# zee-notebook-actual

June 4, 2024

## 1 Zee Case Study (Recommder Systems)

## 2 Problem Statement

Create a Recommender System to show personalized movie recommendations based on ratings given by a user and other users similar to them in order to improve user experience.

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
from datetime import datetime
from sklearn import metrics
%matplotlib inline
```

[ ]:
```
movies = pd.read_fwf("zee-movies.dat", encoding='ISO-8859-1')
ratings = pd.read_fwf('zee-ratings.dat', encoding='ISO-8859-1')
users = pd.read_fwf('zee-users.dat', encoding='ISO-8859-1')
```

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

[ ]:

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

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

[ ]:

| | UserID::MovieID::Rating::Timestamp |
|---|---|
| 0 | 1::1193::5::978300760 |
| 1 | 1::661::3::978302109 |
| 2 | 1::914::3::978301968 |
| 3 | 1::3408::4::978300275 |
| 4 | 1::2355::5::978824291 |

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

[ ]:
```
  UserID::Gender::Age::Occupation::Zip-code
0                        1::F::1::10::48067
1                       2::M::56::16::70072
2                       3::M::25::15::55117
3                        4::M::45::7::02460
4                       5::M::25::20::55455
```

[ ]:
```
#The data is not in the correct format to use,
#Changing the datasets and splitting the data and columns, to get the␣
 ↪appropriate data frames.
```

[ ]:
```
movies = movies["Movie ID::Title::Genres"].str.split("::" , expand = True)
movies.columns = "Movie ID::Title::Genres".split("::")
users = users["UserID::Gender::Age::Occupation::Zip-code"].str.split("::" ,␣
 ↪expand = True)
users.columns = "UserID::Gender::Age::Occupation::Zip-code".split("::")
ratings = ratings['UserID::MovieID::Rating::Timestamp'].str.split("::" , expand␣
 ↪= True)
ratings.columns = 'UserID::MovieID::Rating::Timestamp'.split("::")
```

## 3 Statistical Summary

[ ]:
```
movies.describe()
```

[ ]:
```
       Movie ID             Title Genres
count      3883              3883   3858
unique     3883              3883    360
top           1  Toy Story (1995)  Drama
freq          1                 1    830
```

[ ]:
```
movies.dropna(inplace = True)
movies.isnull().sum()
movies["genres"] = movies["Genres"].str.split("|" , expand = False)
movies["Movie ID"] = movies["Movie ID"].astype(int)
```

[ ]:
```

```

[ ]:
```
def cleangenres(x):
    if x == "None":
        x = np.nan
    else:
        for i in range(len(x)):
            if x[i] in ["" , "A" , "Acti"]:
                x[i] = "Action"
```

```
            if x[i] in ['Adv', 'Advent', 'Adventu', 'Adventur']:
                x[i]  = "Adventure"
            if x[i] in ["Animati"]:
                x[i]  = "Animation"
            if x[i] in ['Chi', 'Chil', 'Childr', 'Childre','Children',␣
↪"Children''", "Children's" ,"Children'"]:
                x[i]  = "Children"

            if x[i] in ['Com', 'Come', 'Comed']:
                x[i]  = "Comedy"
            if x[i] in ['D', 'Docu', 'Documen', 'Document', 'Documenta',␣
↪'Documentary']:
                x[i]  = "Documentary"
            if x[i] in ['Dr', 'Dram', 'Drama']:
                x[i]  = "Drama"
            if x[i] in ['F', 'Fant', 'Fantas', 'Fantasy']:
                x[i]  = "Fantasy"

            if x[i] in ['R', 'Ro','Rom', 'Roma', 'Roman', 'Romance']:
                x[i]  = "Romance"

            if x[i] in ['Music', 'Musical']:
                x[i]  = "Musical"

            if x[i] in ['Horr', 'Horro', 'Horror']:
                x[i]  = "Horror"


            if x[i] in ['S', 'Sci', 'Sci-', 'Sci-F','Sci-Fi']:
                x[i]  = "Sci-Fi"

            if x[i] in ['Th', 'Thri', 'Thrille']:
                x[i]  = "Thriller"

            if x[i] in ['We','Wester', 'Western']:
                x[i]  = "Western"
            if x[i] in ['Wa', 'War']:
                x[i]  = "War"
            else:
                continue
        return x
```

[ ]:
```
movies["Genres"] = movies['genres'].apply(cleangenres)
movies.drop("genres" , inplace = True , axis =1)
```

[ ]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3858 entries, 0 to 3882
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   Movie ID  3858 non-null   int64 
 1   Title     3858 non-null   object
 2   Genres    3858 non-null   object
dtypes: int64(1), object(2)
memory usage: 120.6+ KB
```

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

[ ]:
```
   Movie ID                                Title  \
0         1                    Toy Story (1995)   
1         2                      Jumanji (1995)   
2         3             Grumpier Old Men (1995)   
3         4            Waiting to Exhale (1995)   
4         5  Father of the Bride Part II (1995)   

                         Genres  
0   [Animation, Children, Comedy]  
1  [Adventure, Children, Fantasy]  
2                [Comedy, Romance]  
3                  [Comedy, Drama]  
4                        [Comedy]
```

[ ]:
```
users.describe()
```

[ ]:
```
        UserID Gender   Age Occupation Zip-code
count    6040   6040  6040       6040     6040
unique   6040      2     7         21     3439
top         1      M    25          4    48104
freq        1   4331  2096        759       19
```

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

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

```
memory usage: 236.1+ KB
```

[ ]:
```
ratings.describe()
```

[ ]:
```
          UserID  MovieID   Rating  Timestamp
count    1000209  1000209  1000209    1000209
unique      6040     3706        5     458455
top         4169     2858        4  975528402
freq        2314     3428   348971         30
```

[ ]:
```
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 4 columns):
 #   Column     Non-Null Count    Dtype 
---  ------     --------------    ----- 
 0   UserID     1000209 non-null  object
 1   MovieID    1000209 non-null  object
 2   Rating     1000209 non-null  object
 3   Timestamp  1000209 non-null  object
dtypes: object(4)
memory usage: 30.5+ MB
```

[ ]:
```
ratings["MovieID"] = ratings["MovieID"].astype(int)
```

[ ]:
```
movies.shape , ratings.shape, users.shape
```

[ ]:
```
((3858, 3), (1000209, 4), (6040, 5))
```

## 3.1 Statistical Analysis Observations/Insights on the basis of Individual Data Frames

- Data was required to be converted into readable form as it was not a csv file.
- All the column are presented as Object Values, it needs to be changed according to Business Logic.

### 3.1.1 Movies Data Frame :

- No duplicate values in movies data frame
- Cleaned the Genre column as few Genres were incorrect and spelling were wrong.

### 3.1.2 Users Data Frame :

- Gender , Age , Occupation are categorical values with 2 , 7 , 21 unique values.
- No Duplicate values for user_id

#### 3.1.3 Rating Data Frame :

- Timestamp type is object, which needs to be converted.
- Highest value in rating is 5.
- Rating is categorical and ordinal.

—-> **There are no Null Values in the Data**

# 4 Preprocessing, Exploratory Data Analysis and Feature Engineering

## 4.1 Consolidated Data Frame

[ ]:
```
df = pd.merge(left=ratings , right = users , left_on = "UserID" , right_on␣
 ↪="UserID" )
df = pd.merge(left=df , right = movies , left_on = "MovieID" , right_on ="Movie␣
 ↪ID" )
df.drop("Movie ID" , axis = 1 , inplace = True)
df["Age"] = df["Age"].astype("int")
df["Occupation"] = df["Occupation"].astype("int")
df["Gender"]  = df["Gender"].apply(lambda x : 1 if x=="F" else 0)
df["hours"] = df["Timestamp"].astype("int").apply(lambda x : datetime.
 ↪fromtimestamp(x).hour)
df["year"] = df["Timestamp"].astype("int").apply(lambda x : datetime.
 ↪fromtimestamp(x).year)
df["month"] = df["Timestamp"].astype("int").apply(lambda x : datetime.
 ↪fromtimestamp(x).month)
df["Rating"] = df["Rating"].astype("int")
df["UserID"] = df["UserID"].astype("int")
df["MovieID"] = df["MovieID"].astype("int")
df.dropna(inplace = True)
```

[ ]:
```
def ExtractReleaseYear(x):
    y= x.split("(")
    if len(y) == 2:
        return y[1][:-1]
    elif len(y)==3:
        return y[2][:-1]
    else:
        return np.nan
```

[ ]:
```
df["Release_Year"] = df["Title"].apply(ExtractReleaseYear).astype("int16")
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 996144 entries, 0 to 996143
Data columns (total 14 columns):
```

```
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   UserID        996144 non-null  int64
 1   MovieID       996144 non-null  int64
 2   Rating        996144 non-null  int64
 3   Timestamp     996144 non-null  object
 4   Gender        996144 non-null  int64
 5   Age           996144 non-null  int64
 6   Occupation    996144 non-null  int64
 7   Zip-code      996144 non-null  object
 8   Title         996144 non-null  object
 9   Genres        996144 non-null  object
 10  hours         996144 non-null  int64
 11  year          996144 non-null  int64
 12  month         996144 non-null  int64
 13  Release_Year  996144 non-null  int16
dtypes: int16(1), int64(9), object(4)
memory usage: 108.3+ MB
```

[ ]:
```
df.describe()
```

[ ]:

| | UserID | MovieID | Rating | Gender |
|---|---|---|---|---|
| count | 996144.000000 | 996144.000000 | 996144.000000 | 996144.000000 |
| mean | 3024.002930 | 1867.029726 | 3.579985 | 0.246505 |
| std | 1728.265045 | 1096.028575 | 1.116849 | 0.430976 |
| min | 1.000000 | 1.000000 | 1.000000 | 0.000000 |
| 25% | 1505.000000 | 1032.000000 | 3.000000 | 0.000000 |
| 50% | 3069.000000 | 1836.000000 | 4.000000 | 0.000000 |
| 75% | 4476.000000 | 2770.000000 | 4.000000 | 0.000000 |
| max | 6040.000000 | 3952.000000 | 5.000000 | 1.000000 |

| | Age | Occupation | hours | year |
|---|---|---|---|---|
| count | 996144.000000 | 996144.000000 | 996144.000000 | 996144.000000 |
| mean | 29.726427 | 8.034997 | 9.730529 | 2000.126768 |
| std | 11.748818 | 6.530667 | 7.293934 | 0.422907 |
| min | 1.000000 | 0.000000 | 0.000000 | 2000.000000 |
| 25% | 25.000000 | 2.000000 | 4.000000 | 2000.000000 |
| 50% | 25.000000 | 7.000000 | 8.000000 | 2000.000000 |
| 75% | 35.000000 | 14.000000 | 15.000000 | 2000.000000 |
| max | 56.000000 | 20.000000 | 23.000000 | 2003.000000 |

| | month | Release_Year |
|---|---|---|
| count | 996144.000000 | 996144.000000 |
| mean | 8.715070 | 1986.758458 |
| std | 2.719719 | 14.314470 |
| min | 1.000000 | 1919.000000 |
| 25% | 7.000000 | 1982.000000 |

```
50%          9.000000    1992.000000
75%         11.000000    1997.000000
max         12.000000    2000.000000
```

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

[ ]:
```
(996144, 14)
```

[ ]:
```
df.isnull().sum()
```

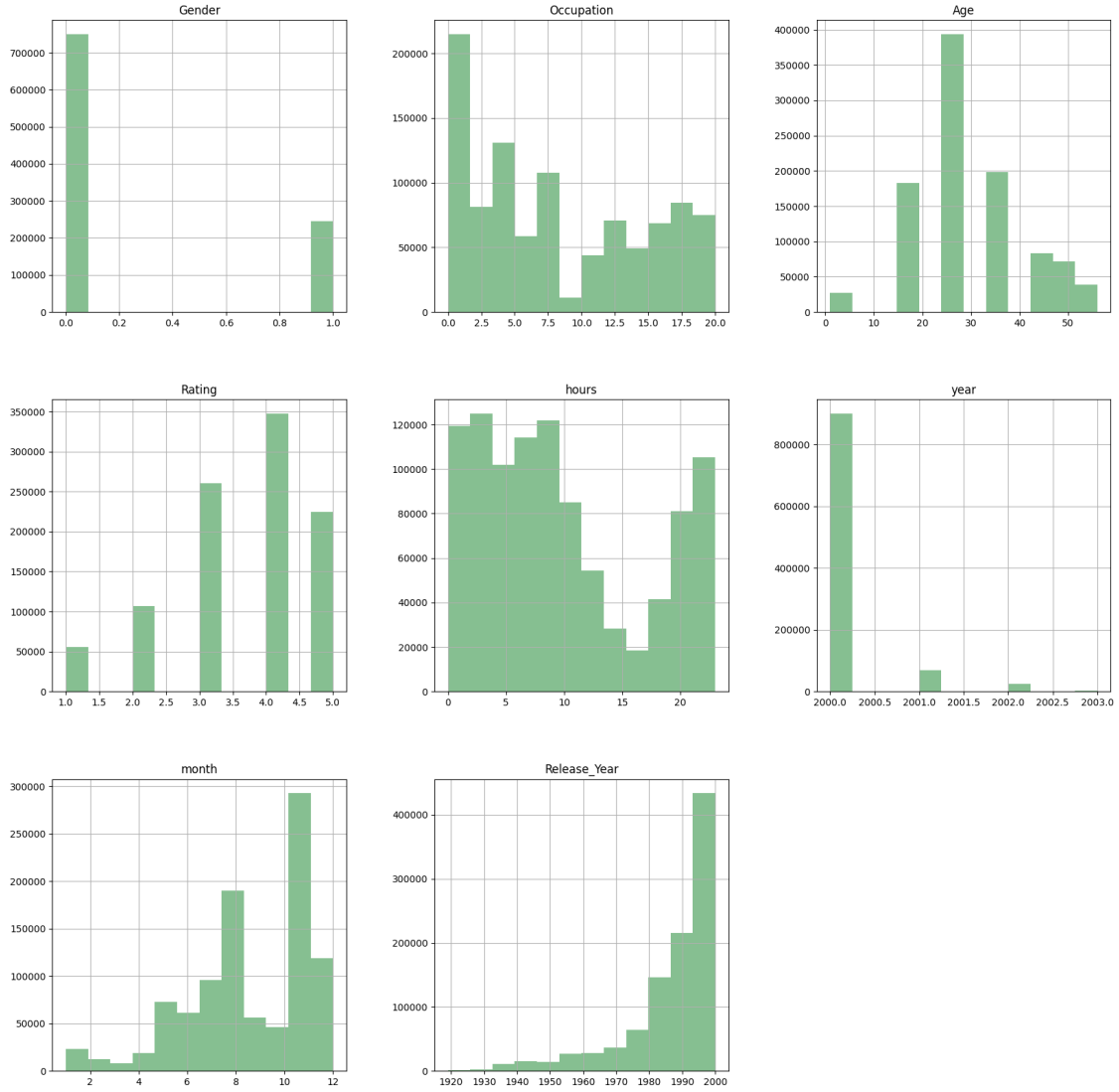
[ ]:
```
UserID          0
MovieID         0
Rating          0
Timestamp       0
Gender          0
Age             0
Occupation      0
Zip-code        0
Title           0
Genres          0
hours           0
year            0
month           0
Release_Year    0
dtype: int64
```

### 4.2 Consolidated Data Frame

- There are no null values in the data frame.
- We have extracted , Release Year for movies. Hour, Year,Month of the time of ratings werre given.
- Few columns are converted to int

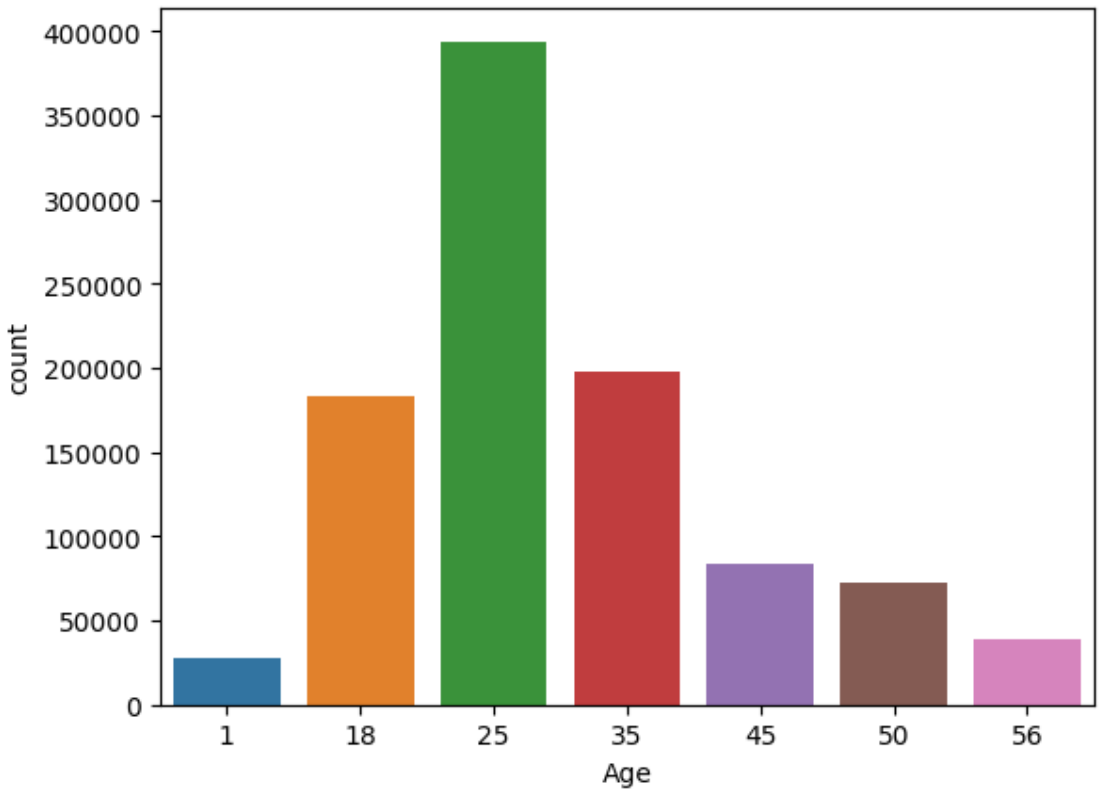
### 4.3 Distributions for Numerical Columns

[ ]:
```
df.hist(column=["Gender" , "Occupation" , "Age" , "Rating" , "hours" , "year" ,␣
 ↪"month" , "Release_Year"] ,grid = True, color='#86bf91', bins = 12,␣
 ↪figsize=(20,20))
plt.show()
```




[ ]:
```
sns.countplot(x = df["Age"])
```

[ ]: <Axes: xlabel='Age', ylabel='count'>



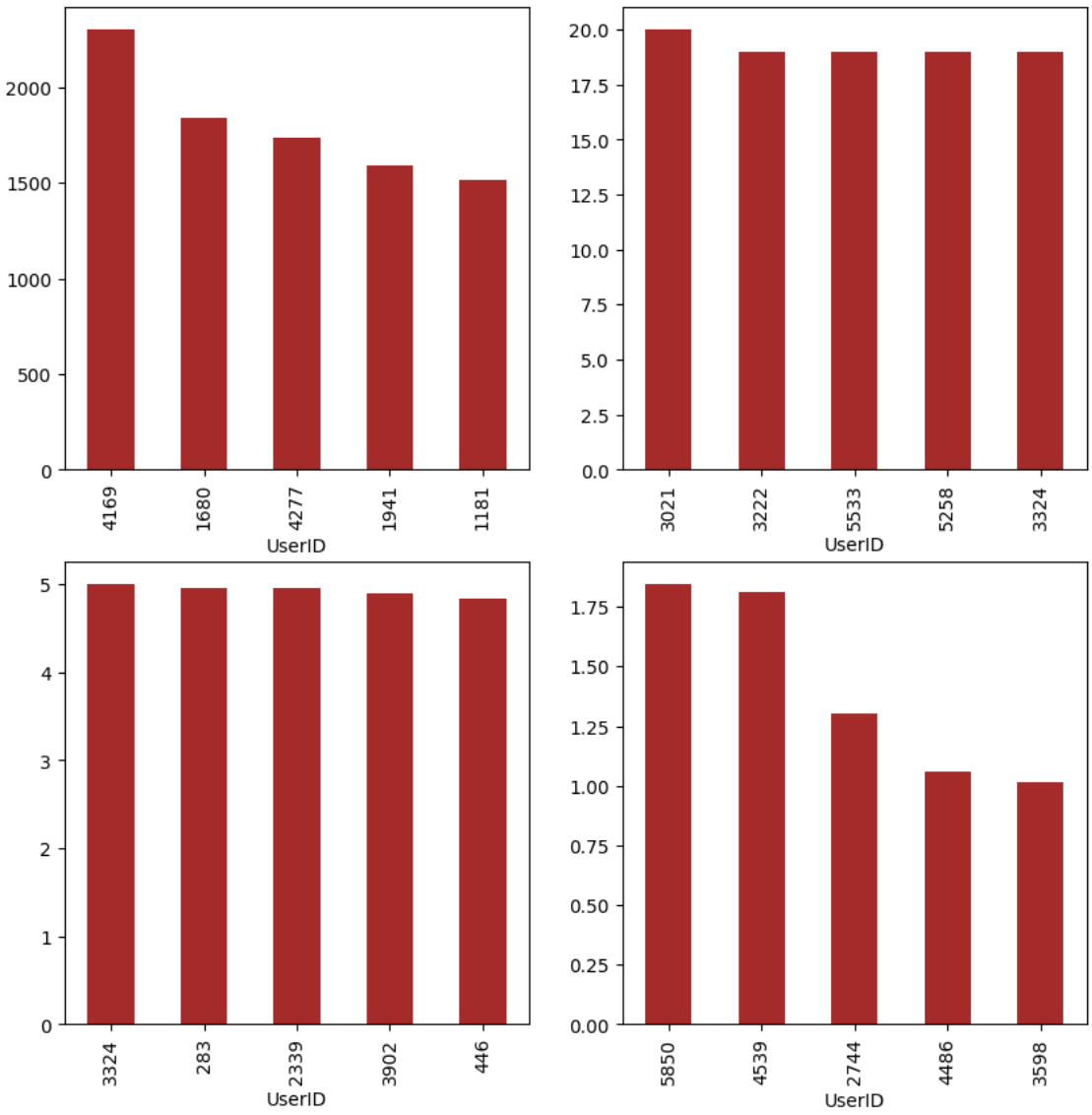

[ ]:

[ ]:
```
def groupbyfunction(x , figursize):
    fig, axes = plt.subplots(2,2 , figsize = figursize)
    df.groupby(x)["Rating"].count().sort_values(ascending = False).head(5).
 ↪plot(kind = "bar" ,  ax = axes[0,0] , color= "brown")
    print("Top 5 count",x,":", df.groupby(x)["Rating"].count().
 ↪sort_values(ascending = False).head(5).index,"\n")

    df.groupby(x)["Rating"].count().sort_values(ascending = False).tail(5).
 ↪plot(kind = "bar" ,  ax = axes[0,1] , color= "brown")
    print("Bottom 5 count",x,":", df.groupby(x)["Rating"].count().
 ↪sort_values(ascending = False).tail(5).index,"\n")


    df.groupby(x)["Rating"].mean().sort_values(ascending = False).head(5).
 ↪plot(kind = "bar" ,  ax = axes[1,0], color= "brown")
    print("Top 5 mean",x,":", df.groupby(x)["Rating"].mean().
 ↪sort_values(ascending = False).head(5).index,"\n")
```

```
    df.groupby(x)["Rating"].mean().sort_values(ascending = False).tail(5).
↪plot(kind = "bar" ,  ax = axes[1,1], color= "brown")
    print("Bottom 5 mean",x,":", df.groupby(x)["Rating"].mean().
↪sort_values(ascending = False).tail(5).index,"\n")
```

[ ]:
```
groupbyfunction("UserID" , (10,10))
```

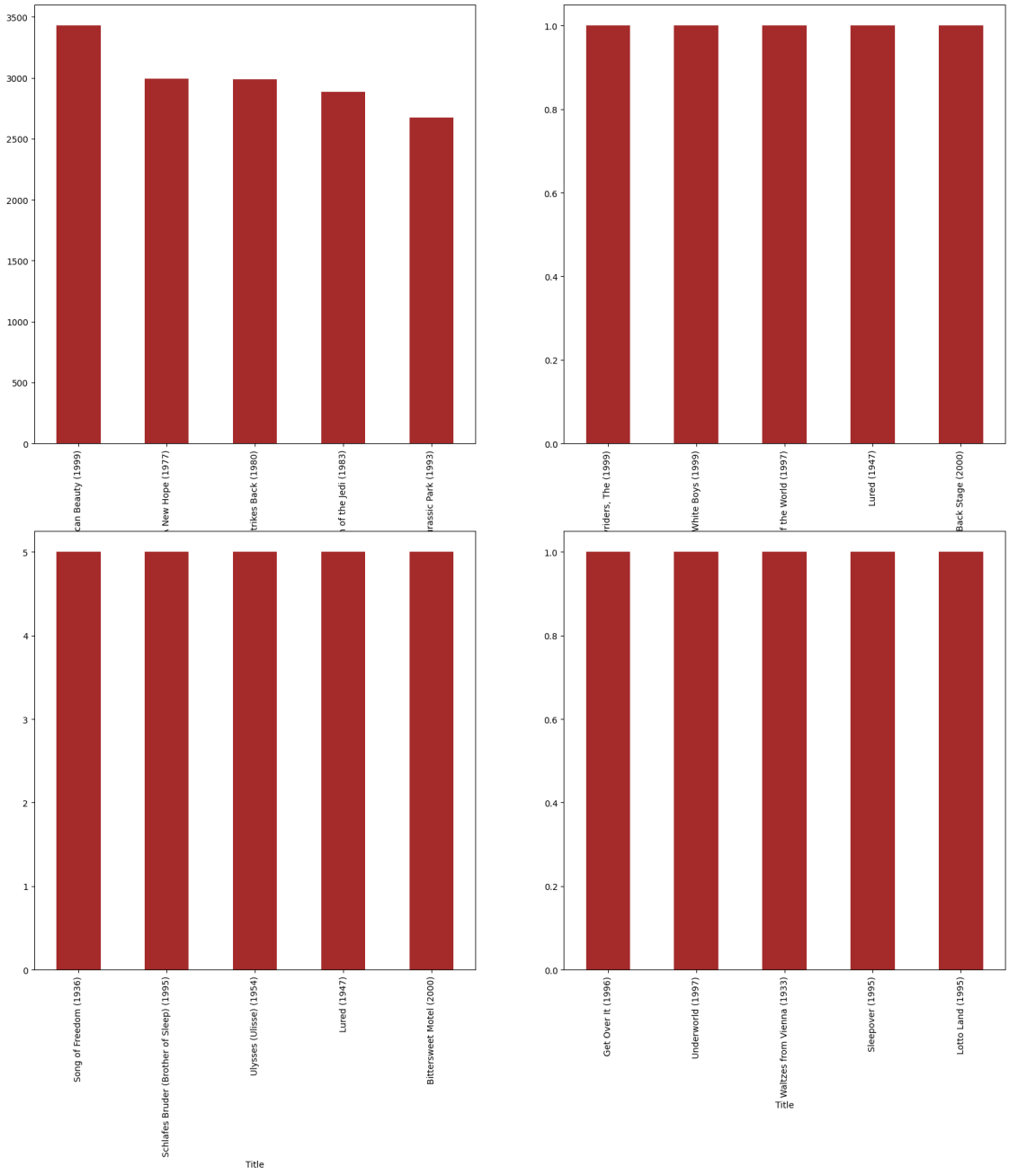
```
Top 5 count UserID : Int64Index([4169, 1680, 4277, 1941, 1181], dtype='int64',
name='UserID')

Bottom 5 count UserID : Int64Index([3021, 3222, 5533, 5258, 3324],
dtype='int64', name='UserID')

Top 5 mean UserID : Int64Index([3324, 283, 2339, 3902, 446], dtype='int64',
name='UserID')

Bottom 5 mean UserID : Int64Index([5850, 4539, 2744, 4486, 3598], dtype='int64',
name='UserID')
```




[ ]:
```
groupbyfunction("Title" , (20,20))
```

```
Top 5 count Title : Index(['American Beauty (1999)', 'Star Wars: Episode IV - A
New Hope (1977)',
       'Star Wars: Episode V - The Empire Strikes Back (1980)',
       'Star Wars: Episode VI - Return of the Jedi (1983)',
       'Jurassic Park (1993)'],
      dtype='object', name='Title')

Bottom 5 count Title : Index(['Joyriders, The (1999)', 'White Boys (1999)',
       'Voyage to the Beginning of the World (1997)', 'Lured (1947)',
       'Back Stage (2000)'],
      dtype='object', name='Title')
```

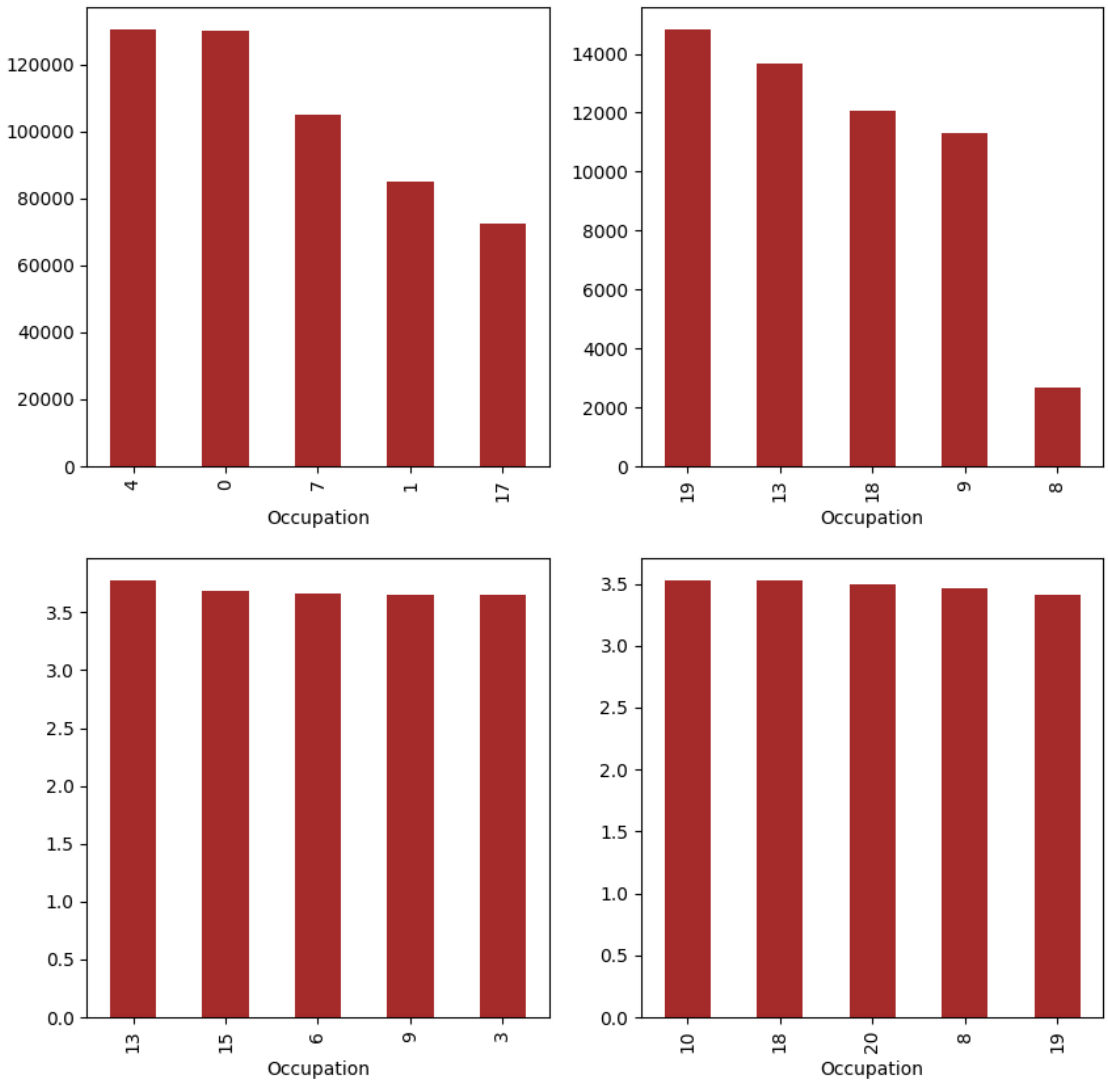
```
Top 5 mean Title : Index(['Song of Freedom (1936)', 'Schlafes Bruder (Brother of
Sleep) (1995)',
       'Ulysses (Ulisse) (1954)', 'Lured (1947)', 'Bittersweet Motel (2000)'],
      dtype='object', name='Title')

Bottom 5 mean Title : Index(['Get Over It (1996)', 'Underworld (1997)', 'Waltzes
from Vienna (1933)',
       'Sleepover (1995)', 'Lotto Land (1995)'],
      dtype='object', name='Title')
```




[ ]:
```
groupbyfunction("Occupation" , (10,10))
```

```
Top 5 count Occupation : Int64Index([4, 0, 7, 1, 17], dtype='int64',
name='Occupation')

Bottom 5 count Occupation : Int64Index([19, 13, 18, 9, 8], dtype='int64',
name='Occupation')
```

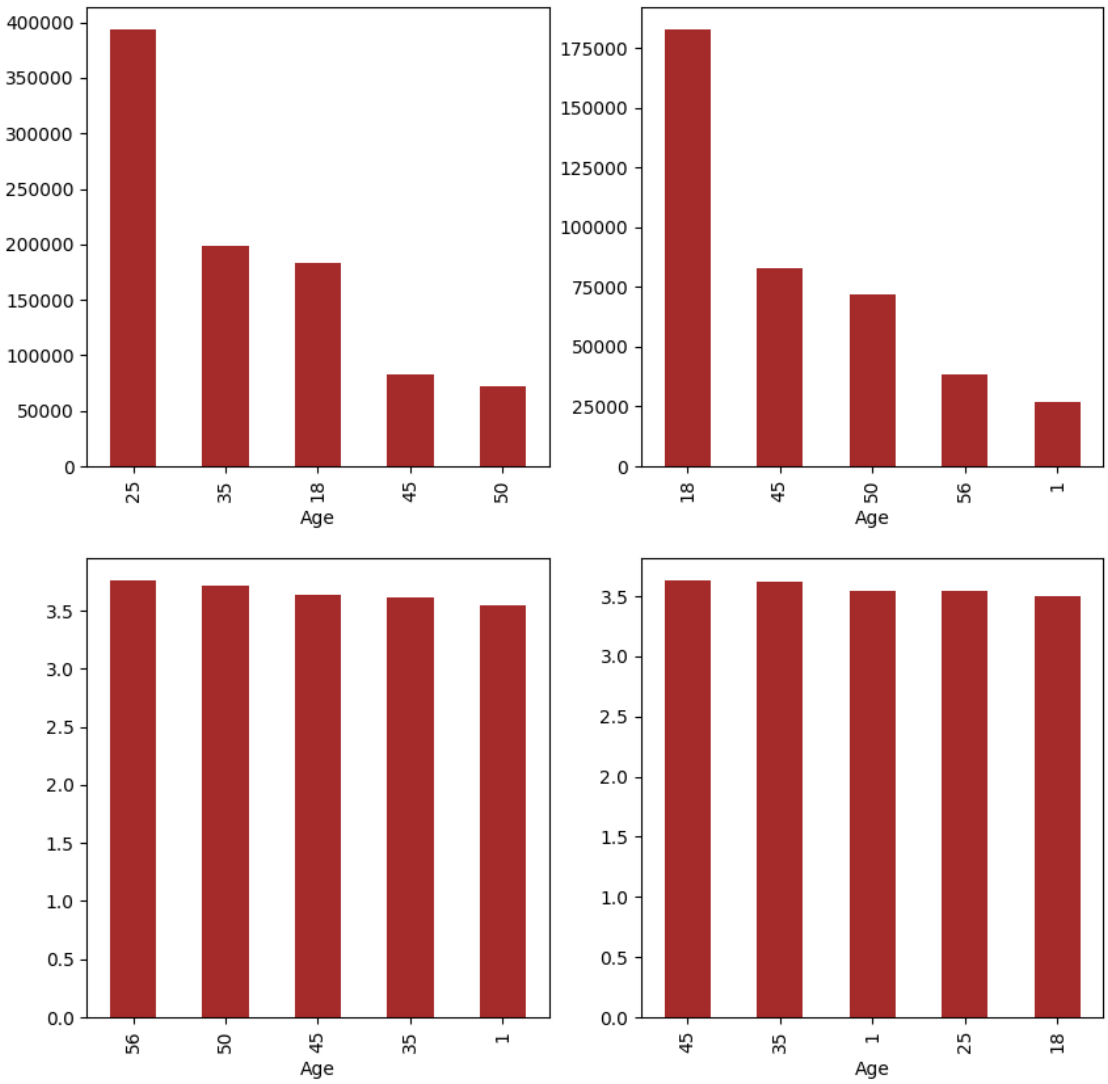
```
Top 5 mean Occupation : Int64Index([13, 15, 6, 9, 3], dtype='int64',
name='Occupation')

Bottom 5 mean Occupation : Int64Index([10, 18, 20, 8, 19], dtype='int64',
name='Occupation')
```




[ ]:
```
groupbyfunction("Age" , figursize=(10,10))
```

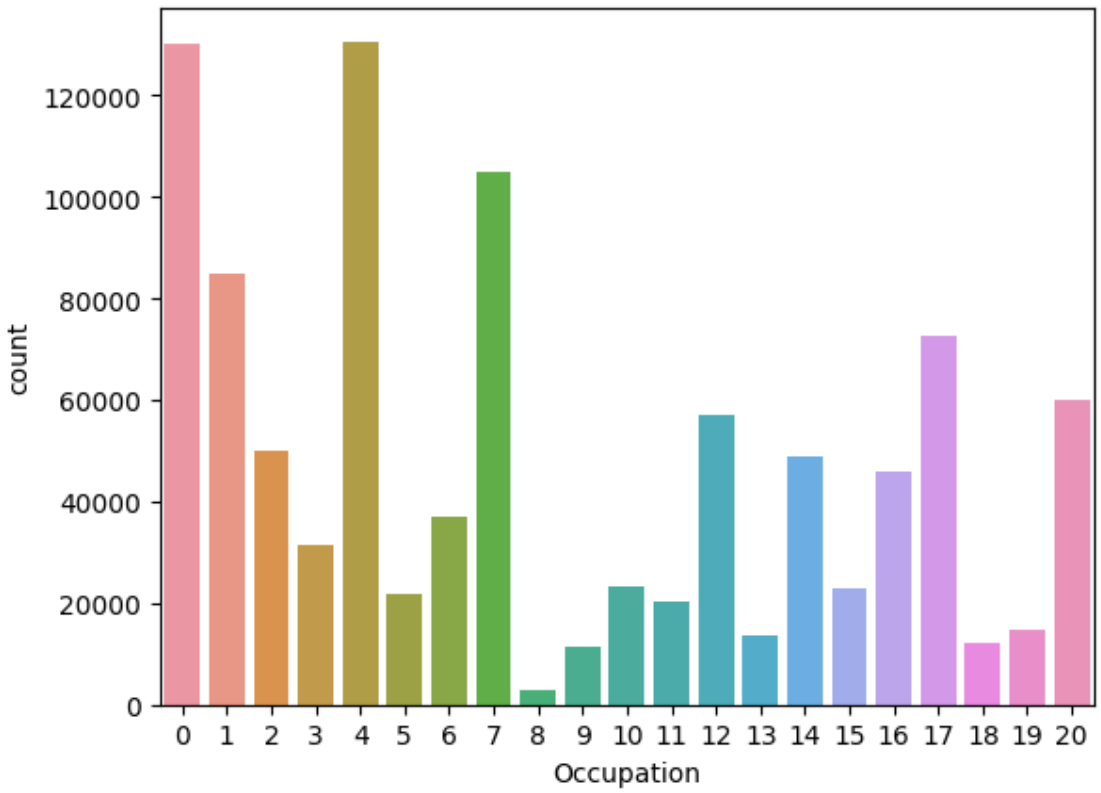
```
Top 5 count Age : Int64Index([25, 35, 18, 45, 50], dtype='int64', name='Age')

Bottom 5 count Age : Int64Index([18, 45, 50, 56, 1], dtype='int64', name='Age')

Top 5 mean Age : Int64Index([56, 50, 45, 35, 1], dtype='int64', name='Age')
```

```
Bottom 5 mean Age : Int64Index([45, 35, 1, 25, 18], dtype='int64', name='Age')
```




[ ]:
```
sns.countplot(x = df["Occupation"])
```

[ ]:
```
<Axes: xlabel='Occupation', ylabel='count'>
```

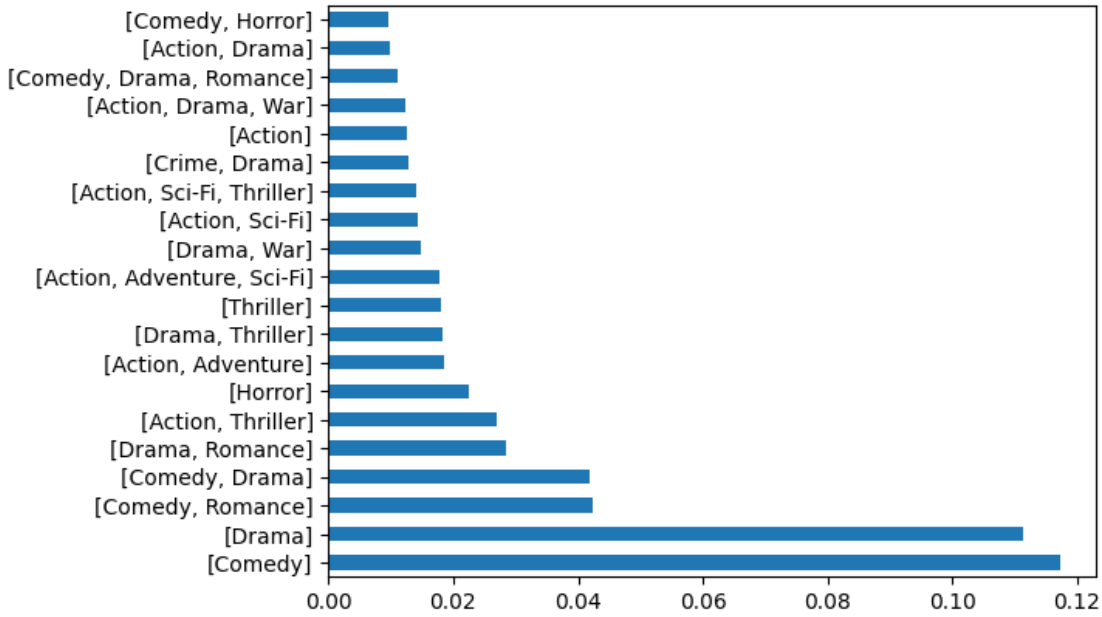



[ ]:
```
df.groupby("Gender")["Rating"].mean()
```

[ ]:
```
Gender
0    3.567107
1    3.619351
Name: Rating, dtype: float64
```

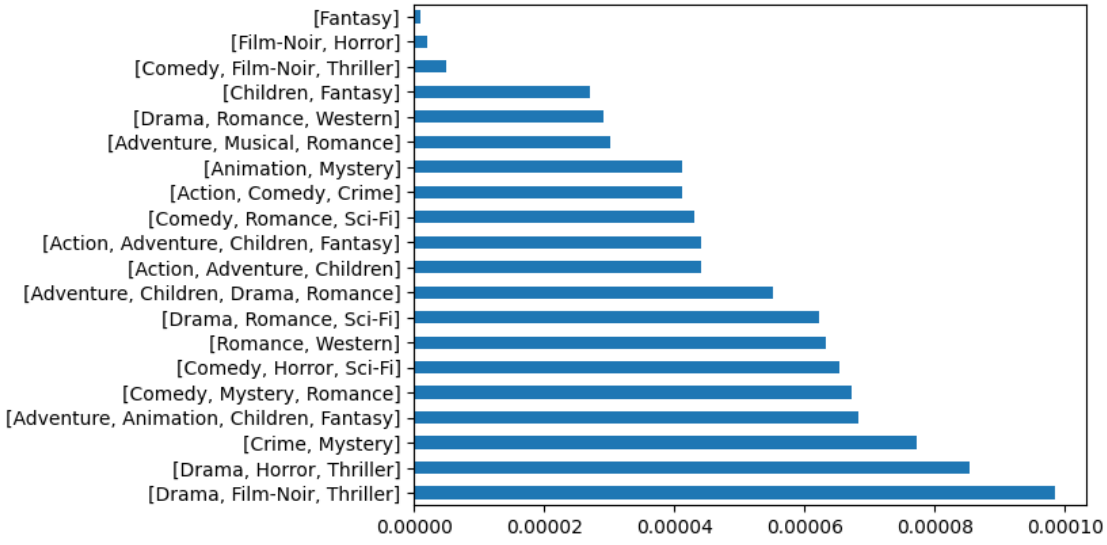
[ ]:
```
df["Genres"].value_counts(normalize=True).head(20).plot(kind = "barh")
```

[ ]:
```
<Axes: >
```




[ ]:
```
df["Genres"].value_counts(normalize=True).tail(20).plot(kind = "barh")
```

[ ]: <Axes: >



# 5 RECOMMENDER SYSTEM

## 5.1 Cosine Similarity with Users

[ ]:
```
u=df.groupby(["UserID","Gender" , "Age" , "Occupation"])["Rating" , "hours" ,␣
  ↪"month" , "year"].mean().reset_index()
u.index = u["UserID"]
u.drop("UserID" , inplace = True , axis = 1)
```

```
/var/folders/8d/h5wxclqj6mq4pjjkr0kf78780000gn/T/ipykernel_22460/621803254.py:1:
FutureWarning: Indexing with multiple keys (implicitly converted to a tuple of
keys) will be deprecated, use a list instead.
  u=df.groupby(["UserID","Gender" , "Age" , "Occupation"])["Rating" , "hours" ,
"month" , "year"].mean().reset_index()
```

[ ]:
```
pd.DataFrame(data = metrics.pairwise.cosine_similarity(u), index=u.index ,␣
  ↪columns= u.index)
```

[ ]:
```
UserID      1         2         3         4         5         6         7     \
UserID
1       1.000000  0.999618  0.999925  0.999756  0.999892  0.999681  0.999827
2       0.999618  1.000000  0.999880  0.999974  0.999854  0.999969  0.999897
3       0.999925  0.999880  1.000000  0.999942  0.999971  0.999895  0.999942
4       0.999756  0.999974  0.999942  1.000000  0.999900  0.999972  0.999960
5       0.999892  0.999854  0.999971  0.999900  1.000000  0.999906  0.999941
…            …         …         …         …         …         …         …
6036    0.999917  0.999871  0.999989  0.999929  0.999989  0.999909  0.999954
6037    0.999746  0.999954  0.999921  0.999990  0.999894  0.999980  0.999979
6038    0.999610  0.999970  0.999853  0.999976  0.999822  0.999977  0.999935
6039    0.999744  0.999951  0.999919  0.999990  0.999887  0.999977  0.999978
6040    0.999918  0.999858  0.999979  0.999936  0.999969  0.999914  0.999977

UserID      8         9         10    …      6031      6032      6033  \
UserID                                …
1       0.999910  0.999906  0.999836  …  0.999948  0.999754  0.999696
2       0.999860  0.999864  0.999907  …  0.999784  0.999971  0.999991
3       0.999980  0.999982  0.999952  …  0.999960  0.999937  0.999917
4       0.999926  0.999919  0.999971  …  0.999896  0.999993  0.999987
5       0.999990  0.999995  0.999938  …  0.999934  0.999919  0.999905
…            …         …         …  …         …         …         …
6036    0.999989  0.999989  0.999957  …  0.999965  0.999941  0.999919
6037    0.999927  0.999910  0.999984  …  0.999909  0.999995  0.999979
6038    0.999856  0.999840  0.999941  …  0.999819  0.999980  0.999977
6039    0.999923  0.999906  0.999984  …  0.999908  0.999993  0.999975
6040    0.999988  0.999976  0.999979  …  0.999988  0.999949  0.999914

UserID      6034      6035      6036      6037      6038      6039      6040
UserID
```

```
1       0.999924  0.999916  0.999917  0.999746  0.999610  0.999744  0.999918
2       0.999877  0.999849  0.999871  0.999954  0.999970  0.999951  0.999858
3       0.999997  0.999972  0.999989  0.999921  0.999853  0.999919  0.999979
4       0.999940  0.999940  0.999929  0.999990  0.999976  0.999990  0.999936
5       0.999983  0.999943  0.999989  0.999894  0.999822  0.999887  0.999969
…            …         …         …         …         …         …         …
6036    0.999997  0.999973  1.000000  0.999924  0.999852  0.999918  0.999990
6037    0.999929  0.999950  0.999924  1.000000  0.999985  1.000000  0.999945
6038    0.999859  0.999880  0.999852  0.999985  1.000000  0.999985  0.999873
6039    0.999925  0.999950  0.999918  1.000000  0.999985  1.000000  0.999942
6040    0.999989  0.999994  0.999990  0.999945  0.999873  0.999942  1.000000

[6040 rows x 6040 columns]
```

### 5.2 Cosine Similarity with Items

[ ]:
```
m = movies.copy()
m = m.explode("Genres")
m.drop_duplicates(inplace=True)
m = pd.pivot(data = m , index='Movie ID', columns='Genres' , values="Title")
m = ~m.isna()
m = m.astype(int)
m = m.reset_index()
m
```

[ ]:
```
Genres  Movie ID  Action  Adventure  Animation  Children  Comedy  Crime  \
0              1       0          0          1         1       1      0
1              2       0          1          0         1       0      0
2              3       0          0          0         0       1      0
3              4       0          0          0         0       1      0
4              5       0          0          0         0       1      0
…            …       …          …          …         …       …      …
3853        3948       0          0          0         0       1      0
3854        3949       0          0          0         0       0      0
3855        3950       0          0          0         0       0      0
3856        3951       0          0          0         0       0      0
3857        3952       0          0          0         0       0      0

Genres  Documentary  Drama  Fantasy  Film-Noir  Horror  Musical  Mystery  \
0                 0      0        0          0       0        0        0
1                 0      0        1          0       0        0        0
2                 0      0        0          0       0        0        0
3                 0      1        0          0       0        0        0
4                 0      0        0          0       0        0        0
…               …      …        …          …       …        …        …
3853              0      0        0          0       0        0        0
3854              0      1        0          0       0        0        0
```

```
3855              0      1        0          0       0        0        0
3856              0      1        0          0       0        0        0
3857              0      1        0          0       0        0        0

Genres  Romance  Sci-Fi  Thriller  War  Western
0             0       0         0    0        0
1             0       0         0    0        0
2             1       0         0    0        0
3             0       0         0    0        0
4             0       0         0    0        0
…           …       …         …  …        …
3853          0       0         0    0        0
3854          0       0         0    0        0
3855          0       0         0    0        0
3856          0       0         0    0        0
3857          0       0         1    0        0

[3858 rows x 19 columns]
```

[ ]:
```
m = m.merge(df.groupby("MovieID")["Rating"].mean() , how = "inner" ,␣
 ↪left_on="Movie ID" , right_on="MovieID")
m.columns
```

[ ]:
```
Index(['Movie ID', 'Action', 'Adventure', 'Animation', 'Children', 'Comedy',
       'Crime', 'Documentary', 'Drama', 'Fantasy', 'Film-Noir', 'Horror',
       'Musical', 'Mystery', 'Romance', 'Sci-Fi', 'Thriller', 'War', 'Western',
       'Rating'],
      dtype='object')
```

[ ]:
```
pd.DataFrame(data = metrics.pairwise.cosine_similarity(m), index=m["Movie ID"]␣
 ↪, columns=m["Movie ID"] )
```

[ ]:
```
Movie ID      1         2         3         4         5         6     \
Movie ID
1         1.000000  0.851178  0.799852  0.702599  0.677668  0.652501
2         0.851178  1.000000  0.840896  0.798880  0.798297  0.799732
3         0.799852  0.840896  1.000000  0.938822  0.944655  0.901137
4         0.702599  0.798880  0.938822  1.000000  0.978037  0.932591
5         0.677668  0.798297  0.944655  0.978037  1.000000  0.957376
…              …         …         …         …         …         …
3948      0.218089  0.482291  0.669814  0.793449  0.845175  0.816646
3949      0.218143  0.482384  0.669839  0.793514  0.845193  0.816710
3950      0.218041  0.482296  0.669762  0.793453  0.845136  0.816650
3951      0.218094  0.482342  0.669802  0.793484  0.845166  0.816681
3952      0.218067  0.482318  0.669781  0.793468  0.845150  0.816699

Movie ID      7         8         9         10    …      3943      3944  \
```

```
Movie ID                                                  …
1         0.607722  0.538955  0.460726  0.498762  …  0.217957  0.217742
2         0.758135  0.768344  0.676283  0.724333  …  0.482178  0.481994
3         0.938195  0.851853  0.827581  0.844165  …  0.669715  0.669555
4         0.959531  0.920248  0.908496  0.915882  …  0.793369  0.793291
5         0.987352  0.956522  0.948544  0.953138  …  0.845100  0.844979
…            …         …         …         …     …        …
3948      0.884937  0.923536  0.953941  0.930644  …  1.000000  1.000000
3949      0.884957  0.923578  0.953975  0.930684  …  1.000000  1.000000
3950      0.884908  0.923539  0.953943  0.930647  …  1.000000  1.000000
3951      0.884934  0.923559  0.953960  0.930666  …  1.000000  1.000000
3952      0.884920  0.923549  0.953951  0.930680  …  1.000000  1.000000

Movie ID      3945      3946      3947      3948      3949      3950  \
Movie ID
1         0.217655  0.217721  0.217997  0.218089  0.218143  0.218041
2         0.481994  0.482022  0.482259  0.482291  0.482384  0.482296
3         0.669392  0.669523  0.669730  0.669814  0.669839  0.669762
4         0.793105  0.793261  0.793376  0.793449  0.793514  0.793453
5         0.844856  0.844955  0.845111  0.845175  0.845193  0.845136
…            …         …         …         …         …         …
3948      1.000000  1.000000  1.000000  1.000000  1.000000  1.000000
3949      1.000000  1.000000  1.000000  1.000000  1.000000  1.000000
3950      1.000000  1.000000  1.000000  1.000000  1.000000  1.000000
3951      1.000000  1.000000  1.000000  1.000000  1.000000  1.000000
3952      1.000000  1.000000  1.000000  1.000000  1.000000  1.000000

Movie ID      3951      3952
Movie ID
1         0.218094  0.218067
2         0.482342  0.482318
3         0.669802  0.669781
4         0.793484  0.793468
5         0.845166  0.845150
…            …         …
3948      1.000000  1.000000
3949      1.000000  1.000000
3950      1.000000  1.000000
3951      1.000000  1.000000
3952      1.000000  1.000000

[3682 rows x 3682 columns]
```

[ ]:

## 6 Pearson Correlation Recommender System

[ ]:
```
pivot_user_item = pd.pivot_table(data=df , index = df["UserID"] ,␣
↪columns=df["MovieID"] ,values = "Rating").fillna(0)
pivot_user_item
```

[ ]:
```
MovieID  1     2     3     4     5     6     7     8     9     10    …  \
UserID                                                                …
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   0.0   0.0   0.0   2.0   0.0   0.0   0.0   0.0  …
…         …     …     …     …     …     …     …     …     …     …    …
6036      0.0   0.0   0.0   2.0   0.0   3.0   0.0   0.0   0.0   0.0  …
6037      0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0  …
6038      0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0  …
6039      0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0  …
6040      3.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0  …

MovieID  3943  3944  3945  3946  3947  3948  3949  3950  3951  3952
UserID
1         0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
2         0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
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   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
…         …     …     …     …     …     …     …     …     …     …
6036      0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
6037      0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
6038      0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
6039      0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
6040      0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0

[6040 rows x 3682 columns]
```

[ ]:
```
sparse_value = pivot_user_item[pivot_user_item==0].count().sum()/
↪(pivot_user_item.shape[0]*pivot_user_item.shape[1])
sparse_value
```

[ ]:
```
0.9552079024141069
```

[ ]:
```
pd.DataFrame(data = pivot_user_item.corrwith(pivot_user_item[1]).
↪sort_values(ascending=False).head(10),columns=["corr"]).reset_index().
↪merge(movies , how = "inner" , left_on="MovieID" , right_on="Movie ID").
↪drop("Movie ID" , axis = 1)
```

[ ]:

| | MovieID | corr | Title | Genres |
|---|---|---|---|---|
| 0 | 1 | 1.000000 | Toy Story (1995) | [Animation, Children, Comedy] |
| 1 | 3114 | 0.487370 | Toy Story 2 (1999) | [Animation, Children, Comedy] |
| 2 | 588 | 0.470753 | Aladdin (1992) | [Animation, Children, Comedy, Musical] |
| 3 | 364 | 0.411131 | Lion King, The (1994) | [Animation, Children, Musical] |
| 4 | 1265 | 0.407547 | Groundhog Day (1993) | [Comedy, Romance] |
| 5 | 2355 | 0.402679 | Bug's Life, A (1998) | [Animation, Children, Comedy] |
| 6 | 595 | 0.395510 | Beauty and the Beast (1991) | [Animation, Children, Musical] |
| 7 | 34 | 0.378794 | Babe (1995) | [Children, Comedy, Drama] |
| 8 | 3253 | 0.370424 | Wayne's World (1992) | [Comedy] |
| 9 | 1923 | 0.357726 | There's Something About Mary (1998) | [Comedy] |

[ ]:

### 6.1 Matrix Factorization Systems

[ ]:
```
rm_raw = df[['UserID', 'MovieID', '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 | 2 | 1193 | 5 |

[ ]:
```
movies
```

[ ]:

| | Movie ID | Title |
|---|---|---|
| 0 | 1 | Toy Story (1995) |
| 1 | 2 | Jumanji (1995) |
| 2 | 3 | Grumpier Old Men (1995) |
| 3 | 4 | Waiting to Exhale (1995) |
| 4 | 5 | Father of the Bride Part II (1995) |
| … | … | … |
| 3878 | 3948 | Meet the Parents (2000) |

```
3879      3949          Requiem for a Dream (2000)
3880      3950                    Tigerland (2000)
3881      3951               Two Family House (2000)
3882      3952                 Contender, The (2000)

                                Genres
0       [Animation, Children, Comedy]
1     [Adventure, Children, Fantasy]
2                    [Comedy, Romance]
3                      [Comedy, Drama]
4                             [Comedy]
…                                …
3878                          [Comedy]
3879                           [Drama]
3880                           [Drama]
3881                           [Drama]
3882                 [Drama, Thriller]

[3858 rows x 3 columns]
```

[ ]:

[ ]:

### 6.2 Questionnaire:

Users of which age group have watched and rated the most number of movies? - Between 25

Users belonging to which profession have watched and rated the most movies? - 0,4,7 (Other , Students , executives)

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

Most of the movies present in our dataset were released in which decade? - 90's

The movie with maximum no. of ratings is _____. - American Beauty

On the basis of approach, Collaborative Filtering methods can be classified into item based and user based.

Pearson Correlation ranges between -1 to 1 whereas, Cosine Similarity belongs to the interval between 0 to 1.

Mention the RMSE and MAPE that you got while evaluating the Matrix Factorization model. - RSME = 1.4681938747852086 - MAPE = 0.4182823520002578

### 6.3 Actionable Insights

- Ratings are provided mostly by men.
- Users are usually generous as mostly they have provided ratings between 3-4.

- Rating 1-2 have been given very few times.
- Users watch movies usually between 12 am to 2 am.
- Less traffic is on the website during 11-5 i.e Corporate hours.
- Mostly rating are presented between October, November , December.
- There is a high rise in the movies released in 1990's.
- People of Age 25 and 35 give highest number of ratings, whereas people over 45 hardly rate.
- Top 5 count UserID : Int64Index([4169, 1680, 4277, 1941, 1181]
- Bottom 5 count UserID : Int64Index([3021, 3222, 5533, 5258, 3324]
- Top 5 mean UserID : Int64Index([3324, 283, 2339, 3902, 446]
- Bottom 5 mean UserID : Int64Index([5850, 4539, 2744, 4486, 3598]
- Top 5 count Title : Index(['American Beauty (1999)', 'Star Wars: Episode IV - A New Hope (1977)', 'Star Wars: Episode V - The Empire Strikes Back (1980)', 'Star Wars: Episode VI - Return of the Jedi (1983)', 'Jurassic Park (1993)']
- Bottom 5 count Title : Index(['Joyriders, The (1999)', 'White Boys (1999)', 'Voyage to the Beginning of the World (1997)', 'Lured (1947)', 'Back Stage (2000)']
- Top 5 mean Title : Index(['Song of Freedom (1936)', 'Schlafes Bruder (Brother of Sleep) (1995)', 'Ulysses (Ulisse) (1954)', 'Lured (1947)', 'Bittersweet Motel (2000)'],
- Bottom 5 mean Title : Index(['Get Over It (1996)', 'Underworld (1997)', 'Waltzes from Vienna (1933)', 'Sleepover (1995)', 'Lotto Land (1995)']

- Top 5 count Occupation : Int64Index([4, 0, 7, 1, 17]
- Bottom 5 count Occupation : Int64Index([19, 13, 18, 9, 8]
- Top 5 mean Occupation : Int64Index([13, 15, 6, 9, 3]
- Bottom 5 mean Occupation : Int64Index([10, 18, 20, 8, 19]
- College students are highly active on the platform.
- Farmers, retired and Craftsmen are the few professions which do not use the Platform alot.
- There is no difference between the mean rating of Male vs Female.
- Most movies belong to Comedy and Drama.
- Performed Recommender System using Cosine Similarity with respect to Item and User.
- Performed Recommender System using Pearson Correlation.
- Observed that the pivot for user vs matrix vs rating will be very sparse. Only 5 percent data is present.
- Performed Matrix Factorizations for recommending.

# 7 Recommendations

1. Zee should encourage users to provide more ratings, espcially women.
2. Recommender systems based on users and item work well with zee.
3. Due to the sparse pivot , between users and items and ratings , Matrrix Factorizations should be used.
4. Regression recommender systems can also be used. They can be more effective.
5. More Comedy and Drama should be recommended.

[ ]: