zee5_recsys

July 10, 2024

[1]:
```python
# Import Libraries
import numpy as np
import pandas as pd
from datetime import datetime
from sklearn.preprocessing import StandardScaler

import warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
df_movies = pd.read_csv("./zee-movies.dat", delimiter='::',␣
↪encoding="windows-1252")
df_ratings = pd.read_csv("./zee-ratings.dat", delimiter='::')
df_users = pd.read_csv("./zee-users.dat", delimiter='::')
```

[3]:
```python
df_movies.head()
```

[3]:

	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

[4]:
```python
df_ratings.head()
```

[4]:

	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

[5]:
```python
df_users.head()
```

[5]:

	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
```

[6]:
```
print(df_movies.shape)
print(df_ratings.shape)
print(df_users.shape)
```

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

[7]:
```
df_movies.nunique()
```

[7]:
```
Movie ID    3883
Title       3883
Genres       301
dtype: int64
```

[8]:
```
df_users.nunique()
```

[8]:
```
UserID        6040
Gender           2
Age              7
Occupation      21
Zip-code      3439
dtype: int64
```

[9]:
```
print(df_movies.isna().sum())
print(df_ratings.isna().sum())
print(df_users.isna().sum())
```

```
Movie ID    0
Title       0
Genres      0
dtype: int64
UserID       0
MovieID      0
Rating       0
Timestamp    0
dtype: int64
UserID        0
Gender        0
Age           0
Occupation    0
Zip-code      0
dtype: int64
```

Filtering only those movies for which the ratings were done most frequently:

[10]:
```
df_ratings.MovieID.value_counts().head(1000)
```

[10]:
```
MovieID
2858    3428
260     2991
1196    2990
1210    2883
480     2672
        …
2318     320
69       319
2819     319
1769     319
1031     319
Name: count, Length: 1000, dtype: int64
```

[11]:
```
select_movies = df_ratings.MovieID.value_counts().head(1000).index.to_list()
len(select_movies)
```

[11]:
```
1000
```

0.1 Transforming Movie Genres into Binary Features

- Extracting year and title from movie title column
- Let's Split and create OHE Columns from Genre String

[12]:
```
import re

def parse_movie_info(movie_string):
    # Regular expression to match the movie name and release year
    pattern = r"^(.*)\s\((\d{4})\)$"
    match = re.match(pattern, movie_string)

    if match:
        movie_name = match.group(1)
        release_year = match.group(2)
        return movie_name, release_year
    else:
        return None, None

# Example usage
input_string = "Inception (2010)"
result = parse_movie_info(input_string)

print(f"Movie Name: {result[0]}")
print(f"Release Year: {result[1]}")
```

```
Movie Name: Inception
```

```
Release Year: 2010
```

[13]:
```python
movies = df_movies.copy()
```

[14]:
```python
movies['movie_name'] = movies['Title'].apply(lambda x: parse_movie_info(x)[0])
movies['release_year'] = movies['Title'].apply(lambda x: parse_movie_info(x)[1])
movies.head()
```

[14]:
```
   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

                    movie_name release_year
0                    Toy Story         1995
1                      Jumanji         1995
2             Grumpier Old Men         1995
3            Waiting to Exhale         1995
4  Father of the Bride Part II         1995
```

[15]:
```python
movies['Genres'] = movies['Genres'].str.split('|')
movies['Genres']
```

[15]:
```
0        [Animation, Children's, Comedy]
1       [Adventure, Children's, Fantasy]
2                      [Comedy, Romance]
3                        [Comedy, Drama]
4                               [Comedy]
                       …
3878                            [Comedy]
3879                             [Drama]
3880                             [Drama]
3881                             [Drama]
3882                   [Drama, Thriller]
Name: Genres, Length: 3883, dtype: object
```

[16]:
```python
movies = movies.explode('Genres')
movies.head()
```

[16]:
```
   Movie ID             Title      Genres movie_name release_year
0         1  Toy Story (1995)   Animation  Toy Story         1995
0         1  Toy Story (1995)  Children's  Toy Story         1995
0         1  Toy Story (1995)      Comedy  Toy Story         1995
1         2    Jumanji (1995)   Adventure    Jumanji         1995
1         2    Jumanji (1995)  Children's    Jumanji         1995
```

[17]:
```python
movies = movies.pivot(index=['Movie ID', 'movie_name', 'release_year'],␣
 ↪columns='Genres', values='Title')
movies.head()
```

[17]:
```
Genres                                                   Action       Adventure  \
Movie ID movie_name                            release_year
1        Toy Story                             1995         NaN             NaN
2        Jumanji                               1995         NaN  Jumanji (1995)
3        Grumpier Old Men                      1995         NaN             NaN
4        Waiting to Exhale                     1995         NaN             NaN
5        Father of the Bride Part II 1995                   NaN             NaN

Genres                                                          Animation  \
Movie ID movie_name                  release_year
1        Toy Story                   1995          Toy Story (1995)
2        Jumanji                     1995                       NaN
3        Grumpier Old Men            1995                       NaN
4        Waiting to Exhale           1995                       NaN
5        Father of the Bride Part II 1995                       NaN

Genres                                                         Children's  \
Movie ID movie_name                  release_year
1        Toy Story                   1995          Toy Story (1995)
2        Jumanji                     1995            Jumanji (1995)
3        Grumpier Old Men            1995                       NaN
4        Waiting to Exhale           1995                       NaN
5        Father of the Bride Part II 1995                       NaN

Genres
Comedy  \
Movie ID movie_name                  release_year
1        Toy Story                   1995                            Toy Story
(1995)
2        Jumanji                     1995
NaN
3        Grumpier Old Men            1995                     Grumpier Old Men
(1995)
4        Waiting to Exhale           1995                    Waiting to Exhale
(1995)
5        Father of the Bride Part II 1995          Father of the Bride Part II
(1995)

Genres                                                   Crime Documentary  \
Movie ID movie_name                  release_year
1        Toy Story                   1995                  NaN         NaN
2        Jumanji                     1995                  NaN         NaN
3        Grumpier Old Men            1995                  NaN         NaN
```

```
4        Waiting to Exhale           1995           NaN         NaN
5        Father of the Bride Part II 1995           NaN         NaN

Genres                                                                 Drama  \
Movie ID movie_name                  release_year
1        Toy Story                   1995                                NaN
2        Jumanji                     1995                                NaN
3        Grumpier Old Men            1995                                NaN
4        Waiting to Exhale           1995          Waiting to Exhale (1995)
5        Father of the Bride Part II 1995                                NaN

Genres                                                     Fantasy Film-Noir  \
Movie ID movie_name                  release_year
1        Toy Story                   1995                      NaN       NaN
2        Jumanji                     1995          Jumanji (1995)        NaN
3        Grumpier Old Men            1995                      NaN       NaN
4        Waiting to Exhale           1995                      NaN       NaN
5        Father of the Bride Part II 1995                      NaN       NaN

Genres                                             Horror Musical Mystery  \
Movie ID movie_name                  release_year
1        Toy Story                   1995             NaN     NaN     NaN
2        Jumanji                     1995             NaN     NaN     NaN
3        Grumpier Old Men            1995             NaN     NaN     NaN
4        Waiting to Exhale           1995             NaN     NaN     NaN
5        Father of the Bride Part II 1995             NaN     NaN     NaN

Genres                                                              Romance  \
Movie ID movie_name                  release_year
1        Toy Story                   1995                               NaN
2        Jumanji                     1995                               NaN
3        Grumpier Old Men            1995          Grumpier Old Men (1995)
4        Waiting to Exhale           1995                               NaN
5        Father of the Bride Part II 1995                               NaN

Genres                                             Sci-Fi Thriller  War Western
Movie ID movie_name                  release_year
1        Toy Story                   1995             NaN      NaN  NaN     NaN
2        Jumanji                     1995             NaN      NaN  NaN     NaN
3        Grumpier Old Men            1995             NaN      NaN  NaN     NaN
4        Waiting to Exhale           1995             NaN      NaN  NaN     NaN
5        Father of the Bride Part II 1995             NaN      NaN  NaN     NaN
```

[18]:
```
movies = ~movies.isna()
movies = movies.astype(int)
movies
```

[18]:
```
Genres                                              Action  Adventure  \
Movie ID movie_name                   release_year
1        Toy Story                    1995               0          0
2        Jumanji                      1995               0          1
3        Grumpier Old Men             1995               0          0
4        Waiting to Exhale            1995               0          0
5        Father of the Bride Part II  1995               0          0
…                                                      …        …
3948     Meet the Parents             2000               0          0
3949     Requiem for a Dream          2000               0          0
3950     Tigerland                    2000               0          0
3951     Two Family House             2000               0          0
3952     Contender, The               2000               0          0

Genres                                              Animation  Children's  \
Movie ID movie_name                   release_year
1        Toy Story                    1995                  1           1
2        Jumanji                      1995                  0           1
3        Grumpier Old Men             1995                  0           0
4        Waiting to Exhale            1995                  0           0
5        Father of the Bride Part II  1995                  0           0
…                                                         …          …
3948     Meet the Parents             2000                  0           0
3949     Requiem for a Dream          2000                  0           0
3950     Tigerland                    2000                  0           0
3951     Two Family House             2000                  0           0
3952     Contender, The               2000                  0           0

Genres                                              Comedy  Crime  Documentary  \
Movie ID movie_name                   release_year
1        Toy Story                    1995               1      0            0
2        Jumanji                      1995               0      0            0
3        Grumpier Old Men             1995               1      0            0
4        Waiting to Exhale            1995               1      0            0
5        Father of the Bride Part II  1995               1      0            0
…                                                      …     …           …
3948     Meet the Parents             2000               1      0            0
3949     Requiem for a Dream          2000               0      0            0
3950     Tigerland                    2000               0      0            0
3951     Two Family House             2000               0      0            0
3952     Contender, The               2000               0      0            0

Genres                                              Drama  Fantasy  Film-Noir  \
Movie ID movie_name                   release_year
1        Toy Story                    1995              0        0          0
2        Jumanji                      1995              0        1          0
3        Grumpier Old Men             1995              0        0          0
```

```
4        Waiting to Exhale           1995                 1        0          0
5        Father of the Bride Part II 1995                 0        0          0
…                                                      …      …        …
3948     Meet the Parents            2000                 0        0          0
3949     Requiem for a Dream         2000                 1        0          0
3950     Tigerland                   2000                 1        0          0
3951     Two Family House            2000                 1        0          0
3952     Contender, The              2000                 1        0          0

Genres                                             Horror  Musical  Mystery  \
Movie ID movie_name                  release_year
1        Toy Story                   1995                0        0        0
2        Jumanji                     1995                0        0        0
3        Grumpier Old Men            1995                0        0        0
4        Waiting to Exhale           1995                0        0        0
5        Father of the Bride Part II 1995                0        0        0
…                                                       …      …      …
3948     Meet the Parents            2000                0        0        0
3949     Requiem for a Dream         2000                0        0        0
3950     Tigerland                   2000                0        0        0
3951     Two Family House            2000                0        0        0
3952     Contender, The              2000                0        0        0

Genres                                             Romance  Sci-Fi  Thriller  \
Movie ID movie_name                  release_year
1        Toy Story                   1995                 0       0         0
2        Jumanji                     1995                 0       0         0
3        Grumpier Old Men            1995                 1       0         0
4        Waiting to Exhale           1995                 0       0         0
5        Father of the Bride Part II 1995                 0       0         0
…                                                        …      …       …
3948     Meet the Parents            2000                 0       0         0
3949     Requiem for a Dream         2000                 0       0         0
3950     Tigerland                   2000                 0       0         0
3951     Two Family House            2000                 0       0         0
3952     Contender, The              2000                 0       0         1

Genres                                             War  Western
Movie ID movie_name                  release_year
1        Toy Story                   1995            0        0
2        Jumanji                     1995            0        0
3        Grumpier Old Men            1995            0        0
4        Waiting to Exhale           1995            0        0
5        Father of the Bride Part II 1995            0        0
…                                                 …      …
3948     Meet the Parents            2000            0        0
3949     Requiem for a Dream         2000            0        0
```

```
3950     Tigerland                    2000            0         0
3951     Two Family House             2000            0         0
3952     Contender, The               2000            0         0

[3883 rows x 18 columns]
```

[19]:
```
movies = movies.reset_index()
movies.head()
```

[19]:
```
Genres  Movie ID                     movie_name release_year  Action  Adventure  \
0              1                      Toy Story         1995       0          0
1              2                        Jumanji         1995       0          1
2              3               Grumpier Old Men         1995       0          0
3              4              Waiting to Exhale         1995       0          0
4              5    Father of the Bride Part II         1995       0          0

Genres  Animation  Children's  Comedy  Crime  Documentary  …  Fantasy  \
0               1           1       1      0            0  …        0
1               0           1       0      0            0  …        1
2               0           0       1      0            0  …        0
3               0           0       1      0            0  …        0
4               0           0       1      0            0  …        0

Genres  Film-Noir  Horror  Musical  Mystery  Romance  Sci-Fi  Thriller  War  \
0               0       0        0        0        0       0         0    0
1               0       0        0        0        0       0         0    0
2               0       0        0        0        1       0         0    0
3               0       0        0        0        0       0         0    0
4               0       0        0        0        0       0         0    0

Genres  Western
0             0
1             0
2             0
3             0
4             0

[5 rows x 21 columns]
```

[20]:
```
movies.set_index('Movie ID', inplace=True, drop='index')
movies = movies.reset_index()
movies.head()
```

[20]:
```
Genres  Movie ID                     movie_name release_year  Action  Adventure  \
0              1                      Toy Story         1995       0          0
1              2                        Jumanji         1995       0          1
2              3               Grumpier Old Men         1995       0          0
```

```
3             4          Waiting to Exhale        1995      0          0
4             5  Father of the Bride Part II      1995      0          0

Genres  Animation  Children's  Comedy  Crime  Documentary  …  Fantasy  \
0               1           1       1      0            0  …        0
1               0           1       0      0            0  …        1
2               0           0       1      0            0  …        0
3               0           0       1      0            0  …        0
4               0           0       1      0            0  …        0

Genres  Film-Noir  Horror  Musical  Mystery  Romance  Sci-Fi  Thriller  War  \
0               0       0        0        0        0       0         0    0
1               0       0        0        0        0       0         0    0
2               0       0        0        0        1       0         0    0
3               0       0        0        0        0       0         0    0
4               0       0        0        0        0       0         0    0

Genres  Western
0             0
1             0
2             0
3             0
4             0

[5 rows x 21 columns]
```

0.1.1 Let's Extract Hour from Timestamp

- Extracting the hour from the timestamp can indeed serve as a valuable user feature.
- By incorporating the hour of the day when users provide ratings, it provides a means to capture time-based patterns and behaviors of users.

[21]:
```
ratings = df_ratings.copy()
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  int64
 1   MovieID    1000209 non-null  int64
 2   Rating     1000209 non-null  int64
 3   Timestamp  1000209 non-null  int64
dtypes: int64(4)
memory usage: 30.5 MB
```

[22]:
```
x = 956716541
datetime.fromtimestamp(x).hour
datetime.fromtimestamp(x).weekday()
# r.tail()
```

[22]: 2

[23]:
```
ratings['hour'] = ratings['Timestamp'].apply(lambda x: datetime.
 ↪fromtimestamp(x).hour)
ratings['day'] = ratings['Timestamp'].apply(lambda x: datetime.fromtimestamp(x).
 ↪day)
ratings['weekday'] = ratings['Timestamp'].apply(lambda x: datetime.
 ↪fromtimestamp(x).weekday())
ratings['month'] = ratings['Timestamp'].apply(lambda x: datetime.
 ↪fromtimestamp(x).month)
ratings['year'] = ratings['Timestamp'].apply(lambda x: datetime.
 ↪fromtimestamp(x).year)
ratings['date'] = ratings['Timestamp'].apply(lambda x: datetime.
 ↪fromtimestamp(x).date())

ratings.head()
```

[23]:
```
   UserID  MovieID  Rating  Timestamp  hour  day  weekday  month  year  \
0       1     1193       5  978300760     3    1        0      1  2001
1       1      661       3  978302109     4    1        0      1  2001
2       1      914       3  978301968     4    1        0      1  2001
3       1     3408       4  978300275     3    1        0      1  2001
4       1     2355       5  978824291     5    7        6      1  2001

         date
0  2001-01-01
1  2001-01-01
2  2001-01-01
3  2001-01-01
4  2001-01-07
```

0.1.2 Now, Let's Read and Merge User Data with Aggregated Values:

[24]:
```
users_ratings_stat = df_users.merge(ratings.groupby('UserID').Rating.mean().
 ↪reset_index(), on='UserID')
users_ratings_stat = users_ratings_stat.merge(ratings.groupby('UserID').hour.
 ↪mean().reset_index(), on='UserID')
users_ratings_stat = users_ratings_stat.merge(ratings.groupby('UserID').day.
 ↪mean().reset_index(), on='UserID')
users_ratings_stat = users_ratings_stat.merge(ratings.groupby('UserID').weekday.
 ↪mean().reset_index(), on='UserID')
```

```
users_ratings_stat = users_ratings_stat.merge(ratings.groupby('UserID').month.
 ↪mean().reset_index(), on='UserID')
users_ratings_stat = users_ratings_stat.merge(ratings.groupby('UserID').year.
 ↪mean().reset_index(), on='UserID')
users_ratings_stat = users_ratings_stat.merge(ratings.groupby('UserID').
 ↪Timestamp.mean().reset_index(), on='UserID')
user_rating_count_mapping = ratings.groupby('UserID').Rating.count()
users_ratings_stat['num_ratings'] = users_ratings_stat.UserID.apply(lambda x:␣
 ↪user_rating_count_mapping[x])
users_ratings_stat.head()
```

[24]:
```
   UserID Gender  Age  Occupation Zip-code    Rating       hour        day  \
0       1      F    1          10    48067  4.188679   3.792453   2.471698
1       2      M   56          16    70072  3.713178   2.968992   1.000000
2       3      M   25          15    55117  3.901961   2.215686   1.000000
3       4      M   45           7    02460  4.190476   1.000000   1.000000
4       5      M   25          20    55455  3.146465  11.656566  31.000000

    weekday  month    year     Timestamp  num_ratings
0  1.471698    1.0  2001.0  9.784297e+08           53
1  0.000000    1.0  2001.0  9.782993e+08          129
2  0.000000    1.0  2001.0  9.782978e+08           51
3  0.000000    1.0  2001.0  9.782942e+08           21
4  6.000000   12.0  2000.0  9.782445e+08          198
```

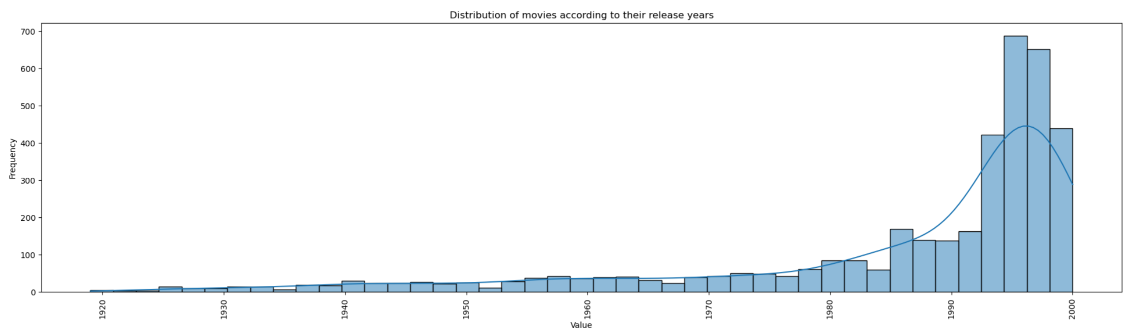
0.1.3 Possible plots:

- Movies release years histogram
- Movies and no. of genres histogram
- Ratings distribution
- Timestamp of rating time graph
- User zipcode mapping
- Occupation histogram for user
- User age histogram
- Gender histogram
- Age to rating correlation
- Age to movie year correlation
- Gender to rating correlation
- Gender to movie year correlation
- Gender + age to rating correlation

[25]:
```
# Movies release years histogram
import matplotlib.pyplot as plt
import seaborn as sns


def plot_hist(data, description, figsize = (24, 6)):
```

```
    # Create histogram
    plt.figure(figsize=figsize)
    # plt.hist(movies.release_year, edgecolor='black')
    sns.histplot(data, kde=True)

    # Add title and labels
    plt.title(description)
    plt.xlabel('Value')
    plt.ylabel('Frequency')
    # Rotate x-axis labels
    plt.xticks(rotation=90)


    # Show the plot
    plt.show()
```

[26]:
```
movies = movies.dropna()
movies.release_year = movies.release_year.astype(int)

# Movies release years histogram
plot_hist(np.sort(movies.release_year), "Distribution of movies according to␣
↪their release years")
```

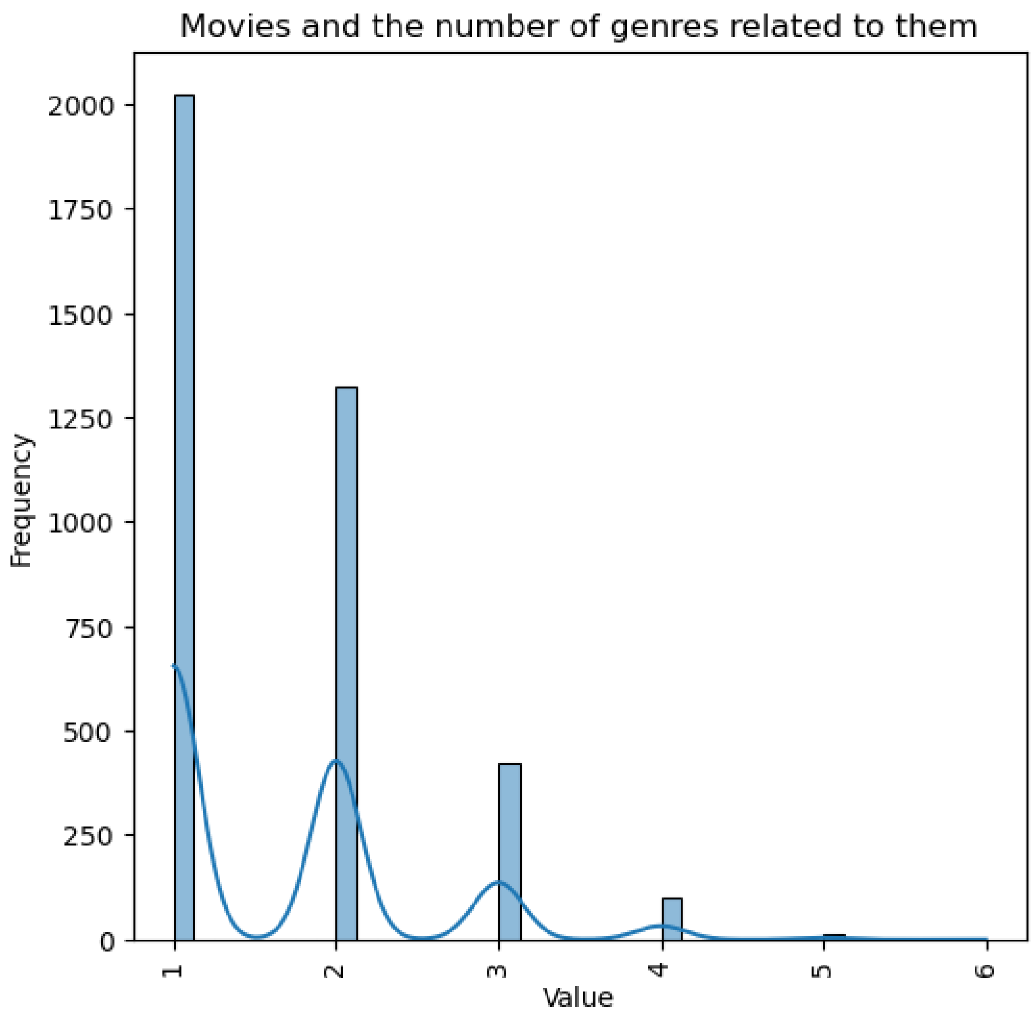


[27]:
```
users = df_users.copy()
```

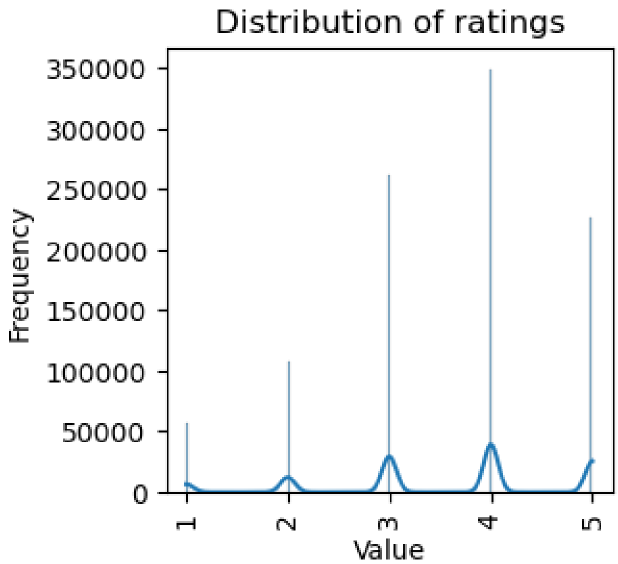
[28]:
```
genre_columns = ['Action', 'Adventure',
       'Animation', 'Children\'s', 'Comedy', 'Crime', 'Documentary', 'Drama',
       'Fantasy', 'Film-Noir', 'Horror', 'Musical', 'Mystery', 'Romance',
       'Sci-Fi', 'Thriller', 'War', 'Western']

def compute_total_genres(row):
    count = 0
    for column in genre_columns:
        count += row[column]
    return count
```

```
movies['genre_count'] = movies.apply(lambda row: compute_total_genres(row),␣
 ↪axis = 1)
```

[29]:
```
# Movies and no. of genres histogram
plot_hist(np.sort(movies.genre_count), "Movies and the number of genres related␣
 ↪to them", (6,6))
```

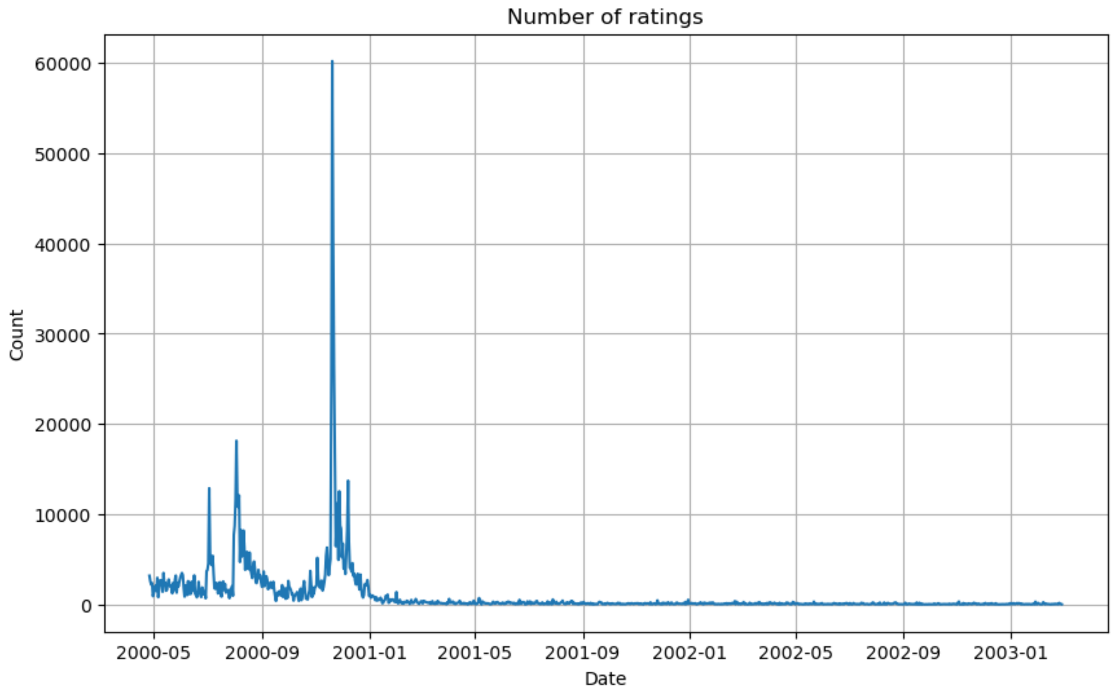


[30]:
```
# Ratings distribution
plot_hist(np.sort(ratings.Rating.astype(int)), "Distribution of ratings", (3,3))
```



[31]:

```
# Timestamp of rating time graph

import matplotlib.pyplot as plt
num_ratings_vs_date = ratings.groupby('date').Rating.count()

# Plotting the time series
plt.figure(figsize=(10, 6))
num_ratings_vs_date.plot()
plt.title('Number of ratings')
plt.xlabel('Date')
plt.ylabel('Count')
plt.grid(True)
plt.show()
```



[32]:
```
users.head()
```

[32]:

	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

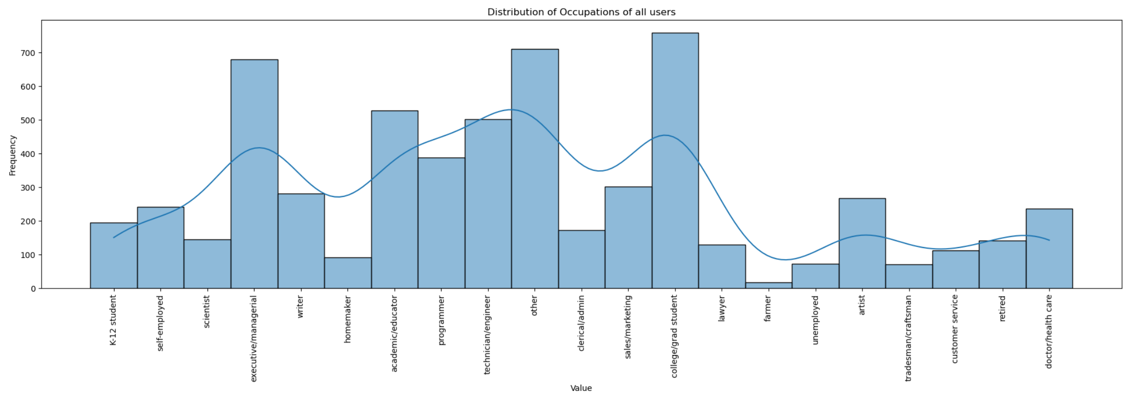
[33]:
```
# User zipcode mapping

# import folium
# from geopy.geocoders import Nominatim

# # Initialize geolocator
# geolocator = Nominatim(user_agent="geoapiExercises")

# # Function to get latitude and longitude from zip code
# def get_lat_lon(zip_code):
#     try:
#         location = geolocator.geocode(zip_code)
#         print(location.latitude, location.longitude)
#         return location.latitude, location.longitude
#     except:
```

```
#         print("This is not done")
#         return None, None

# # Apply the function to get coordinates
# users['lat_lon'] = users['Zip-code'].apply(get_lat_lon)
# users[['latitude', 'longitude']] = pd.DataFrame(users['lat_lon'].tolist(),␣
↪index=users.index)

# # Create a map centered around the mean latitude and longitude
# map_center = [users['latitude'].mean(), users['longitude'].mean()]
# mymap = folium.Map(location=map_center, zoom_start=5)

# # Add markers to the map
# for idx, row in users.iterrows():
#     folium.Marker(location=[row['latitude'], row['longitude']],␣
↪popup=row['Zip-code']).add_to(mymap)

# # Save the map to an HTML file
# mymap.save("map.html")
```

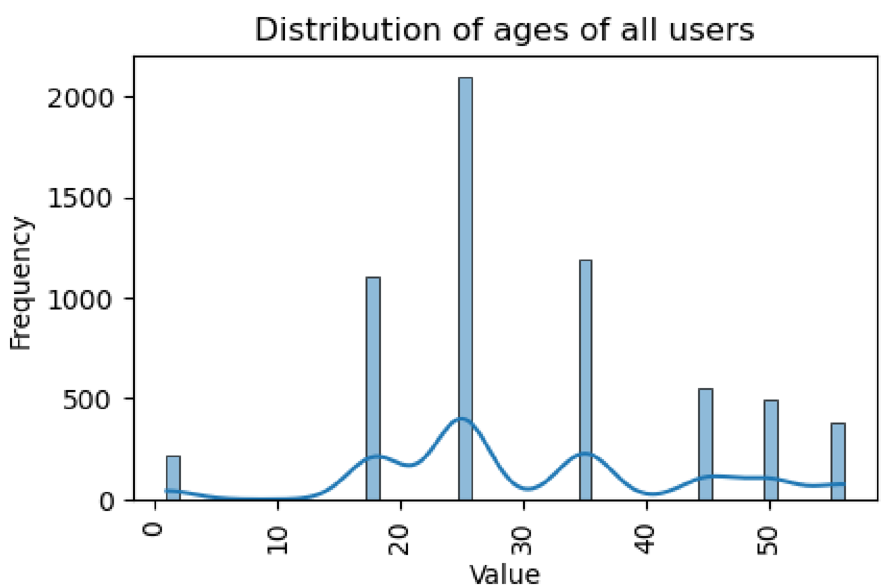
[34]:

```
# Occupation histogram for user

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

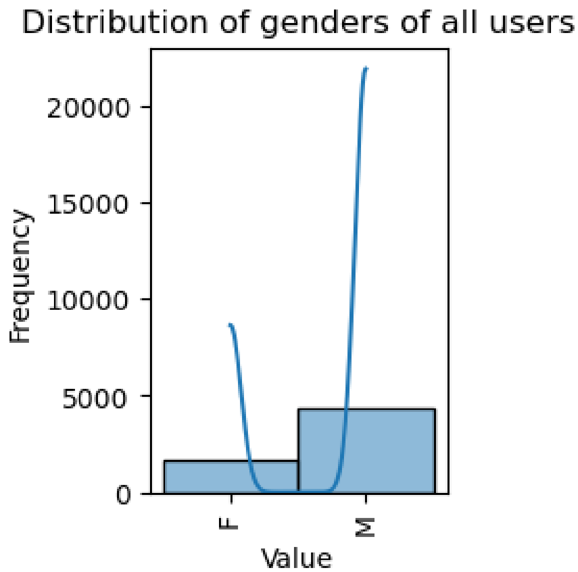
```
users['Occupation_name'] = users.Occupation.apply(lambda x: occupation_mapping[x])

plot_hist(users.Occupation_name, "Distribution of Occupations of all users")
```



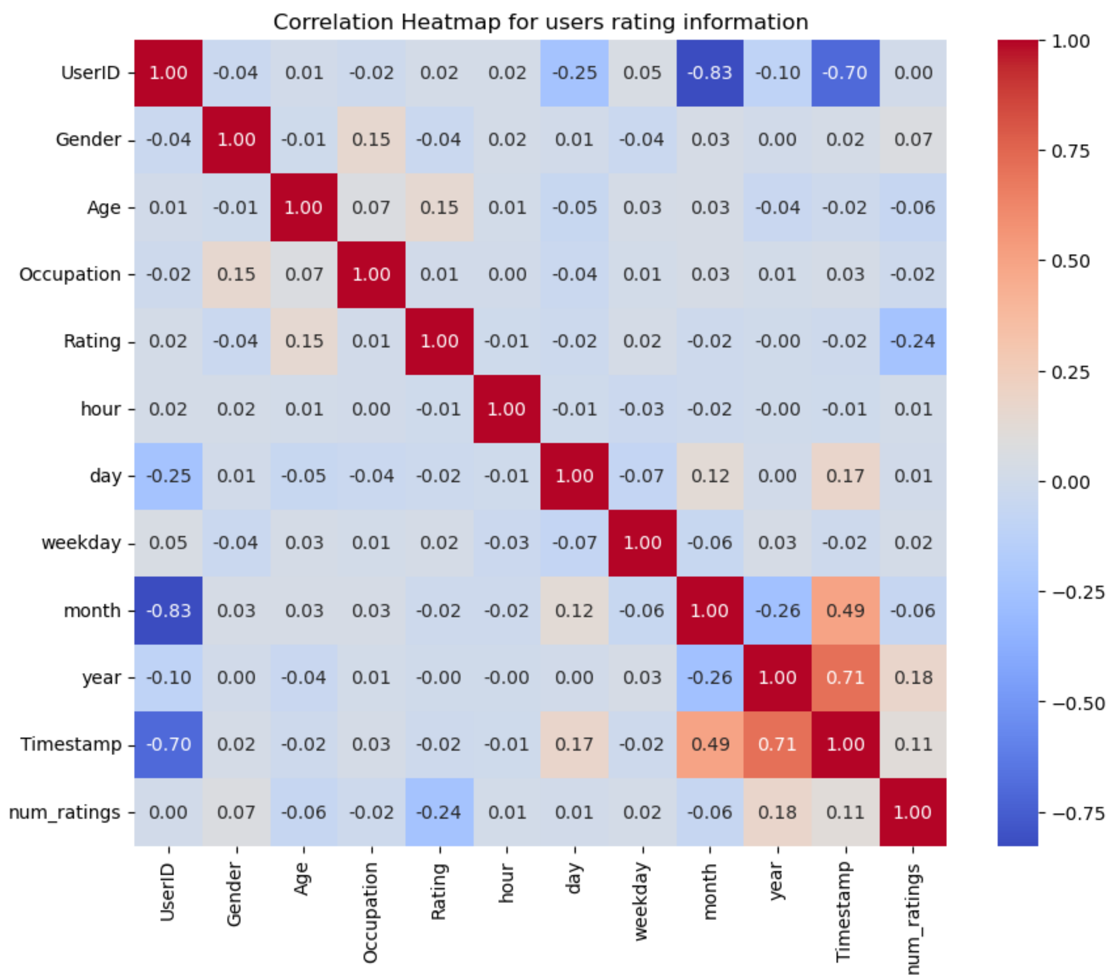
[35]:
```
plot_hist(users.Age, "Distribution of ages of all users", figsize=(5,3))
```



[36]:
```
plot_hist(users.Gender, "Distribution of genders of all users", figsize=(2,3))
```



[37]:
```
# correlation heatmap for user vs ratings info
def gender_to_num(genderName):
    if genderName == 'M':
        return 1
    else:
        return 0
users_ratings_stat['Gender'] = users_ratings_stat.Gender.apply(lambda x:␣
 ↪gender_to_num(x))
users_ratings_numeric = users_ratings_stat.select_dtypes(include=['int64',␣
 ↪'float64'])

corr = users_ratings_numeric.corr()

# Create the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, fmt=".2f", cmap='coolwarm', cbar=True)
plt.title('Correlation Heatmap for users rating information')
plt.show()
```



We can see that there is some correlation between Age and Rating and also between num_ratings and Rating. We should keep these columns while making our recommender system

0.1.4 Data analysis over

[38]:

```
users['num_ratings'] = users_ratings_stat.UserID.apply(lambda x:␣
↪user_rating_count_mapping[x])
users_movie_rating = ratings.merge(users, on='UserID')
users_movie_rating = users_movie_rating.merge(movies, left_on='MovieID',␣
↪right_on='Movie ID', how="inner")
users_movie_rating = users_movie_rating[['UserID', 'MovieID', 'Rating',␣
↪'movie_name',  'date', 'release_year', 'Action', 'Adventure',
       'Animation', 'Children\'s', 'Comedy', 'Crime', 'Documentary', 'Drama',
       'Fantasy', 'Film-Noir', 'Horror', 'Musical', 'Mystery', 'Romance',
       'Sci-Fi', 'Thriller', 'War', 'Western', 'num_ratings']]
users_movie_rating.rename(columns={'date': 'rating_date'}, inplace=True)
users_movie_rating.head()
```

[38]:
```
   UserID  MovieID  Rating                      movie_name rating_date  \
0       1     1193       5  One Flew Over the Cuckoo's Nest  2001-01-01
1       2     1193       5  One Flew Over the Cuckoo's Nest  2001-01-01
2      12     1193       4  One Flew Over the Cuckoo's Nest  2000-12-31
3      15     1193       4  One Flew Over the Cuckoo's Nest  2000-12-30
4      17     1193       5  One Flew Over the Cuckoo's Nest  2000-12-30

   release_year  Action  Adventure  Animation  Children's  …  Film-Noir  \
0          1975       0          0          0           0  …          0
1          1975       0          0          0           0  …          0
2          1975       0          0          0           0  …          0
3          1975       0          0          0           0  …          0
4          1975       0          0          0           0  …          0

   Horror  Musical  Mystery  Romance  Sci-Fi  Thriller  War  Western  \
0       0        0        0        0       0         0    0        0
1       0        0        0        0       0         0    0        0
2       0        0        0        0       0         0    0        0
3       0        0        0        0       0         0    0        0
4       0        0        0        0       0         0    0        0

   num_ratings
0           53
1          129
2           23
3          201
4          211

[5 rows x 25 columns]
```

0.1.5 Recommend using Pearson coefficient

[39]:
```python
from scipy.stats import pearsonr

def string_to_numeric_array(s):
    return np.array([ord(char) for char in s])

def top_correlated_movies(input_string, movie_list, top_n=5):
    input_numeric_array = string_to_numeric_array(input_string.lower())
    correlations = []

    for movie in movie_list:
        if(len(movie) > 2):
            shorter_movie_length = min(len(input_numeric_array), len(movie))
            movie_numeric_array = string_to_numeric_array(movie.lower())
            correlation, _ = pearsonr(input_numeric_array[0:
↪shorter_movie_length], movie_numeric_array[0:shorter_movie_length])
```

```python
            correlations.append((movie, correlation))

    # Sort correlations based on the absolute value of correlation coefficient␣
 ↪(higher is better)
    correlations.sort(key=lambda x: abs(x[1]), reverse=True)

    # Get the top n movies with highest correlations
    top_movies = correlations[:top_n]

    return top_movies

top_movies=[]
# Example input from user
user_input = input("Enter a movie name: ")
if(len(user_input) < 2):
    print("Input of length less that 2 is not accepted")
else:
    # Find top 5 movies with highest Pearson correlation coefficient
    top_movies = top_correlated_movies(user_input, list(movies.movie_name))

    # Print the results
    print(f"\nTop 5 movies most correlated with '{user_input}':")
    for i, (movie, correlation) in enumerate(top_movies, 1):
        print(f"{i}. {movie} (Correlation: {correlation:.2f})")
```

```
Enter a movie name: Toy Story

Top 5 movies most correlated with 'Toy Story':
1. Toy Story (Correlation: 1.00)
2. Toy Story 2 (Correlation: 1.00)
3. Kim (Correlation: 1.00)
4. Kika (Correlation: 0.99)
5. Man Facing Southeast (Hombre Mirando al Sudeste) (Correlation: 0.99)
```

0.1.6 Recommend using Cosine Similarity

[43]:

```python
from sklearn.metrics.pairwise import cosine_similarity

user_input = input("Enter a movie to check which are the most relevant movies␣
 ↪with it: ")

temp = movies[['Action', 'Adventure',
       'Animation', 'Children\'s', 'Comedy', 'Crime', 'Documentary', 'Drama',
       'Fantasy', 'Film-Noir', 'Horror', 'Musical', 'Mystery', 'Romance',
       'Sci-Fi', 'Thriller', 'War', 'Western']]

# Compute the cosine similarity matrix
```

```
movie_similarity_matrix = cosine_similarity(temp)

# Convert the matrix to a DataFrame for better readability
movie_similarity_matrix_df = pd.DataFrame(movie_similarity_matrix, index=movies.
↪movie_name, columns=movies.movie_name)
if user_input in (movie_similarity_matrix_df.index):
    results = movie_similarity_matrix_df.loc[user_input].
↪sort_values(ascending=False)[0:6]
    if(user_input in results.index):
        results.drop(user_input, inplace=True)


    # Print the results
    print(f"\nTop 5 movies most correlated with '{user_input}' according to␣
↪cosine similarity: ")
    for i in range(5):
        movie = results.index[i]
        correlation = results[i]
        print(f"{i+1}. {movie} (Correlation: {correlation:.2f})")
else:
    print("Movie not found in database. Please try with some other movie name.")
```

```
Enter a movie to check which are the most relevant movies with it: Toy Story

Top 5 movies most correlated with 'Toy Story' according to cosine similarity:
1. American Tail: Fievel Goes West, An (Correlation: 1.00)
2. Rugrats Movie, The (Correlation: 1.00)
3. Toy Story 2 (Correlation: 1.00)
4. Chicken Run (Correlation: 1.00)
5. Adventures of Rocky and Bullwinkle, The (Correlation: 1.00)
```

[44]:
```
movie_similarity_matrix_df.head()
```

[44]:
```
movie_name                    Toy Story   Jumanji  Grumpier Old Men  \
movie_name
Toy Story                      1.000000  0.333333          0.408248
Jumanji                        0.333333  1.000000          0.000000
Grumpier Old Men               0.408248  0.000000          1.000000
Waiting to Exhale              0.408248  0.000000          0.500000
Father of the Bride Part II    0.577350  0.000000          0.707107

movie_name                    Waiting to Exhale  Father of the Bride Part II  \
movie_name
Toy Story                              0.408248                     0.577350
Jumanji                                0.000000                     0.000000
Grumpier Old Men                       0.500000                     0.707107
Waiting to Exhale                      1.000000                     0.707107
```

```
Father of the Bride Part II          0.707107                     1.000000

movie_name                        Heat   Sabrina  Tom and Huck  Sudden Death  \
movie_name
Toy Story                          0.0  0.408248      0.408248           0.0
Jumanji                            0.0  0.000000      0.816497           0.0
Grumpier Old Men                   0.0  1.000000      0.000000           0.0
Waiting to Exhale                  0.0  0.500000      0.000000           0.0
Father of the Bride Part II        0.0  0.707107      0.000000           0.0

movie_name                        GoldenEye  …  Bamboozled   Bootmen  \
movie_name                                   …
Toy Story                          0.000000  …    0.577350  0.408248
Jumanji                            0.333333  …    0.000000  0.000000
Grumpier Old Men                   0.000000  …    0.707107  0.500000
Waiting to Exhale                  0.000000  …    0.707107  1.000000
Father of the Bride Part II        0.000000  …    1.000000  0.707107

movie_name                        Digimon: The Movie  Get Carter  Get Carter  \
movie_name
Toy Story                                   0.666667    0.000000         0.0
Jumanji                                     0.666667    0.000000         0.0
Grumpier Old Men                            0.000000    0.000000         0.0
Waiting to Exhale                           0.000000    0.408248         0.0
Father of the Bride Part II                 0.000000    0.000000         0.0

movie_name                        Meet the Parents  Requiem for a Dream  Tigerland  \
movie_name
Toy Story                                 0.577350             0.000000   0.000000
Jumanji                                   0.000000             0.000000   0.000000
Grumpier Old Men                          0.707107             0.000000   0.000000
Waiting to Exhale                         0.707107             0.707107   0.707107
Father of the Bride Part II               1.000000             0.000000   0.000000

movie_name                        Two Family House  Contender, The
movie_name
Toy Story                                 0.000000             0.0
Jumanji                                   0.000000             0.0
Grumpier Old Men                          0.000000             0.0
Waiting to Exhale                         0.707107             0.5
Father of the Bride Part II               0.000000             0.0

[5 rows x 3882 columns]
```

[45]:

```
users['Gender_numeric'] = users.Gender.apply(lambda x: gender_to_num(x))
temp = users[['Gender_numeric', 'Age', 'Occupation', 'num_ratings']]
```

```python
# Compute the cosine similarity matrix
user_similarity_matrix = cosine_similarity(temp)

user_similarity_matrix_df = pd.DataFrame(user_similarity_matrix, index=users.
 ↪UserID, columns=users.UserID)

user_similarity_matrix_df.head()
```

[45]:
```
UserID      1         2         3         4         5         6         7     \
UserID
1       1.000000  0.923727  0.908048  0.453834  0.990679  0.828739  0.668963
2       0.923727  1.000000  0.988445  0.752428  0.960317  0.979433  0.902616
3       0.908048  0.988445  1.000000  0.781114  0.935468  0.975935  0.899476
4       0.453834  0.752428  0.781114  1.000000  0.539125  0.868662  0.952147
5       0.990679  0.960317  0.935468  0.539125  1.000000  0.884476  0.749728

UserID      8         9         10    …     6031      6032      6033  \
UserID                                …
1       0.982445  0.977570  0.980841  …  0.932651  0.918728  0.786609
2       0.973160  0.983634  0.942621  …  0.991113  0.998667  0.959070
3       0.948017  0.970738  0.902372  …  0.960161  0.979641  0.968550
4       0.580749  0.627759  0.495429  …  0.693379  0.747841  0.906890
5       0.998525  0.992962  0.994510  …  0.972371  0.959825  0.843149

UserID      6034      6035      6036      6037      6038      6039      6040
UserID
1       0.666627  0.980902  0.985615  0.963900  0.350974  0.929051  0.984316
2       0.861595  0.943364  0.923944  0.976151  0.680934  0.991846  0.939738
3       0.913300  0.903334  0.883846  0.941006  0.696861  0.961383  0.901206
4       0.934022  0.497281  0.446037  0.604387  0.987887  0.701414  0.485568
5       0.710423  0.994688  0.991825  0.991119  0.451014  0.969895  0.995244

[5 rows x 6040 columns]
```

0.1.7 Recommend using KNN and Cosine Similarity sklearn

[46]:
```python
dataset = pd.merge(ratings, movies, left_on='MovieID', right_on='Movie ID')
```

[47]:
```python
dataset = dataset[['UserID', 'movie_name', 'Rating']]
dataset.head()
```

[47]:
```
   UserID                      movie_name  Rating
0       1  One Flew Over the Cuckoo's Nest       5
1       2  One Flew Over the Cuckoo's Nest       5
2      12  One Flew Over the Cuckoo's Nest       4
3      15  One Flew Over the Cuckoo's Nest       4
4      17  One Flew Over the Cuckoo's Nest       5
```

[48]:
```
table = dataset.pivot_table(index='movie_name', columns='UserID',␣
↪values='Rating')
```

[49]:
```
table = table.fillna(0)
table.head()
```

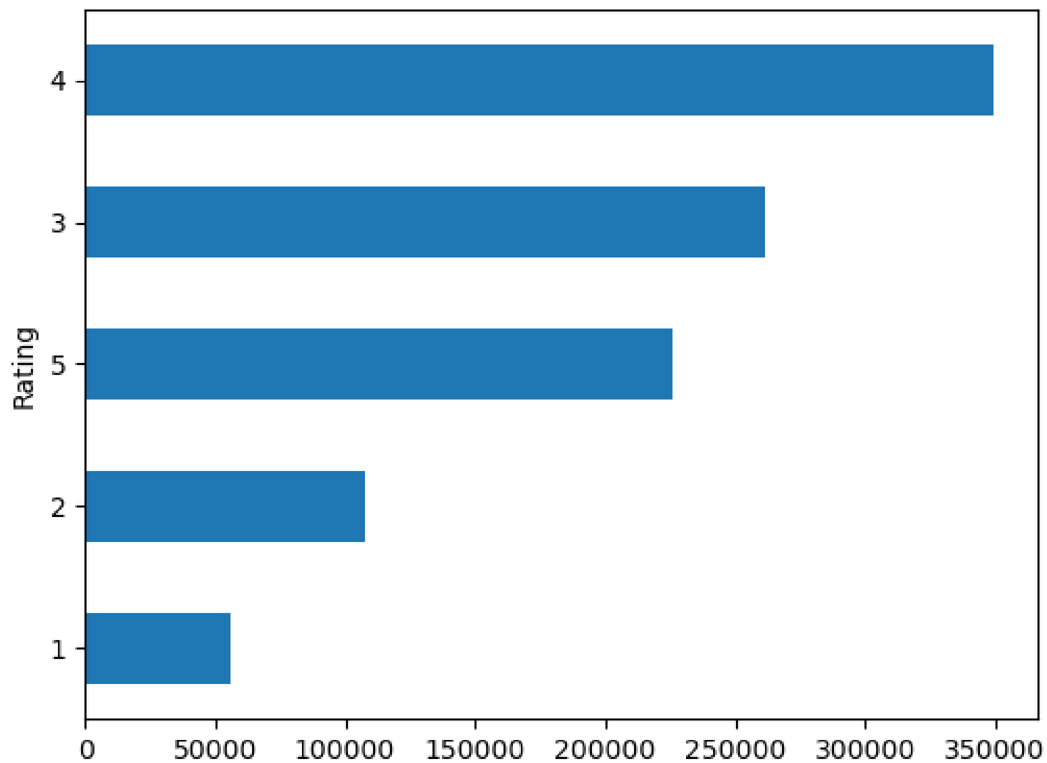
[49]:
```
UserID                  1     2     3     4     5     6     7     8     9     \
movie_name
$1,000,000 Duck          0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
'Night Mother            0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
'Til There Was You       0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
'burbs, The              0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
…And Justice for All   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0

UserID                  10    …  6031  6032  6033  6034  6035  6036  6037  \
movie_name                    …
$1,000,000 Duck          0.0  …   0.0   0.0   0.0   0.0   0.0   0.0   0.0
'Night Mother            0.0  …   0.0   0.0   0.0   0.0   0.0   3.0   0.0
'Til There Was You       0.0  …   0.0   0.0   0.0   0.0   0.0   0.0   0.0
'burbs, The              4.0  …   0.0   0.0   0.0   0.0   0.0   0.0   0.0
…And Justice for All   0.0  …   0.0   0.0   0.0   0.0   0.0   0.0   0.0

UserID                  6038  6039  6040
movie_name
$1,000,000 Duck          0.0   0.0   0.0
'Night Mother            0.0   0.0   0.0
'Til There Was You       0.0   0.0   0.0
'burbs, The              0.0   0.0   0.0
…And Justice for All   0.0   0.0   0.0

[5 rows x 6040 columns]
```

[50]:
```
table.loc['Toy Story', :].values.reshape(1, -1)
```

[50]:
```
array([[5., 0., 0., …, 0., 0., 3.]])
```

[51]:
```
dataset.Rating.value_counts().sort_values().plot(kind='barh')
```

[51]:
```
<Axes: ylabel='Rating'>
```



[52]:
```
table.values
```

[52]:
```
array([[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., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.]])
```

[53]:
```
from scipy.sparse import csr_matrix

matrix = csr_matrix(table.values)
```

[54]:
```
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.neighbors import NearestNeighbors

knn = NearestNeighbors(metric= 'cosine', algorithm= 'brute')
knn.fit(matrix)
```

[54]:
```
NearestNeighbors(algorithm='brute', metric='cosine')
```

[55]:
```python
user_query_index = np.random.choice(table.shape[1])
user_query_index
```

[55]: 212

[56]:
```python
table.index[user_query_index]
```

[56]: 'Artemisia'

[57]:
```python
table.iloc[user_query_index, :]
```

[57]:
```
UserID
1       0.0
2       0.0
3       0.0
4       0.0
5       0.0
       …
6036    0.0
6037    0.0
6038    0.0
6039    0.0
6040    0.0
Name: Artemisia, Length: 6040, dtype: float64
```

[58]:
```python
input_data = table.iloc[user_query_index, :].values.reshape(1, -1)
distances, indices = knn.kneighbors(input_data, n_neighbors = 6)
```

Generating recommendation using KNN for the selected movie

[59]:
```python
for i in range(0, len(distances.flatten())):
    # the below line will be printed anyway
    # we always start i = 0
    # just getting the variable i ready to print for which book we are
    # generating the recommendation for:
    if i == 0:
        print('Recommendation for {0}:\n'.format(table.index[user_query_index]))
    else:
        print('{0}: {1}, with distance of {2}:'.format(i, table.index[indices.
 ↪flatten()[i]], distances.flatten()[i]))
```

```
Recommendation for Artemisia:

1: Conceiving Ada, with distance of 0.6776175236255572:
2: Live Flesh, with distance of 0.7217993936103348:
3: Modern Affair, A, with distance of 0.7321808008165558:
4: School of Flesh, The (L' École de la chair), with distance of
0.7606827894347603:
5: Bloody Child, The, with distance of 0.7673789474003823:
```

0.1.8 Recommend using matrix factorization

Using cmfrec library Collective matrix factorisation for recommender systems Documentation: https://cmfrec.readthedocs.io/en/latest/

- cmfrec library requires input in the form of dataframe not as sparse matrix.
- It required 3 columns UserId, ItemId, Rating.
- An instance of the CMF model is created with various hyperparameters:
- method="als": Specifies the alternating least squares (ALS) optimization method, commonly used for matrix factorization in recommendation systems.
- k=2: Sets the number of latent factors to 2, determining the dimensionality of the latent factor space.
- lambda_=0.1: Sets the regularization strength to 0.1. Regularization is used to prevent overfitting in the model.
- user_bias=False: Indicates that user bias terms are not included in the model. User bias represents a user's overall rating tendency.
- item_bias=False: Excludes item bias terms in the model. Item bias represents an item's overall rating tendency.
- verbose=False: Suppresses verbose output, controlling whether the model's training progress is displayed.

[60]:
```
rm_raw = ratings[['UserID', 'MovieID', 'Rating']].copy()
rm_raw.columns = ['UserId', 'ItemId', 'Rating']  # Lib requires specific column␣
↪names
rm_raw.head()
```

[60]:

	UserId	ItemId	Rating
0	1	1193	5
1	1	661	3
2	1	914	3
3	1	3408	4
4	1	2355	5

[63]:
```
!pip install cmfrec
```

```
Collecting cmfrec
  Using cached cmfrec-3.5.1.post10-cp311-cp311-macosx_14_0_arm64.whl
Collecting cython (from cmfrec)
  Obtaining dependency information for cython from https://files.pythonhosted.or
g/packages/b6/83/b0a63fc7b315edd46821a1a381d18765c1353d201246da44558175cddd56/Cy
thon-3.0.10-py2.py3-none-any.whl.metadata
  Downloading Cython-3.0.10-py2.py3-none-any.whl.metadata (3.2 kB)
Collecting numpy>=1.25 (from cmfrec)
  Obtaining dependency information for numpy>=1.25 from https://files.pythonhost
ed.org/packages/01/4a/611a907421d8098d5edc8c2b10c3583796ee8da4156f8f7de52c2f4c9d
```

```
90/numpy-2.0.0-cp311-cp311-macosx_14_0_arm64.whl.metadata
  Downloading numpy-2.0.0-cp311-cp311-macosx_14_0_arm64.whl.metadata (60 kB)
                             60.9/60.9 kB
1.5 MB/s eta 0:00:00a 0:00:01
Requirement already satisfied: scipy in
/Users/vaibhavmotwani/anaconda3/lib/python3.11/site-packages (from cmfrec)
(1.11.1)
Requirement already satisfied: pandas in
/Users/vaibhavmotwani/anaconda3/lib/python3.11/site-packages (from cmfrec)
(2.0.3)
Collecting findblas (from cmfrec)
  Using cached findblas-0.1.26.post1-py3-none-any.whl
Requirement already satisfied: python-dateutil>=2.8.2 in
/Users/vaibhavmotwani/anaconda3/lib/python3.11/site-packages (from
pandas->cmfrec) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/Users/vaibhavmotwani/anaconda3/lib/python3.11/site-packages (from
pandas->cmfrec) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in
/Users/vaibhavmotwani/anaconda3/lib/python3.11/site-packages (from
pandas->cmfrec) (2023.3)
Collecting numpy>=1.25 (from cmfrec)
  Obtaining dependency information for numpy>=1.25 from https://files.pythonhost
ed.org/packages/1a/2e/151484f49fd03944c4a3ad9c418ed193cfd02724e138ac8a9505d056c5
82/numpy-1.26.4-cp311-cp311-macosx_11_0_arm64.whl.metadata
  Downloading numpy-1.26.4-cp311-cp311-macosx_11_0_arm64.whl.metadata (114 kB)
                            114.8/114.8

kB 3.7 MB/s eta 0:00:00
Requirement already satisfied: six>=1.5 in
/Users/vaibhavmotwani/anaconda3/lib/python3.11/site-packages (from python-
dateutil>=2.8.2->pandas->cmfrec) (1.16.0)
Downloading Cython-3.0.10-py2.py3-none-any.whl (1.2 MB)
                         1.2/1.2 MB
5.4 MB/s eta 0:00:0000:0100:01m
Downloading numpy-1.26.4-cp311-cp311-macosx_11_0_arm64.whl (14.0 MB)
                         14.0/14.0 MB
3.6 MB/s eta 0:00:0000:0100:01
Installing collected packages: findblas, numpy, cython, cmfrec
  Attempting uninstall: numpy
    Found existing installation: numpy 1.24.3
    Uninstalling numpy-1.24.3:
      Successfully uninstalled numpy-1.24.3
```

```
ERROR: pip's dependency resolver does not currently take into account all
the packages that are installed. This behaviour is the source of the following
dependency conflicts.
tables 3.8.0 requires blosc2~=2.0.0, which is not installed.
gensim 4.3.0 requires FuzzyTM>=0.4.0, which is not installed.
numba 0.57.1 requires numpy<1.25,>=1.21, but you have numpy 1.26.4 which is
incompatible.
Successfully installed cmfrec-3.5.1.post10 cython-3.0.10
findblas-0.1.26.post1 numpy-1.26.4
```

[64]:
```
from cmfrec import CMF
import time

model = CMF(method="als", k=2, lambda_=0.1, user_bias=False, item_bias=False,␣
 ↪verbose=False)

start = time.time()
model.fit(rm_raw)
end = time.time()
print(f"Time Elapsed in trainig: {end-start}")
```

```
Time Elapsed in trainig: 1.2690629959106445
```

[65]:
```
model.A_.shape, model.B_.shape
```

[65]:
```
((6040, 2), (3706, 2))
```

[66]:
```
rm_raw.Rating.mean(), model.glob_mean_
```

[66]:
```
(3.581564453029317, 3.581564426422119)
```

[67]:
```
rm = ratings.pivot(index = 'UserID', columns ='MovieID', values = 'Rating').
 ↪fillna(0)
rm.head()
```

[67]:
```
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]
```

[68]:
```
from sklearn.metrics import mean_squared_error as mse
rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_
print("MSE for the above model: " + str(mse(rm.values[rm > 0], rm__[rm > 0])**0.
 ↪5))
```

```
MSE for the above model: 1.3043536493177685
```

[69]:
```
from sklearn.metrics import mean_absolute_percentage_error as mape
rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_
print("MAPE for the above model: " + str(mape(rm.values[rm > 0], rm__[rm >␣
 ↪0])**0.5))
```

```
MAPE for the above model: 0.6136484117493751
```

[70]:
```
movies.head()
```

[70]:
```
Genres  Movie ID                     movie_name  release_year  Action  \
0              1                      Toy Story          1995       0
1              2                        Jumanji          1995       0
2              3               Grumpier Old Men          1995       0
3              4              Waiting to Exhale          1995       0
4              5   Father of the Bride Part II          1995       0

Genres  Adventure  Animation  Children's  Comedy  Crime  Documentary  …  \
0               0          1           1       1      0            0  …
1               1          0           1       0      0            0  …
2               0          0           0       1      0            0  …
3               0          0           0       1      0            0  …
4               0          0           0       1      0            0  …

Genres  Film-Noir  Horror  Musical  Mystery  Romance  Sci-Fi  Thriller  War  \
0               0       0        0        0        0       0         0    0
1               0       0        0        0        0       0         0    0
2               0       0        0        0        1       0         0    0
3               0       0        0        0        0       0         0    0
4               0       0        0        0        0       0         0    0

Genres  Western  genre_count
0             0            3
1             0            3
```

```
2               0               2
3               0               2
4               0               1

[5 rows x 22 columns]
```

[71]:
```python
# n: no of items to recommend
top_items = model.topN(user=10, n=10)
movies.loc[movies["Movie ID"].isin(top_items)]
```

[71]:
```
Genres  Movie ID                                          movie_name  \
638          643                        Peanuts - Die Bank zahlt alles
883          895                                         Venice/Venice
1397        1421                                         Grateful Dead
2469        2538                                            Dancemaker
2754        2823  Spiders, The (Die Spinnen, 1. Teil: Der Golden…
2842        2911                           Grandfather, The (El Abuelo)
3311        3380                                           Railroaded!
3462        3531                              All the Vermeers in New York
3748        3818                                             Pot O' Gold
3822        3892                                    Anatomy (Anatomie)

Genres  release_year  Action  Adventure  Animation  Children's  Comedy  Crime  \
638             1996       0          0          0           0       1      0
883             1992       0          0          0           0       0      0
1397            1995       0          0          0           0       0      0
2469            1998       0          0          0           0       0      0
2754            1919       1          0          0           0       0      0
2842            1998       0          0          0           0       0      0
3311            1947       0          0          0           0       0      0
3462            1990       0          0          0           0       1      0
3748            1941       0          0          0           0       1      0
3822            2000       0          0          0           0       0      0

Genres  Documentary  …  Film-Noir  Horror  Musical  Mystery  Romance  \
638               0  …          0       0        0        0        0
883               0  …          0       0        0        0        0
1397              1  …          0       0        0        0        0
2469              1  …          0       0        0        0        0
2754              0  …          0       0        0        0        0
2842              0  …          0       0        0        0        0
3311              0  …          1       0        0        0        0
3462              0  …          0       0        0        0        1
3748              0  …          0       0        1        0        0
3822              0  …          0       1        0        0        0

Genres  Sci-Fi  Thriller  War  Western  genre_count
```

638	0	0	0	0	1
883	0	0	0	0	1
1397	0	0	0	0	1
2469	0	0	0	0	1
2754	0	0	0	0	2
2842	0	0	0	0	1
3311	0	0	0	0	1
3462	0	0	0	0	3
3748	0	0	0	0	2
3822	0	0	0	0	1

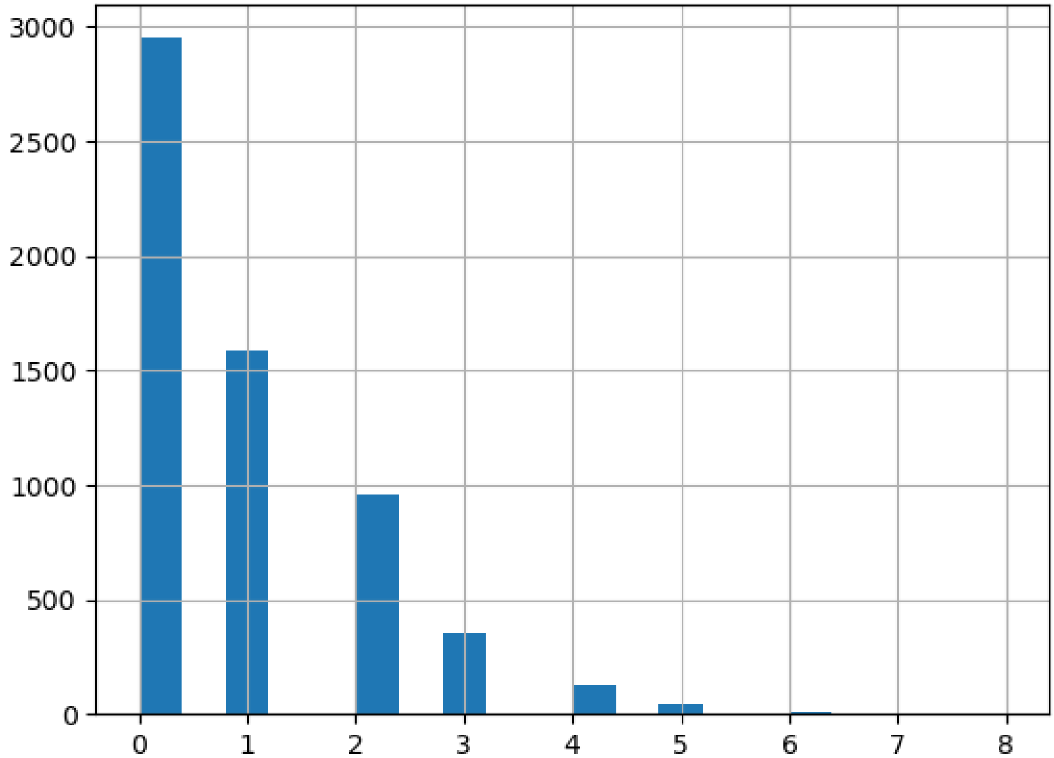
[10 rows x 22 columns]

Calculating Average OverLap

[72]:
```
overlap= []
num_rec = []
n = 20
for user in ratings.UserID.unique():
    top_items = model.topN(user=user, n=n)
    user_movies = ratings.loc[(ratings.UserID==user)].MovieID
    valid_rec = set(top_items).intersection(set(user_movies)) # I can only␣
 ↪measure by what was in the training data

    _ = len(set(ratings.loc[ratings.UserID==user].sort_values(by='Rating',␣
 ↪ascending=False).head(n).MovieID).intersection(set(valid_rec)))
    overlap.append(_)
    num_rec.append(len(valid_rec))

print('avg_perc_overlap:', np.array(overlap).mean() / np.array(num_rec).mean())
pd.Series(overlap).hist(bins=20)
```

```
avg_perc_overlap: 0.3445217280326718
```

[72]: <Axes: >



K-precision

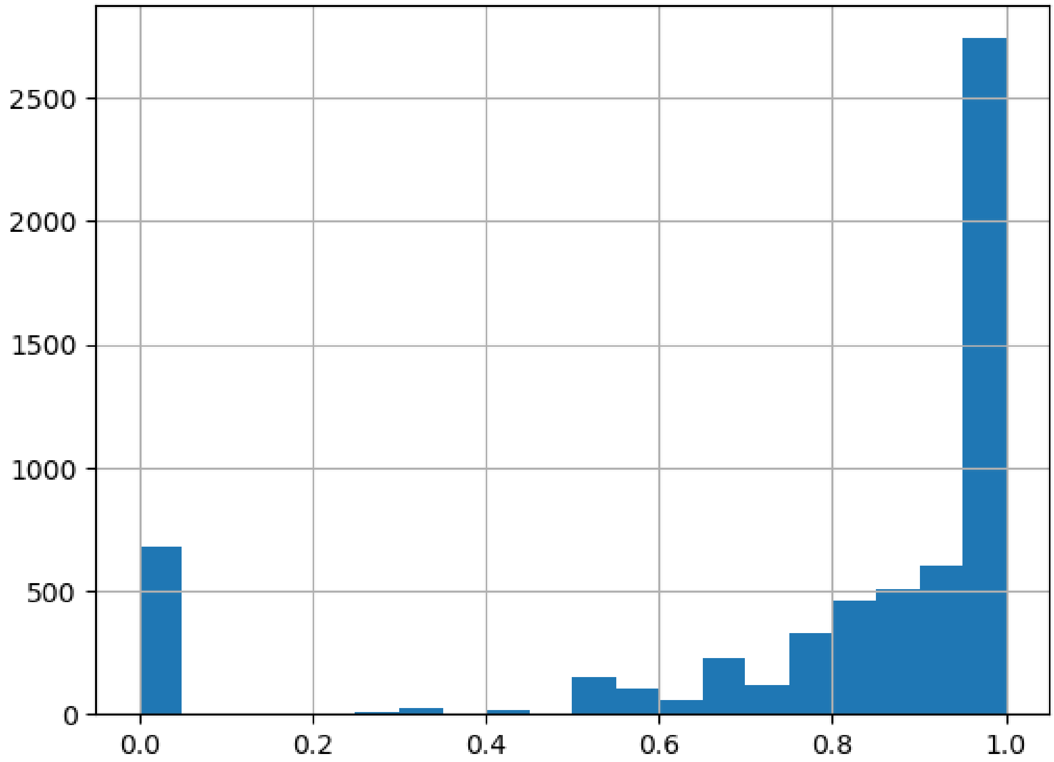
Out of K predictions, how many of those K were relevant?

[73]:
```
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)
```

avg: 0.7941254267523916

[73]: <Axes: >



Item-Item and User-User similarity matrix using MF embeddings with d = 4

[74]:
```
model = CMF(method="als", k=4, lambda_=0.1, user_bias=False, item_bias=False,␣
↪verbose=False)

model.fit(rm_raw)

print(model.A_.shape, model.B_.shape)
```

(6040, 4) (3706, 4)

[75]:
```
embedded_users_array = model.A_
embedded_users_df = pd.DataFrame(embedded_users_array)
embedded_users_df['UserID'] = embedded_users_df.index + 1
embedded_users_df.head()
```

[75]:
```
          0         1         2         3  UserID
0 -0.127591 -0.152649  0.073956  0.014985       1
1 -0.166674 -0.115769 -0.262104 -0.270889       2
2 -0.119248  0.011038 -0.332830  0.127275       3
3  0.263413 -0.338235 -0.211824 -0.356052       4
4  0.439278  0.028768 -0.210001 -0.103933       5
```

[76]:
```
embedded_movies_array = model.B_
embedded_movies_df = pd.DataFrame(embedded_movies_array)
embedded_movies_df['MovieID'] = embedded_movies_df.index + 1
embedded_movies_df = embedded_movies_df.merge(movies, left_on='MovieID',␣
↪right_on='Movie ID', how="inner")
embedded_movies_df = embedded_movies_df[['MovieID',   'movie_name', 0, 1, 2, 3]]
embedded_movies_df.head()
```

[76]:
```
   MovieID                   movie_name         0         1         2  \
0        1                    Toy Story  0.681755 -4.451891 -1.456907
1        2                      Jumanji  0.305415 -1.293005  2.252264
2        3             Grumpier Old Men -1.629499 -3.767879  0.057835
3        4            Waiting to Exhale -2.297714 -2.023359 -0.242263
4        5  Father of the Bride Part II -1.275383 -2.542525  0.067054

          3
0  0.623703
1  0.792580
2 -1.566576
3 -0.194461
4  0.132657
```

[77]:
```
temp = embedded_movies_df[[0, 1, 2, 3]]

# Compute the cosine similarity matrix
movie_similarity_matrix = cosine_similarity(temp)

# Convert the matrix to a DataFrame for better readability
movie_similarity_matrix_df = pd.DataFrame(movie_similarity_matrix,␣
↪index=embedded_movies_df.movie_name, columns=embedded_movies_df.movie_name)

movie_similarity_matrix_df.head()
```

[77]:
```
movie_name                   Toy Story   Jumanji  Grumpier Old Men  \
movie_name
Toy Story                     1.000000  0.243567          0.695979
Jumanji                       0.243567  1.000000          0.271746
Grumpier Old Men              0.695979  0.271746          1.000000
Waiting to Exhale             0.522231  0.144460          0.862147
Father of the Bride Part II   0.767282  0.405268          0.915132
```

```
movie_name                  Waiting to Exhale  Father of the Bride Part II  \
movie_name
Toy Story                            0.522231                     0.767282
Jumanji                              0.144460                     0.405268
Grumpier Old Men                     0.862147                     0.915132
Waiting to Exhale                    1.000000                     0.916435
Father of the Bride Part II          0.916435                     1.000000

movie_name                      Heat   Sabrina  Tom and Huck  Sudden Death  \
movie_name
Toy Story                   0.948973  0.807188      0.969814      0.588493
Jumanji                     0.126584  0.124824      0.213427      0.468337
Grumpier Old Men            0.758269  0.914218      0.798084      0.954136
Waiting to Exhale           0.724711  0.917738      0.710791      0.734096
Father of the Bride Part II  0.864234  0.953834      0.882289      0.833508

movie_name                  GoldenEye  …  Predator 2  Running Man, The  \
movie_name                             …
Toy Story                    0.849512  …    0.187683         -0.187683
Jumanji                      0.284281  …    0.787033         -0.787033
Grumpier Old Men             0.962745  …    0.644434         -0.644434
Waiting to Exhale            0.752316  …    0.493285         -0.493285
Father of the Bride Part II   0.893178  …    0.592788         -0.592788

movie_name                   Starman  Brother from Another Planet, The  \
movie_name
Toy Story                   0.068096                         -0.342019
Jumanji                     0.824836                          0.703748
Grumpier Old Men           -0.130242                          0.183969
Waiting to Exhale          -0.015271                          0.171955
Father of the Bride Part II  0.183414                          0.161865

movie_name                  Alien Nation   Mad Max  \
movie_name
Toy Story                       0.401123  0.942487
Jumanji                         0.551256  0.240298
Grumpier Old Men                0.815102  0.499973
Waiting to Exhale               0.507551  0.215608
Father of the Bride Part II      0.630446  0.532296

movie_name                  Mad Max 2 (a.k.a. The Road Warrior)  \
movie_name
Toy Story                                             -0.882572
Jumanji                                               -0.051833
Grumpier Old Men                                      -0.856117
Waiting to Exhale                                     -0.832180
```

```
Father of the Bride Part II                            -0.902946

movie_name                   Mad Max Beyond Thunderdome  Bird on a Wire  \
movie_name
Toy Story                                     -0.130158        0.194384
Jumanji                                        0.393247       -0.520400
Grumpier Old Men                               0.291255        0.569964
Waiting to Exhale                             -0.097018        0.756488
Father of the Bride Part II                   -0.010381        0.487669

movie_name                   Angel Heart
movie_name
Toy Story                       0.875937
Jumanji                         0.226801
Grumpier Old Men                0.298411
Waiting to Exhale               0.053800
Father of the Bride Part II     0.389199

[5 rows x 3637 columns]
```

[78]:

```python
temp = embedded_users_df[[0, 1, 2, 3]]

# Compute the cosine similarity matrix
user_similarity_matrix = cosine_similarity(temp)

# Convert the matrix to a DataFrame for better readability
user_similarity_matrix_df = pd.DataFrame(user_similarity_matrix,
 ↪index=embedded_users_df.UserID, columns=embedded_users_df.UserID)

user_similarity_matrix_df.head()
```

[78]:

```
UserID       1         2         3         4         5         6         7    \
UserID
1       1.000000  0.170103 -0.114736 -0.023483 -0.730620  0.198021  0.706207
2       0.170103  1.000000  0.443404  0.576851  0.031150  0.898441 -0.010590
3      -0.114736  0.443404  1.000000 -0.044441  0.024544  0.189157  0.391775
4      -0.023483  0.576851 -0.044441  1.000000  0.630551  0.330476 -0.083172
5      -0.730620  0.031150  0.024544  0.630551  1.000000 -0.211846 -0.415672

UserID       8         9         10   …      6031      6032      6033  \
UserID                                …
1       0.302334 -0.263075  0.956633  … -0.087113 -0.199153  0.235181
2      -0.154776  0.357164  0.427887  …  0.716629  0.190380  0.967050
3       0.455016  0.822323  0.058423  …  0.701142 -0.132900  0.555875
4       0.082339  0.381510  0.046103  … -0.090641  0.899136  0.357558
5       0.059542  0.502422 -0.728975  … -0.226129  0.812116 -0.166764
```

```
UserID      6034      6035      6036      6037      6038      6039      6040
UserID
1      -0.490261 -0.385200 -0.309235 -0.260994  0.150330  0.075981 -0.508371
2      -0.398616  0.475633  0.297296  0.676744  0.820793  0.827002  0.249295
3      -0.192374  0.514526 -0.029510  0.297888 -0.071948  0.422620 -0.025062
4       0.440751  0.745867  0.918480  0.917035  0.859293  0.865973  0.847021
5       0.844038  0.784255  0.866427  0.722518  0.276507  0.426876  0.946257

[5 rows x 6040 columns]
```

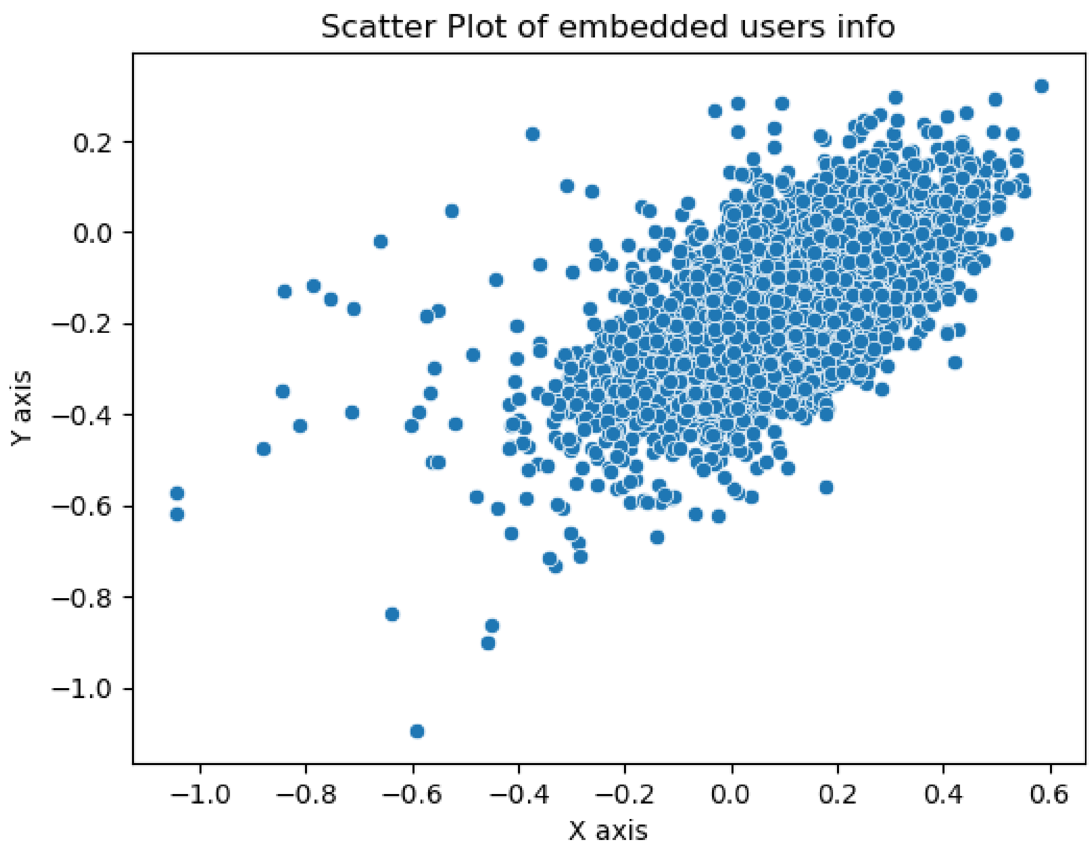
Get d=2 embeddings, and plot the results. Write down your analysis from this visualisation. (Compare with other visualization techniques)

[80]:
```
# Modelling MF embedding with d = 2
model = CMF(method="als", k=2, lambda_=0.1, user_bias=False, item_bias=False,␣
 ↪verbose=False)
model.fit(rm_raw)
print(model.A_.shape, model.B_.shape)

# Computing embedded users array
embedded_users_array = model.A_
embedded_users_df = pd.DataFrame(embedded_users_array)
embedded_users_df['UserID'] = embedded_users_df.index + 1

# Computing movies users array
embedded_movies_array = model.B_
embedded_movies_df = pd.DataFrame(embedded_movies_array)
embedded_movies_df['MovieID'] = embedded_movies_df.index + 1
embedded_movies_df = embedded_movies_df.merge(movies, left_on='MovieID',␣
 ↪right_on='Movie ID', how="inner")
embedded_movies_df = embedded_movies_df[['MovieID',   'movie_name', 0, 1]]

# Computing cosine similarity for movies array
temp = embedded_movies_df[[0, 1]]
movie_similarity_matrix = cosine_similarity(temp)
movie_similarity_matrix_df = pd.DataFrame(movie_similarity_matrix,␣
 ↪index=embedded_movies_df.movie_name, columns=embedded_movies_df.movie_name)

# Computing cosine similarity for users array
temp = embedded_users_df[[0, 1]]
user_similarity_matrix = cosine_similarity(temp)
user_similarity_matrix_df = pd.DataFrame(user_similarity_matrix,␣
 ↪index=embedded_users_df.UserID, columns=embedded_users_df.UserID)
```

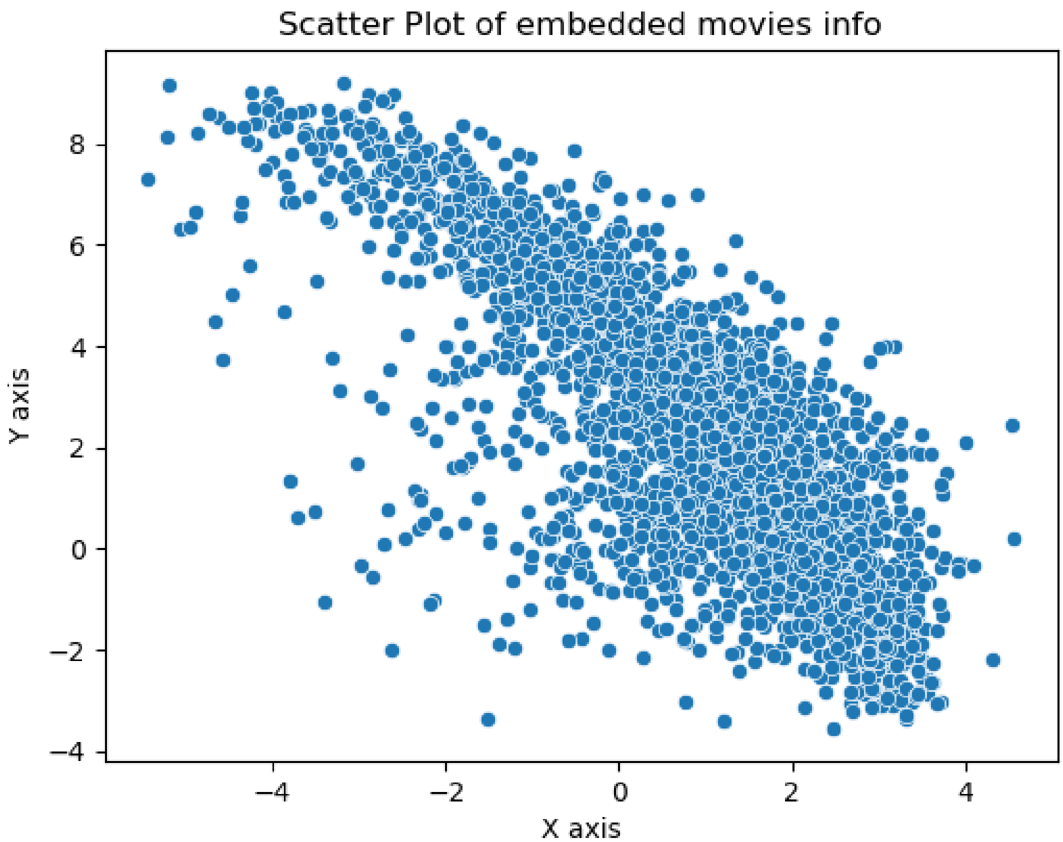
```
(6040, 2) (3706, 2)
```

[81]:
```
sns.scatterplot(x=embedded_users_df[0], y=embedded_users_df[1])
```

```
# Adding labels and title
plt.xlabel('X axis')
plt.ylabel('Y axis')
plt.title('Scatter Plot of embedded users info')

# Show plot
plt.show()
```



[82]:
```
sns.scatterplot(x=embedded_movies_df[0], y=embedded_movies_df[1])

# Adding labels and title
plt.xlabel('X axis')
plt.ylabel('Y axis')
plt.title('Scatter Plot of embedded movies info')

# Show plot
plt.show()
```



[83]:

```
def get_decade(year):
    # Ensure the input is an integer
    try:
        year = int(year)
    except ValueError:
        return "Invalid input. Please enter a valid year."

    # Calculate the decade
    decade = (year // 10) * 10
    return decade - 1900

movies['decade'] = movies['release_year'].apply(lambda x: get_decade(x))
movies.groupby('decade').decade.value_counts().sort_values(ascending=False)
```

[83]:

```
decade
90      2283
80       597
70       247
60       191
50       168
```

```
100    156
40     126
30      77
20      34
10       3
Name: count, dtype: int64
```

[84]:
```
ratings.groupby('MovieID').count().sort_values(by=['UserID'], ascending=False)
movies[movies['Movie ID'] == 2858]
```

[84]:
```
Genres  Movie ID       movie_name  release_year  Action  Adventure  Animation  \
2789        2858  American Beauty          1999       0          0          0

Genres  Children's  Comedy  Crime  Documentary  …  Horror  Musical  Mystery  \
2789             0       1      0            0  …       0        0        0

Genres  Romance  Sci-Fi  Thriller  War  Western  genre_count  decade
2789          0       0         0    0        0            2      90

[1 rows x 23 columns]
```

0.2 Questions:

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

  `25-34`

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

  `College/Student`

- 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? a. 70s b. 90s c. 50s d.80s

  `90s`

- The movie with maximum no. of ratings is ____.

  `American Beauty`

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

  ```
  1. Castle, The (Correlation: 1.00)
  2. Night Shift (Correlation: 1.00)
  3. EDtv (Correlation: 1.00)
  ```

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

  `1. Item`

```
2. User
```

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

```
1. -1 to 1
2. 0 to 1
```

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

```
MSE for the above MF model: 1.3043536493177685
MAPE for the above MF model: 0.6149695011299233
```

- Give the sparse 'row' matrix representation for the following dense matrix - [[1 0] [3 7]]

```
Row indices: [0, 1, 1]
Column indices: [0, 0, 1]
Values: [1, 3, 7]
```

[ ]:
```

```