Project_11_Zee

November 20, 2022

0.1 PROBLEM STATEMENT

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

0.1.1 My Views:

- Giving personalized and relevant movie recommendations to the users is a very important task for **Zee** to increase engagement and user experience.
- Better engagement would mean people would be spending more time on **Zee's** platform, through which people would develop an affinity for **Zee**
- Existing users would renew their subscriptions and as a reult Churn would reduce, which would also impact Revenue.
- If the experience is good, more people would be interested to take **Zee** subscription, which can directly increase revenue.
- Better do No recommendation than doing a wrong recommendation.

0.2 Data Dictionary:

0.2.1 1) RATINGS FILE DESCRIPTION

All ratings are contained in the file "ratings.dat" and are in the following format: **UserID::MovieID::Rating::Timestamp**

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

0.2.2 2) USERS FILE DESCRIPTION

User information is in the file "users.dat" and is in the following format: **UserID::Gender::Age::Occupation::Zip-code**

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

- Gender is denoted by a "M" for male and "F" for female
- Age is chosen from the following ranges: 1: "Under 18", 18: "18-24", 25: "25-34", 35: "35-44", 45: "45-49", 50: "50-55", 56: "56+"

- Occupation is chosen from the following choices: 0: "other" or not specified, 1: "academic/educator", 2: "artist", 3: "clerical/admin", 4: "college/grad student", 5: "customer service", 6: "doctor/health care", 7: "executive/managerial", 8: "farmer", 9: "homemaker", 10: "K-12 student", 11: "lawyer", 12: "programmer", 13: "retired", 14: "sales/marketing", 15: "scientist", 16: "self-employed", 17: "technician/engineer", 18: "tradesman/craftsman", 19: "unemployed", 20: "writer"

0.2.3 3) MOVIES FILE DESCRIPTION

Movie information is in the file "movies.dat" and is in the following format: **MovieID::Title::Genres**

- Titles are identical to titles provided by the IMDB (including year of release)
- Genres are pipe-separated and are selected from the following genres: Action, Adventure, Animation, Children's, Comedy, Crime, Documentary, Drama, Fantasy, Film-Noir, Horror, Musical, Mystery, Romance, Sci-Fi, Thriller, War, Western

[3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import cross_validate
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from cmfrec import CMF
from sklearn.metrics import mean_squared_error,mean_absolute_percentage_error
```

0.2.4 Movies Dataset

[4]:
```
movies=pd.read_fwf('/zee-movies.dat',encoding='ISO-8859-1')
movies=pd.DataFrame(data=(movies['Movie ID::Title::Genres'].str.split('::')).
 ↪tolist(),columns=movies.columns[0].split('::'))
movies.rename(columns={'Movie ID':'MovieID'},inplace=True)
display(movies.head())

print('Shape:',movies.shape) # There are 3833 rows.
```

```
  MovieID                               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
```

```
Shape: (3883, 3)
```

[5]:
```python
# Checking for missing values.
print(movies.isna().sum())
# There are 25 movies for which Genre is not present. We can remove these␣
↪movies.

# Making a copy of the original dataset.
movies_original=movies.copy()

# Removing the movies which has "Genre" missing.
movies_to_remove=list(movies.loc[movies['Genres'].isna(),'MovieID'])
movies=movies[~movies['MovieID'].isin(movies_to_remove)].reset_index(drop=True)
```

```
MovieID     0
Title       0
Genres     25
dtype: int64
```

[6]:
```python
# Getting Release Year for every movie and removing year from Title.
movies['Release_Year']=movies['Title'].apply(lambda x : x[-5:-1])

# Lets check if there are any wrong values for "Release_Year".
print(movies['Release_Year'].unique()) # Everything seems okay.
```

```
['1995' '1994' '1996' '1976' '1993' '1992' '1988' '1967' '1977' '1965'
 '1982' '1962' '1990' '1991' '1989' '1937' '1940' '1969' '1981' '1973'
 '1970' '1960' '1955' '1956' '1959' '1968' '1980' '1975' '1986' '1948'
 '1943' '1950' '1946' '1987' '1997' '1974' '1958' '1949' '1972' '1998'
 '1933' '1952' '1951' '1957' '1961' '1954' '1934' '1944' '1963' '1942'
 '1941' '1964' '1953' '1939' '1947' '1945' '1938' '1935' '1936' '1926'
 '1932' '1930' '1971' '1979' '1966' '1978' '1985' '1983' '1984' '1931'
 '1922' '1927' '1929' '1928' '1925' '1923' '1999' '1919' '2000' '1920'
 '1921']
```

[7]:
```python
# Removing year from Title for every movie.
movies['Title']=movies['Title'].apply(lambda x : x[:-7])
```

[8]:
```python
#Checking Movies Dataset Information
print(movies.info())

# Changing 'MoviedID' and "Release_Year" columns to integer datatype.
movies[['MovieID','Release_Year']]=movies[['MovieID','Release_Year']].
↪astype('int')
movies_original[['MovieID']]=movies_original[['MovieID']].astype('int')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3858 entries, 0 to 3857
Data columns (total 4 columns):
```

```
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   MovieID       3858 non-null   object
 1   Title         3858 non-null   object
 2   Genres        3858 non-null   object
 3   Release_Year  3858 non-null   object
dtypes: object(4)
memory usage: 120.7+ KB
None
```

[9]:
```
# Exploding the Dataset.
movies_exploded=movies.copy()
movies_exploded['Genres']=movies_exploded['Genres'].str.split('|')
movies_exploded=movies_exploded.explode(column='Genres')
display(movies_exploded.head(5))
```

	MovieID	Title	Genres	Release_Year
0	1	Toy Story	Animation	1995
0	1	Toy Story	Children's	1995
0	1	Toy Story	Comedy	1995
1	2	Jumanji	Adventure	1995
1	2	Jumanji	Children's	1995

[10]:
```
print('Movies Shape:',movies.shape)
print('Exploded_Movies Shape:',movies_exploded.shape)
```

```
Movies Shape: (3858, 4)
Exploded_Movies Shape: (6341, 4)
```

[11]:
```
# Checking for number of unique movies.
print('Unique Movies:',movies['MovieID'].nunique())

# Checking for number of unique Genres.
print('Unique Genres:',movies_exploded['Genres'].nunique())
print()

# From the information provided earlier, we know that there are 18 Genres only,␣
↪which are:
# Action, Adventure, Animation, Children's, Comedy, Crime, Documentary, Drama,␣
↪Fantasy, Film-Noir, Horror, Musical"
# "Mystery, Romance, Sci-Fi, Thriller, War, Western".
# But from the dataset provided, there are 63 unique Genres. We need to inspect␣
↪further.

# Checking the unique categories of Genre.
movies_exploded['Genres'].unique()
```

```
Unique Movies: 3858
Unique Genres: 63
```

[11]:
```
array(['Animation', "Children's", 'Comedy', 'Adventure', 'Fantasy',
       'Romance', 'Drama', 'Action', 'Crime', 'Thriller', 'Horror',
       'Sci-Fi', 'Documentary', 'War', 'Musical', 'Mystery', 'Film-Noir',
       'Dram', 'Western', 'Chil', '', 'Fantas', 'Dr', 'D', 'Documenta',
       'Wester', 'Fant', 'Music', 'Childre', 'Childr', 'Rom', 'Animati',
       'Children', 'Come', "Children'", 'Sci-F', 'Adv', 'Adventu',
       'Horro', 'Docu', 'S', 'Sci-', 'Document', 'Th', 'Roman', 'Documen',
       'We', 'F', 'Ro', 'R', 'Sci', 'Chi', 'Thri', 'Adventur', 'Advent',
       'Acti', 'Roma', 'A', 'Comed', 'Com', 'Thrille', 'Wa', 'Horr'],
      dtype=object)
```

[12]:
```
# Observation 1 - There is a Genre which is an empty string. We can therefore␣
 ↪remove these movies.
movies=movies.loc[~(movies['Genres']=='')]
movies_exploded=movies_exploded.loc[~(movies_exploded['Genres']=='')]


# Observation2 - There are a lot of Genres which have spelling variations. We␣
 ↪need to correct the mistyped names.
def function(x):
    if x in ['A','Acti','Action']:
        return 'Action'
    if x in ['Adv','Advent','Adventu','Adventur','Adventure']:
        return "Adventure"
    if x in ['Animati','Animation']:
        return "Animation"
    if x in␣
 ↪['Chi','Chil','Childr','Childre','Children',"Children'","Children's"]:
        return "Childrens"
    if x in ['Com','Come','Comed','Comedy']:
        return "Comedy"
    if x in ['Crime']:
        return "Crime"
    if x in ['D','Docu','Documen','Document','Documenta','Documentary'] :
        return "Documentary"
    if x in ['Dr','Dram','Drama']:
        return "Drama"
    if x in ['F','Fant','Fantas','Fantasy']:
        return "Fantasy"
    if x in ['Film-Noir']:
        return "Film_Noir"
    if x in ['Horr','Horro','Horror']:
        return "Horror"
    if x in ['Musical','Music']:
        return "Musical"
```

```python
    if x in ['Mystery']:
        return "Mystery"
    if x in ['R','Ro','Rom','Roma','Roman','Romance']:
        return "Romance"
    if x in ['S','Sci','Sci-','Sci-F','Sci-Fi']:
        return "Sci_Fi"
    if x in ['Th','Thri','Thrille','Thriller']:
        return "Thriller"
    if x in ['Wa','War']:
        return "War"
    if x in ["We",'Wester','Western']:
        return "Western"

movies_exploded['Genres']=movies_exploded['Genres'].apply(function)
```

[13]:
```python
# Removing duplicate entries if there are any.
print(movies_exploded.duplicated().sum()) # There is 1 entry which is duplicate.

# Removing the duplicate entry.
movies_exploded=movies_exploded[~movies_exploded.duplicated()]
```

1

[14]:
```python
# Final Look at the Dataset.
movies_exploded.head()
```

[14]:

	MovieID	Title	Genres	Release_Year
0	1	Toy Story	Animation	1995
0	1	Toy Story	Childrens	1995
0	1	Toy Story	Comedy	1995
1	2	Jumanji	Adventure	1995
1	2	Jumanji	Childrens	1995

[15]:
```python
# Checking for number of unique movies.
print('Unique Movies:',movies_exploded['MovieID'].nunique())

# Checking for number of unique Genres.
print('Unique Genres:',movies_exploded['Genres'].nunique())

# Checking for number of Release Years.
print('Unique Release Years:',movies_exploded['Release_Year'].nunique())

# Checking the shape of the dataset.
print('Exploded Movies Dataset Shape:',movies_exploded.shape)
print()

# Checking Exploded_Movies Info.
display(movies_exploded.info())
```

```
Unique Movies: 3856
Unique Genres: 18
Unique Release Years: 81
Exploded Movies Dataset Shape: (6332, 4)

<class 'pandas.core.frame.DataFrame'>
Int64Index: 6332 entries, 0 to 3857
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   MovieID       6332 non-null   int64
 1   Title         6332 non-null   object
 2   Genres        6332 non-null   object
 3   Release_Year  6332 non-null   int64
dtypes: int64(2), object(2)
memory usage: 247.3+ KB

None
```

[16]:
```python
movies_pivot=movies_exploded.
 ↪pivot(index='MovieID',columns='Genres',values='Title')
movies_pivot=(~movies_pivot.isna()).astype('int')
movies_pivot.head()
```

[16]:
```
Genres   Action  Adventure  Animation  Childrens  Comedy  Crime  Documentary  \
MovieID
1             0          0          1          1       1      0            0
2             0          1          0          1       0      0            0
3             0          0          0          0       1      0            0
4             0          0          0          0       1      0            0
5             0          0          0          0       1      0            0

Genres   Drama  Fantasy  Film_Noir  Horror  Musical  Mystery  Romance  Sci_Fi  \
MovieID
1            0        0          0       0        0        0        0       0
2            0        1          0       0        0        0        0       0
3            0        0          0       0        0        0        1       0
4            1        0          0       0        0        0        0       0
5            0        0          0       0        0        0        0       0

Genres   Thriller  War  Western
MovieID
1               0    0        0
2               0    0        0
3               0    0        0
4               0    0        0
5               0    0        0
```

[16]:

```

```

0.2.5 Users Dataset

[17]:
```
users=pd.read_fwf('/zee-users.dat',encoding='ISO-8859-1')
users=pd.DataFrame(data=users['UserID::Gender::Age::Occupation::Zip-code'].str.
↪split('::').tolist(),columns=users.columns[0].split('::'))
users.head()
```

[17]:

	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

[18]:
```
# Checking for missing values.
print(users.isna().sum())
print()
# There are no missing values in users dataset.

# Checking the shape of the dataset.
print('Users Shape',users.shape)
```

```
UserID        0
Gender        0
Age           0
Occupation    0
Zip-code      0
dtype: int64

Users Shape (6040, 5)
```

[19]:
```
# Checking the information of the users dataset.
display(users.info())

# Changing data type of the variables.
users[['UserID', 'Age', 'Occupation']]=users[['UserID', 'Age', 'Occupation']].
↪astype('int')
```

```
<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

None

[20]:
```
# Checking number of unique categories in different variables.
print('Users:',users['UserID'].nunique())
print('Gender:',users['Gender'].nunique())
print('Age:',users['Age'].nunique())
print('Occupation:',users['Occupation'].nunique())
print('Zip Code:',users['Zip-code'].nunique())
```

```
Users: 6040
Gender: 2
Age: 7
Occupation: 21
Zip Code: 3439
```

[21]:
```
# Encoding Gender variable.
users['Gender']=users['Gender'].map({'F':0,'M':1})
```

[21]:
```
```

0.2.6 Ratings Dataset

[22]:
```
ratings=pd.read_fwf('/zee-ratings.dat',encoding='ISO-8859-1')
ratings=pd.DataFrame(data=ratings['UserID::MovieID::Rating::Timestamp'].str.
↪split('::').tolist(),columns=ratings.columns[0].split('::'))
ratings.head()
```

[22]:

	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

[23]:
```
# Checking the information of Ratings Dataset.
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
```

[24]:
```python
# Changing the data type of all the variable to 'int'.
ratings=ratings.astype('int')
```

[25]:
```python
# Extracting Hour from Timestamp variable.
ratings['Hour']=ratings['Timestamp'].apply(lambda x : datetime.fromtimestamp(x).
 ↪hour)
```

[26]:
```python
# Checking for missing values.
print(ratings.isna().sum())
print()
# There are no missing values in users dataset.

# Checking the shape of the dataset.
print('Ratings Shape',ratings.shape)
```

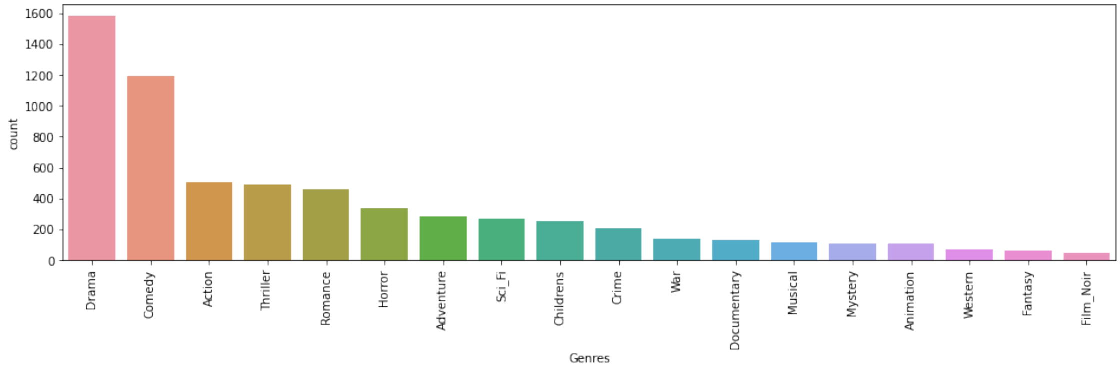
```
UserID       0
MovieID      0
Rating       0
Timestamp    0
Hour         0
dtype: int64

Ratings Shape (1000209, 5)
```

[26]:
```python

```

0.3 EDA

Q1) Availability of Genres in Zee.

[27]:
```python
plt.figure(figsize=(16,4))
sns.countplot(data=movies_exploded,x='Genres',order=movies_exploded['Genres'].
 ↪value_counts().index)
plt.xticks(rotation=90)
plt.show()
```



[28]:
```
# Top 5 occuring Genres.
display(np.round(movies_exploded['Genres'].value_counts(normalize=True)*100,2)[:
↪5])
```

```
Drama       24.98
Comedy      18.78
Action       7.93
Thriller     7.71
Romance      7.30
Name: Genres, dtype: float64
```

[29]:
```
# Bottom 5 occuring Genres.
display(np.round(movies_exploded['Genres'].
↪value_counts(normalize=True)*100,2)[-5:])
```

```
Mystery      1.66
Animation    1.64
Western      1.07
Fantasy      0.99
Film_Noir    0.69
Name: Genres, dtype: float64
```

Q2) Few Recent Movies.

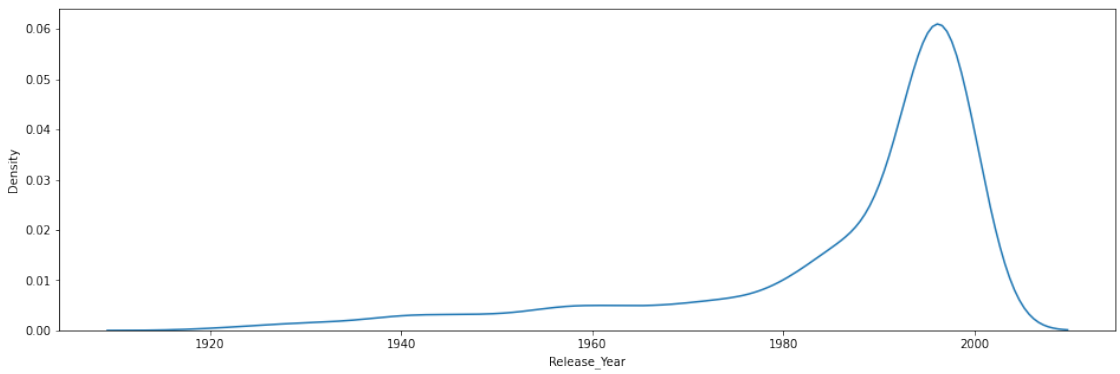
[30]:
```
temp=movies[movies['Release_Year']==np.max(movies['Release_Year'])]
print('Max Release Year:'
      ,np.max(movies['Release_Year']))
print('Number of movies released in Year 2000:',len(temp))
print('Total Movies Released:',len(movies))
print('Few Recent Movies are:')
for i in range(5):
    print(str(i+1)+': ',temp.iloc[i,1])
```

```
Max Release Year: 2000
Number of movies released in Year 2000: 156
Total Movies Released: 3856
```

```
Few Recent Movies are:
1:  Supernova
2:  Down to You
3:  Isn't She Great?
4:  Scream 3
5:  Gun Shy
```

Q3) Distribution of Release Years of the movies.

[31]:
```python
plt.figure(figsize=(16,5))
sns.kdeplot(movies['Release_Year'])
plt.show()
```

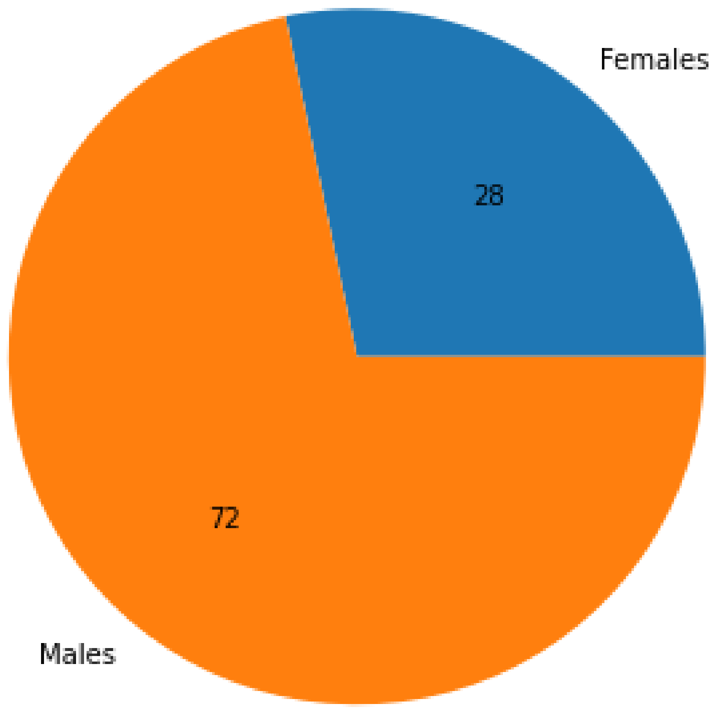


[32]:
```python
movies[['Release_Year']].describe().T

# Most movies are between Year 1980 and Year 2000.
```

[32]:
```
               count         mean        std     min     25%     50%     75%  \
Release_Year  3856.0  1986.092324  16.900818  1919.0  1982.0  1994.0  1997.0

                 max
Release_Year  2000.0
```

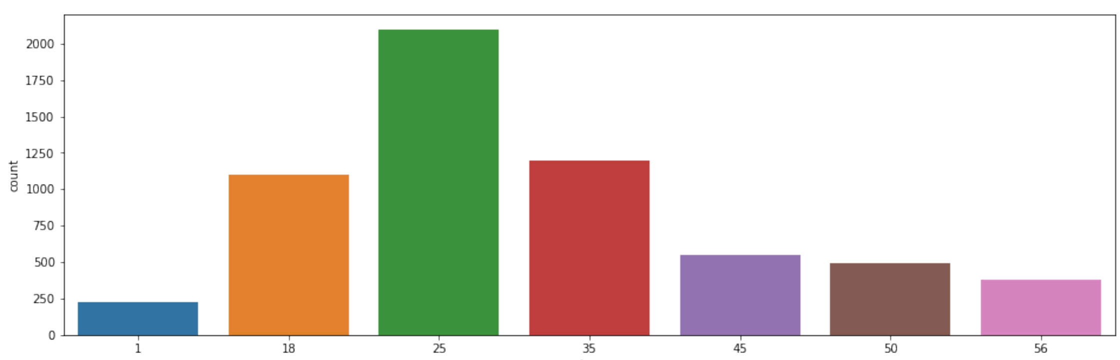
Q4) Proportion of Male and Females.

[33]:
```python
temp=users['Gender'].value_counts(normalize=True).sort_index().tolist()
plt.figure(figsize=(6,6))
plt.pie(temp,labels=['Females','Males'],autopct='%1.0f')
plt.show()

# Male:Female = 72:28
```



Q5) Distribution of Ages of the customers.

[34]:
```
plt.figure(figsize=(16,5))
sns.countplot(data=users,x='Age')
plt.show()
```

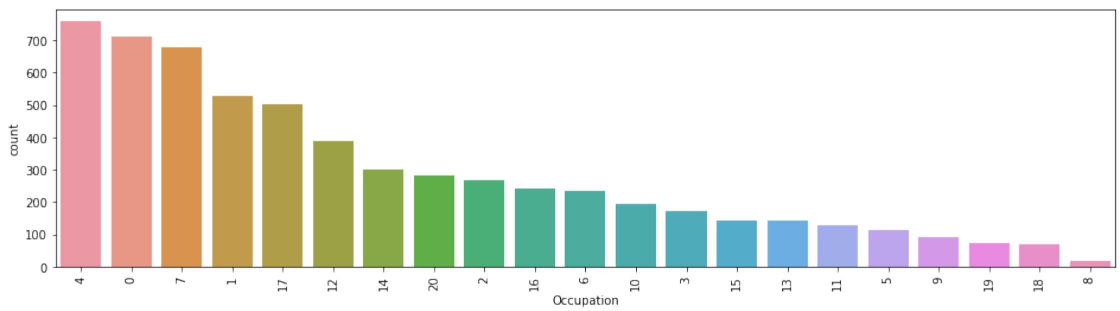


[35]:
```
display(np.round(users['Age'].value_counts(normalize=True)*100,2))

# Most people are between 18 and 44 years of Age.
# - 18: "18-24"
# - 25: "25-34"
# - 35: "35-44"
```

```
25    34.70
35    19.75
18    18.26
45     9.11
50     8.21
56     6.29
1      3.68
Name: Age, dtype: float64
```

Q6) Which are the occupations for which customers are available in Zee's platform?

[36]:
```
plt.figure(figsize=(16,4))
sns.countplot(data=users,x='Occupation',order=users['Occupation'].
 ↪value_counts().index)
plt.xticks(rotation=90)
plt.show()
```



[37]:
```
# Top 5 occupations.
np.round(users['Occupation'].value_counts(normalize=True)*100)[:5]
# 4: "college/grad student"
# 0: "other" or not specified
# 7: "executive/managerial"
# 1: "academic/educator"
# 17: "technician/engineer"
```

[37]:
```
4     13.0
0     12.0
7     11.0
1      9.0
```

```
17     8.0
Name: Occupation, dtype: float64
```

[38]:
```
# Bottom 5 occupations.
np.round(users['Occupation'].value_counts(normalize=True)*100)[-5:]
# 5: "customer service"
# 9: "homemaker"
# 19: "unemployed"
# 18: "tradesman/craftsman"
# 8: "farmer"
```

[38]:
```
5     2.0
9     2.0
19    1.0
18    1.0
8     0.0
Name: Occupation, dtype: float64
```

Q7) Which Movies have the most number of ratings?

[39]:
```
temp=ratings.groupby('MovieID').count()['Rating'].sort_values(ascending=False)[:
 ↪10].index
print('Top 10 Movies that have the most number of ratings')
movies.loc[movies['MovieID'].isin(temp),'Title'].tolist()
```

```
Top 10 Movies that have the most number of ratings
```

[39]:
```
['Star Wars: Episode IV - A New Hope',
 'Jurassic Park',
 'Terminator 2: Judgment Day',
 'Silence of the Lambs, The',
 'Star Wars: Episode V - The Empire Strikes Back',
 'Star Wars: Episode VI - Return of the Jedi',
 'Back to the Future',
 'Saving Private Ryan',
 'Matrix, The',
 'American Beauty']
```

Q8) Which Movies have the highest and lowest average ratings.

- Criteria: There should be atleast 50 ratings for the movie.

[40]:
```
temp=ratings['MovieID'].value_counts()
temp=temp[temp>=50].index
top_5=ratings[ratings['MovieID'].isin(temp)].groupby(by='MovieID').
 ↪mean()['Rating'].sort_values(ascending=False)[:5]
bottom_5=ratings[ratings['MovieID'].isin(temp)].groupby(by='MovieID').
 ↪mean()['Rating'].sort_values(ascending=False)[-5:]
```

[41]:
```
# Top 5 Movies with highest average Ratings.
print(movies.loc[movies['MovieID'].isin(top_5.index),'Title'].tolist())
# There are only 4 movies here. Seems like there is 1 movie which we removed␣
↪earlier because of missing Genre.
# Lets get the names of all 5 movies from original movies dataset.

print()
print(movies_original.loc[movies_original['MovieID'].isin(top_5.index),'Title'].
↪tolist())
# "'Seven Samurai (The Magnificent Seven) (Shichinin no samurai) (195'" is the␣
↪movie which has missing Genre. Lets confirm.

display(movies_original[movies_original['Title']=='Seven Samurai (The␣
↪Magnificent Seven) (Shichinin no samurai) (195'])
```

```
['Shawshank Redemption, The', 'Close Shave, A', 'Godfather, The', 'Sanjuro']

['Shawshank Redemption, The (1994)', 'Close Shave, A (1995)', 'Godfather, The
(1972)', 'Seven Samurai (The Magnificent Seven) (Shichinin no samurai) (195',
'Sanjuro (1962)']
```

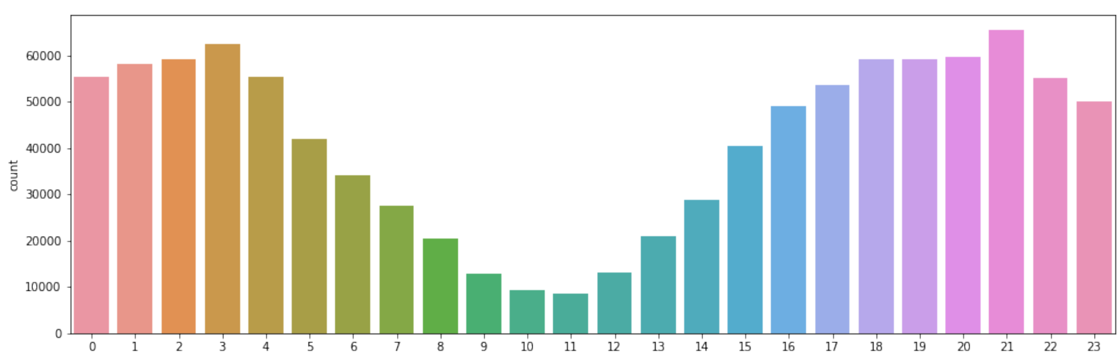
	MovieID	Title	Genres
1950	2019	Seven Samurai (The Magnificent Seven) (Shichin…	None

[42]:
```
# Bottom 5 Movies with least average Ratings.
print(movies.loc[movies['MovieID'].isin(bottom_5.index),'Title'].tolist())
```

```
['Kazaam', 'Problem Child 2', 'Iron Eagle IV', 'Meatballs III', 'Battlefield
Earth']
```

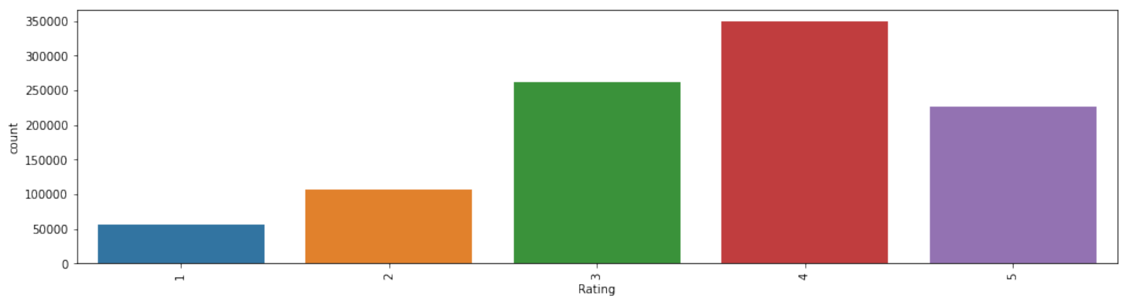
Q9) Distribution of Hour to understand the watching convenience time of the users.

[43]:
```
plt.figure(figsize=(16,5))
sns.countplot(data=ratings,x='Hour')
plt.show()

# Most users don't prefer watching between Hour 12 and Hour 20.
```



Q10) Distribution of Ratings

[44]:
```
plt.figure(figsize=(16,4))
sns.countplot(data=ratings,x='Rating')
plt.xticks(rotation=90)
plt.show()
```

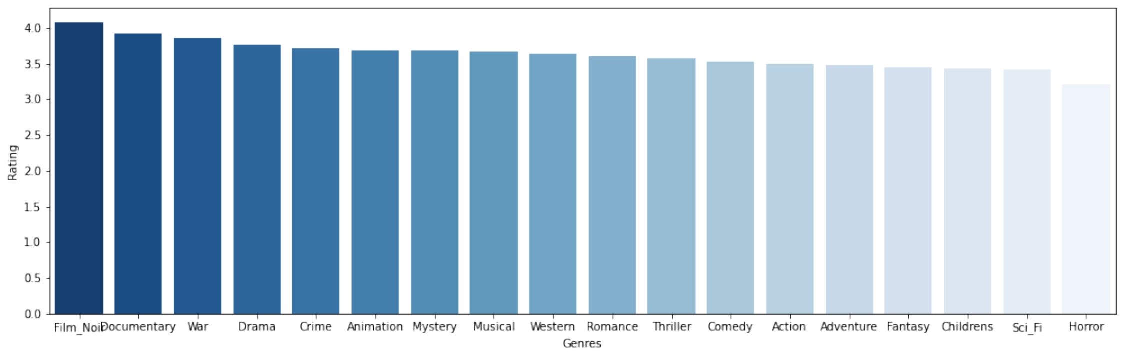


[45]:
```
# Percentage wise distribution of Ratings.
np.round(ratings['Rating'].value_counts(normalize=True)*100)

# About 35 percent of the rated movies are "4". This is a good percentage.
```

[45]:
```
4    35.0
3    26.0
5    23.0
2    11.0
1     6.0
Name: Rating, dtype: float64
```

Q11) Average Ratings of Different Genres?

[46]:
```
temp=pd.merge(left=ratings,right=movies_exploded,on='MovieID')
temp=temp.groupby(by='Genres')['Rating'].mean().sort_values(ascending=False).
↪reset_index()

plt.figure(figsize=(17,5))
sns.barplot(data=temp,y='Rating',x='Genres',palette='Blues_r')
plt.show()
```



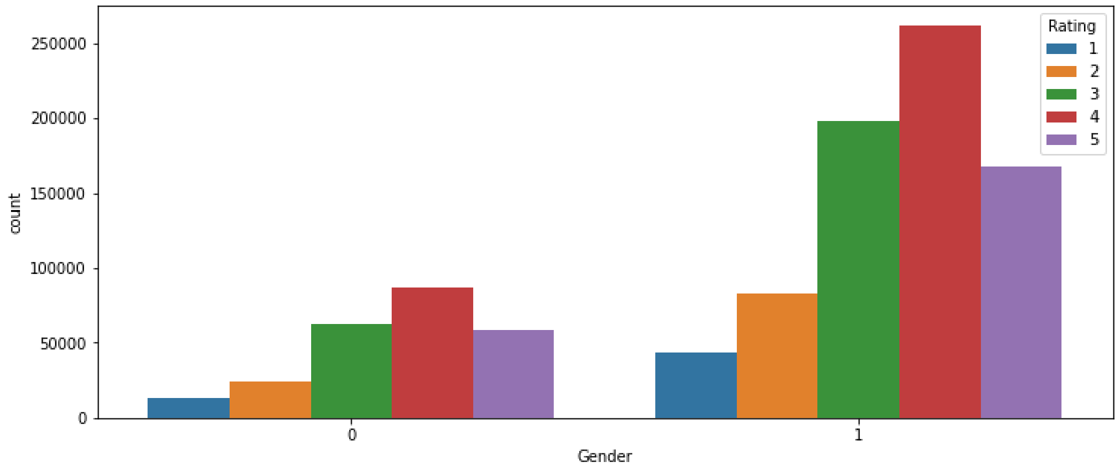
[47]:
```
display(temp.T)

# "Film_Noir","Documentary" and "War" are the best rated Genres.
# "Childrens","Sci_Fi" and "Horror" are the worst rated Genres.
```

```
                0            1         2         3         4          5  \
Genres  Film_Noir  Documentary       War     Drama     Crime  Animation
Rating   4.075188      3.92111  3.857115  3.760356  3.708781   3.681149

              6         7        8         9        10        11        12  \
Genres  Mystery   Musical  Western   Romance  Thriller    Comedy    Action
Rating  3.67469  3.665105  3.63777  3.596233  3.568161  3.522711   3.48857

               13        14         15        16       17
Genres  Adventure   Fantasy  Childrens    Sci_Fi   Horror
Rating   3.477666  3.453678   3.427365  3.412587  3.21645
```

Q12) Distribution of Ratings with Genders

[48]:
```
temp=pd.merge(left=ratings,right=users,on='UserID')
temp
plt.figure(figsize=(12,5))
sns.countplot(data=temp,hue='Rating',x='Gender')
# plt.show()
```

[48]: <matplotlib.axes._subplots.AxesSubplot at 0x7f538d9bce90>



[49]:
```
# Percentage wise distribution of Ratings Gender wise
np.round(pd.crosstab(temp['Gender'],temp['Rating'],normalize='index')*100,2)

# Seems like there isn't much difference between the distribution of ratings of␣
↪Men and Women.
```

[49]:

Rating	1	2	3	4	5
Gender					
0	5.42	9.96	25.55	35.32	23.76
1	5.68	11.01	26.30	34.75	22.26

[49]:
```
```

1 A) Item-Item Based Similarity.

1.1 1) Recommender System based on Pearson Correlation

[50]:
```
# Returns similar most movies.

def get_similar_movies(movies,similarity_matrix,movie_number):
    movie_name=movies.loc[movies['MovieID']==movie_number,'Title'].tolist()[0]
    similar_movies_order=similarity_matrix.loc[movie_number].
↪sort_values(ascending=False)
    similar_movies_id=similar_movies_order.index.tolist()
    similar_movies_id.remove(movie_number)
    similar_movies_id=similar_movies_id[:10]
    similar_movies_df=pd.DataFrame(np.
↪array([similar_movies_id,similar_movies_order.loc[similar_movies_id]])).T
    similar_movies_df.columns=['MovieID','Correlation']
```

```
    similar_movies_df=pd.
↪merge(left=movies,right=similar_movies_df,on='MovieID')[['MovieID','Title','Correlation','R
    similar_movies_df=similar_movies_df.sort_values(by='Correlation')

    return movie_name,similar_movies_df
```

[51]:
```
# Higher the Correlation Coefficient, higher the similarity.
movie_number=1
similarity_matrix=movies_pivot[:1000].T.corr()
item_item_recommendations=get_similar_movies(movies,similarity_matrix,movie_number)

print('Movie Name:',item_item_recommendations[0])
display('Recommendations:',item_item_recommendations[1])
```

Movie Name: Toy Story

'Recommendations:'

	MovieID	Title	Correlation	Release_Year
0	54	Big Green, The	0.790569	1995
2	374	Richie Rich	0.790569	1994
3	586	Home Alone	0.790569	1990
5	596	Pinocchio	0.790569	1940
6	616	Aristocats, The	0.790569	1970
7	709	Oliver & Company	0.790569	1988
8	837	Matilda	0.790569	1996
9	881	First Kid	0.790569	1996
1	239	Goofy Movie, A	0.836660	1995
4	588	Aladdin	0.836660	1992

[51]:

1.2 2) Recommender System based on Hamming Distance

[52]:
```
# Returns similar most movies.

def get_similar_movies(movies,similarity_matrix,movie_number):
    movie_name=movies.loc[movies['MovieID']==movie_number,'Title'].tolist()[0]
    similar_movies_order=similarity_matrix.loc[movie_number].sort_values()
    similar_movies_id=similar_movies_order.index.tolist()
    similar_movies_id.remove(movie_number)
    similar_movies_id=similar_movies_id[:10]
    similar_movies_df=pd.DataFrame(np.
↪array([similar_movies_id,similar_movies_order.loc[similar_movies_id]])).T
    similar_movies_df.columns=['MovieID','Distance']
    similar_movies_df=pd.
↪merge(left=movies,right=similar_movies_df,on='MovieID')[['MovieID','Title','Distance','Rele
    similar_movies_df=similar_movies_df.sort_values(by='Distance')
```

```python
    return movie_name,similar_movies_df
```

[53]:
```python
# Defining the Hamming_Distance Function to calculate similarity between movies.
↪Lower the distance, higher is the similarity.
def hamming_distance_function(df):
    movie_ids=df.index
    df=df.values
    n=len(df)
    temp=[]
    for movie1 in df:
        arr=[]
        for movie2 in df:
            arr.append(np.sum(np.abs(movie1-movie2)))
        temp.append(arr)
    return pd.DataFrame(temp,index=movie_ids,columns=movie_ids)
```

[54]:
```python
# Finding similar movies.

movie_number=1
similarity_matrix=hamming_distance_function(movies_pivot.iloc[:1000])
item_item_recommendations=get_similar_movies(movies,similarity_matrix,movie_number)

print('Movie Name:',item_item_recommendations[0])
display('Recommendations:',item_item_recommendations[1])
```

```
Movie Name: Toy Story
```

```
'Recommendations:'
```

	MovieID	Title	Distance	Release_Year
0	54	Big Green, The	1	1995
1	244	Gumby: The Movie	1	1995
2	250	Heavyweights	1	1994
3	313	Swan Princess, The	1	1994
4	355	Flintstones, The	1	1994
5	374	Richie Rich	1	1994
6	575	Little Rascals, The	1	1994
7	709	Oliver & Company	1	1988
8	801	Harriet the Spy	1	1996
9	837	Matilda	1	1996

[55]:
```python
# Preview of User User Similarity Matrix
similarity_matrix.head()
```

[55]:
```
MovieID  1     2     3     4     5     6     7     8     9     10    …  \
MovieID                                                             …
1             0     4     3     3     2     6     3     3     4     6 …
2             4     0     5     5     4     6     5     1     4     4 …
```

```
3           3     5     0     2     1     5     0     4     3     5  ...
4           3     5     2     0     1     5     2     4     3     5  ...
5           2     4     1     1     0     4     1     3     2     4  ...

MovieID  1011  1012  1013  1014  1015  1016  1017  1018  1019  1020
MovieID
1           2     3     3     2     3     1     3     2     4     2
2           2     3     3     4     1     3     1     4     0     4
3           3     4     4     3     4     2     4     3     5     1
4           3     2     2     1     4     2     4     3     5     1
5           2     3     3     2     3     1     3     2     4     0

[5 rows x 1000 columns]
```

[55]:

2 B) User-User Based Similarity.

[56]:

```python
# Creating a merged users dataset to find similar users.
temp=ratings.groupby(by='UserID')[['Rating','Hour']].mean()
temp=pd.
 ↪merge(left=temp,right=users,on='UserID')[['UserID','Rating','Hour','Gender','Age','Occupati


# Encoding age categories
mapper={1:1, 18:2, 25:3, 35:4, 45:5, 50:6, 56:7,}
temp['Age']=temp['Age'].map(mapper)
display(temp.head())

# One_Hot_Encoding "Occupation" variable.
encoder=OneHotEncoder(sparse=False,drop='first',dtype='int')
occupation_ohe_df=pd.DataFrame(data=encoder.
 ↪fit_transform(temp[['Occupation']]),columns=encoder.get_feature_names_out())

# Dropping original "Occupation" variable
temp.drop(columns=['Occupation'],inplace=True)
temp=pd.concat((temp,occupation_ohe_df),axis=1)

# Scaling the "Rating", "Hour" and "Age".
scaler=StandardScaler()
scaled_columns=['Rating', 'Hour', 'Age']
remaining_columns=['UserID','Gender', 'Occupation_1',␣
 ↪'Occupation_2','Occupation_3', 'Occupation_4',
                    'Occupation_5', 'Occupation_6', 'Occupation_7',␣
 ↪'Occupation_8', 'Occupation_9', 'Occupation_10',
```

```
                    'Occupation_11', 'Occupation_12', 'Occupation_13',␣
↪'Occupation_14','Occupation_15', 'Occupation_16',
                    'Occupation_17', 'Occupation_18', 'Occupation_19',␣
↪'Occupation_20']
temp_scaled=pd.DataFrame(data=scaler.
↪fit_transform(temp[scaled_columns]),columns=scaled_columns)
users_df=pd.concat((temp_scaled,temp[remaining_columns]),axis=1)
users_df.index=users_df['UserID']
users_df.drop(columns=['UserID'],inplace=True)
display(users_df.head())
```

```
   UserID    Rating       Hour  Gender  Age  Occupation
0       1  4.188679  22.245283       0    1          10
1       2  3.713178  21.155039       1    7          16
2       3  3.901961  21.000000       1    3          15
3       4  4.190476  20.000000       1    5           7
4       5  3.146465   6.015152       1    3          20

          Rating      Hour       Age  Gender  Occupation_1  Occupation_2  \
UserID
1       1.131261  1.414540 -1.747373       0             0             0
2       0.024380  1.261846  2.251920       1             0             0
3       0.463832  1.240132 -0.414276       1             0             0
4       1.135444  1.100078  0.918822       1             0             0
5      -1.294827 -0.858566 -0.414276       1             0             0

        Occupation_3  Occupation_4  Occupation_5  Occupation_6  …  \
UserID                                                          …
1                  0             0             0             0  …
2                  0             0             0             0  …
3                  0             0             0             0  …
4                  0             0             0             0  …
5                  0             0             0             0  …

        Occupation_11  Occupation_12  Occupation_13  Occupation_14  \
UserID
1                   0              0              0              0
2                   0              0              0              0
3                   0              0              0              0
4                   0              0              0              0
5                   0              0              0              0

        Occupation_15  Occupation_16  Occupation_17  Occupation_18  \
UserID
1                   0              0              0              0
2                   0              1              0              0
3                   1              0              0              0
4                   0              0              0              0
```

```
5                        0                  0                  0                  0

          Occupation_19  Occupation_20
UserID
1                        0                  0
2                        0                  0
3                        0                  0
4                        0                  0
5                        0                  1

[5 rows x 24 columns]
```

[57]:
```python
# Returns similar most movies.

def get_similar_movies(movies_original,ratings,similarity_matrix,user_number):
    temp=similarity_matrix.loc[user_number]
    temp=temp.drop(index=user_number)
    most_closest_user=temp[temp==temp.min()].index.tolist()[0]

# Lets get the list of of movies which are rated highly by the␣
 ↪most_closest_user.
    temp=ratings[ratings['UserID']==most_closest_user].
 ↪sort_values(by='Rating',ascending=False).iloc[:10][['MovieID','Rating']]
    temp=pd.merge(left=temp,right=movies,on='MovieID')


    return user_number,most_closest_user,temp
```

2.1 2) Recommender System based on KNN Distance

[58]:
```python
# Defining the KNN_Distance Function to measure similarity between users. Lower␣
 ↪the distance, higher is the similarity.
def knn_function(df):
    user_ids=df.index
    df=df.values
    n=len(df)
    temp=[]
    for user1 in df:
        arr=[]
        for user2 in df:
            arr.append(np.sum(user1-user2)**2)
        temp.append(arr)
    return pd.DataFrame(temp,index=user_ids,columns=user_ids)
```

[59]:
```python
user_number=1
similarity_matrix=knn_function(users_df.iloc[:1000])
```

```
user_user_recommendations=get_similar_movies(movies_original,ratings,similarity_matrix,user_nu

print('User_Number:',user_user_recommendations[0])
print('Most_Closest_User:',user_user_recommendations[1])
display('Recommendations',user_user_recommendations[2])
```

```
User_Number: 1
Most_Closest_User: 726
```

```
'Recommendations'
```

```
   MovieID  Rating                                              Title  \
0     2997       5                              Being John Malkovich
1     2424       5                                   You've Got Mail
2     1188       5                                  Strictly Ballroom
3      265       5  Like Water for Chocolate (Como agua para choco…
4      837       5                                            Matilda
5      838       5                                               Emma
6     1680       5                                      Sliding Doors
7     2171       5                             Next Stop, Wonderland
8     1784       5                                 As Good As It Gets
9      509       5                                        Piano, The

                 Genres  Release_Year
0                Comedy          1999
1        Comedy|Romance          1998
2        Comedy|Romance          1992
3                Drama|          1992
4     Children's|Comedy          1996
5  Comedy|Drama|Romance          1996
6         Drama|Romance          1998
7  Comedy|Drama|Romance          1998
8          Comedy|Drama          1997
9         Drama|Romance          1993
```

[59]:

```

```

2.2 Recommender System based on Cosine Similarity

[60]:

```
# Defining the Cosine Function to measure similarity between users. Lower the␣
↪distance, higher is the similarity.
def cosine_function(df):
    user_ids=df.index
    df=df.values
    n=len(df)
    temp=[]
    for user1 in df:
        arr=[]
```

```
        for user2 in df:
            arr.append(np.dot(user1,user2)/(np.linalg.norm(user1)*np.linalg.
↪norm(user2)))
        temp.append(arr)
    return pd.DataFrame(temp,index=user_ids,columns=user_ids)
```

[61]:
```
user_number=1
similarity_matrix=cosine_function(users_df.iloc[:1000])

user_user_recommendations=get_similar_movies(movies_original,ratings,similarity_matrix,user_nu

print('User_Number:',user_user_recommendations[0])
print('Most_Closest_User:',user_user_recommendations[1])
display('Recommendations',user_user_recommendations[2])
```

```
User_Number: 1
Most_Closest_User: 910

'Recommendations'

   MovieID  Rating                           Title             Genres  \
0     1250       5  Bridge on the River Kwai, The          Drama|War
1     1957       5               Chariots of Fire              Drama
2     1013       5               Parent Trap, The   Children's|Drama
3     1949       5         Man for All Seasons, A              Drama
4     1784       5              As Good As It Gets       Comedy|Drama
5      151       5                        Rob Roy  Drama|Romance|War
6     2284       5                   Bandit Queen              Drama
7      953       5          It's a Wonderful Life              Drama
8     3341       5                 Born Yesterday             Comedy
9     1641       5                 Full Monty, The             Comedy

   Release_Year
0          1957
1          1981
2          1961
3          1966
4          1997
5          1995
6          1994
7          1946
8          1950
9          1997
```

[61]:

3 C) Recommender System based on Matrix Factorization

[90]:
```
rm = ratings.pivot(index = 'UserID', columns ='MovieID', values = 'Rating').
 ↪fillna(0)
rm.head()
```

[90]:
```
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  …

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

[5 rows x 3706 columns]
```

[63]:
```
rm_raw = ratings[['UserID', 'MovieID', 'Rating']].copy()
rm_raw.columns = ['UserId', 'ItemId', 'Rating']  # Lib requires specific column␣
 ↪names
rm_raw.head(3)
```

[63]:
```
   UserId  ItemId  Rating
0       1    1193       5
1       1     661       3
2       1     914       3
```

[64]:
```
# !pip install cmfrec
from cmfrec import CMF

# Takings no of embeddings=2
model = CMF(method="als", k=2, lambda_=0.1, user_bias=False, item_bias=False,␣
 ↪verbose=False)
model.fit(rm_raw)
```

[64]:
```
Collective matrix factorization model
(explicit-feedback variant)
```

[68]:
```
model.A_.shape, model.B_.shape
```

[68]: ((6040, 2), (3706, 2))

[73]:
```
rm_raw.Rating.mean(), model.glob_mean_
```

[73]: (3.581564453029317, 3.581564426422119)

[94]:
```
rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_
mse=mean_squared_error(rm.values[rm > 0], rm__[rm > 0])**0.5
mape=mean_absolute_percentage_error(rm.values[rm > 0], rm__[rm > 0])**0.5
print('MSE:',mse)
print('MAPE',mape)
```

```
MSE: 1.3043536679938734
MAPE 0.6136484131429432
```

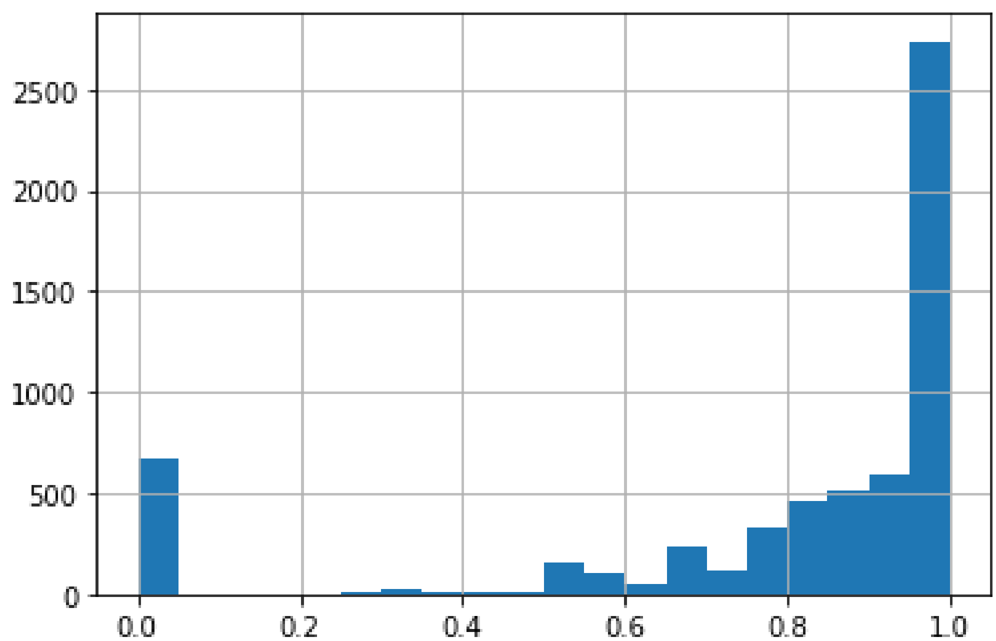
[82]:
```
# Getting the top 10 movie recommendations for User 1.
top_items = model.topN(user=1, n=10)
movies_original.loc[movies_original.MovieID.isin(top_items)]
```

[82]:
```
      MovieID                                              Title  \
638       643              Peanuts - Die Bank zahlt alles (1996)
883       895                                Venice/Venice (1992)
1397     1421                                Grateful Dead (1995)
2754     2823  Spiders, The (Die Spinnen, 1. Teil: Der Golden…
2842     2911                 Grandfather, The (El Abuelo) (1998)
3264     3333                Killing of Sister George, The (1968)
3311     3380                                  Railroaded! (1947)
3462     3531                 All the Vermeers in New York (1990)
3748     3818                                 Pot O' Gold (1941)
3822     3892                         Anatomy (Anatomie) (2000)

                    Genres
638                 Comedy
883                  Drama
1397           Documentary
2754                  Acti
2842                 Drama
3264                 Drama
3311             Film-Noir
3462  Comedy|Drama|Romance
3748        Comedy|Musical
3822                Horror
```

[103]:
```
# Precision - If I made K predictions, how many of those K were relevant?
overlap=[]
for user in ratings.UserID.unique():
    recommendations = model.topN(user=user, n=100)
    user_movies = ratings.loc[(ratings.UserID==user)].MovieID
```

```
    valid_rec = set(recommendations).intersection(set(user_movies)) # I can␣
↪only measure by what was in the training data
    relevant_items = ratings.loc[(ratings.UserID==user) & (ratings.Rating>=4)].
↪MovieID
    try:
        _ = len(set(recommendations).intersection(set(relevant_items))) /␣
↪len(valid_rec)
    except:
        _ = 0
    overlap.append(_)

overlap = np.array(overlap)
print('avg:', overlap.mean())
pd.Series(overlap).hist(bins=20)
plt.show()
```

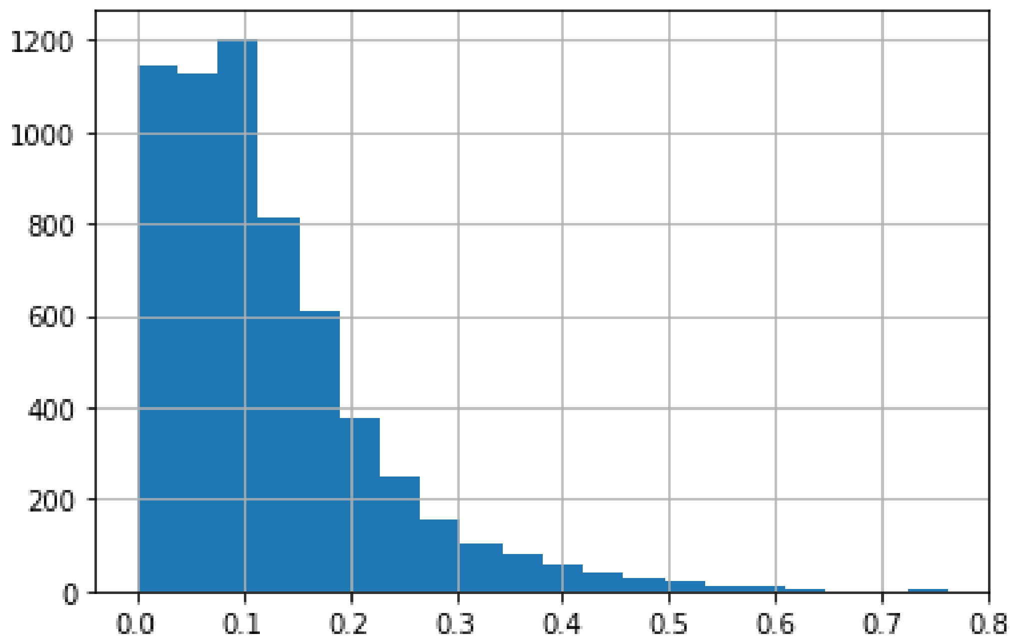
```
avg: 0.7941254267523916
```



[108]:
```
# Overlap - if I make, K predictions, how many relevant items was able to find?
overlap=[]
for user in ratings.UserID.unique():
    recommendations = model.topN(user=user, n=100)
    user_movies = ratings.loc[(ratings.UserID==user)].MovieID

    valid_rec = set(recommendations).intersection(set(user_movies)) # I can␣
↪only measure by what was in the training data
```

```
    relevant_items = ratings.loc[(ratings.UserID==user) & (ratings.Rating>=4)].
↪MovieID
    try:
        _ = len(set(recommendations).intersection(set(relevant_items))) /␣
↪len(set(relevant_items))
    except:
        _ = 0
    overlap.append(_)

overlap = np.array(overlap)
print('avg:', overlap.mean())
pd.Series(overlap).hist(bins=20)
plt.show()
```

```
avg: 0.1206196870105706
```




```
[ ]:
```

4 Handling a Cold Start Problem

For newly joined users, we wouldn't have all the User Information. This is a cold start problem. To handle this, we can ask for their favorite Genres. There are various ways we can recommend movies to new users. Some of them are:

- Recommend the most popular movies based on highest average Rating.
- Recommend the most recent movies.

- Recommend the movies which match with the new users's preferred Genres.
- Recommend the highest average rated movies on the basis of their location, i.e. Zip Code.

```
[ ]:
```