future )                                     (Groundhog Day )
27   (Back to the Future )              (Star Wars: Episode IV - A New Hope )
529  (Back to the Future )                                      (Forrest Gump )
489  (Back to the Future )       (Star Wars: Episode I - The Phantom Menace )
195  (Back to the Future )                                       (Matrix, The )
182  (Back to the Future )                                     (Jurassic Park )
692  (Back to the Future )                      (Shawshank Redemption, The )
279  (Back to the Future )                      (Silence of the Lambs, The )
615  (Back to the Future )                               (Shakespeare in Love )
451  (Back to the Future )                                             (Fargo )
355  (Back to the Future )                               (Saving Private Ryan )
637  (Back to the Future )                                  (Sixth Sense, The )
557  (Back to the Future )                                        (Braveheart )
129  (Back to the Future )                                   (American Beauty )

     antecedent support  consequent support  support  confidence  lift  \
627                0.32                0.23     0.12        0.38  1.67
589                0.32                0.23     0.12        0.38  1.64
249                0.32                0.27     0.14        0.43  1.63
177                0.32                0.28     0.15        0.46  1.62
241                0.32                0.27     0.14        0.43  1.62
492                0.32                0.25     0.13        0.39  1.56
193                0.32                0.29     0.15        0.45  1.54
15                 0.32                0.37     0.18        0.55  1.50
656                0.32                0.25     0.12        0.38  1.48
595                0.32                0.26     0.12        0.38  1.48
147                0.32                0.32     0.15        0.47  1.47
155                0.32                0.32     0.15        0.46  1.46
```

39	0.32	0.36	0.17	0.53	1.46
363	0.32	0.29	0.13	0.41	1.45
27	0.32	0.38	0.18	0.54	1.44
529	0.32	0.27	0.13	0.39	1.42
489	0.32	0.28	0.13	0.39	1.41
195	0.32	0.32	0.15	0.45	1.40
182	0.32	0.34	0.15	0.46	1.36
692	0.32	0.29	0.12	0.37	1.31
279	0.32	0.33	0.14	0.43	1.30
615	0.32	0.30	0.12	0.38	1.28
451	0.32	0.32	0.13	0.40	1.26
355	0.32	0.33	0.13	0.42	1.25
637	0.32	0.30	0.12	0.38	1.25
557	0.32	0.31	0.12	0.39	1.23
129	0.32	0.43	0.15	0.47	1.09

	leverage	conviction
627	0.05	1.24
589	0.05	1.24
249	0.05	1.29
177	0.06	1.32
241	0.05	1.29
492	0.05	1.23
193	0.05	1.29
15	0.06	1.41
656	0.04	1.20
595	0.04	1.20
147	0.05	1.28
155	0.05	1.27
39	0.05	1.35
363	0.04	1.22
27	0.05	1.36
529	0.04	1.19
489	0.04	1.19
195	0.04	1.24
182	0.04	1.22
692	0.03	1.14
279	0.03	1.17
615	0.03	1.13
451	0.03	1.14
355	0.03	1.14
637	0.02	1.12
557	0.02	1.12
129	0.01	1.07

0.0.2 *Recommendations according to movie genres*

[53]:
```
# Exploding feature genres


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

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

[53]:
```
         user_id  movie_id  rating  timestamp        date  hours gender  age  \
1              2      1193       5  978298413  2000-12-31     21      M   56
2             12      1193       4  978220179  2000-12-30     23      M   25
3             15      1193       4  978199279  2000-12-30     18      M   25
4             17      1193       5  978158471  2000-12-30      6      M   50
5             18      1193       4  978156168  2000-12-30      6      F   18
…            …        …       …          …           …      …    …   …
1000206     5780      2845       1  958153068  2000-12-05     17      M   18
1000207     5851      3607       5  957756608  2000-08-05      3      F   18
1000207     5851      3607       5  957756608  2000-08-05      3      F   18
1000207     5851      3607       5  957756608  2000-08-05      3      F   18
1000208     5938      2909       4  957273353  2000-02-05     13      M   25

         occupation zip_code                                 title  \
1                16    70072       One Flew Over the Cuckoo's Nest
2                12    32793       One Flew Over the Cuckoo's Nest
3                 7    22903       One Flew Over the Cuckoo's Nest
4                 1    95350       One Flew Over the Cuckoo's Nest
5                 3    95825       One Flew Over the Cuckoo's Nest
…              …        …                                   …
1000206          17    92886                            White Boys
1000207          20    55410                    One Little Indian
1000207          20    55410                    One Little Indian
1000207          20    55410                    One Little Indian
1000208           1    35401  Five Wives, Three Secretaries and Me

              genres  release_year
1              Drama          1975
2              Drama          1975
3              Drama          1975
4              Drama          1975
5              Drama          1975
…               …             …
1000206        Drama          1999
1000207       Comedy          1973
1000207        Drama          1973
```

```
1000207      Western          1973
1000208  Documentary          1998

[1958837 rows x 13 columns]
```

[54]:
```python
df3 = df2.copy().sample(1000000)
```

[55]:
```python
df2
```

[55]:
```
         user_id  movie_id  rating  timestamp       date  hours gender  age  \
1              2      1193       5  978298413 2000-12-31     21      M   56
2             12      1193       4  978220179 2000-12-30     23      M   25
3             15      1193       4  978199279 2000-12-30     18      M   25
4             17      1193       5  978158471 2000-12-30      6      M   50
5             18      1193       4  978156168 2000-12-30      6      F   18
…            …        …       …          …         …     …    …  …
1000206     5780      2845       1  958153068 2000-12-05     17      M   18
1000207     5851      3607       5  957756608 2000-08-05      3      F   18
1000207     5851      3607       5  957756608 2000-08-05      3      F   18
1000207     5851      3607       5  957756608 2000-08-05      3      F   18
1000208     5938      2909       4  957273353 2000-02-05     13      M   25

         occupation zip_code                                 title  \
1                16    70072       One Flew Over the Cuckoo's Nest
2                12    32793       One Flew Over the Cuckoo's Nest
3                 7    22903       One Flew Over the Cuckoo's Nest
4                 1    95350       One Flew Over the Cuckoo's Nest
5                 3    95825       One Flew Over the Cuckoo's Nest
…               …       …                                   …
1000206          17    92886                            White Boys
1000207          20    55410                     One Little Indian
1000207          20    55410                     One Little Indian
1000207          20    55410                     One Little Indian
1000208           1    35401  Five Wives, Three Secretaries and Me

              genres  release_year
1              Drama          1975
2              Drama          1975
3              Drama          1975
4              Drama          1975
5              Drama          1975
…                …            …
1000206        Drama          1999
1000207       Comedy          1973
1000207        Drama          1973
1000207      Western          1973
1000208  Documentary          1998
```

```
[1958837 rows x 13 columns]
```

[56]:
```
df2 = df2.sample(700000)
```

[57]:
```
# from tensorflow.keras import backend as K
# K.clear_session()
```

[58]:
```
data = df2.groupby(['user_id','genres'])['movie_id'].sum().unstack().
 ↪reset_index().fillna(0).set_index('user_id')
data = (data>0).astype(int)
```

[59]:
```
data.head()
```

[59]:
```
genres   Action  Adventure  Animation  Children's  Comedy  Crime  Documentary  \
user_id
2             1          1          0           0       1      1            0
3             1          1          0           1       1      0            0
4             1          1          0           1       0      0            0
5             1          1          1           1       1      1            1
6             1          1          1           1       1      1            0

genres   Drama  Fantasy  Film-Noir  Horror  Musical  Mystery  Romance  Sci-Fi  \
user_id
2            1        0          1       0        0        1        1       1
3            1        1          0       0        0        1        1       1
4            1        0          0       1        0        0        0       1
5            1        0          1       1        1        1        1       1
6            1        1          0       0        1        0        1       0

genres   Thriller  War  Western
user_id
2               1    1        0
3               1    1        1
4               1    1        1
5               1    1        1
6               1    1        1
```

[60]:
```
from mlxtend.frequent_patterns import apriori

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

[61]:
```
itemset.shape
```

[61]:
```
(2253, 3)
```

[62]:
```
itemset.loc[itemset['itemsets'].apply(lambda x: len(x)) >= 2]
```

[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 x 3 columns]
```

[63]:
```
from mlxtend.frequent_patterns import association_rules
rules = association_rules(itemset,metric='lift',min_threshold=1)

rules.head()
```

[63]:
```
  antecedents consequents  antecedent support  consequent support  support  \
0    (Comedy)     (Drama)                0.98                0.99     0.97
1     (Drama)    (Comedy)                0.99                0.98     0.97
2     (Drama)    (Action)                0.99                0.95     0.94
3    (Action)     (Drama)                0.95                0.99     0.94
4    (Comedy)    (Action)                0.98                0.95     0.93

   confidence  lift  leverage  conviction
0        0.99  1.00      0.00        1.06
1        0.98  1.00      0.00        1.03
2        0.95  1.00      0.00        1.04
3        0.99  1.00      0.00        1.21
4        0.95  1.00      0.00        1.05
```

[64]:
```
rules.antecedents.value_counts()
```

[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
```

[65]:
```python
rules.loc[rules.antecedents == rules.antecedents.iloc[15]].
 ↪sort_values(by='lift',ascending=False)
```

[65]:
```
      antecedents                                        consequents  \
82419  (Thriller)  (Horror, Action, Comedy, Sci-Fi, Drama, Crime,…
75457  (Thriller)        (Horror, Action, Sci-Fi, Drama, Crime, War)
81919  (Thriller)       (Horror, Action, Comedy, Sci-Fi, Crime, War)
88373  (Thriller)  (Horror, Action, Comedy, Drama, Crime, War, Ad…
74621  (Thriller)               (Horror, Action, Sci-Fi, Crime, War)
…            …                                                  …
151    (Thriller)                                  (Comedy, Romance)
99     (Thriller)                                          (Romance)
20     (Thriller)                                    (Comedy, Drama)
12     (Thriller)                                            (Drama)
15     (Thriller)                                           (Comedy)

       antecedent support  consequent support  support  confidence  lift  \
82419                0.93                0.51     0.51        0.55  1.07
75457                0.93                0.51     0.51        0.55  1.07
81919                0.93                0.51     0.51        0.55  1.07
88373                0.93                0.51     0.50        0.54  1.07
74621                0.93                0.51     0.51        0.55  1.07
…                     …                 …       …           …    …
151                  0.93                0.89     0.83        0.89  1.01
99                   0.93                0.90     0.84        0.91  1.01
20                   0.93                0.97     0.90        0.97  1.00
12                   0.93                0.99     0.92        0.99  1.00
15                   0.93                0.98     0.91        0.98  1.00

       leverage  conviction
82419      0.03        1.08
75457      0.03        1.08
81919      0.03        1.08
88373      0.03        1.08
74621      0.03        1.08
…           …         …
151        0.01        1.06
99         0.01        1.07
20         0.00        1.09
12         0.00        1.19
15         0.00        1.05

[1064 rows x 9 columns]
```

0.0.3 *Apriori Algorithm Ends*

[66]:
```
df2.head()
```

[66]:
```
        user_id  movie_id  rating  timestamp        date  hours gender  age  \
735006     4683      2642       1  963676881  2000-07-15     16      M   25
740271     5734        11       5  976312039  2000-08-12     21      F   25
579188      117        10       4  977501371  2000-12-22     16      M   25
996457     5795       888       2  958146185  2000-12-05     15      M   25
384904     3017        25       4  970507008  2000-02-10     17      F   35

        occupation zip_code  \
735006           0    22101
740271          14    10022
579188          17    33314
996457           1    92688
384904           9    85255

                                                   title      genres  \
735006                                      Superman III      Action
740271                           American President, The      Comedy
579188                                         GoldenEye    Thriller
996457  Land Before Time III: The Time of the Great Gi…  Children's
384904                                  Leaving Las Vegas     Romance

        release_year
735006          1983
740271          1995
579188          1995
996457          1995
384904          1995
```

[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='movie_id').rename(columns={'title': 'recommendation_title'}).
 ↪drop(columns=['movie_id'])
  ranks = ranks.sort_values(by=['query', 'distance'])
  return ranks
```

[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()
```

[68]:
```
genres    Action  Adventure  Animation  Children's  Comedy  Crime  \
movie_id
1              0          0          1           1       1      0
2              0          1          0           1       0      0
3              0          0          0           0       1      0
4              0          0          0           0       1      0
5              0          0          0           0       1      0

genres    Documentary  Drama  Fantasy  Film-Noir  Horror  Musical  Mystery  \
movie_id
1                   0      0        0          0       0        0        0
2                   0      0        1          0       0        0        0
3                   0      0        0          0       0        0        0
4                   0      1        0          0       0        0        0
5                   0      0        0          0       0        0        0

genres    Romance  Sci-Fi  Thriller  War  Western
movie_id
1               0       0         0    0        0
2               0       0         0    0        0
3               1       0         0    0        0
4               0       0         0    0        0
5               0       0         0    0        0
```

[69]:
```
similarity_based_recsys(m,movies[['movie_id', 'title']],movies.
 ↪movie_id,cosine_similarity)
```

[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 x 5 columns]
```

[70]:
```
similarity_based_recsys(m,movies[['movie_id', 'title']],movies.
 ↪movie_id,pearson_sim)
```

[70]:
```
       query  candidate  distance      query_tittle  \
10201      1       1196     -0.28  Toy Story (1995)
```

```
10331      1      1210     -0.28  Toy Story (1995)
10841      1      1264     -0.28  Toy Story (1995)
19681      1      2322     -0.28  Toy Story (1995)
1451       1       160     -0.24  Toy Story (1995)
…        …       …        …              …
8540      10       990      1.00  GoldenEye (1995)
12820     10      1499      1.00  GoldenEye (1995)
13250     10      1552      1.00  GoldenEye (1995)
14750     10      1744      1.00  GoldenEye (1995)
32450     10      3755      1.00  GoldenEye (1995)

                                    recommendation_title
10201  Star Wars: Episode V - The Empire Strikes Back…
10331  Star Wars: Episode VI - Return of the Jedi (1983)
10841                                        Diva (1981)
19681                                     Soldier (1998)
1451                                        Congo (1995)
…                                                      …
8540                                 Maximum Risk (1996)
12820                                    Anaconda (1997)
13250                                     Con Air (1997)
14750                                   Firestorm (1998)
32450                          Perfect Storm, The (2000)

[34270 rows x 5 columns]
```

[71]:

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

[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]])
```

[72]:

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

[72]:

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

[73]:

```
ratings.head()
```

[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

```
3         1      3408        4  978300275  2000-12-31     22
4         1      2355        5  978824291  2001-06-01     23
```

[74]:
```
rm = ratings.pivot(index = 'user_id', columns ='movie_id', values = 'rating').
 ↪fillna(0)
rm.astype(int).head()
```

[74]:
```
movie_id  1     2     3     4     5     6     7     8     9     10    …  \
user_id                                                                 …
1            5     0     0     0     0     0     0     0     0     0  …
2            0     0     0     0     0     0     0     0     0     0  …
3            0     0     0     0     0     0     0     0     0     0  …
4            0     0     0     0     0     0     0     0     0     0  …
5            0     0     0     0     0     2     0     0     0     0  …

movie_id  3943  3944  3945  3946  3947  3948  3949  3950  3951  3952
user_id
1            0     0     0     0     0     0     0     0     0     0
2            0     0     0     0     0     0     0     0     0     0
3            0     0     0     0     0     0     0     0     0     0
4            0     0     0     0     0     0     0     0     0     0
5            0     0     0     0     0     0     0     0     0     0

[5 rows x 3706 columns]
```

[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)
```

[75]:
```
   UserId  ItemId  Rating
0       1    1193       5
1       1     661       3
```

[76]:
```
from cmfrec import CMF
```

[77]:
```
# from cmfrec import CMF

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

[77]:
```
Collective matrix factorization model
(explicit-feedback variant)
```

[78]:
```
model.A_.shape
```

[78]: (6040, 3)

[79]:
```
model.B_.shape
```

[79]: (3706, 3)

[80]:
```
model.A_
```

[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)
```

[81]:
```
cmfrec.csr_matrix(model.A_)
```

[81]:
```
<6040x3 sparse matrix of type '<class 'numpy.float32'>'
        with 18120 stored elements in Compressed Sparse Row format>
```

[82]:
```
model.B_
```

[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)
```

[83]:
```
cmfrec.csr_matrix(model.B_)
```

[83]:
```
<3706x3 sparse matrix of type '<class 'numpy.float32'>'
        with 11118 stored elements in Compressed Sparse Row format>
```

[84]:
```
top_items = model.topN(user=4, n=10)
movies.loc[movies.movie_id.isin(top_items)]
```

[84]:
```
     movie_id                                              title  \
49         50                             Usual Suspects, The (1995)
52         53                                      Lamerica (1994)
735       745                                  Close Shave, A (1995)
740       750    Dr. Strangelove or: How I Learned to Stop Worr…
847       858                                  Godfather, The (1972)
910       922        Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)
911       923                                    Citizen Kane (1941)
```

```
1950      2019  Seven Samurai (The Magnificent Seven) (Shichin…
2836      2905                                     Sanjuro (1962)
3269      3338                              For All Mankind (1989)

                         genres
49              Crime|Thriller
52                       Drama
735   Animation|Comedy|Thriller
740                 Sci-Fi|War
847         Action|Crime|Drama
910                  Film-Noir
911                      Drama
1950              Action|Drama
2836          Action|Adventure
3269               Documentary
```

[85]:

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

[86]:

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

[86]:

```
1.3321351755683746
```

[129]:

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

[129]:

```
1.3321351755683746
```

[130]:

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

[130]:

```
0.3796718211689346
```

[89]:

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

[89]:

```
movie_id  1     2     3     4     5     6     7     8     9     10    …  \
movie_id                                                              …
1         1.00  0.20  0.31  0.33  0.54 -0.20  0.30  0.29 -0.11 -0.20  …
2         0.20  1.00 -0.16 -0.16 -0.11 -0.20 -0.16  0.79 -0.11  0.20  …
3         0.31 -0.16  1.00  0.44  0.67 -0.16  1.00 -0.12 -0.09 -0.16  …
4         0.33 -0.16  0.44  1.00  0.71 -0.16  0.44 -0.12 -0.09 -0.16  …
5         0.54 -0.11  0.67  0.71  1.00 -0.11  0.67 -0.09 -0.06 -0.11  …
…          …    …    …    …    …    …    …    …    …    …   …
3948      0.54 -0.11  0.67  0.71  1.00 -0.11  0.67 -0.09 -0.06 -0.11  …
3949     -0.11 -0.11 -0.09  0.66 -0.06 -0.11 -0.09 -0.09 -0.06 -0.11  …
```

```
3950     -0.11 -0.11 -0.09  0.66 -0.06 -0.11 -0.09 -0.09 -0.06 -0.11  …
3951     -0.11 -0.11 -0.09  0.66 -0.06 -0.11 -0.09 -0.09 -0.06 -0.11  …
3952     -0.16 -0.16 -0.12  0.42 -0.09  0.32 -0.12 -0.12 -0.09  0.32  …

movie_id  3943  3944  3945  3946  3947  3948  3949  3950  3951  3952
movie_id
1          0.54  0.22  0.63 -0.20 -0.11  0.54 -0.11 -0.11 -0.11 -0.16
2         -0.11 -0.15  0.60 -0.20 -0.11 -0.11 -0.11 -0.11 -0.11 -0.16
3          0.67  0.31 -0.16 -0.16 -0.09  0.67 -0.09 -0.09 -0.09 -0.12
4          0.71  0.97 -0.16  0.33 -0.09  0.71  0.66  0.66  0.66  0.42
5          1.00  0.52 -0.11 -0.11 -0.06  1.00 -0.06 -0.06 -0.06 -0.09
…         …    …    …    …    …    …    …    …    …    …
3948       1.00  0.52 -0.11 -0.11 -0.06  1.00 -0.06 -0.06 -0.06 -0.09
3949      -0.06  0.82 -0.11  0.58 -0.06 -0.06  1.00  1.00  1.00  0.69
3950      -0.06  0.82 -0.11  0.58 -0.06 -0.06  1.00  1.00  1.00  0.69
3951      -0.06  0.82 -0.11  0.58 -0.06 -0.06  1.00  1.00  1.00  0.69
3952      -0.09  0.54 -0.16  0.81  0.69 -0.09  0.69  0.69  0.69  1.00

[3428 rows x 3428 columns]
```

[90]:
```
# correlated_movie_matrix.to_dict()
```

[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(ascending=False).head(10).index.to_list())]["title"]))
    return movies[movies.movie_id.isin(correlated_movie_matrix[INDEX].
 ↪sort_values(ascending=False).head(10).index.to_list())]["title"]
    # return r
```

[92]:
```
d = recommend_movie_based_on_correlation('Braveheart')
```

```
Braveheart (1995)
110
```

[93]:
```
d
```

[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
```

[94]:
```
type(recommend_movie_based_on_correlation('Toy Story'))
```

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

[94]:
```
pandas.core.series.Series
```

[95]:
```
recommend_movie_based_on_correlation('Toy Story')
```

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

[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
```

[96]:
```
# recommend_movie_based_on_correlation('Gladiator')
```

[97]:
```
import pickle
```

[98]:
```
pickle.dump(movies,open('movie.pkl','wb'))
```

[99]:
```
!cp ./movie.pkl /content/drive/MyDrive/Scaler/datasets
```

[100]:
```
movies.head()
```

[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
```

[101]:

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

[102]:

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

[103]:

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

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

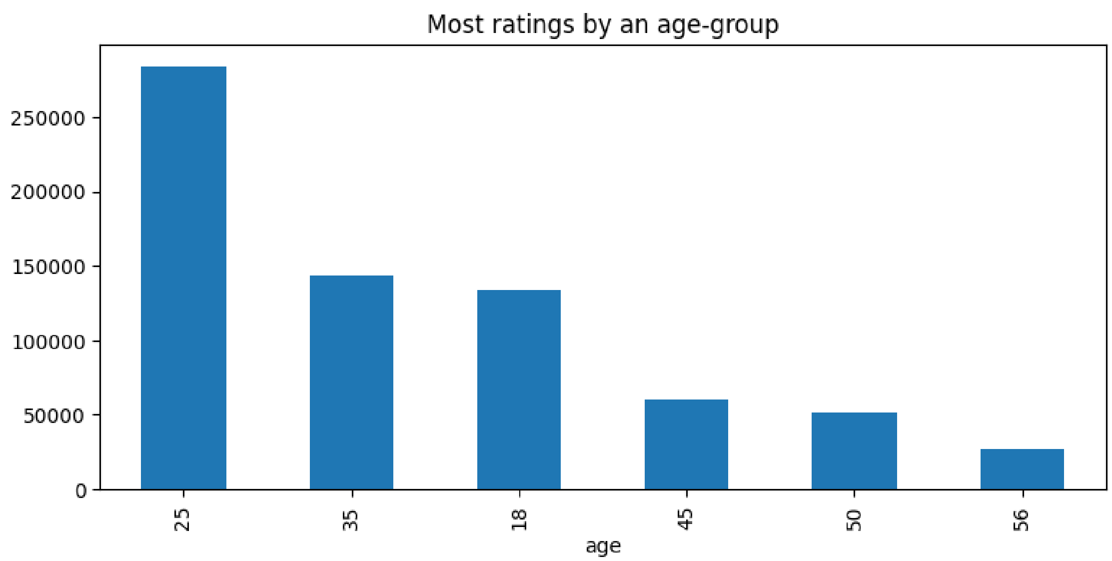
[104]:

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

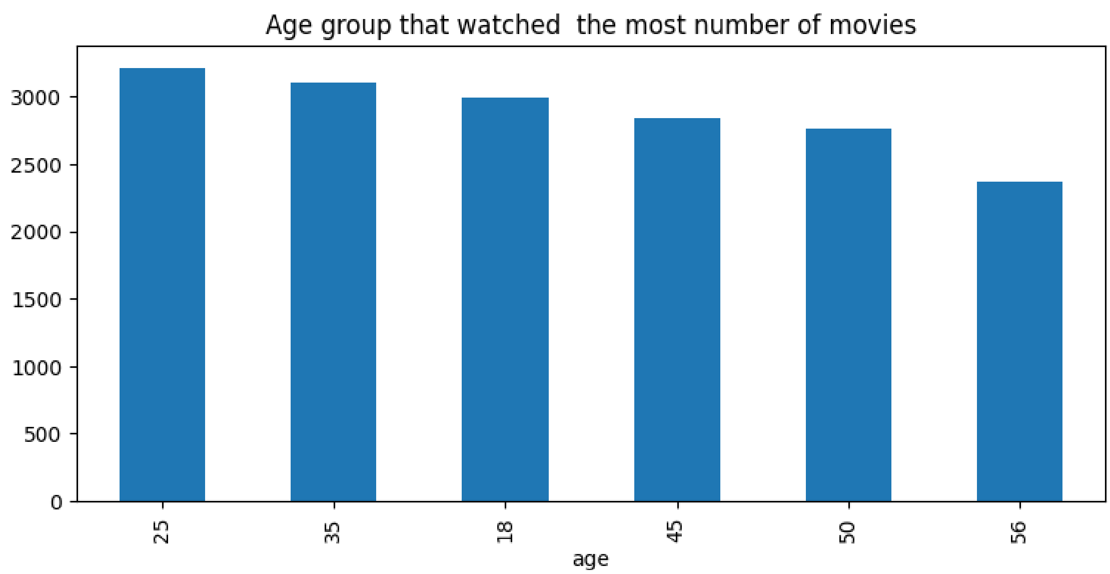
[105]:

```
# 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. Falling back to DejaVu Sans.
```



[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()
```

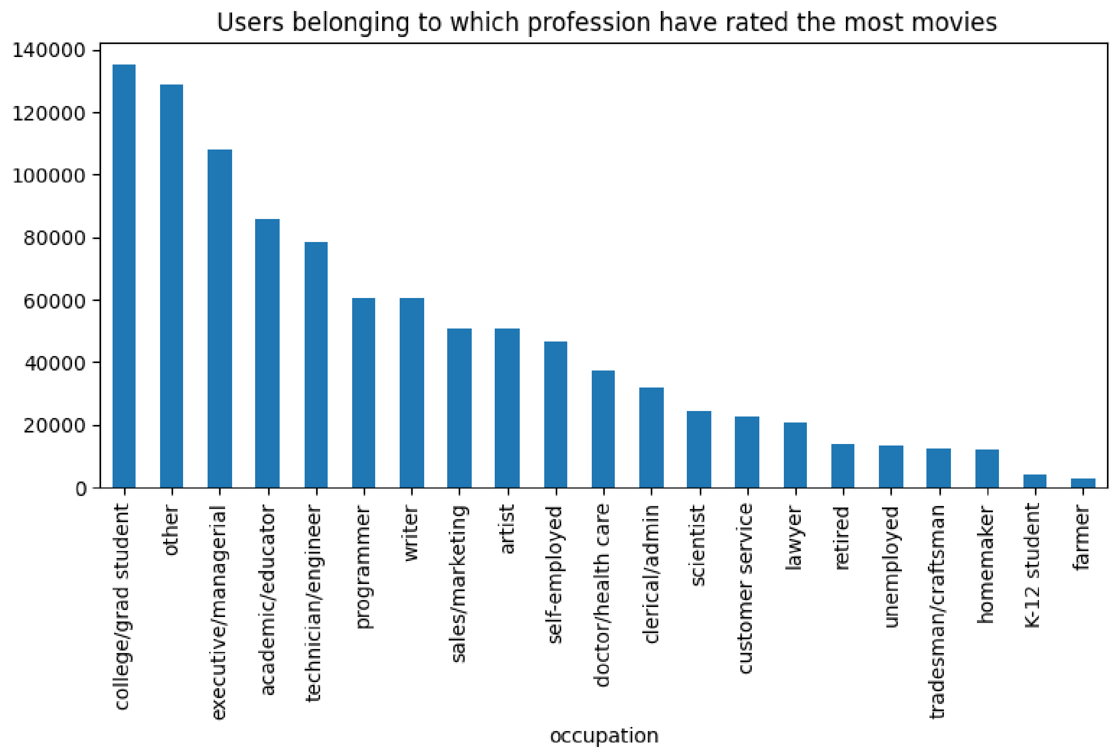


0.0.5 Users belonging to which profession have watched and rated the most movies?

[107]:
```
mapit = {0: "other", 1: "academic/educator" ,2: "artist" ,3: "clerical/admin"␣
 ↪,4: "college/grad student" ,5: "customer service" ,6: "doctor/health care"␣
 ↪,7: "executive/managerial" ,8: "farmer" ,9: "homemaker" ,10: "K-12 student"␣
 ↪,11: "lawyer" ,12: "programmer" ,13: "retired" ,14: "sales/marketing" ,15:␣
 ↪"scientist" ,16: "self-employed" ,17: "technician/engineer" ,18: "tradesman/
 ↪craftsman" ,19: "unemployed", 20: "writer"}

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

[108]:
```
# Most ratings by an agegroup
plt.figure(figsize=(9,4))

df3.groupby(['occupation'])['rating'].count().sort_values(ascending=False).
 ↪plot(kind='bar')
```

```
plt.title(' Users belonging to which profession have rated the most␣
 ↪movies',fontsize=12,fontname='Comic Sans MS')
plt.show()
```



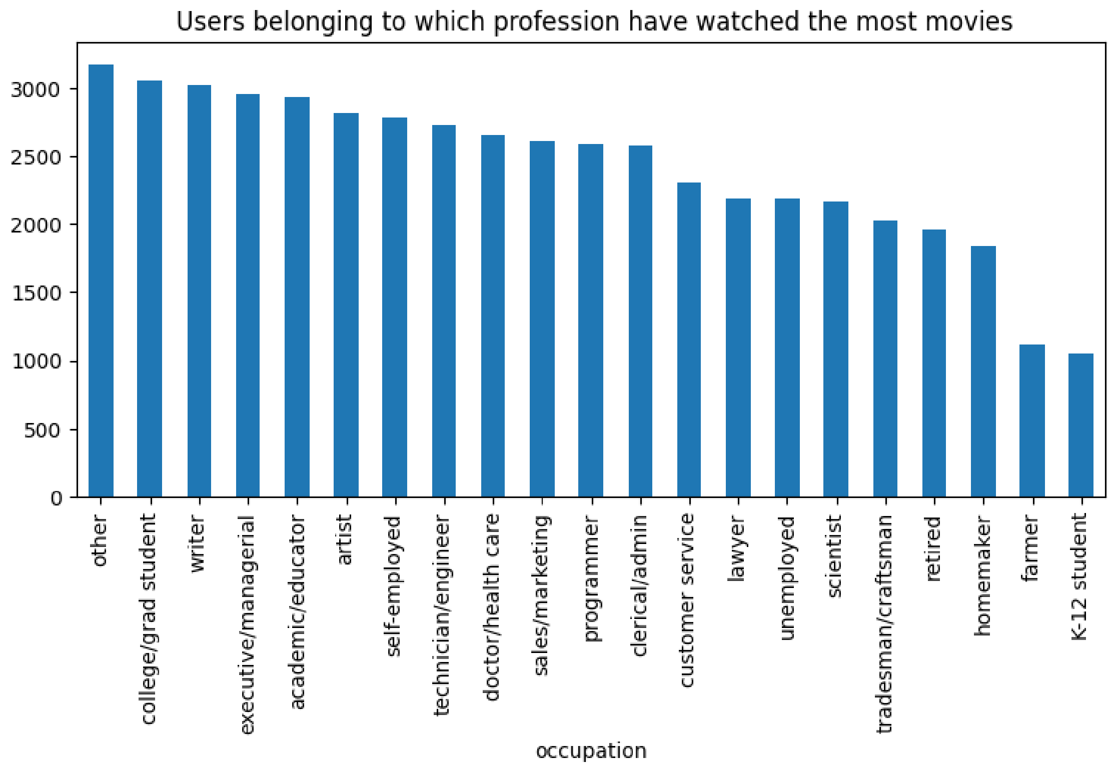
[109]:
```
df3
```

[109]:
```
        user_id  movie_id  rating   timestamp        date  hours gender  age  \
115541     4956      1084       4   962638726  2000-03-07     15      M   35
361393     1873      3155       4   974740115  2000-11-20     17      M   35
6098        502      1197       5   976210655  2000-07-12     17      M   35
792171     3441       122       2   967308615  2000-08-26     16      F   25
473069      193      1374       3  1035342850  2002-10-23      3      F   45
…           …         …       …          …           …      …     …   …
263553     1944      1127       5   974692037  2000-11-20      3      F   18
865084     2106      2491       2   975439895  2000-11-28     19      F   18
274216     2581      3744       3   974065088  2000-12-11     21      M   25
869660     1755      2443       3  1037947827  2002-11-22      6      F   18
669903     2567      3635       3   973958742  2000-11-11     16      M   25

                 occupation zip_code                         title  \
115541            scientist    77007             Bonnie and Clyde
361393 executive/managerial     2127            Anna and the King
6098       doctor/health care    55126           Princess Bride, The
```

```
792171       sales/marketing    94109                        Boomerang
473069             scientist    44106  Star Trek: The Wrath of Khan
…                          …        …                            …
263553  college/grad student    93107                      Abyss, The
865084                writer   495321           Simply Irresistible
274216                lawyer    60611                         Shaft
869660  college/grad student    77005               Playing by Heart
669903                 other     6451            Spy Who Loved Me, The

           genres  release_year
115541      Drama          1967
361393    Romance          1999
6098    Adventure          1987
792171     Comedy          1992
473069     Sci-Fi          1982
…             …            …
263553  Adventure          1989
865084     Comedy          1999
274216      Crime          2000
869660    Romance          1998
669903     Action          1977

[1000000 rows x 13 columns]
```

[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()
```

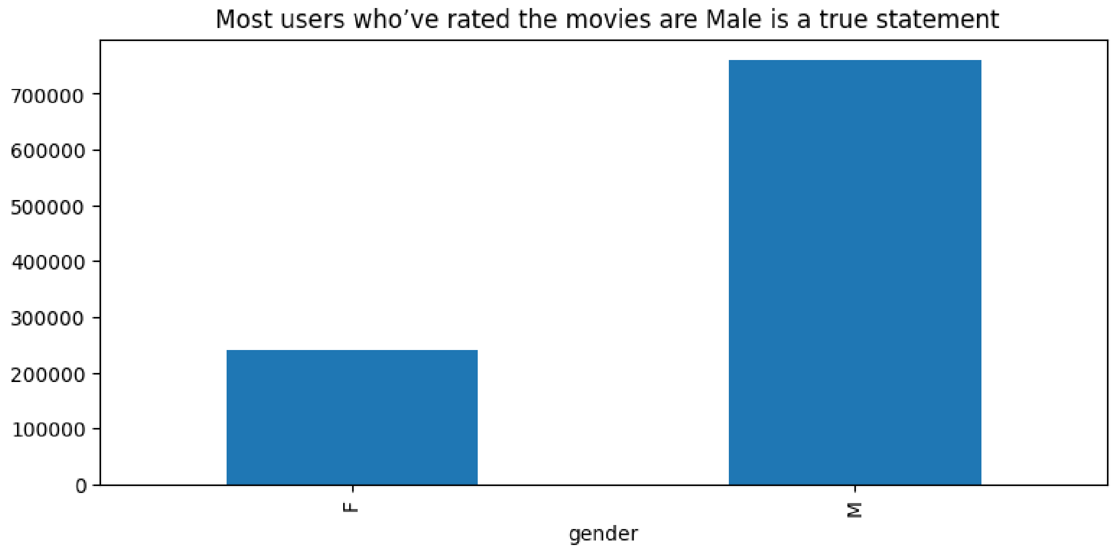


[111]:
```
df3.head()
```

[111]:
```
        user_id  movie_id  rating   timestamp        date  hours gender  age  \
115541     4956      1084       4   962638726  2000-03-07     15      M   35
361393     1873      3155       4   974740115  2000-11-20     17      M   35
6098        502      1197       5   976210655  2000-07-12     17      M   35
792171     3441       122       2   967308615  2000-08-26     16      F   25
473069      193      1374       3  1035342850  2002-10-23      3      F   45

                  occupation zip_code                          title  \
115541             scientist    77007               Bonnie and Clyde
361393  executive/managerial     2127              Anna and the King
6098      doctor/health care    55126            Princess Bride, The
792171       sales/marketing    94109                      Boomerang
473069             scientist    44106  Star Trek: The Wrath of Khan

           genres  release_year
115541      Drama          1967
361393    Romance          1999
6098    Adventure          1987
792171     Comedy          1992
473069     Sci-Fi          1982
```

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

[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()
```



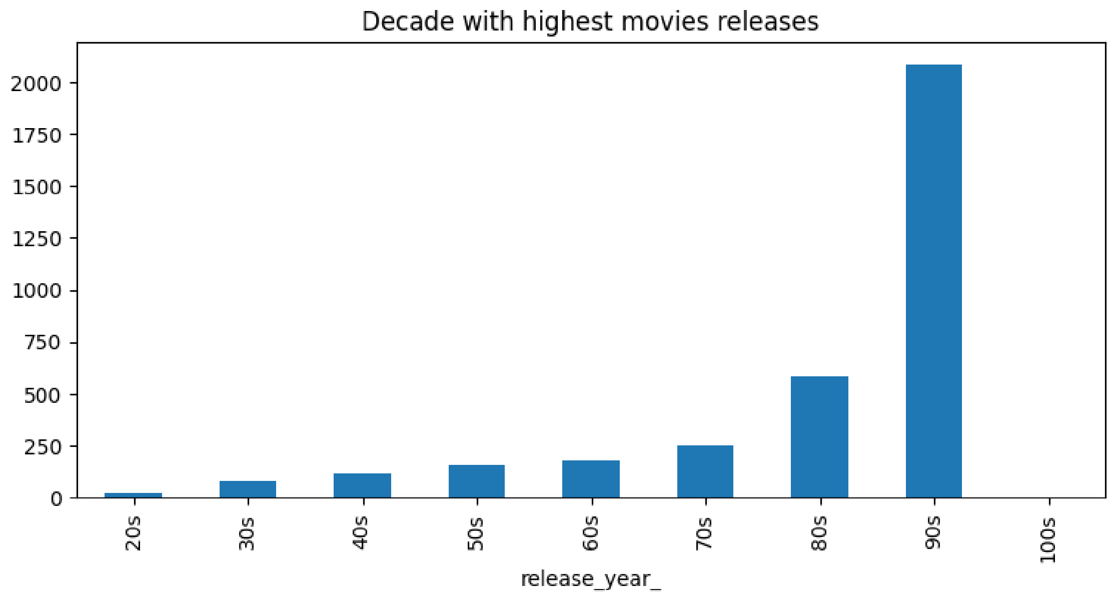
0.0.7 Most of the movies present in our dataset were released in which decade?

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

[113]:
```
n = df3.groupby(['release_year'])['movie_id'].nunique().
↪sort_values(ascending=False).reset_index()
```

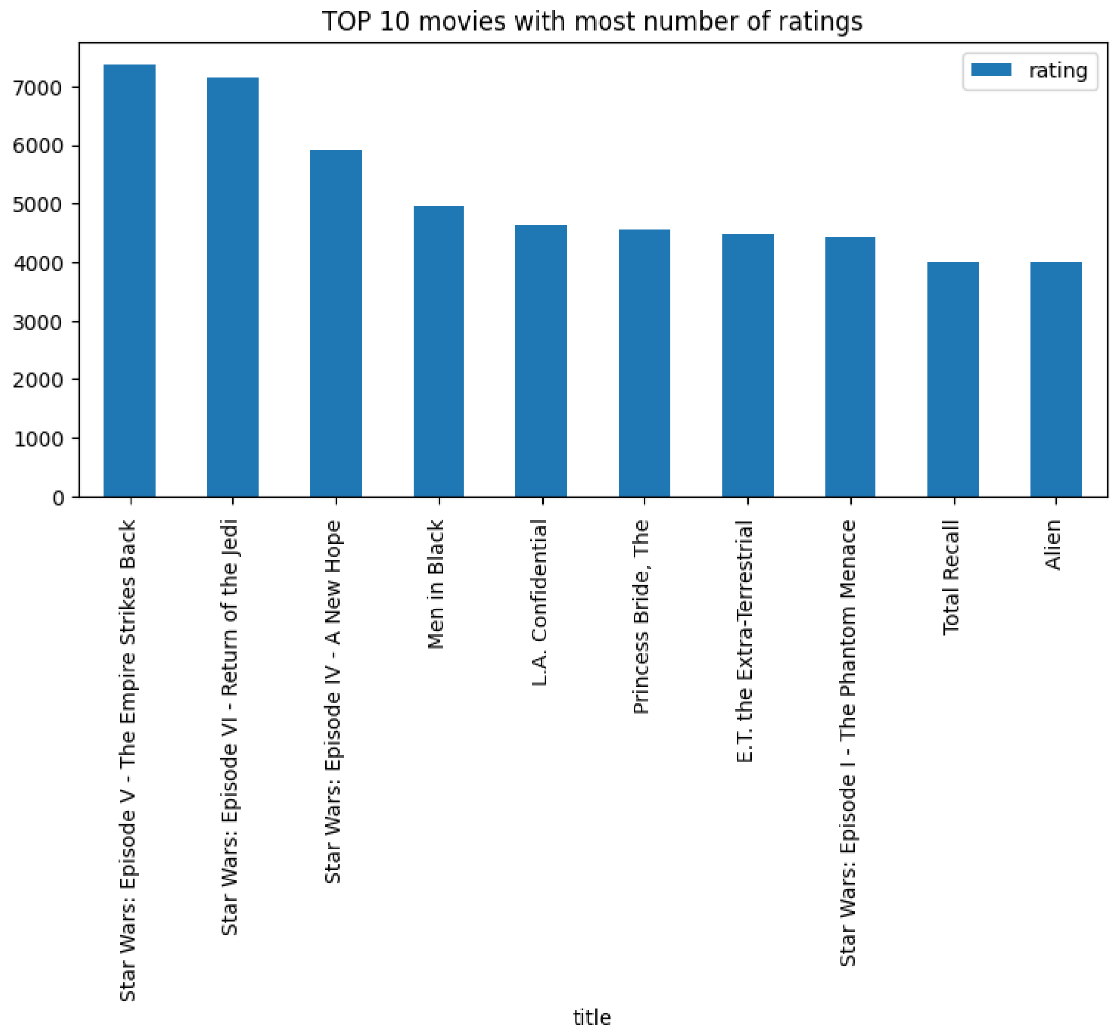
[114]:
```
bins = [1920,1930,1940,1950,1960,1970,1980,1990,2000,2010]

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

[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()
```



0.0.8 The movie with maximum no. of ratings is _____.

[125]:
```
df3.groupby("title")["rating"].count().reset_index().
↪sort_values(by="rating",ascending=False).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()
```



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

[128]:
```
recommend_movie_based_on_correlation('Liar Liar')[:3]
```

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

[128]:
```
117    Steal Big, Steal Little (1995)
407                 You So Crazy (1994)
658                     Faithful (1996)
Name: title, dtype: object
```

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

ITEM-ITEM BASED AND USER-USER BASED

0.0.11 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.

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

[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
```

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

[[1 0] [3 7]]

[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
```

[ ]:
```

```

0.0.14 5 Top rated Recommended Movies as per age :

[142]:
```
age_groups = df3.age.unique()
```

[143]:
```
for age_ in age_groups:
  print(age_)
  print("------")
  print(df3[df3.age == age_].groupby("title")["rating"].count().
↪sort_values(ascending=False).head())
  print()
  print()
```

```python
print()
```

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

[ ]:

0.1 # Questions and Answers :

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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**

0.2 #### 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