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

```
# !pip·install·skimpy
```

```
# pip·install·cmfrec
```

```
import cmfrec
```

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

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

```
# 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')
```

```
# 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
```

```
# finding shapes

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

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

```
ratings.dropna(inplace=True)

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

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

```
# 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)
```

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

```
# 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
________________________________________
```

```
# finding missing values

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

```
(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

```
# finding duplicates

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

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

ratings dataset has 24 duplicate rows

```
# removing duplicates

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

```
0
```

DESCRIBE AND INFO

```
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
(         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)
```

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

	count	mean	std	min	10%	25%	50%	75%	90%	95%	99%
user_id	1000209	3024	1728	1	669	1506	3070	4476	5443	5740	5978
movie_id	1000209	1865	1096	1	357	1030	1835	2770	3430	3675	3871
rating	1000209	3	1	1	2	3	4	4	5	5	5
timestamp	1000209	972243695	12152558	956703932	960681570	965302637	973018006	975220939	978133376	993074152	1029360403
hours	1000209	11	7	0	1	4	14	19	22	23	23

```
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
(       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)
```

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

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

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

	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

```
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
(       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)
```

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

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

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

	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

```
ratings.head()
```

	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

```
movies.head()
```

	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

```
users.head()
```

	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

```
# merging all three datasets

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


# 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('()')


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


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


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


df.shape
```

```
(959268, 13)
```

```
df.head()
```

	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-	23	M	25	12	32793	One Flew Over the Cuckoo's	Drama	1975

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


df.head()
```

	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-	18	M	25	7	22903	One Flew Over the Cuckoo's	Drama	1975

Apriori Algorithm

Recommendations according to movie title

```
df
```

	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
5	18	1193	4	978156168	2000-12-30	6	F	18	3	95825	One Flew Over the Cuckoo's Nest	Drama
...	...	...	...	...	...	...	...	...	...	...	...	...
1000204	5949	2198	5	958846401	2000-05-20	18	M	18	17	47901	Modulations	Documentary
1000205	5675	2703	3	976029116	2000-05-12	15	M	35	14	30030	Broken Vessels	Drama
1000206	5780	2845	1	958153068	2000-12-05	17	M	18	17	92886	White Boys	Drama

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

```
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
```

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

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

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

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

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

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

```
data.head()
```

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	Ir
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

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

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

```
itemset.shape
```

```
(578, 3)
```

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

	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 × 3 columns

```
from mlxtend.frequent_patterns import association_rules
```

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

```
rules
```

	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

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

```
(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
```

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

	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
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

Recommendations according to movie genres

```
# Exploding feature genres


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

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

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

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

```
df2
```

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

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

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

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

```
data.head()
```

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

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

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

```
itemset.shape
```

```
(2253, 3)
```

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

	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	1085	0.50	(Comedy, Sci-Fi, Drama, War, Thriller, Fantasy)

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

```
rules.head()
```

	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

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

```
(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
```

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

	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

Apriori Algorithm Ends

```
df2.head()
```

	user_id	movie_id	rating	timestamp	date	hours	gender	age	occupation	zip_code	title	genres	release_year
735006	4683	2642	1	963676881	2000-07-15	16	M	25	0	22101	Superman III	Action	1983
740271	5734	11	5	976312039	2000-08-12	21	F	25	14	10022	American President, The	Comedy	1995
579188	117	10	4	977501371	2000-12-22	16	M	25	17	33314	GoldenEye	Thriller	1995
996457	5795	888	2	958146185	2000-	15	M	25	1	92688	Land Before Time III:	Children's	1995

Several similaity mesuring functions and similarity based recommender system function

```
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'})
  ranks = ranks.merge(movies[['movie_id', 'title']], left_on='candidate', right_on='movie_id').rename(columns={'title': 'recommendat
  ranks = ranks.sort_values(by=['query', 'distance'])
  return ranks
```

Pivot table for item item based recommender system

```
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()
```

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

Item item based recommender system using cosine similarity

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

	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

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

	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)
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

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

```
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]])
```

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

```
<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)

```
ratings.head()
```

	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

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

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

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

	UserId	ItemId	Rating
0	1	1193	5
1	1	661	3

```
from cmfrec import CMF
```

```
# from cmfrec import CMF

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

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

```
model.A_.shape
```

```
(6040, 3)
```

```
model.B_.shape
```

```
(3706, 3)
```

```
model.A_
```

```
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)
```

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

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

```
model.B_
```

```
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)
```

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

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

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

	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

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

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

```
1.3321351755683746
```

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

```
1.3321351755683746
```

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

```
0.3796718211689346
```

Movie Recommendations on the basis of pearson correlation

```
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
```

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

3428 rows × 3428 columns

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

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

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

```
Braveheart (1995)
110
```

```
d
```

```
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
```

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

```
Toy Story (1995)
1
pandas.core.series.Series
```

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

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

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

```
import pickle
```

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

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

```
movies.head()
```

	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

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

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

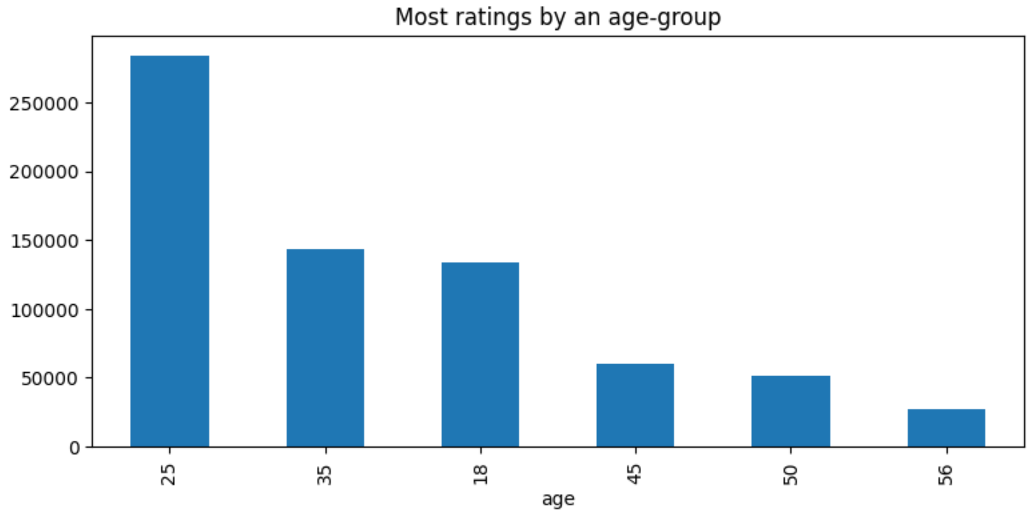
```
pickle.dump(df2[['title']].to_dict(),open('titles_.pkl','wb'))
!cp ./titles_.pkl /content/drive/MyDrive/Scaler/datasets
```

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

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

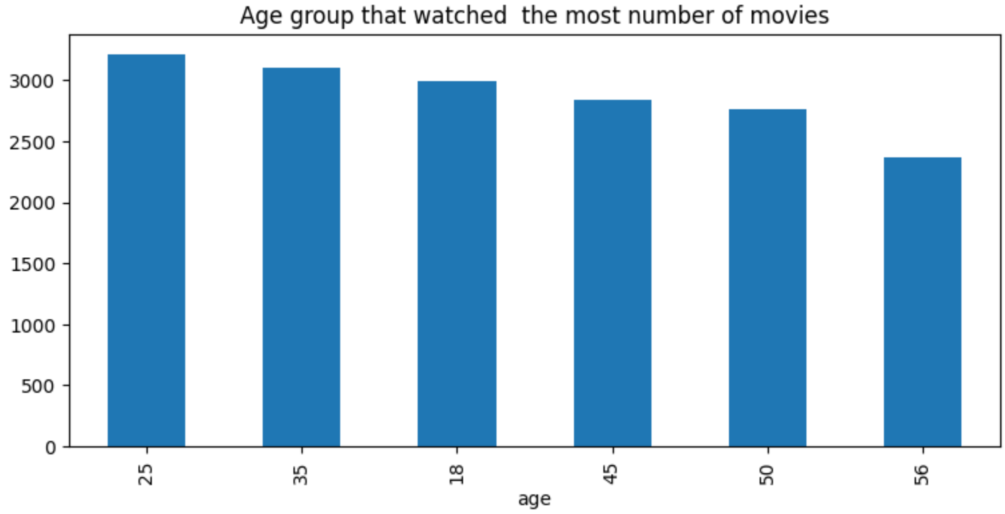
```
# Most ratings by an agegroup
plt.figure(figsize=(9,4))

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.
```




```
# 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')
```

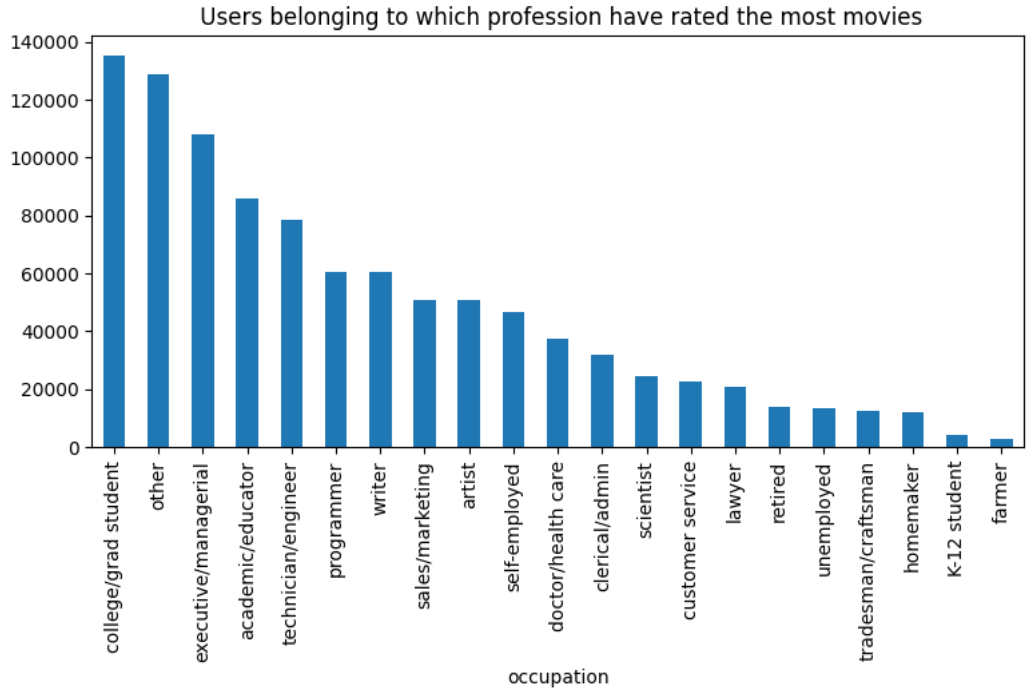
```
plt.show()
```



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

```
mapit = {0: "other", 1: "academic/educator" ,2: "artist" ,3: "clerical/admin" ,4: "college/grad student" ,5: "customer service" ,6:

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

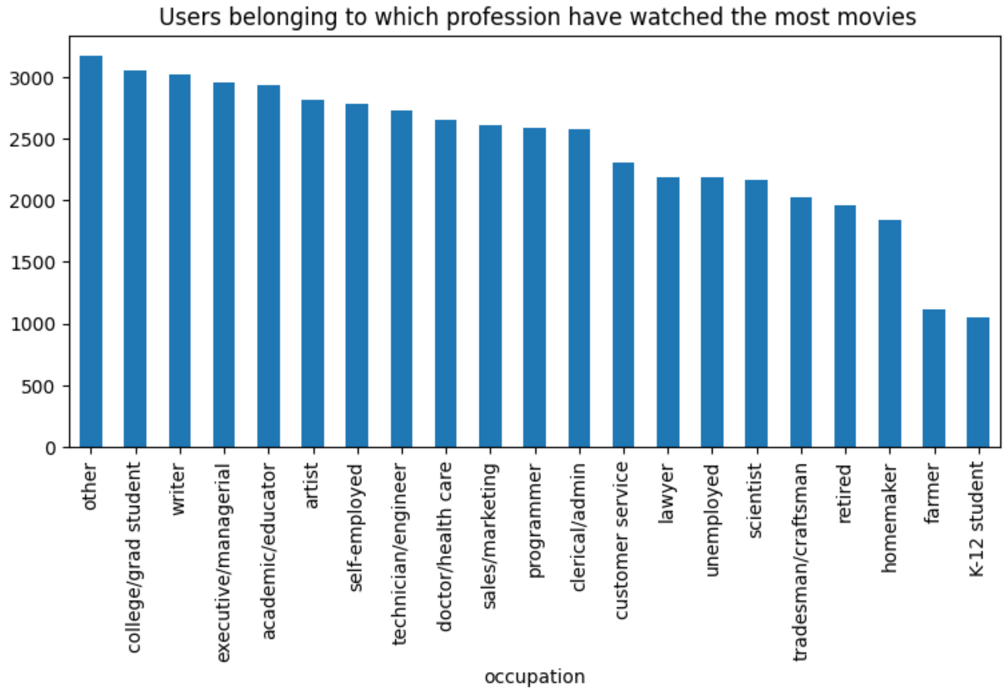
```
# Most ratings by an agegroup
plt.figure(figsize=(9,4))

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()
```




```
df3
```

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

```
# 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()
```

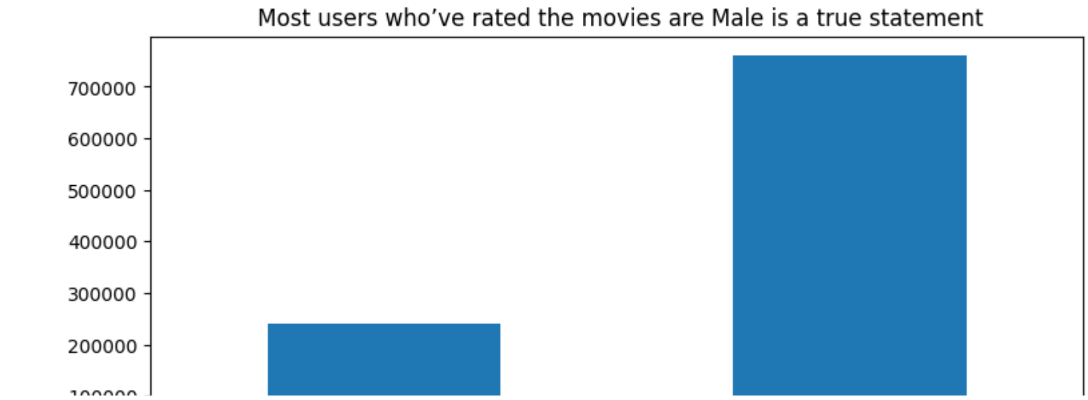



```
df3.head()
```

	user_id	movie_id	rating	timestamp	date	hours	gender	age	occupation	zip_code	title	genres	relea
115541	4956	1084	4	962638726	2000-03-07	15	M	35	scientist	77007	Bonnie and Clyde	Drama	
361393	1873	3155	4	974740115	2000-11-20	17	M	35	executive/managerial	2127	Anna and the King	Romance	
6098	502	1197	5	976210655	2000-07-12	17	M	35	doctor/health care	55126	Princess Bride, The	Adventure	
792171	3441	122	2	967308615	2000-08-26	16	F	25	sales/marketing	94109	Boomerang	Comedy	

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

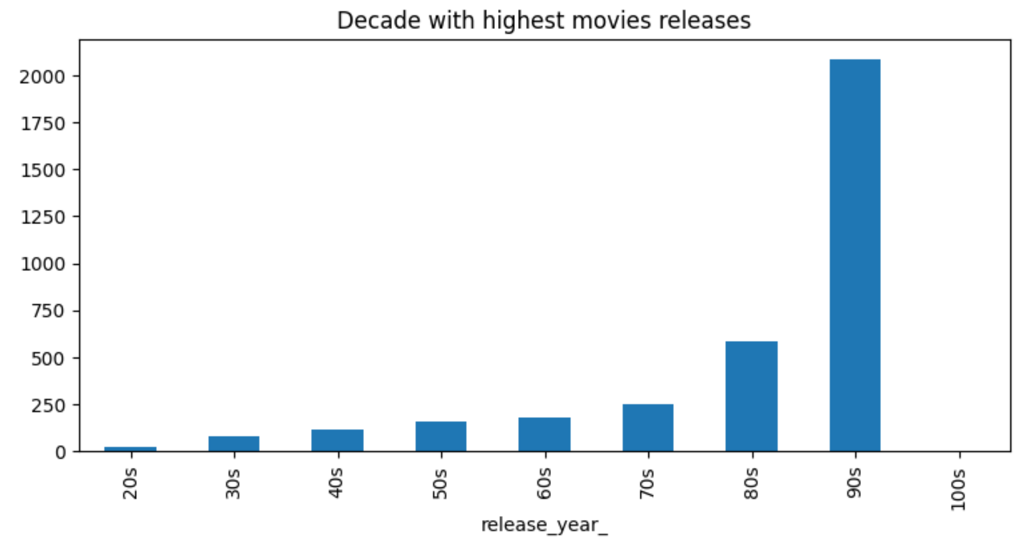
```
plt.figure(figsize=(9,4))
df3.groupby(['gender'])['rating'].count().plot(kind='bar')
plt.title(' Most users who've rated the movies are Male is a true statement',fontsize=12,fontname='Comic Sans MS')
plt.show()
```



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

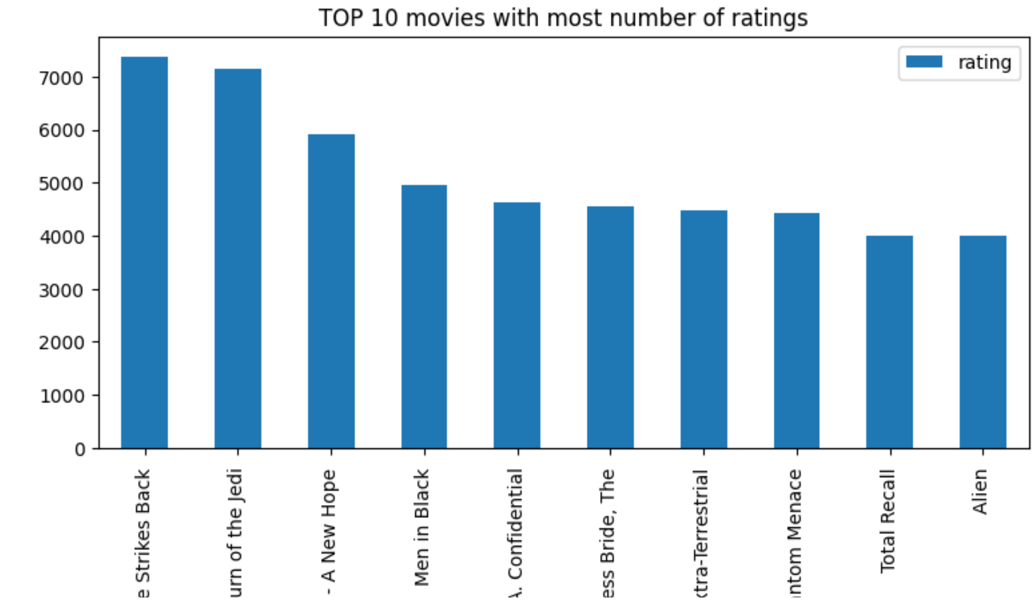
70s b. 90s c. 50s d.80s

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


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)


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 ___.

```
df3.groupby("title")["rating"].count().reset_index().sort_values(by="rating",ascending=False).set_index('title').head(10).plot(kind
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.

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

```
Liar Liar (1997)
1485
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.

```
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]]

```
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
```

5 Top rated Recommended Movies as per age :

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


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

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

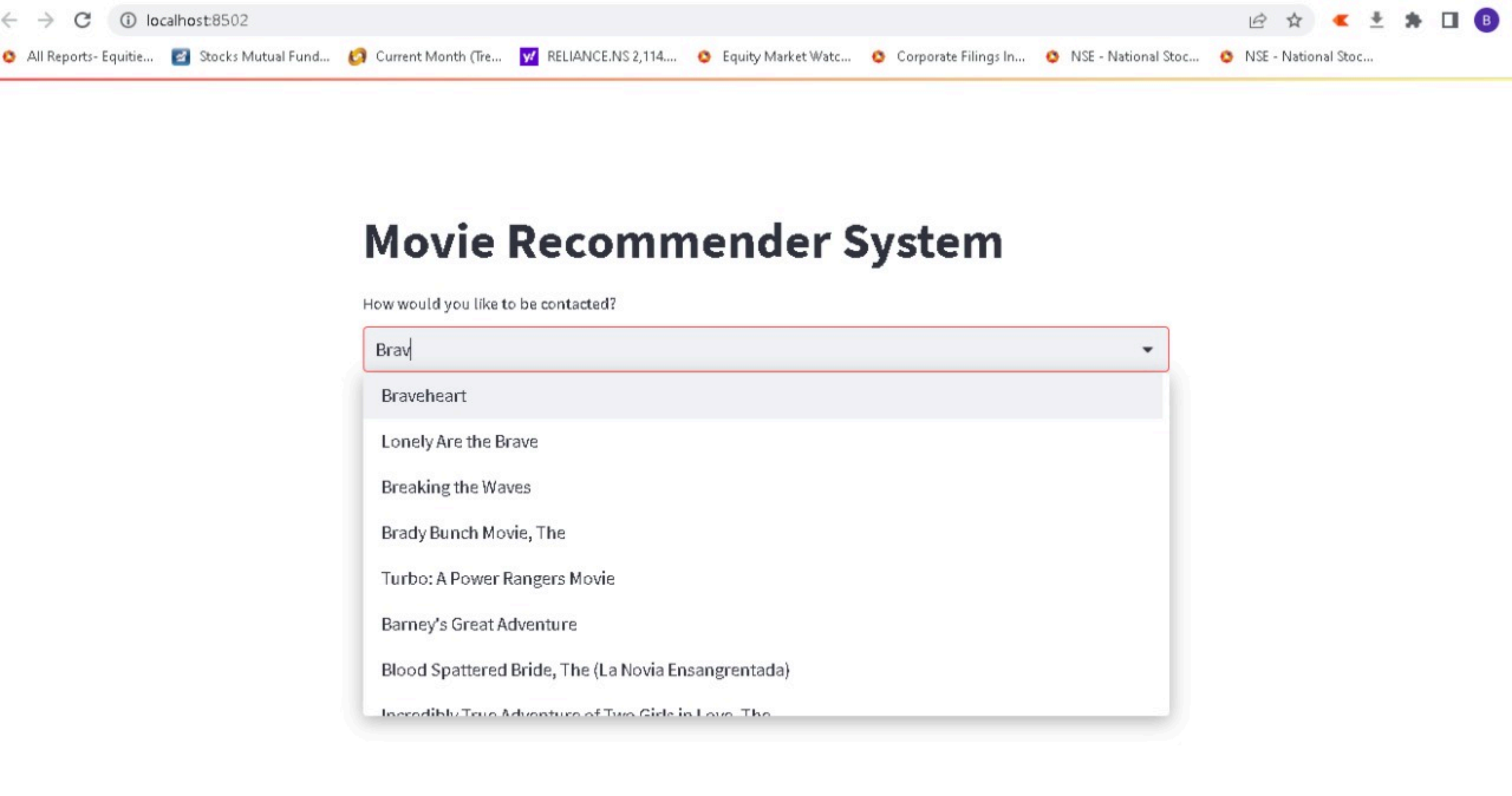
- RMSE : 1.3321351755683746

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

Deployed this Movie Recommender System in web, here are some snippets...


localhost:8502
All Reports- Equitie...
Stocks Mutual Fund...
Current Month (Tre...
RELIANCE.NS 2,114....
Equity Market Watc...
Corporate Filings In...
NSE - National Stoc...
NSE - National Stoc...
Movie Recommender System
How would you like to be contacted?
Brav
Braveheart
Lonely Are the Brave
Breaking the Waves
Brady Bunch Movie, The
Turbo: A Power Rangers Movie
Barney's Great Adventure
Blood Spattered Bride, The (La Novia Ensangrentada)

Movie Recommender System

How would you like to be contacted?

Braveheart

Recommend

Braveheart (1995)

Full Metal Jacket (1987)

Boat, The (Das Boot) (1981)

Glory (1989)

G.I. Jane (1997)

Saving Private Ryan (1998)

Thin Red Line, The (1998)

Longest Day, The (1962)