Zee_rec_system

March 20, 2023

1 Zee Recommender System

1.1 Business problem:

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

1.2 Data Dictionary:

1.2.1 1. Ratings data

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

1.2.2 2. Users data

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”

1.2.3 3. Movies data

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

Additional view:

In this case study, we will explore different recommendation approaches. We start by data processing and feature extraction to create item(movie) profile, user profile, and utility (user-movie-ratings) matrices. We then define several helper functions to compute item-item and user-user similarity matrices based on Cosine distance, dot product, and Pearson correlation. We also define helper function to find similar similar items and users based on the given similarity measure. Finally, we define and evaluate different recommendation approaches such as item based, collaborative filtering using matrix factorization, and user based recommendations.

2 Solution

2.1 Import data and check basic characteristics

[1]:
```
#common imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
#mount google drive
#from google.colab import drive
#drive.mount('/content/drive')

import os, sys
#from google.colab import drive
#drive.mount('/content/drive')
nb_path = '/content/notebooks'

try:
  if(os.path.islink(nb_path)):
    #os.unlink(nb_path)
    pass;
  else:
    os.symlink('/content/drive/My Drive/Colab Notebooks/zee_rec_packages',␣
 ↪nb_path)

except BaseException as error:
    print(error)

if(nb_path not in sys.path):
  sys.path.insert(0,nb_path)

#!pip install --target=$nb_path cmfrec
```

```
about to create symlink
```

[3]:
```
#read data
movies = pd.read_csv("drive/MyDrive/Scaler-case-studies/Zee-recommender-system/
↪data/zee-movies.dat", engine='python', sep="::", encoding = "ISO-8859-1")
users = pd.read_csv("drive/MyDrive/Scaler-case-studies/Zee-recommender-system/
↪data/zee-users.dat", engine='python', sep="::", encoding = "ISO-8859-1")
ratings = pd.read_csv("drive/MyDrive/Scaler-case-studies/Zee-recommender-system/
↪data/zee-ratings.dat", engine='python', sep="::", encoding = "ISO-8859-1")
```

[4]:
```
print('movies:', movies.shape)
print('users:', users.shape)
print('ratings:', ratings.shape)
```

```
movies: (3883, 3)
users: (6040, 5)
ratings: (1000209, 4)
```

[5]:
```
movies.head(3)
```

[5]:
```
   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
```

[6]:
```
users.head(3)
```

[6]:
```
   UserID Gender  Age  Occupation Zip-code
0       1      F    1          10    48067
1       2      M   56          16    70072
2       3      M   25          15    55117
```

[7]:
```
ratings.head(3)
```

[7]:
```
   UserID  MovieID  Rating  Timestamp
0       1     1193       5  978300760
1       1      661       3  978302109
2       1      914       3  978301968
```

[8]:
```
#rename 'Movie ID' to 'MovieID' for consistency.
movies.rename(columns={'Movie ID': 'MovieID'}, inplace=True)
```

[9]:
```
#missing value check
print(movies.isna().sum())
print(users.isna().sum())
print(ratings.isna().sum())
```

```
MovieID    0
Title      0
```

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

[10]:
```python
print('Total number of unique movies: ', movies['MovieID'].nunique())
print('Total number of rated movies (rated by atleast one user): ',
 ↪ratings['MovieID'].nunique())
print('Total number of unrated movies: ', movies['MovieID'].nunique() -
 ↪ratings['MovieID'].nunique())
```

```
Total number of unique movies:  3883
Total number of rated movies (rated by atleast one user):  3706
Total number of unrated movies:  177
```

[11]:
```python
print('Total number of unique users: ', users['UserID'].nunique())
print('Total number of active users (who have rated atleast one movie): ',
 ↪ratings['UserID'].nunique())
print('Total number of inactive users: ', users['UserID'].nunique() -
 ↪ratings['UserID'].nunique())
```

```
Total number of unique users:  6040
Total number of active users (who have rated atleast one movie):  6040
Total number of inactive users:  0
```

2.2 Data preprocessing and EDA

2.2.1 movies data

[12]:
```python
movies.head(5)
```

[12]:

	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

[13]:
```python
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   MovieID  3883 non-null   int64
 1   Title    3883 non-null   object
 2   Genres   3883 non-null   object
dtypes: int64(1), object(2)
memory usage: 91.1+ KB
```

[14]:
```
#extract release_year as a feature
movies['release_year'] = movies['Title'].str.strip().str.extract(r'^.+\((?
 ↪P<release_year>[0-9]+)\)$').astype('int')
movies['release_year'].value_counts()
```

[14]:
```
1996    345
1995    342
1998    337
1997    315
1999    283
       …
1923      3
1919      3
1922      2
1920      2
1921      1
Name: release_year, Length: 81, dtype: int64
```

[15]:
```
#check for any missing values
movies['release_year'].isna().sum()
```

[15]: 0

[16]:
```
movies['Genres']
```

[16]:
```
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
```

[17]:
```python
m = movies.copy()
m['Genres'] = movies['Genres'].str.split("|")
m = m.drop(['Genres'],axis=1).merge(m['Genres'].explode(), left_index=True,␣
↪right_index=True)
m = m.pivot(index=['MovieID', 'Title', 'release_year'],columns='Genres',␣
↪values='Title')
m = (~m.isna()).astype('int')
m = m.reset_index()
m.columns.names = [None]
m
```

[17]:
```
      MovieID                               Title  release_year  Action  \
0           1                    Toy Story (1995)          1995       0
1           2                      Jumanji (1995)          1995       0
2           3             Grumpier Old Men (1995)          1995       0
3           4            Waiting to Exhale (1995)          1995       0
4           5  Father of the Bride Part II (1995)          1995       0
…         …                                   …           …     …
3878     3948             Meet the Parents (2000)          2000       0
3879     3949          Requiem for a Dream (2000)          2000       0
3880     3950                    Tigerland (2000)          2000       0
3881     3951             Two Family House (2000)          2000       0
3882     3952               Contender, The (2000)          2000       0

      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  …
…           …          …           …     …    …          …  …
3878          0          0           0       1      0            0  …
3879          0          0           0       0      0            0  …
3880          0          0           0       0      0            0  …
3881          0          0           0       0      0            0  …
3882          0          0           0       0      0            0  …

      Fantasy  Film-Noir  Horror  Musical  Mystery  Romance  Sci-Fi  Thriller  \
0           0          0       0        0        0        0       0         0
1           1          0       0        0        0        0       0         0
2           0          0       0        0        0        1       0         0
3           0          0       0        0        0        0       0         0
4           0          0       0        0        0        0       0         0
…         …        …     …      …      …      …     …       …
3878        0          0       0        0        0        0       0         0
```

```
3879        0         0       0        0        0        0       0         0
3880        0         0       0        0        0        0       0         0
3881        0         0       0        0        0        0       0         0
3882        0         0       0        0        0        0       0         1

      War  Western
0       0        0
1       0        0
2       0        0
3       0        0
4       0        0
…    …       …
3878    0        0
3879    0        0
3880    0        0
3881    0        0
3882    0        0

[3883 rows x 21 columns]
```

2.2.2 Users data

[18]:
```python
users.head()
```

[18]:
```
   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
```

[19]:
```python
users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6040 entries, 0 to 6039
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   UserID      6040 non-null   int64
 1   Gender      6040 non-null   object
 2   Age         6040 non-null   int64
 3   Occupation  6040 non-null   int64
 4   Zip-code    6040 non-null   object
dtypes: int64(3), object(2)
memory usage: 236.1+ KB
```

[20]:
```python
users.describe()
```

[20]:

	UserID	Age	Occupation
count	6040.000000	6040.000000	6040.000000
mean	3020.500000	30.639238	8.146854
std	1743.742145	12.895962	6.329511
min	1.000000	1.000000	0.000000
25%	1510.750000	25.000000	3.000000
50%	3020.500000	25.000000	7.000000
75%	4530.250000	35.000000	14.000000
max	6040.000000	56.000000	20.000000

[21]:
```
#check Gender column
users['Gender'].value_counts()
```

[21]:
```
M    4331
F    1709
Name: Gender, dtype: int64
```

[22]:
```
#convert to a binary column
users['Gender'] = users['Gender'].map({'M' : 1, 'F': 0})
```

[23]:
```
users['Gender'].value_counts()
```

[23]:
```
1    4331
0    1709
Name: Gender, dtype: int64
```

[24]:
```
#check Age column
users['Age'].value_counts()
```

[24]:
```
25    2096
35    1193
18    1103
45     550
50     496
56     380
1      222
Name: Age, dtype: int64
```

[25]:
```
#map Age to descriptive category names
users['Age'] = users['Age'].astype('string').map({
  '1': 'Under 18',
  '18': '18-24',
  '25': '25-34',
  '35': '35-44',
  '45': '45-49',
  '50': '50-55',
  '56': '56+'
```

```
})
```

[26]:
```
users['Age']
```

[26]:
```
0       Under 18
1            56+
2          25-34
3          45-49
4          25-34
          …
6035       25-34
6036       45-49
6037         56+
6038       45-49
6039       25-34
Name: Age, Length: 6040, dtype: object
```

[27]:
```
#one hot encode age
u = pd.merge(users, pd.get_dummies(users['Age'], prefix='age'),␣
 ↪left_index=True, right_index=True).drop(['Age'],axis=1)
u.head()
```

[27]:
```
   UserID  Gender  Occupation Zip-code  age_18-24  age_25-34  age_35-44  \
0       1       0          10    48067          0          0          0
1       2       1          16    70072          0          0          0
2       3       1          15    55117          0          1          0
3       4       1           7    02460          0          0          0
4       5       1          20    55455          0          1          0

   age_45-49  age_50-55  age_56+  age_Under 18
0          0          0        0             1
1          0          0        1             0
2          0          0        0             0
3          1          0        0             0
4          0          0        0             0
```

[28]:
```
#check occupation
users['Occupation'].value_counts()
```

[28]:
```
4     759
0     711
7     679
1     528
17    502
12    388
14    302
20    281
```

```
2     267
16    241
6     236
10    195
3     173
15    144
13    142
11    129
5     112
9      92
19     72
18     70
8      17
Name: Occupation, dtype: int64
```

[29]:
```
#map Occupation to descriptive names
users['Occupation'] = users['Occupation'].astype('string').map({
  '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",
})
```

[30]:
```
#one hot encode occupation
u = pd.merge(u, pd.get_dummies(users['Occupation']), left_index=True,␣
↪right_index=True).drop(['Occupation'],axis=1)
u.head()
```

[30]:
```
   UserID  Gender  Zip-code  age_18-24  age_25-34  age_35-44  age_45-49  \
0       1       0     48067          0          0          0          0
```

```
1       2       1    70072          0          0          0          0
2       3       1    55117          0          1          0          0
3       4       1    02460          0          0          0          1
4       5       1    55455          0          1          0          0

   age_50-55  age_56+  age_Under 18  …  other  programmer  retired  \
0          0        0             1  …      0           0        0
1          0        1             0  …      0           0        0
2          0        0             0  …      0           0        0
3          0        0             0  …      0           0        0
4          0        0             0  …      0           0        0

   sales/marketing  scientist  self-employed  technician/engineer  \
0                0          0              0                    0
1                0          0              1                    0
2                0          1              0                    0
3                0          0              0                    0
4                0          0              0                    0

   tradesman/craftsman  unemployed  writer
0                    0           0       0
1                    0           0       0
2                    0           0       0
3                    0           0       0
4                    0           0       1

[5 rows x 31 columns]
```

[31]:
```
#check zip code
users['Zip-code'].value_counts()
```

[31]:
```
48104    19
22903    18
55104    17
94110    17
55455    16
         ..
80236     1
19428     1
33073     1
99005     1
14706     1
Name: Zip-code, Length: 3439, dtype: int64
```

Note: Indian Zipcodes are five digit numbers. Their format is as shown below.

[32]:
```
#check unique Zip-Code counts
users['Zip-code'].nunique()
```

[32]:
```
3439
```

[33]:
```
#check number of unique Region+subregion combinations
users['Zip-code'].str.extract(r'(?P<region_and_subregion>\d\d).*').
 ↪value_counts()
```

[33]:
```
region_and_subregion
55                      415
94                      378
60                      239
02                      221
92                      217
                      …
86                        5
82                        5
25                        3
51                        2
69                        1
Length: 100, dtype: int64
```

[34]:
```
#check number of unique regions.
users['Zip-code'].str.extract(r'(?P<region>\d).*').value_counts()
```

[34]:
```
region
9         1468
0          662
1          662
5          659
4          607
2          441
6          430
7          419
3          386
8          306
dtype: int64
```

Observations:

1. Our intuition tells us that users who belong to the same **subregion** (that is combination of region and subregion codes) are more likely to share some movie preferences compared to those who do not. Similarly, users who belong to the same **region**, regardless of their subregion, are more likley to have shared movie preferences than those who belong to different regions (though the effect may be weaker at regional level than at subregon level).

2. Subregions are linked to regions and therefore must be interpreted together with their region

code.

3. The number of unique Zip-codes are high (~3.4K). If we hot-encode at Zip-code level, we will generate highly sparse data. Also, using Zip-code data for user similarity may prove to be too granular. We can instead create on **region** and **subregion** features and one-hot-encode them.

[35]:
```
#create region and subregion features
users['Zip-code'] = users['Zip-code'].str.strip()
users['region'] = users['Zip-code'].str.extract(r'(?P<region>\d).*')
users['subregion'] = users['Zip-code'].str.extract(r'(?P<region>\d\d).*')
```

[36]:
```
#one hot encode region and subregion. Drop zip-code
u = pd.merge(u, pd.get_dummies(users['region'], prefix='r'), left_index=True,␣
↪right_index=True)
u = pd.merge(u, pd.get_dummies(users['subregion'], prefix='sr'),␣
↪left_index=True, right_index=True)
u = u.drop(['Zip-code'], axis=1)
```

[37]:
```
u.columns
```

[37]:
```
Index(['UserID', 'Gender', 'age_18-24', 'age_25-34', 'age_35-44', 'age_45-49',
       'age_50-55', 'age_56+', 'age_Under 18', 'K-12 student',
       …
       'sr_90', 'sr_91', 'sr_92', 'sr_93', 'sr_94', 'sr_95', 'sr_96', 'sr_97',
       'sr_98', 'sr_99'],
      dtype='object', length=140)
```

2.2.3 Ratings data

[38]:
```
ratings.head()
```

[38]:

	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

[39]:
```
ratings.info()
```

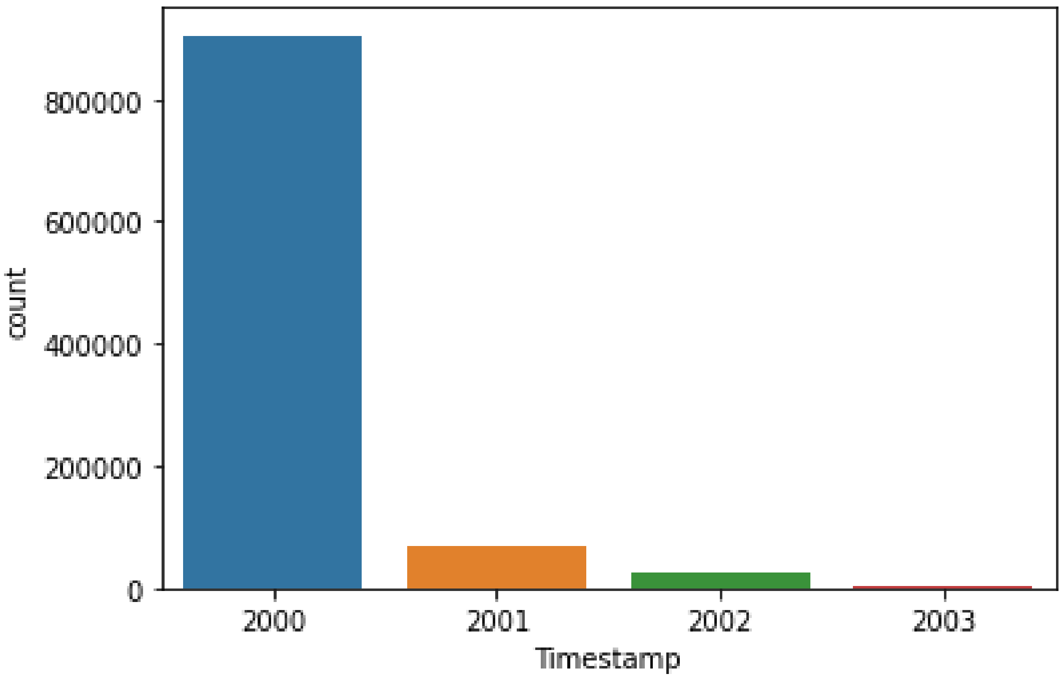
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 4 columns):
 #   Column     Non-Null Count    Dtype
---  ------     --------------    -----
 0   UserID     1000209 non-null  int64
 1   MovieID    1000209 non-null  int64
```

```
 2   Rating     1000209 non-null  int64
 3   Timestamp  1000209 non-null  int64
dtypes: int64(4)
memory usage: 30.5 MB
```

[40]:
```python
#convert timestamp (in seconds) to datetime
ratings['Timestamp'] = ratings['Timestamp'].transform(lambda x: pd.Timestamp(x,␣
↪unit='s'))
```

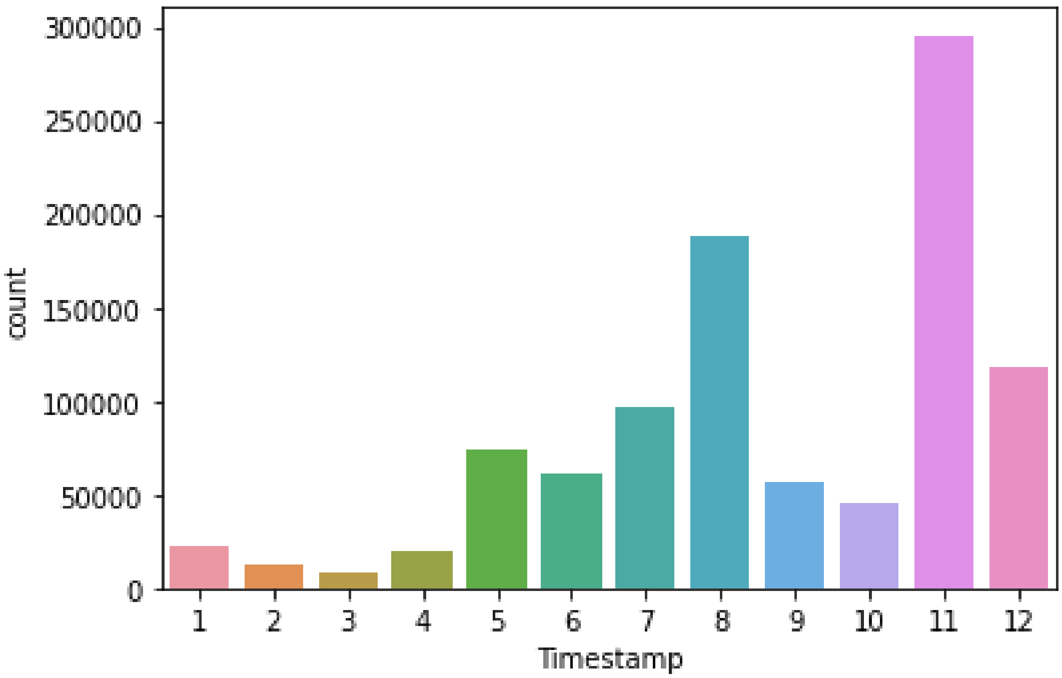
[41]:
```python
#check year distribution
sns.countplot(x=ratings['Timestamp'].dt.year)
```

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



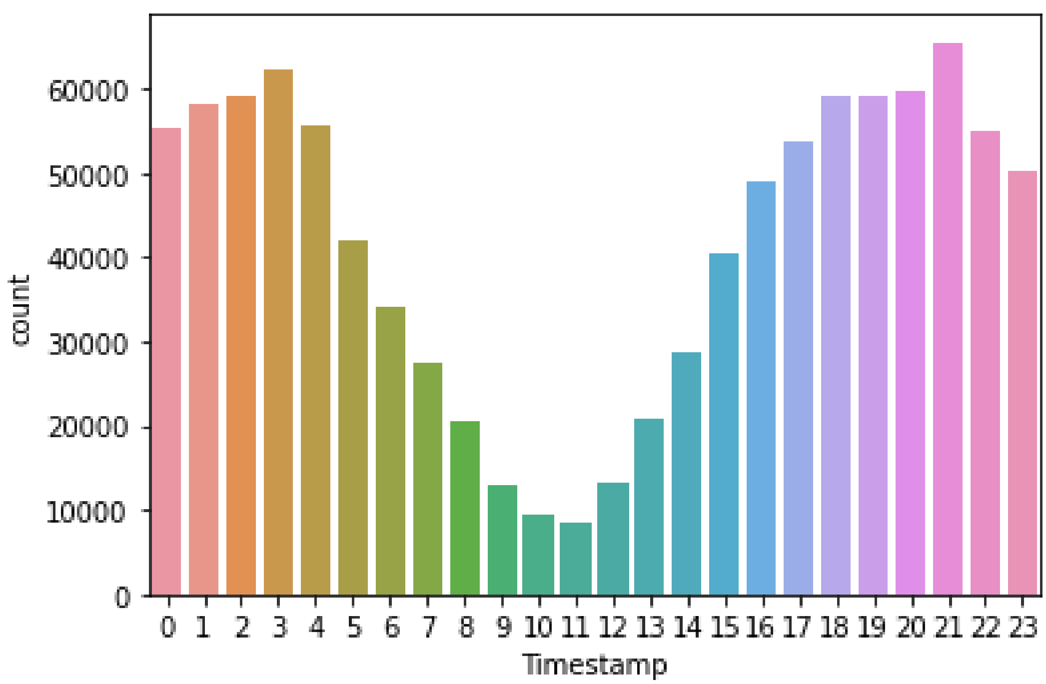
[42]:
```python
#check month distribution
sns.countplot(x=ratings['Timestamp'].dt.month)
```

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



[43]:
```
#check hour distribution
sns.countplot(x=ratings['Timestamp'].dt.hour)
```

[43]:
```
<Axes: xlabel='Timestamp', ylabel='count'>
```



Note: Hours are cyclic in nature, and therfore regular arithmetic may not provide intended results. For example, *23 hour* is closer to *02 hour* than *17 hour*. Similarly, mean of *23 hour* and *03 hour* should be *01 hour* and not *13 hour*. To avoid such issues, we will use circular encoding.

For each hour, we extract its sin(or y) and cosine(or x) components and use them as features.

```
hour_sin = sin(2*pi*hour / 24)
hour_cos = cos(2*pi*hour / 24)
```

To average multiple hours, we can average their sin and cos components as follow.

```
hour_sin_new = (hour_sin1 + hour_sin2) / 2
hour_cos_new = (hour_cos1 + hour_cos2) / 2
```

Finally, we can find hour from its sin and consin components as follow.

```
hour = (arctan(hour_sin / hour_cos) * 12) / pi
```

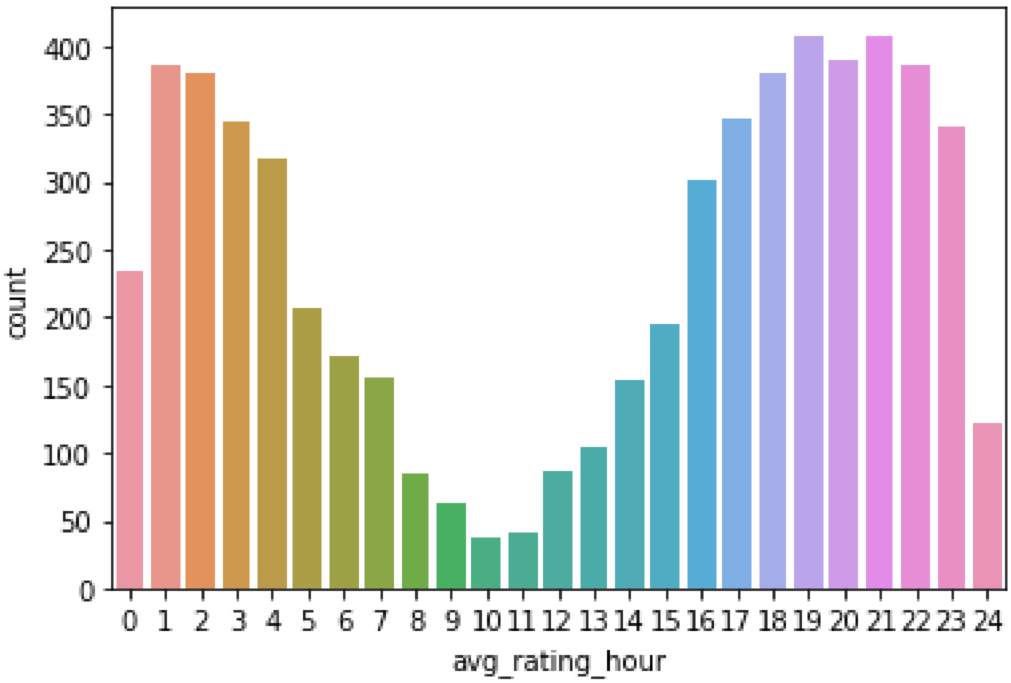
[44]:
```
#extract rating hour value.
ratings['rating_hour'] = ratings['Timestamp'].dt.hour

#extract rating hour sin and cos components
mul = (2*np.pi)/24
ratings['rating_hour_sin'] = np.round(np.sin(mul * ratings['rating_hour']), 2)
ratings['rating_hour_cos'] = np.round(np.cos(mul * ratings['rating_hour']), 2)
```

[44]:
```
```

[45]:
```
# find average rating hour for each user
df_temp = ratings.groupby('UserID')[['rating_hour_sin', 'rating_hour_cos']].
 ↪mean()
df_temp.rename(columns = {'rating_hour_sin': 'avg_rating_hour_sin',␣
 ↪'rating_hour_cos': 'avg_rating_hour_cos'}, inplace=True)
df_temp['avg_rating_hour'] = (np.arctan2(df_temp['avg_rating_hour_sin'],␣
 ↪df_temp['avg_rating_hour_cos']) * 12) / np.pi

mask_neg_hours = df_temp['avg_rating_hour'] < 0
df_temp.loc[mask_neg_hours, 'avg_rating_hour'] =␣
 ↪df_temp[mask_neg_hours]['avg_rating_hour'] + 24
df_temp['avg_rating_hour'] = np.round(df_temp['avg_rating_hour']).astype('int')
```

[46]:
```
sns.countplot(x=df_temp['avg_rating_hour'])
```

[46]:
```
<Axes: xlabel='avg_rating_hour', ylabel='count'>
```



[47]:
```
#add avg_rating_hour, avg_rating_hour_sin, and avg_rating_hour_cos as features␣
↪to users dataframe
u = pd.merge(u, df_temp.reset_index(), left_on='UserID', right_on='UserID')
u.head()
```

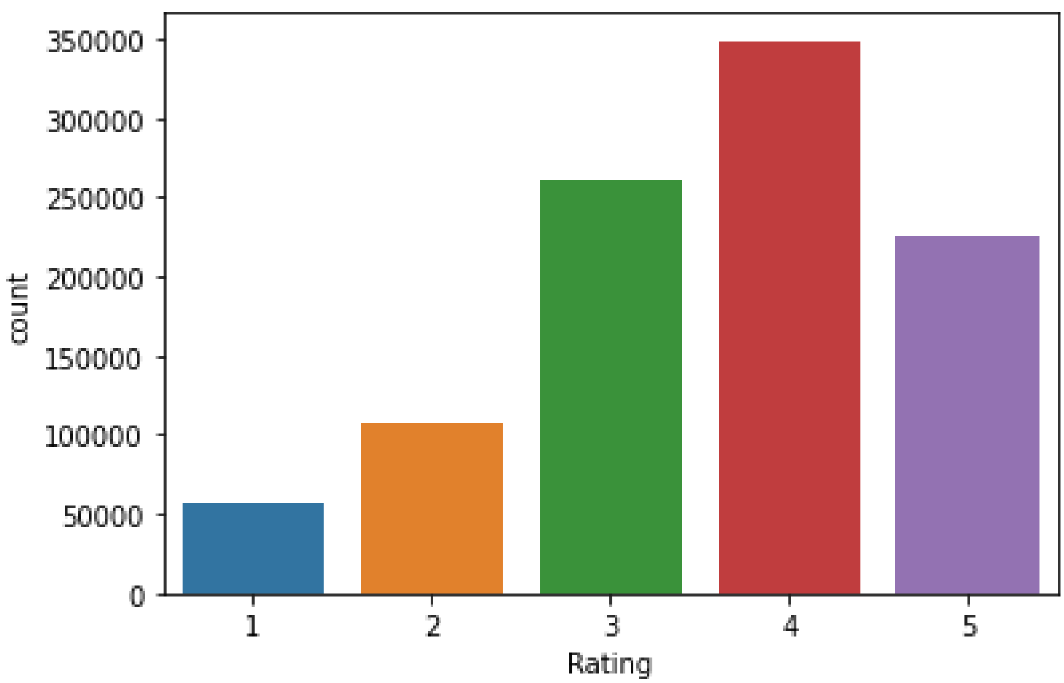
[47]:
```
   UserID  Gender  age_18-24  age_25-34  age_35-44  age_45-49  age_50-55  \
0       1       0          0          0          0          0          0
1       2       1          0          0          0          0          0
2       3       1          0          1          0          0          0
3       4       1          0          0          0          1          0
4       5       1          0          1          0          0          0

   age_56+  age_Under 18  K-12 student  …  sr_93  sr_94  sr_95  sr_96  \
0        0             1             1  …      0      0      0      0
1        1             0             0  …      0      0      0      0
2        0             0             0  …      0      0      0      0
3        0             0             0  …      0      0      0      0
4        0             0             0  …      0      0      0      0

   sr_97  sr_98  sr_99  avg_rating_hour_sin  avg_rating_hour_cos  \
0      0      0      0            -0.441132             0.894528
1      0      0      0            -0.677442             0.734806
2      0      0      0            -0.710000             0.710000
3      0      0      0            -0.870000             0.500000
```

```
4       0       0       0               0.993182              -0.003939

   avg_rating_hour
0               22
1               21
2               21
3               20
4                6

[5 rows x 143 columns]
```

[48]:
```
#drop timestamp column
ratings.drop('Timestamp', axis=1, inplace=True)
```

[49]:
```
#check ratings feature
sns.countplot(x=ratings['Rating'])
```

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



[50]:
```
ratings['Rating'].describe()
```

[50]:
```
count    1.000209e+06
mean     3.581564e+00
std      1.117102e+00
min      1.000000e+00
```

```
25%      3.000000e+00
50%      4.000000e+00
75%      4.000000e+00
max      5.000000e+00
Name: Rating, dtype: float64
```

[51]:
```
#find 'user_avg_rating' and 'user_rating_cnt'
df_temp = ratings.groupby('UserID').agg({'Rating': ['mean', 'count']})
df_temp.columns = df_temp.columns.droplevel(0)
df_temp = df_temp.rename(columns={'mean':'user_avg_rating', 'count':
 ↪'user_rating_cnt'}).reset_index()
df_temp.head(3)
```

[51]:

	UserID	user_avg_rating	user_rating_cnt
0	1	4.188679	53
1	2	3.713178	129
2	3	3.901961	51

[52]:
```
#add user_avg_rating and user_rating_cnt features
u = pd.merge(u, df_temp, left_on='UserID', right_on='UserID')
```

[53]:
```
#find average movie rating as well as total rating count for each movie
df_temp = ratings.groupby('MovieID').agg({'Rating': ['mean', 'count']})
df_temp.columns = df_temp.columns.droplevel(0)
df_temp = df_temp.rename(columns={'mean':'movie_avg_rating', 'count':
 ↪'movie_rating_cnt'}).reset_index()
df_temp
```

[53]:

	MovieID	movie_avg_rating	movie_rating_cnt
0	1	4.146846	2077
1	2	3.201141	701
2	3	3.016736	478
3	4	2.729412	170
4	5	3.006757	296
…	…	…	…
3701	3948	3.635731	862
3702	3949	4.115132	304
3703	3950	3.666667	54
3704	3951	3.900000	40
3705	3952	3.780928	388

[3706 rows x 3 columns]

[54]:
```
#add movie_avg_rating and movie_rating_cnt features
m = pd.merge(m, df_temp, left_on='MovieID', right_on='MovieID', how='left').
 ↪fillna(0)
```

[55]:
```
m.shape
```

[55]:
```
(3883, 23)
```

[56]:
```
str(m.columns.tolist())
```

[56]:
```
'[\'MovieID\', \'Title\', \'release_year\', \'Action\', \'Adventure\',
\'Animation\', "Children\'s", \'Comedy\', \'Crime\', \'Documentary\', \'Drama\',
\'Fantasy\', \'Film-Noir\', \'Horror\', \'Musical\', \'Mystery\', \'Romance\',
\'Sci-Fi\', \'Thriller\', \'War\', \'Western\', \'movie_avg_rating\',
\'movie_rating_cnt\']'
```

[57]:
```
str(ratings.columns.tolist())
```

[57]:
```
"['UserID', 'MovieID', 'Rating', 'rating_hour', 'rating_hour_sin',
'rating_hour_cos']"
```

2.2.4 Merge all dataframes together

[58]:
```
data_agg = pd.merge(m, pd.merge(u, ratings, on='UserID'), left_on='MovieID',␣
↪right_on='MovieID')
data_agg.head(10)
```

[58]:
```
   MovieID             Title  release_year  Action  Adventure  Animation  \
0        1  Toy Story (1995)          1995       0          0          1
1        1  Toy Story (1995)          1995       0          0          1
2        1  Toy Story (1995)          1995       0          0          1
3        1  Toy Story (1995)          1995       0          0          1
4        1  Toy Story (1995)          1995       0          0          1
5        1  Toy Story (1995)          1995       0          0          1
6        1  Toy Story (1995)          1995       0          0          1
7        1  Toy Story (1995)          1995       0          0          1
8        1  Toy Story (1995)          1995       0          0          1
9        1  Toy Story (1995)          1995       0          0          1

   Children's  Comedy  Crime  Documentary  …  sr_99  avg_rating_hour_sin  \
0           1       1      0            0  …      0            -0.441132
1           1       1      0            0  …      0             0.874225
2           1       1      0            0  …      0             0.541151
3           1       1      0            0  …      0             0.260000
4           1       1      0            0  …      0             0.201571
5           1       1      0            0  …      0             0.974033
6           1       1      0            0  …      0            -0.237725
7           1       1      0            0  …      1             0.260000
8           1       1      0            0  …      0            -0.788980
9           1       1      0            0  …      0             0.181175
```

```
   avg_rating_hour_cos  avg_rating_hour  user_avg_rating  user_rating_cnt  \
0             0.894528               22         4.188679               53
1             0.489859                4         3.901408               71
2             0.833094                2         3.884892              139
3             0.970000                1         3.735849              106
4             0.937681                1         4.114713              401
5             0.212721                5         3.649180              305
6             0.691686               23         3.572549              255
7             0.970000                1         2.909091               22
8             0.260395               19         3.315789              304
9             0.468350                1         2.960000              400

   Rating  rating_hour  rating_hour_sin  rating_hour_cos
0       5           23            -0.26             0.97
1       4            4             0.87             0.50
2       4            3             0.71             0.71
3       5            1             0.26             0.97
4       5            1             0.26             0.97
5       4            5             0.97             0.26
6       5           21            -0.71             0.71
7       3            1             0.26             0.97
8       4           19            -0.97             0.26
9       3           22            -0.50             0.87

[10 rows x 172 columns]
```

[59]:

```python
#view all columns of merged data frame.
from IPython.core.display import display, HTML
coldisplay = "<div style='max-width:700px'>"
for i,col in enumerate(data_agg.columns):
  coldisplay += col + '  ,'
coldisplay += "</div>"
HTML(coldisplay)
```

[59]:

```
<IPython.core.display.HTML object>
```

2.2.5 Create the utility matrix (user-item rating matrix)

[60]:

```python
utility = ratings.pivot(index='UserID', columns='MovieID', values='Rating')
avg_user_rating = utility.mean(axis=1).values.reshape(-1,1) #calculate average user rating
utility = (utility - avg_user_rating) #mean center ratings
utility = utility.fillna(0)
```

2.2.6 Create item (movie) profile matrix

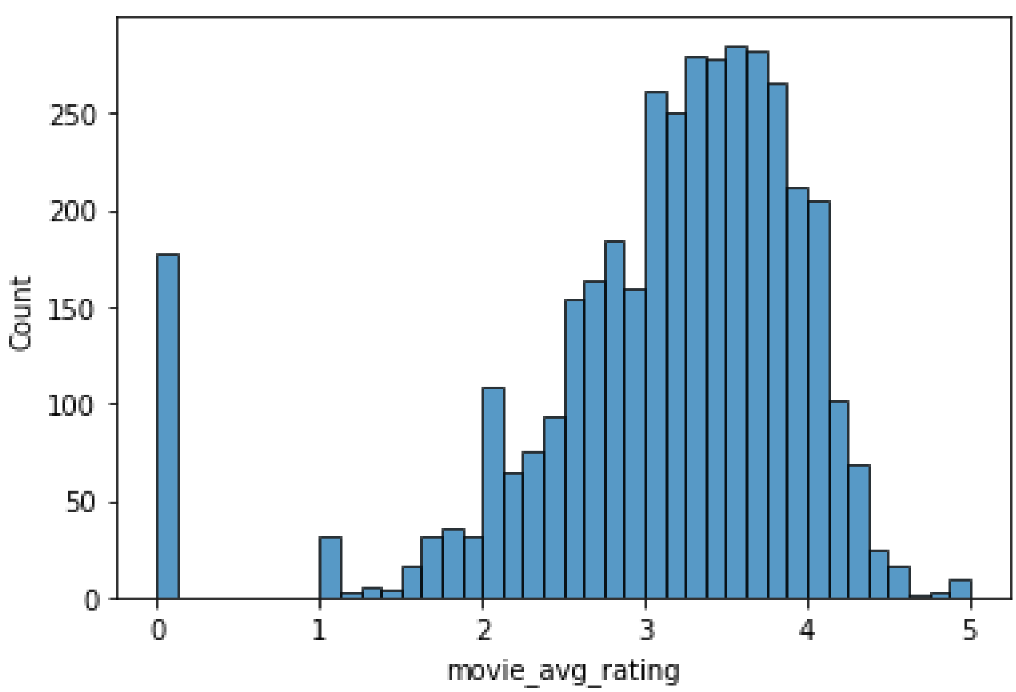
[61]:
```
#create movie profile dataframe. Each row represents a movie vector.
m_profile = m.copy()
m_profile.drop(['Title'], axis=1, inplace=True)
m_profile.set_index('MovieID', inplace=True)
m_profile
```

[61]:
```
         release_year  Action  Adventure  Animation  Children's  Comedy  \
MovieID
1                1995       0          0          1           1       1
2                1995       0          1          0           1       0
3                1995       0          0          0           0       1
4                1995       0          0          0           0       1
5                1995       0          0          0           0       1
…                 …      …         …         …          …       …
3948             2000       0          0          0           0       1
3949             2000       0          0          0           0       0
3950             2000       0          0          0           0       0
3951             2000       0          0          0           0       0
3952             2000       0          0          0           0       0

         Crime  Documentary  Drama  Fantasy  …  Horror  Musical  Mystery  \
MovieID                                      …
1            0            0      0        0  …       0        0        0
2            0            0      0        1  …       0        0        0
3            0            0      0        0  …       0        0        0
4            0            0      1        0  …       0        0        0
5            0            0      0        0  …       0        0        0
…        …           …      …       …  …      …       …       …
3948         0            0      0        0  …       0        0        0
3949         0            0      1        0  …       0        0        0
3950         0            0      1        0  …       0        0        0
3951         0            0      1        0  …       0        0        0
3952         0            0      1        0  …       0        0        0

         Romance  Sci-Fi  Thriller  War  Western  movie_avg_rating  \
MovieID
1              0       0         0    0        0          4.146846
2              0       0         0    0        0          3.201141
3              1       0         0    0        0          3.016736
4              0       0         0    0        0          2.729412
5              0       0         0    0        0          3.006757
…          …      …        …   …       …               …
3948           0       0         0    0        0          3.635731
3949           0       0         0    0        0          4.115132
3950           0       0         0    0        0          3.666667
```

```
3951              0        0          0    0        0           3.900000
3952              0        0          1    0        0           3.780928

         movie_rating_cnt
MovieID
1                  2077.0
2                   701.0
3                   478.0
4                   170.0
5                   296.0
…                   …
3948                862.0
3949                304.0
3950                 54.0
3951                 40.0
3952                388.0

[3883 rows x 21 columns]
```

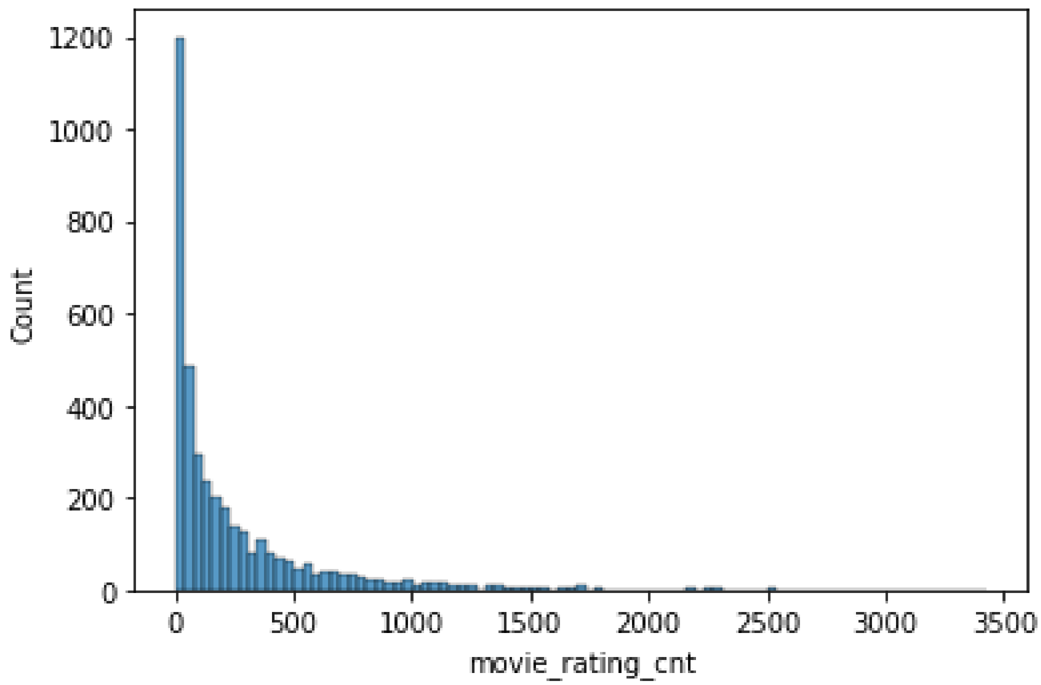
[62]:
```
#check distribution of movie_avg_rating
sns.histplot(x=m_profile['movie_avg_rating'])
```

[62]: <Axes: xlabel='movie_avg_rating', ylabel='Count'>



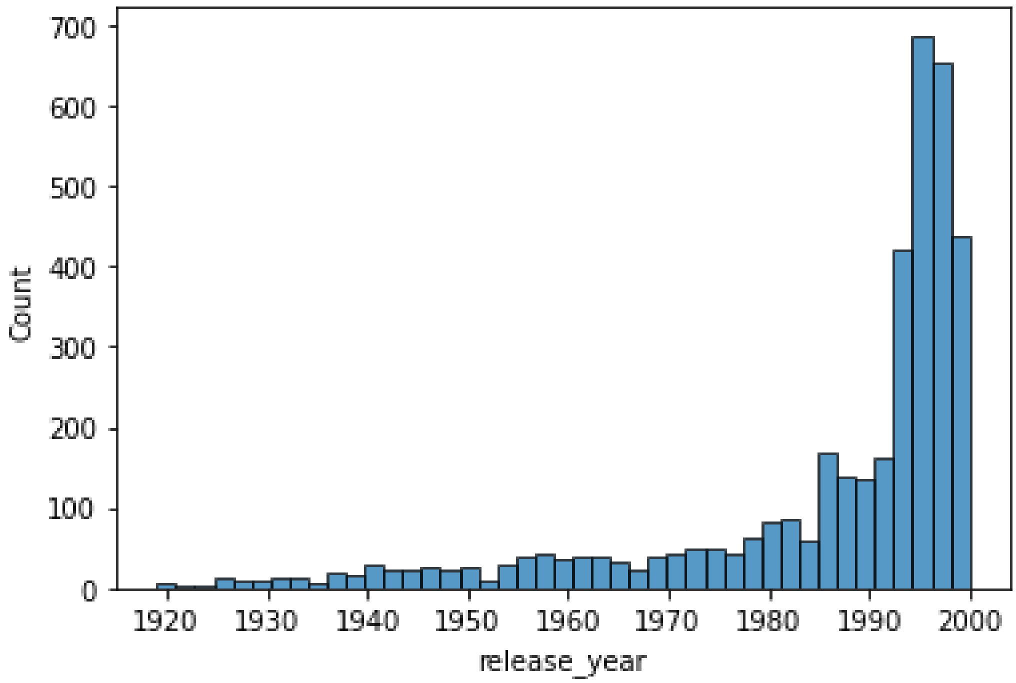
[63]:
```
#check distribution of movie_rating_cnt
sns.histplot(x=m_profile['movie_rating_cnt'])
```

[63]: <Axes: xlabel='movie_rating_cnt', ylabel='Count'>



[64]:
```
#check distribution of release_year
sns.histplot(x=m_profile['release_year'])
```

[64]: <Axes: xlabel='release_year', ylabel='Count'>

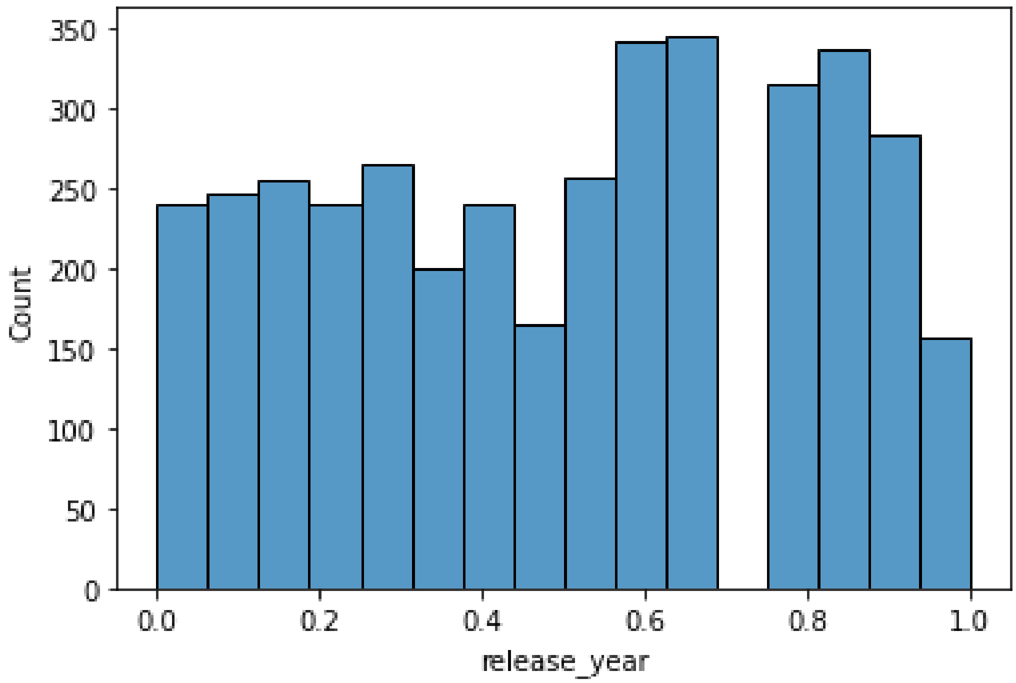


Note: 'release_year' has left skewed distribution whrease 'movie_rating_cnt' has right skewed distribution. We will use quantile-transformation to convert them to [0,1] range. 'movie_avg_rating', on the other hand, has relatively symmetric distribution. So we will use StandardScaler.

[65]:
```
#apply quantile transform to release_year and movie_rating_cnt
from sklearn.preprocessing import QuantileTransformer
qt = QuantileTransformer(n_quantiles=100, random_state=0)
res = qt.fit_transform(m[['release_year','movie_rating_cnt']].values.
 ↪reshape(-1,2))
m_profile['release_year'] = res[:,0]
m_profile['movie_rating_cnt'] = res[:,1]
```

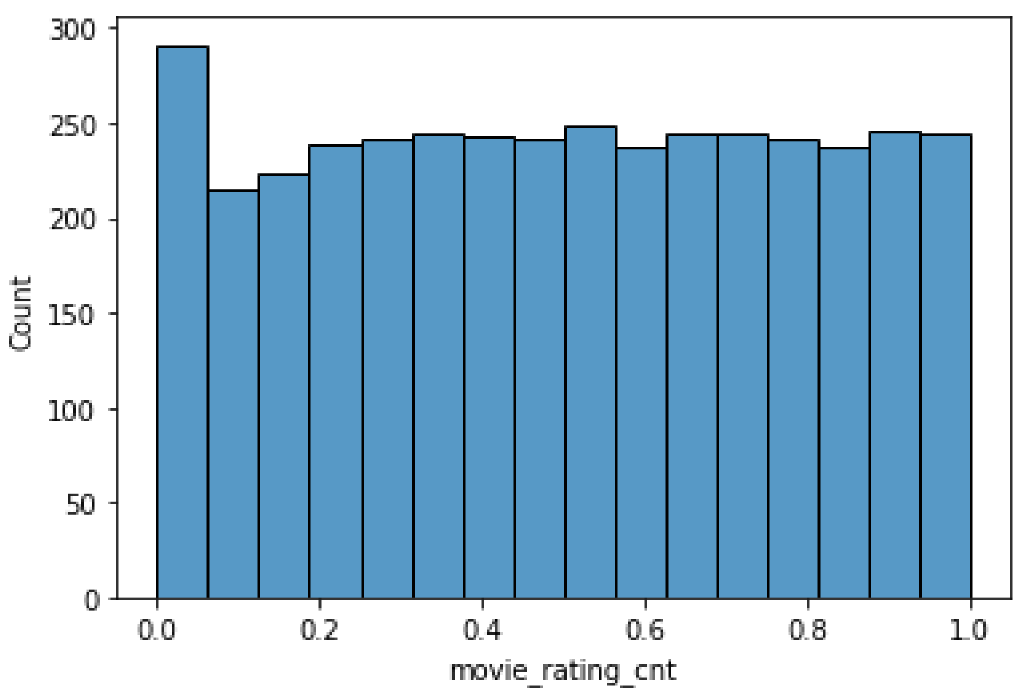
[66]:
```
#check distribution again after quantile transform
sns.histplot(x=m_profile['release_year'])
```

[66]: <Axes: xlabel='release_year', ylabel='Count'>



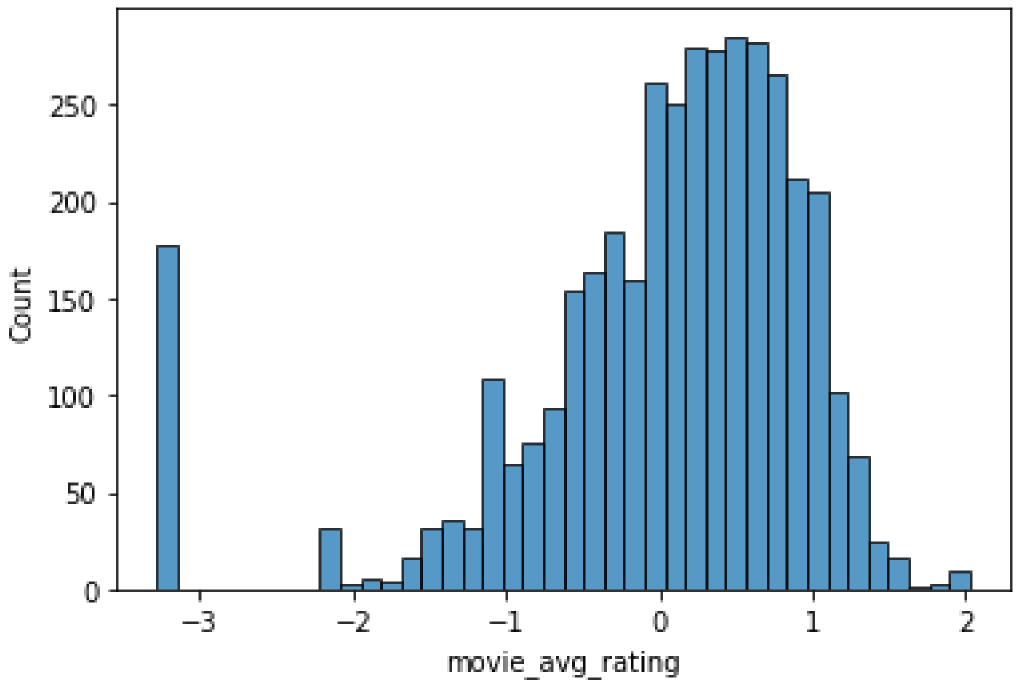

```
[67]: #check distribution again after quantile transform
      sns.histplot(x=m_profile['movie_rating_cnt'])
```

[67]: <Axes: xlabel='movie_rating_cnt', ylabel='Count'>



[68]:
```
#apply standard scaling to movie_avg_rating
from sklearn.preprocessing import StandardScaler

rating_ss = StandardScaler()
rating_ss.fit(m['movie_avg_rating'].values.reshape(-1,1))
res = rating_ss.transform(m['movie_avg_rating'].values.reshape(-1,1))
m_profile['movie_avg_rating'] = res[:,0]
sns.histplot(x=m_profile['movie_avg_rating'])
```

[68]: <Axes: xlabel='movie_avg_rating', ylabel='Count'>



[69]:
```
# from sklearn.preprocessing import MinMaxScaler

# mm = MinMaxScaler(feature_range=(-1,1))
# res = mm.fit_transform(m_profile[['movie_avg_rating']])
# m_profile['movie_avg_rating'] = res[:,0]
# sns.histplot(x=m_profile['movie_avg_rating'])
```

[70]:
```
#check final movie profile dataframe
m_profile
```

[70]:

```
         release_year  Action  Adventure  Animation  Children's  Comedy  \
MovieID
1            0.585859       0          0          1           1       1
2            0.585859       0          1          0           1       0
3            0.585859       0          0          0           0       1
4            0.585859       0          0          0           0       1
5            0.585859       0          0          0           0       1
…                 …      …        …        …         …       …
3948         1.000000       0          0          0           0       1
3949         1.000000       0          0          0           0       0
3950         1.000000       0          0          0           0       0
3951         1.000000       0          0          0           0       0
3952         1.000000       0          0          0           0       0

         Crime  Documentary  Drama  Fantasy  …  Horror  Musical  Mystery  \
MovieID                                      …
1            0            0      0        0  …       0        0        0
2            0            0      0        1  …       0        0        0
3            0            0      0        0  …       0        0        0
4            0            0      1        0  …       0        0        0
5            0            0      0        0  …       0        0        0
…        …          …      …      …   …      …      …       …
3948         0            0      0        0  …       0        0        0
3949         0            0      1        0  …       0        0        0
3950         0            0      1        0  …       0        0        0
3951         0            0      1        0  …       0        0        0
3952         0            0      1        0  …       0        0        0

         Romance  Sci-Fi  Thriller  War  Western  movie_avg_rating  \
MovieID
1              0       0         0    0        0          1.119896
2              0       0         0    0        0          0.116582
3              1       0         0    0        0         -0.079056
4              0       0         0    0        0         -0.383883
5              0       0         0    0        0         -0.089643
…            …     …       …   …      …                …
3948           0       0         0    0        0          0.577645
3949           0       0         0    0        0          1.086249
3950           0       0         0    0        0          0.610466
3951           0       0         0    0        0          0.858013
3952           0       0         1    0        0          0.731687

         movie_rating_cnt
MovieID
1                0.991883
2                0.898493
3                0.831031
```

```
4                0.594517
5                0.725543
…                   …
3948             0.928887
3949             0.733220
3950             0.370370
3951             0.313131
3952             0.788675

[3883 rows x 21 columns]
```

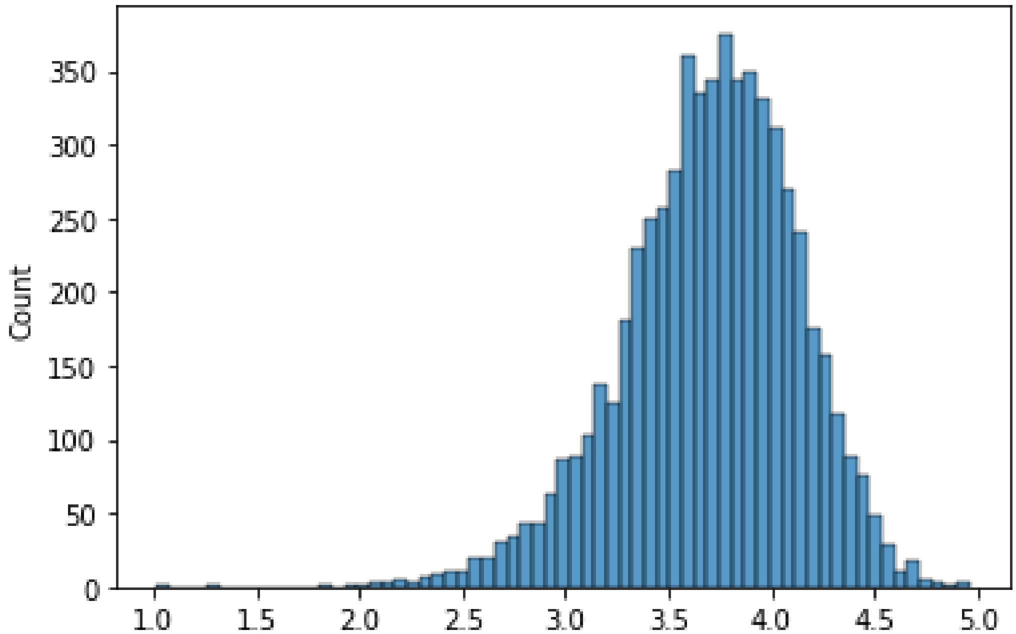
2.2.7 Create user profile matrix (combining user data and ratings)

[71]:
```
u.head()
```

[71]:
```
   UserID  Gender  age_18-24  age_25-34  age_35-44  age_45-49  age_50-55  \
0       1       0          0          0          0          0          0
1       2       1          0          0          0          0          0
2       3       1          0          1          0          0          0
3       4       1          0          0          0          1          0
4       5       1          0          1          0          0          0

   age_56+  age_Under 18  K-12 student  …  sr_95  sr_96  sr_97  sr_98  \
0        0             1             1  …      0      0      0      0
1        1             0             0  …      0      0      0      0
2        0             0             0  …      0      0      0      0
3        0             0             0  …      0      0      0      0
4        0             0             0  …      0      0      0      0

   sr_99  avg_rating_hour_sin  avg_rating_hour_cos  avg_rating_hour  \
0      0            -0.441132             0.894528               22
1      0            -0.677442             0.734806               21
2      0            -0.710000             0.710000               21
3      0            -0.870000             0.500000               20
4      0             0.993182            -0.003939                6

   user_avg_rating  user_rating_cnt
0         4.188679               53
1         3.713178              129
2         3.901961               51
3         4.190476               21
4         3.146465              198

[5 rows x 145 columns]
```

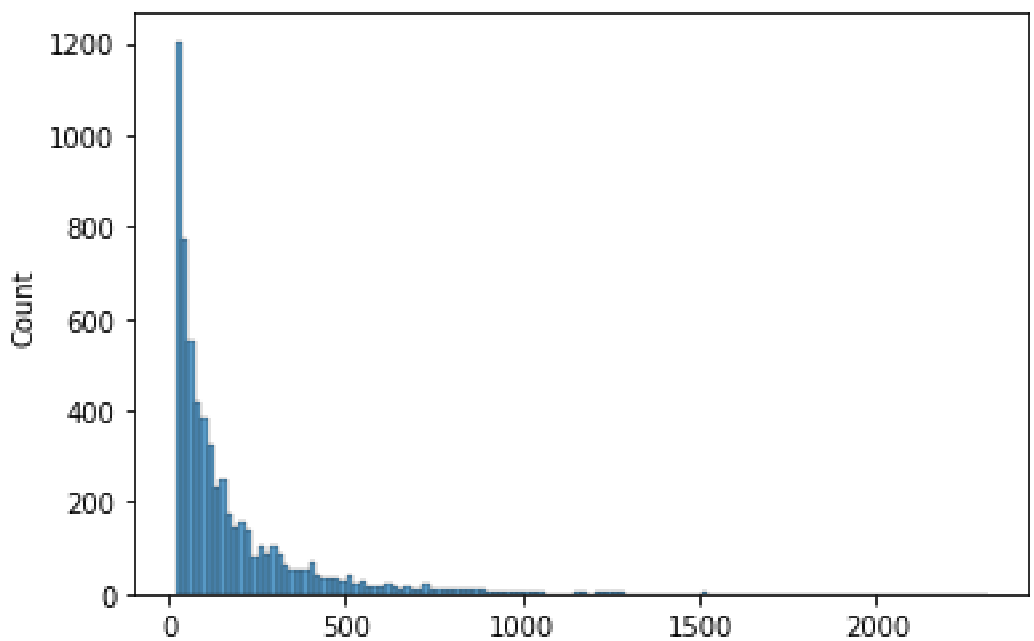
[72]:
```
#check distribution of user_rating_cnt
sns.histplot(x=u['user_avg_rating'].values)
```

[72]: <Axes: ylabel='Count'>



[73]:
```
sns.histplot(x=u['user_rating_cnt'].values)
```

[73]: <Axes: ylabel='Count'>

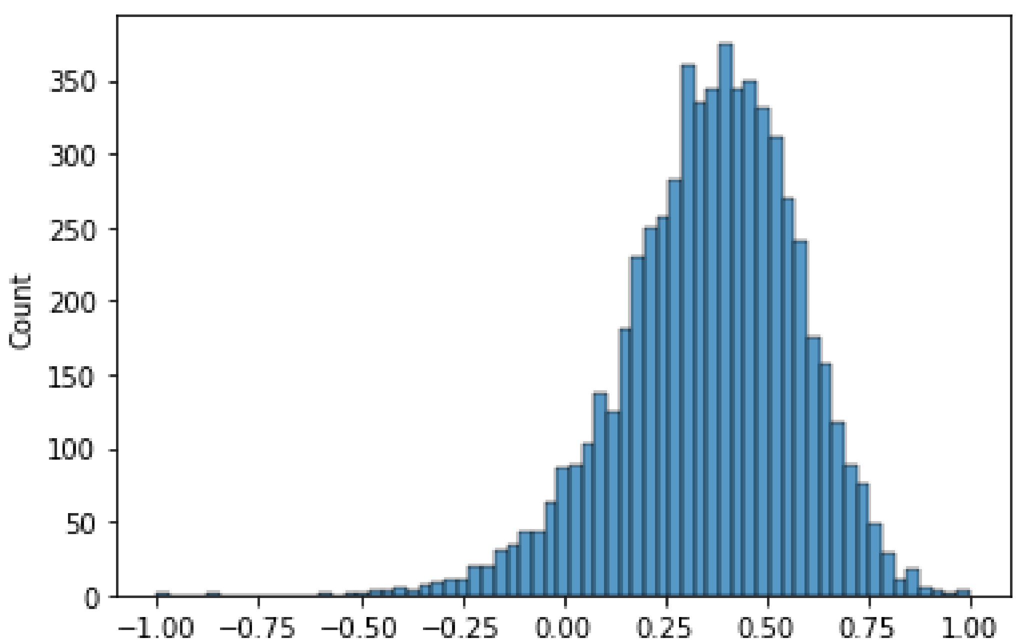


Observation: *user_rating_cnt* is positively skewed distribution. We can apply log transform or quantile transform. We will choose quantile transform in this case study. *user_avg_rating* is somewhat symmetric. We can use minmaxscaler to fit it to [-1,1] range.

[74]:
```
from sklearn.preprocessing import MinMaxScaler

u2 = u.copy()
u2 = u2.set_index("UserID")
u2.drop('avg_rating_hour', axis=1, inplace=True) #we use sin and cosine␣
 ↪components instead

#minmax scale avg_rating
user_mm = MinMaxScaler(feature_range=(-1,1))
u2['user_avg_rating'] = user_mm.fit_transform(u2[['user_avg_rating']])[:,0]

#quantile transform rating_cnt
user_qt = QuantileTransformer(n_quantiles=100, random_state=0)
u2['user_rating_cnt'] = user_qt.fit_transform(u2[['user_rating_cnt']])[:,0]
```

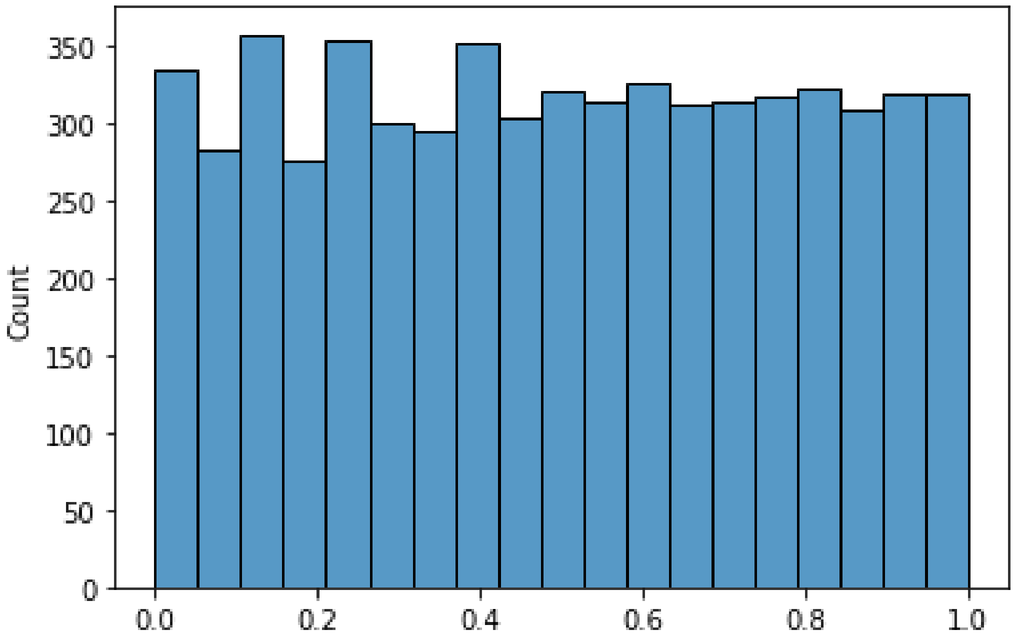
[75]:
```
#check transformed avg_rating
sns.histplot(x=u2['user_avg_rating'].values)
```

[75]:
```
<Axes: ylabel='Count'>
```



[76]:
```
#check transformed rating cnt
sns.histplot(x=u2['user_rating_cnt'].values)
```

[76]: <Axes: ylabel='Count'>



[77]:
```
#finally merge user attributes with ratings data to form user profile.
u_profile = u2.merge(utility, left_index=True, right_index=True)
u2 = None
u_profile.head()
```

[77]:
```
        Gender  age_18-24  age_25-34  age_35-44  age_45-49  age_50-55  \
UserID
1            0          0          0          0          0          0
2            1          0          0          0          0          0
3            1          0          1          0          0          0
4            1          0          0          0          1          0
5            1          0          1          0          0          0

        age_56+  age_Under 18  K-12 student  academic/educator  …  3943  \
UserID                                                          …
1             0             1             1                  0  …   0.0
2             1             0             0                  0  …   0.0
3             0             0             0                  0  …   0.0
4             0             0             0                  0  …   0.0
5             0             0             0                  0  …   0.0
```

```
        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
2        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
4        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

[5 rows x 3849 columns]
```

2.3 Item Based Recommendations

2.3.1 Define Similarity matrix helper functions

In this section, we first define inner product similarity matrix function using original matrix. We then also define a similar function using sparse matrix (sklearn csr_matrix) and compare their performance. Later, we will similarly define functions for **Pearson correlation based similariy** and **cosine similarity**.

[78]:
```
from scipy.sparse import csr_matrix, lil_matrix

#define csr_matrix for item(movies) profile, user profile, and utility matrices
sparse_movies_profile = csr_matrix(m_profile)
sparse_user_profile = csr_matrix(u_profile)
sparse_utility = csr_matrix(utility)
```

[79]:
```
import time

#compute dot product similarity matrix (for non sparse data).
def compute_dot_product_similarity_matrix_nonsparse(df):
  n, m = df.shape
  name = df.index.name
  if type(name) != str:
    name = 'item'

  ids = pd.DataFrame({name: df.index.values}) #item/user/element ids

  ret = ids.merge(ids, how='cross')
  ret['value'] = 0
  t1 = time.time()
  for i in range(n):
    id = df.index[i]
    query = df.iloc[i].values.reshape(1, m ,1)
    candidates = df.values.reshape(n, m ,1)

    grid = np.concatenate((np.repeat(query, repeats=n, axis=0), candidates),␣
↪axis=2)
    res = grid.prod(axis=2).sum(axis=1)
```

```
    ret.iloc[i*n: (i+1)*n, 2] = res

  t2 = time.time()
  ret = ret.pivot(index=f'{name}_x', columns=f'{name}_y', values='value')
  t3 = time.time()

  print(f'time to compute similarity: {t2-t1}, time to pivot: {t3-t2}')

  return ret

#computes dot product similarity on sparse matrix
def compute_dot_product_similarity_matrix_sparse(ids, vectors, name='item'):
  n, m = vectors.shape
  name = 'item'

  ret = pd.DataFrame({name: ids}) #item/user/element ids
  ret = ret.merge(ret, how='cross')
  ret['value'] = 0

  t1 = time.time()
  for i in range(n):
    query = vectors[i].toarray().ravel()
    res = vectors.dot(query)
    ret.iloc[i*n: (i+1)*n, 2] = res

  t2 = time.time()
  ret = ret.pivot(index=f'{name}_x', columns=f'{name}_y', values='value')
  t3 = time.time()

  print(f'time to compute similarity: {t2-t1}, time to pivot: {t3-t2}')

  return ret
```

[80]:
```
#compute dot product similarity matrix for 200 users (regular matrix)
n = 200
ut_small = utility.iloc[:n].copy() #consider only 200 users
compute_dot_product_similarity_matrix_nonsparse(ut_small)
```

```
time to compute similarity: 4.472267150878906, time to pivot:
0.01401972770690918
```

[80]:
```
UserID_y        1           2          3          4          5          6    \
UserID_x
1         24.113208    1.817464  -1.103589   0.387242  -1.309510   1.543715
2          1.817464  128.387597   1.861833  -0.912145  -5.840185  -1.508462
3         -1.103589    1.861833  48.509804   1.427638  -3.449495  -0.530793
4          0.387242   -0.912145   1.427638  23.238095  -0.209235   1.073105
```

```
5          -1.309510   -5.840185  -3.449495  -0.209235  252.752525  -5.072983
…              …           …          …          …           …          …
196        -0.404481   -2.802810   1.050245   0.758929    4.961490  -4.607394
197        -3.051458    3.002114   4.053476   0.173160    2.877870  -3.165173
198         2.685468    8.234726   2.194371  -1.072245   23.283428  -4.543127
199         0.136722   12.694146   5.687738  -4.102345   -2.885233 -10.211057
200        -0.640784    0.000000  -0.984917   0.000000   -4.720474   1.789274

UserID_y          7          8          9         10   …        191        192  \
UserID_x                                               …
1          0.287888   0.718746   2.554290  -0.367713   … -0.333333   1.509218
2          2.915979  -0.251910   5.805616  -0.883528   …  1.000000   8.971030
3          1.651486  -3.053181  -1.265261   0.354310   …  2.163399   4.327171
4         -0.622120   1.624529   0.872417  -3.081938   …  0.539683  -6.803810
5          0.611600   7.911998   2.041166  -1.312854   …  3.324916  23.846378
…              …          …          …          …   …         …          …
196        0.020161   4.035072   0.066038   3.207918   …  1.583333   1.481429
197        0.909091  -1.538914   4.975986  -0.312854   …  1.818182   7.587532
198        4.484041  14.698962   7.185941  17.760342   …  1.584872  81.733132
199        0.518536  24.785622  10.315404   2.350355   …  2.310945  74.750874
200        0.000000  -0.752075   1.191582   0.183675   … -0.294872   4.963077

UserID_y         193        194        195        196        197         198  \
UserID_x
1          -2.040075 -0.393348   0.666208  -0.404481  -3.051458    2.685468
2          -4.040682 -0.517803  14.047521  -2.802810   3.002114    8.234726
3           0.638470 -1.159189   6.369353   1.050245   4.053476    2.194371
4           0.648170 -0.795803   3.392365   0.758929   0.173160   -1.072245
5           4.260748 -2.486218   4.386659   4.961490   2.877870   23.283428
…               …         …          …          …          …           …
196         2.164256 -0.018008   2.436588  19.875000   0.068182    3.843997
197         3.313298  0.000000   6.918491   0.068182  23.818182    0.133605
198        16.461458  0.486651  53.839727   3.843997   0.133605  379.187335
199         2.507524  1.156590  51.729019   2.137593   3.764586   42.445024
200         0.998411  1.391786  -0.453023  -0.036058   0.000000   -0.453115

UserID_y          199        200
UserID_x
1            0.136722  -0.640784
2           12.694146   0.000000
3            5.687738  -0.984917
4           -4.102345   0.000000
5           -2.885233  -4.720474
…                …          …
196          2.137593  -0.036058
197          3.764586   0.000000
198         42.445024  -0.453115
```

```
199       476.350746   5.916475
200         5.916475  40.346154

[200 rows x 200 columns]
```

[81]:
```
#compute dot product similarity matrix for 200 users (regular matrix)
n = 200
ut_small = utility.iloc[:n].copy() #consider only 200 users
compute_dot_product_similarity_matrix_sparse(ut_small.index.values,
 ↪csr_matrix(ut_small))
```

```
time to compute similarity: 0.10673189163208008, time to pivot:
0.014732837677001953
```

[81]:
```
item_y          1           2          3          4          5          6    \
item_x
1       24.113208    1.817464  -1.103589   0.387242   -1.309510   1.543715
2        1.817464  128.387597   1.861833  -0.912145   -5.840185  -1.508462
3       -1.103589    1.861833  48.509804   1.427638   -3.449495  -0.530793
4        0.387242   -0.912145   1.427638  23.238095   -0.209235   1.073105
5       -1.309510   -5.840185  -3.449495  -0.209235  252.752525  -5.072983
…             …          …          …          …          …          …
196     -0.404481   -2.802810   1.050245   0.758929    4.961490  -4.607394
197     -3.051458    3.002114   4.053476   0.173160    2.877870  -3.165173
198      2.685468    8.234726   2.194371  -1.072245   23.283428  -4.543127
199      0.136722   12.694146   5.687738  -4.102345   -2.885233 -10.211057
200     -0.640784    0.000000  -0.984917   0.000000   -4.720474   1.789274

item_y         7          8          9          10   …       191        192  \
item_x                                                …
1       0.287888   0.718746   2.554290  -0.367713  …  -0.333333   1.509218
2       2.915979  -0.251910   5.805616  -0.883528  …   1.000000   8.971030
3       1.651486  -3.053181  -1.265261   0.354310  …   2.163399   4.327171
4      -0.622120   1.624529   0.872417  -3.081938  …   0.539683  -6.803810
5       0.611600   7.911998   2.041166  -1.312854  …   3.324916  23.846378
…            …          …          …          …  …        …          …
196     0.020161   4.035072   0.066038   3.207918  …   1.583333   1.481429
197     0.909091  -1.538914   4.975986  -0.312854  …   1.818182   7.587532
198     4.484041  14.698962   7.185941  17.760342  …   1.584872  81.733132
199     0.518536  24.785622  10.315404   2.350355  …   2.310945  74.750874
200     0.000000  -0.752075   1.191582   0.183675  …  -0.294872   4.963077

item_y         193        194        195        196        197        198  \
item_x
1        -2.040075  -0.393348   0.666208  -0.404481  -3.051458   2.685468
2        -4.040682  -0.517803  14.047521  -2.802810   3.002114   8.234726
3         0.638470  -1.159189   6.369353   1.050245   4.053476   2.194371
```

```
4          0.648170 -0.795803   3.392365   0.758929   0.173160   -1.072245
5          4.260748 -2.486218   4.386659   4.961490   2.877870   23.283428
…               …         …          …          …          …           …
196        2.164256 -0.018008   2.436588  19.875000   0.068182    3.843997
197        3.313298  0.000000   6.918491   0.068182  23.818182    0.133605
198       16.461458  0.486651  53.839727   3.843997   0.133605  379.187335
199        2.507524  1.156590  51.729019   2.137593   3.764586   42.445024
200        0.998411  1.391786  -0.453023  -0.036058   0.000000   -0.453115

item_y          199        200
item_x
1          0.136722  -0.640784
2         12.694146   0.000000
3          5.687738  -0.984917
4         -4.102345   0.000000
5         -2.885233  -4.720474
…                …          …
196        2.137593  -0.036058
197        3.764586   0.000000
198       42.445024  -0.453115
199      476.350746   5.916475
200        5.916475  40.346154

[200 rows x 200 columns]
```

Observations: We can observe that working with csr_matrix is much faster compared to regular matrices. We will next define helper functions for computing similarity matrices using pearson correlation and cosine similarity measures. We will be using csr_matrix for performance reasons.

[82]:
```python
from scipy.stats import pearsonr
from sklearn.metrics.pairwise import cosine_similarity

#computes Pearson correlation pairwise similarity matrix (input is sparse␣
↪matrix)
def compute_pearson_similarity_matrix_sparse(ids, vectors, rounding_scale=3):
  n, m = vectors.shape
  name = 'item'

  ret = pd.DataFrame({name: ids}) #item/user/element ids
  ret = ret.merge(ret, how='cross')
  ret['value'] = 0

  t1 = time.time()
  corr_mat = lil_matrix((n, n))
  for i in range(n):
    for j in range(i+1, n):
```

```
        item1, item2 = vectors[i].toarray().ravel(), vectors[j].toarray().
↪ravel()
        corr, _ = pearsonr(item1, item2)
        corr_mat[i, j] = corr_mat[j, i] = np.round(corr, rounding_scale)
  #corr_mat = corr_mat.tocsr()
  #return corr_mat
  t2 = time.time()
  print('Time taken: ', t2-t1)
  return pd.DataFrame(corr_mat.toarray(), index=ids, columns=ids)

#computes pairwise cosine similarity matrix (input is sparse matrix)
def compute_cosine_similarity_matrix_sparse(ids, vectors, rounding_scale=3):
  t1 = time.time()
  res = np.round(cosine_similarity(vectors), rounding_scale)
  t2 = time.time()
  print('Time taken: ', t2-t1)
  return pd.DataFrame(res, index=ids, columns=ids)
```

2.3.2 Item based similarity using (modified) Pearson correlation

Approach: Find items(movies) which are similar to the given item(movie) using Pearson correlation as similarity measure. For each candidate movie and the given query movie, we can compute correlation in two basic ways.

1. Compute correlation using all features. However, with this approach, becuase of sparsity of vectors, computed correlation score may not be accurate.
2. Compute correlation using only common non-zero features of the query and candidate vectors. This should work well as long as there are sufficient number of common non-zero features between two vectors. If, however, there are very small subset of common features (E.g. two movies belonging to entirely different set of genres, but released in the same year and with same ratings will be considered highly similar)

One implementation approach is to combine both the approaches by taking minimum of the above two correlation scores as the final correlation value.

```
corr = pearsonr(query, candidate)

if specialcorr == True:
  let cf = set of common non-zero features of both query and candidate.
  corr_common_feat =  pearsonr(query[cf], candidate[cf])
  corr = min(corr, corr_common_feat)
```

Higher positive correlation implies more similarity, higher negative correlation implies more dissimilarity, and zero correlation implies unrelated movies. For recommendations, we return movies with highest positive correlation values.

[83]:
```
#find similar movies based on modified pearson correlation.
def find_similar_movies_pearson(query_obj = None, query_id = None, topN=0,␣
↪corrtype='both', rounding_scale=3):
```

```python
n, m = m_profile.shape
name = 'item'

ret = pd.DataFrame({name: m_profile.index.values}) #item/user/element ids
ret['corr'] = 0

if query_id is not None:
  query = m_profile.loc[query_id]
elif query_obj is not None:
  query = query_obj
else:
  raise "must supply one of query_obj or query_id"

query_mask = query != 0 #features where query movie has non-zero entries

t1 = time.time()

#compute correlation
for i in range(n):

  candidate = m_profile.iloc[i]
  #regular correlation
  corr1, _ = pearsonr(query, candidate)

  if corrtype == 'both' or corrtype == 'subset':  #also compute correlation based on common features. Take min of both correlations as the final correlation.
    candidate_mask = candidate != 0 #feature where candidate movie has non-zero entries
    and_mask = query_mask & candidate_mask #features where both query and candidate movie have non-zero entries

    if(and_mask.sum() > 2):
      #compute pearson correlation on the subset of features
      corr2, _ = pearsonr(query[and_mask], candidate[and_mask])
    else: #subset too small. default to standard
      corr2 = np.NAN

  if(corrtype == 'both'):
    corr = min([corr1, corr2])
  elif(corrtype == 'subset' and ~np.isnan(corr2)):
    corr = corr2
  else: #standard correlation using all features
    corr = corr1

  ret.iloc[i,1] = corr
```

```
    ret['corr'] = np.round(ret['corr'], rounding_scale)

    #remove query object from result if necessary
    if query_id is not None:
      ret = ret[ret[name] != query_id].copy()

    #sort by correlation in descending
    ret = ret.sort_values(by='corr', ascending=False)

    #return topN if asked
    if(topN > 0):
      ret = ret[:topN]

    t2 = time.time()
    print('Time taken: ', t2-t1)
    return ret
```

Example 1: Find top 5 movies similar to movie id 1.

[84]:
```
qid = 1
res = find_similar_movies_pearson(query_id=qid, topN=5)
res
```

```
Time taken:  13.690950632095337
```

[84]:

	item	corr
1205	1223	0.865
1132	1148	0.862
3360	3429	0.858
2070	2139	0.855
3327	3396	0.854

[85]:
```
#show query movies and movies similar movies it
m_profile.loc[[qid] + res['item'].values.tolist()]
```

[85]:

```
         release_year  Action  Adventure  Animation  Children's  Comedy  \
MovieID
1            0.585859       0          0          1           1       1
1223         0.419192       0          0          1           0       1
1148         0.454545       0          0          1           0       1
3429         0.378788       0          0          1           0       1
2139         0.242424       0          0          1           1       0
3396         0.212121       0          0          0           1       1

         Crime  Documentary  Drama  Fantasy  …  Horror  Musical  Mystery  \
MovieID                                      …
1            0            0      0        0  …       0        0        0
```

```
1223          0            0       0        0   ...      0        0        0
1148          0            0       0        0   ...      0        0        0
3429          0            0       0        0   ...      0        0        0
2139          0            0       0        0   ...      0        0        0
3396          0            0       0        0   ...      0        0        0

         Romance  Sci-Fi  Thriller  War  Western  movie_avg_rating  \
MovieID
1              0       0         0    0        0          1.119896
1223           0       0         0    0        0          1.347649
1148           0       0         0    0        0          1.502982
3429           0       0         0    0        0          1.320324
2139           0       0         0    0        0          0.805973
3396           0       0         0    0        0          0.811526

         movie_rating_cnt
MovieID
1                0.991883
1223             0.828580
1148             0.931714
3429             0.708028
2139             0.775741
3396             0.907625

[6 rows x 21 columns]
```

Example 2: Find top 10 movies similar to a movie with the characteristics defined as follow.

- release_year : 1995
- genres : Crime, Thriller
- rating : 4

[86]:

```
release_year = qt.transform([[1995, 0]])[0][0]
rating = rating_ss.transform([[4]])[0][0]

qobj = pd.Series([release_year, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
 ↪0, 0, rating, 0])
res = find_similar_movies_pearson(query_obj=qobj, topN=5)
res
```

```
Time taken:  12.235384941101074
```

[86]:

	item	corr
653	659	0.930
2883	2952	0.914
46	47	0.861
49	50	0.860
2848	2917	0.855

[87]:
```
#show similar movies
m_profile.loc[res['item'].values.tolist()]
```

[87]:
```
         release_year  Action  Adventure  Animation  Children's  Comedy  \
MovieID
659          0.106061       0          0          0           0       0
2952         0.676768       0          0          0           0       0
47           0.585859       0          0          0           0       0
50           0.585859       0          0          0           0       0
2917         0.232323       0          0          0           0       0

         Crime  Documentary  Drama  Fantasy  …  Horror  Musical  Mystery  \
MovieID                                      …
659          1            0      0        0  …       0        0        0
2952         1            0      0        0  …       0        0        0
47           1            0      0        0  …       0        0        0
50           1            0      0        0  …       0        0        0
2917         1            0      0        0  …       0        0        0

         Romance  Sci-Fi  Thriller  War  Western  movie_avg_rating  \
MovieID
659            0       0         1    0        0          0.667048
2952           0       0         1    0        0          0.696023
47             0       0         1    0        0          1.077007
50             0       0         1    0        0          1.512710
2917           0       0         1    0        0          0.997784

         movie_rating_cnt
MovieID
659              0.247475
2952             0.614966
47               0.961040
50               0.990117
2917             0.842239

[5 rows x 21 columns]
```

2.3.3 item-item cosine similarity matrix

[88]:
```
movies_sm = compute_cosine_similarity_matrix_sparse(m_profile.index.values,␣
↪sparse_movies_profile)
movies_sm
```

```
Time taken:  0.4716513156890869
```

[88]:
```
         1      2      3      4      5      6      7      8      9      10    \
1    1.000  0.491  0.505  0.377  0.606  0.422  0.607  0.443  0.098  0.362
```

```
2     0.491  1.000  0.304  0.242  0.352  0.284  0.310  0.835  0.266  0.520
3     0.505  0.304  1.000  0.635  0.818  0.273  0.972  0.250  0.336  0.294
4     0.377  0.242  0.635  1.000  0.783  0.155  0.570  0.231  0.359  0.201
5     0.606  0.352  0.818  0.783  1.000  0.312  0.787  0.298  0.402  0.338
…     …     …     …     …     …     …     …     …     …     …
3948  0.747  0.408  0.742  0.636  0.901  0.489  0.804  0.324  0.323  0.459
3949  0.555  0.349  0.330  0.494  0.386  0.510  0.456  0.261  0.171  0.440
3950  0.437  0.306  0.306  0.588  0.368  0.411  0.391  0.274  0.229  0.366
3951  0.467  0.282  0.265  0.508  0.319  0.427  0.380  0.241  0.152  0.363
3952  0.454  0.332  0.333  0.516  0.391  0.649  0.411  0.263  0.232  0.621

      …   3943   3944   3945   3946   3947   3948   3949   3950   3951  \
1     …  0.570  0.120  0.161  0.014  0.337  0.747  0.555  0.437  0.467
2     …  0.330  0.146  0.497  0.201  0.203  0.408  0.349  0.306  0.282
3     …  0.762  0.509  0.215  0.271  0.186  0.742  0.330  0.306  0.265
4     …  0.748  0.901  0.321  0.586  0.083  0.636  0.494  0.588  0.508
5     …  0.945  0.646  0.269  0.331  0.209  0.901  0.386  0.368  0.319
…    …     …     …     …     …     …     …     …     …     …
3948  …  0.906  0.426  0.068  0.235  0.360  1.000  0.670  0.599  0.594
3949  …  0.453  0.252 -0.119  0.323  0.394  0.670  1.000  0.961  0.974
3950  …  0.487  0.443  0.020  0.463  0.299  0.599  0.961  1.000  0.990
3951  …  0.443  0.339 -0.080  0.370  0.322  0.594  0.974  0.990  1.000
3952  …  0.441  0.330  0.003  0.599  0.745  0.591  0.858  0.848  0.837

       3952
1     0.454
2     0.332
3     0.333
4     0.516
5     0.391
…     …
3948  0.591
3949  0.858
3950  0.848
3951  0.837
3952  1.000

[3883 rows x 3883 columns]
```

[88]:

```

```

2.3.4 user-user cosine similarity matrix

[89]:

```
users_sm = compute_cosine_similarity_matrix_sparse(users['UserID'].values,␣
  ↪sparse_user_profile, rounding_scale=1)
users_sm
```

```
Time taken:  4.935536623001099
```

[89]:

```
      1     2     3     4     5     6     7     8     9     10    …  6031  \
1      1.0   0.1   0.0   0.1  -0.0   0.1   0.0   0.0   0.1   0.0  …   0.0
2      0.1   1.0   0.0   0.0  -0.0  -0.0   0.1   0.0   0.1   0.0  …   0.0
3      0.0   0.0   1.0   0.1   0.0   0.0   0.1  -0.0   0.0   0.0  …  -0.0
4      0.1   0.0   0.1   1.0  -0.0   0.0   0.1   0.0   0.0  -0.0  …  -0.0
5     -0.0  -0.0   0.0  -0.0   1.0  -0.0   0.0   0.1   0.0  -0.0  …   0.0
…    …   …   …   …   …   …   …   …   …   …  …   …
6036  -0.0   0.1   0.0   0.0   0.1  -0.0   0.0   0.1   0.0   0.0  …   0.0
6037   0.0   0.1   0.0   0.0  -0.0  -0.0   0.0   0.0   0.1   0.0  …   0.0
6038   0.0   0.0   0.1  -0.0  -0.0  -0.0   0.1   0.0   0.1   0.1  …  -0.0
6039   0.0   0.0   0.1   0.1   0.0  -0.0   0.0   0.0   0.0   0.0  …   0.0
6040   0.0   0.0  -0.0   0.0   0.1   0.0   0.0   0.1   0.0  -0.0  …  -0.0

      6032  6033  6034  6035  6036  6037  6038  6039  6040
1      0.0   0.1   0.0   0.1  -0.0   0.0   0.0   0.0   0.0
2      0.0   0.1   0.0   0.1   0.1   0.1   0.0   0.0   0.0
3      0.1   0.0   0.1   0.0   0.0   0.0   0.1   0.1  -0.0
4      0.1   0.0   0.1  -0.0   0.0   0.0  -0.0   0.1   0.0
5      0.0   0.0   0.0   0.1   0.1  -0.0  -0.0   0.0   0.1
…    …   …   …   …   …   …   …   …   …
6036   0.0   0.1   0.1   0.1   1.0   0.0  -0.0   0.0   0.1
6037   0.1   0.0   0.0   0.0   0.0   1.0   0.0   0.1   0.1
6038   0.0   0.1   0.0   0.0  -0.0   0.0   1.0   0.1  -0.0
6039   0.0   0.0   0.1   0.0   0.0   0.1   0.1   1.0   0.1
6040   0.1   0.0   0.1  -0.0   0.1   0.1  -0.0   0.1   1.0

[6040 rows x 6040 columns]
```

2.3.5 item based similarity using cosine similarity

[90]:

```python
#find similar movies based on cosine similarity among movies.
def find_similar_movies_cosine(query_obj = None, query_id = None, topN=0,␣
 ↪rounding_scale=3):
  n, m = m_profile.shape
  name = 'item'

  ret = pd.DataFrame({name: m_profile.index.values}) #item/user/element ids
  ret['similarity'] = 0

  if query_id is not None:
    query = m_profile.loc[query_id]
  elif query_obj is not None:
    query = query_obj
  else:
    raise "must supply one of query_obj or query_id"
```

```
    t1 = time.time()

    #compute cosine similarity
    ret['similarity'] = np.round(cosine_similarity(m_profile.values, query.values.
↪reshape(1,-1)), rounding_scale)

    #remove query object from result if necessary
    if query_id is not None:
      ret = ret[ret[name] != query_id].copy()

    #sort by similarity in descending
    ret = ret.sort_values(by='similarity', ascending=False)

    #return topN if asked
    if(topN > 0):
      ret = ret[:topN]

    t2 = time.time()
    print('Time taken: ', t2-t1)
    return ret
```

Example 1: Find top 5 movies similar to movie id 1.

[91]:
```
qid = 1
res = find_similar_movies_cosine(query_id=qid, topN=5)
res
```

```
Time taken:  0.013625860214233398
```

[91]:

	item	similarity
3045	3114	0.991
2286	2355	0.985
3682	3751	0.978
2072	2141	0.942
1205	1223	0.896

[92]:
```
#show query movies and movies similar movies it
m_profile.loc[[qid] + res['item'].values.tolist()]
```

[92]:

MovieID	release_year	Action	Adventure	Animation	Children's	Comedy	\
1	0.585859	0	0	1	1	1	
3114	0.924242	0	0	1	1	1	
2355	0.843434	0	0	1	1	1	
3751	1.000000	0	0	1	1	1	
2141	0.308081	0	0	1	1	1	

```
1223         0.419192       0           0          1            0        1

         Crime  Documentary  Drama  Fantasy  …  Horror  Musical  Mystery  \
MovieID                                      …
1            0            0      0        0  …       0        0        0
3114         0            0      0        0  …       0        0        0
2355         0            0      0        0  …       0        0        0
3751         0            0      0        0  …       0        0        0
2141         0            0      0        0  …       0        0        0
1223         0            0      0        0  …       0        0        0

         Romance  Sci-Fi  Thriller  War  Western  movie_avg_rating  \
MovieID
1              0       0         0    0        0          1.119896
3114           0       0         0    0        0          1.196368
2355           0       0         0    0        0          0.809608
3751           0       0         0    0        0          0.836379
2141           0       0         0    0        0          0.357492
1223           0       0         0    0        0          1.347649

         movie_rating_cnt
MovieID
1                0.991883
3114             0.984857
2355             0.988535
3751             0.974501
2141             0.797432
1223             0.828580

[6 rows x 21 columns]
```

Example 2: Find top 10 movies similar to a movie with the characteristics defined as follow.

- release_year : 1995
- genres : Crime, Thriller
- rating : 4

[93]:
```
release_year = qt.transform([[1995, 0]])[0][0]
rating = rating_ss.transform([[4]])[0][0]

qobj = pd.Series([release_year, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
 ↪0, 0, rating, 0])
res = find_similar_movies_cosine(query_obj=qobj, topN=5)
res
```

```
Time taken:  0.006042957305908203
```

[93]:

```
      item  similarity
653    659       0.942
2883  2952       0.931
46      47       0.888
49      50       0.887
2848  2917       0.883
```

[94]:

```python
#show similar movies
m_profile.loc[res['item'].values.tolist()]
```

[94]:

```
         release_year  Action  Adventure  Animation  Children's  Comedy  \
MovieID
659          0.106061       0          0          0           0       0
2952         0.676768       0          0          0           0       0
47           0.585859       0          0          0           0       0
50           0.585859       0          0          0           0       0
2917         0.232323       0          0          0           0       0

         Crime  Documentary  Drama  Fantasy  …  Horror  Musical  Mystery  \
MovieID                                      …
659          1            0      0        0  …       0        0        0
2952         1            0      0        0  …       0        0        0
47           1            0      0        0  …       0        0        0
50           1            0      0        0  …       0        0        0
2917         1            0      0        0  …       0        0        0

         Romance  Sci-Fi  Thriller  War  Western  movie_avg_rating  \
MovieID
659            0       0         1    0        0          0.667048
2952           0       0         1    0        0          0.696023
47             0       0         1    0        0          1.077007
50             0       0         1    0        0          1.512710
2917           0       0         1    0        0          0.997784

         movie_rating_cnt
MovieID
659              0.247475
2952             0.614966
47               0.961040
50               0.990117
2917             0.842239

[5 rows x 21 columns]
```

[94]:

2.3.6 item based cosine similarity using sklearn NearestNeighbors

[ ]:
```
from sklearn.neighbors import NearestNeighbors


def find_similar_movies_cosine_knn(query_obj = None, query_id = None, k=5,␣
↪rounding_scale=3):
  n, m = m_profile.shape
  name = 'item'

  ret = pd.DataFrame(columns={name: [], 'cosine_distance': []}) #item/user/
↪element ids
  ret['cosine_distance'] = 0

  if query_id is not None:
    query = m_profile.loc[query_id].values
  elif query_obj is not None:
    query = query_obj
  else:
    raise "must supply one of query_obj or query_id"

  t1 = time.time()

  # Create NearestNeighbors model
  nbrs = NearestNeighbors(n_neighbors=k+1, algorithm='auto', metric='cosine').
↪fit(m_profile.values)

  # Find the nearest neighbors
  distances, indices = nbrs.kneighbors(query.reshape(1,-1))

  ret[name] = indices.flatten()
  ret['cosine_distance'] = np.round(distances.flatten(), rounding_scale)

  #remove query object from result if necessary
  if query_id is not None:
    ret = ret[ret[name] != query_id].copy()

  if(ret.shape[0] > k):
    ret = ret[1:k+1]

  #sort by similarity in descending
  ret = ret.sort_values(by='cosine_distance', ascending=True)

  t2 = time.time()
  print('Time taken: ', t2-t1)
  return ret
```

Example 1: Find top 5 movies similar to movie id 1.

[154]:
```
qid = 1
res = find_similar_movies_cosine_knn(query_id=qid, k=5)
res
```

```
Time taken:  0.025053024291992188
```

[154]:

	item	cosine_distance
1	3045	0.009
2	2286	0.015
3	3682	0.022
4	2072	0.058
5	584	0.104

[155]:
```
#show query movies and movies similar movies it
m_profile.loc[[qid] + res['item'].values.tolist()]
```

[155]:

MovieID	release_year	Action	Adventure	Animation	Children's	Comedy	\
1	0.585859	0	0	1	1	1	
3045	0.419192	0	0	0	0	1	
2286	0.222222	0	0	0	0	1	
3682	0.171717	0	0	0	0	0	
2072	0.363636	0	0	0	0	1	
584	0.454545	0	0	0	0	0	

MovieID	Crime	Documentary	Drama	Fantasy	…	Horror	Musical	Mystery	\
					…				
1	0	0	0	0	…	0	0	0	
3045	0	0	1	0	…	0	0	0	
2286	0	0	0	0	…	0	0	0	
3682	0	0	0	0	…	0	0	0	
2072	0	0	0	0	…	0	0	0	
584	0	0	1	0	…	0	0	0	

MovieID	Romance	Sci-Fi	Thriller	War	Western	movie_avg_rating	\
1	0	0	0	0	0	1.119896	
3045	0	0	0	0	0	0.002087	
2286	0	0	0	0	0	-0.614933	
3682	0	0	0	0	1	0.635726	
2072	0	0	0	0	0	-0.191349	
584	0	0	0	0	0	0.964104	

MovieID	movie_rating_cnt
1	0.991883
3045	0.513709

```
2286              0.328283
3682              0.644444
2072              0.732182
584               0.060606

[6 rows x 21 columns]
```

2.4 Collaborative filtering - Matrix factorization

[95]:
```
#create rating matrix. We also add those movies which do not have any ratings.␣
↪This is to ensure that we get all movies when we create embeddings.
df_temp = pd.merge(movies[['MovieID']], ratings, how='left')
df_temp['Rating'] = df_temp['Rating'].fillna(0).astype('int')
df_temp['UserID'] = df_temp['UserID'].fillna(users['UserID'][0]).astype('int')

rm = df_temp.pivot(index='UserID', columns='MovieID', values='Rating').fillna(0)
```

Train/test strategy For each user, we set aside roughly 20% ratings for test and the remaining for training.

[96]:
```
#Helper function to create train and test ratings matrices.
def create_train_test_matrices(rm, test_frac=0.2):
  n, m =  rm.shape

  t1 = time.time()

  #create train and test matrices.
  train_rm = rm.copy()
  test_rm = rm.copy()

  #holds indices of movies starting from 1 (so that we can use 0 as the absence␣
↪of rating)
  m_indices = np.array([i for i in range(1, m+1)])

  for i in range(n): #for each user
    user_row = rm.iloc[i].values
    is_rating_present = (user_row > 0).astype('int')

    # find indices where ratings are present
    user_rating_indices = is_rating_present * m_indices
    user_rating_indices = pd.Series(user_rating_indices[user_rating_indices > 0␣
↪] - 1)

    #compute test size
    test_size = int(round(user_rating_indices.shape[0] * test_frac))
```

```
    #randomly choose indices as test
    test_indices = np.random.choice(a=user_rating_indices, size=test_size,␣
↪replace=False)
    train_indices = user_rating_indices[~user_rating_indices.isin(test_indices)]

    #create train and test mask
    test_mask, train_mask = np.zeros(m), np.zeros(m)
    test_mask[test_indices] = 1
    train_mask[train_indices] = 1

    train_rm.iloc[i] = train_rm.iloc[i] * train_mask
    test_rm.iloc[i] = test_rm.iloc[i] * test_mask

  t2 = time.time()
  print('time taken to create train test matrices: ', t2-t1)

  return train_rm, test_rm
```

[97]:
```
#create train test rating matrices (with 80:20 proportion).
train_rm, test_rm = create_train_test_matrices(rm, test_frac=0.2)
```

```
time taken to create train test matrices:  7.1581761837005615
```

[98]:
```
#check number of ratings in train matrix
train_ratings_cnt = (~train_rm[train_rm > 0].isna()).sum(axis=1).sum()
train_ratings_cnt
```

[98]: 800193

[99]:
```
#check number of ratings in test matrix
test_ratings_cnt = (~test_rm[test_rm > 0].isna()).sum(axis=1).sum()
test_ratings_cnt
```

[99]: 200016

[100]:
```
#confirm that total number ratings =  number of train ratings +  number of test␣
↪ratings
total_ratings_cnt = (~rm[rm > 0].isna()).sum(axis=1).sum()
total_ratings_cnt == (train_ratings_cnt + test_ratings_cnt)
```

[100]: True

Matrix factorization using cmfrec

[101]:
```
from cmfrec import CMF
from sklearn.metrics import mean_squared_error as mse,␣
↪mean_absolute_percentage_error as mape
```

[102]:
```
#get long form raw rm from wide form rm
def get_rm_raw_from_rm(rm, keep_items_with_no_ratings=True):

  rm = rm.copy()

  if keep_items_with_no_ratings == True:
    #find all items without any ratings.
    #For these items, add dummy rating of 6 against first user.
    #We do so, because when we remove all zero ratings after converting to long␣
  ↪form,
    #we want to preserve atleast one rating for these items.
    #before returning, we convert these dummy ratings to zero.

    items_with_no_ratings = rm.loc[:, rm.sum(axis=0) == 0].columns.values
    rm.loc[rm.index[0], items_with_no_ratings] = 6

  #unstack to get long form
  rm_raw = rm.unstack()
  rm_raw = rm_raw[rm_raw > 0] #take only positive ratings
  rm_raw = rm_raw.reset_index()[['UserID', 'MovieID', 0]]
  rm_raw.columns = ['UserId', 'ItemId', 'Rating']
  rm_raw[rm_raw == 6] = 0 #assign zero rating wherever we had set dummy rating.
  return rm_raw

#compute and return rmse and mape
def compute_error_metrics(actual, predicted):
  rmse_err = mse(actual, predicted)**0.5
  mape_err = mape(actual, predicted)
  return rmse_err, mape_err
```

Prepare train and test data in long format

[103]:
```
#prepare raw rm from train data (preserve all items without any rating)
train_rm_raw = get_rm_raw_from_rm(train_rm, keep_items_with_no_ratings=True)
train_rm_raw.head()
```

[103]:

	UserId	ItemId	Rating
0	1	1	5.0
1	0	1	4.0
2	8	1	4.0
3	9	1	5.0
4	10	1	5.0

[104]:
```
#prepare raw rm from test data (don't preserve items without ratings)
test_rm_raw = get_rm_raw_from_rm(test_rm, keep_items_with_no_ratings=False)
test_rm_raw.head()
```

[104]:

	UserId	ItemId	Rating
0	28	1	3.0
1	73	1	3.0
2	75	1	5.0
3	76	1	5.0
4	78	1	4.0

Create model on train data

[105]:
```
#create model and fit on training data
model = CMF(method="als", k=4, lambda_=0.1, user_bias=False, item_bias=False,␣
↪verbose=False)
model.fit(train_rm_raw)
```

[105]:
```
Collective matrix factorization model
(explicit-feedback variant)
```

[106]:
```
model.A_.shape, model.B_.shape
```

[106]:
```
((6040, 4), (3883, 4))
```

Test performance on train data

[107]:
```
#compute performance on train data
train_rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_
train_actual = train_rm.values[train_rm > 0]
train_pred = train_rm__[train_rm > 0]
train_pred_tr = np.round(np.clip(train_pred, 1, 5)).astype('int')

train_rmse_err, train_mape_err = compute_error_metrics(train_actual,␣
↪train_pred_tr)
print(train_rmse_err, train_mape_err)
```

```
1.2040033339668108 0.3367440105074651
```

Test performance on test data

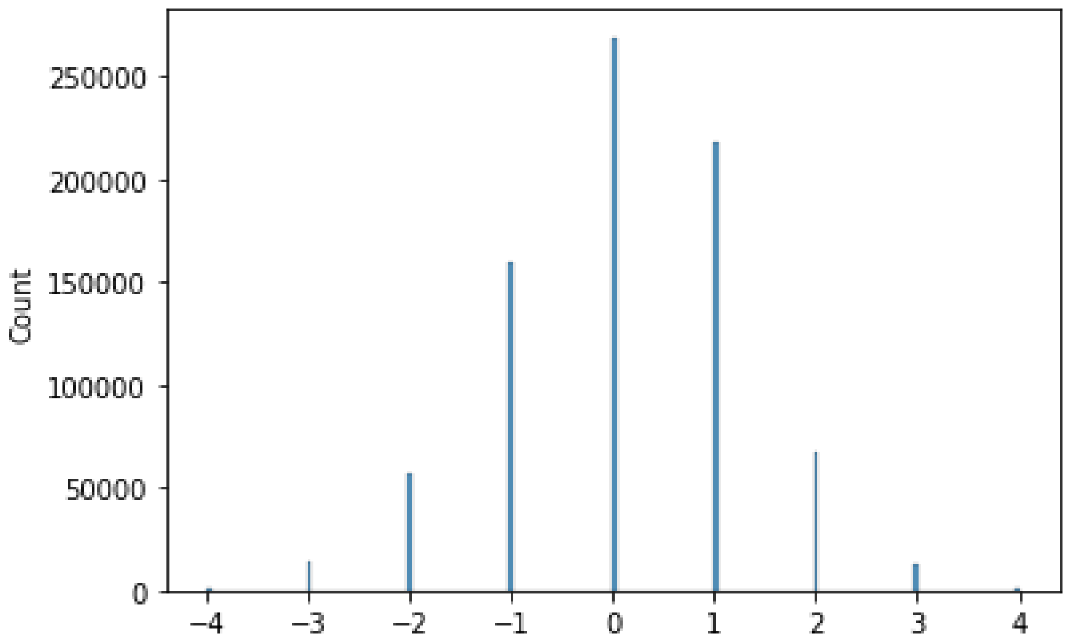
[108]:
```
#compute performance on test data
test_actual = test_rm_raw['Rating']
test_pred = model.predict(test_rm_raw['UserId'], test_rm_raw['ItemId'])
test_pred_tr = np.round(np.clip(test_pred, 1, 5)).astype('int')

test_rmse_err, test_mape_err = compute_error_metrics(test_actual, test_pred_tr)
print(test_rmse_err, test_mape_err)
```

```
0.9205173609568992 0.24883384329253652
```

plot distribution of train and test residuals

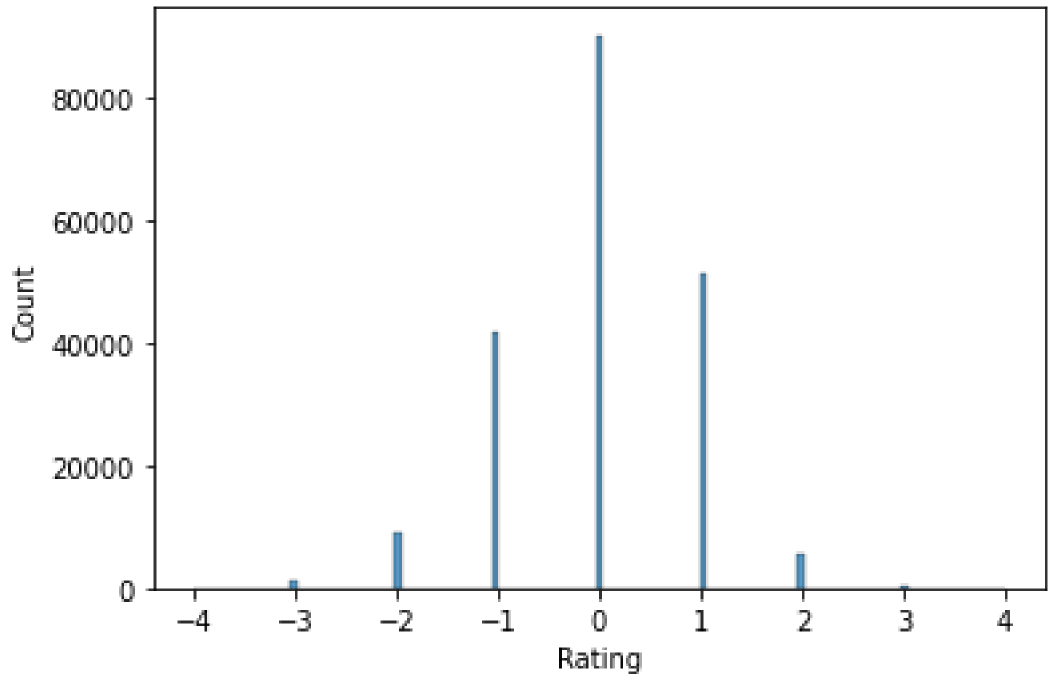
[109]:
```
# plot train errors
sns.histplot(train_actual - train_pred_tr)
```

[109]: <Axes: ylabel='Count'>



[110]:
```
# plot test errors
sns.histplot(test_actual - test_pred_tr)
```

[110]: <Axes: xlabel='Rating', ylabel='Count'>



2.4.1 Embeddings for item-item and user-user similarity

In this section, we find item-item and user-user similarity using the embeddings created by matrix factorization. We then compare the resultant similarity matrices against the corresponding similarity matrices computed from original data.

[111]:
```
import matplotlib.pyplot as plt

# helper function to visualize similarity matrix
def visualize_similarity_mat(sm, sm2, figsize=None, cmap='crest', center=None,␣
 ↪ax=None, title1="", title2=""):
  single = sm2 is None
  if figsize is None:
    figsize = (10, 8) if single else (16, 6)

  fig, axes = None, ax
  if axes is None:
    r = 1
    c = 1 if single else 2
    fig, axes = plt.subplots(r, c, figsize=figsize)

  if np.array(axes).ndim == 0:
    axes = np.array(axes).reshape(1)

  sns.heatmap(sm, cmap=cmap, center=center, ax=axes[0])
```

```
  axes[0].set_title(title1)

  if not single:
    sns.heatmap(sm2, cmap=cmap, center=center, ax=axes[1])
    axes[1].set_title(title2)

  plt.show()

def plot_similarity_dist(sm1, sm2):
  fig, axes = plt.subplots(1, 2, figsize=(16,6))
  sns.histplot(x=sm1.values.flatten(), ax=axes[0])
  sns.histplot(x=sm2.values.flatten(), ax=axes[1])
  plt.show()

def get_similarity_matrix_subset(sm, ids=None, n=None):
  if ids is None:
    ids = np.random.choice(a=sm.index.values, size=n, replace=False)

  return sm.loc[ids, ids], ids
```

Create user and movie embeddings for d=4 and d=2

[112]:
```
#creating user and item embeddings (d=4)
rm_raw = get_rm_raw_from_rm(rm)
model_d4 = CMF(method="als", k=4, lambda_=0.1, user_bias=False,␣
 ↪item_bias=False, verbose=False)
model_d4.fit(rm_raw)

user_embedding_d4 = csr_matrix(model_d4.A_)
item_embedding_d4 = csr_matrix(model_d4.B_)
```

[113]:
```
#creating user and item embeddings (d=2)
rm_raw = get_rm_raw_from_rm(rm)
model_d2 = CMF(method="als", k=2, lambda_=0.1, user_bias=False,␣
 ↪item_bias=False, verbose=False)
model_d2.fit(rm_raw)

user_embedding_d2 = csr_matrix(model_d2.A_)
item_embedding_d2 = csr_matrix(model_d2.B_)
```

create similarity matrices using *Raw* data We create the following similarity matrices

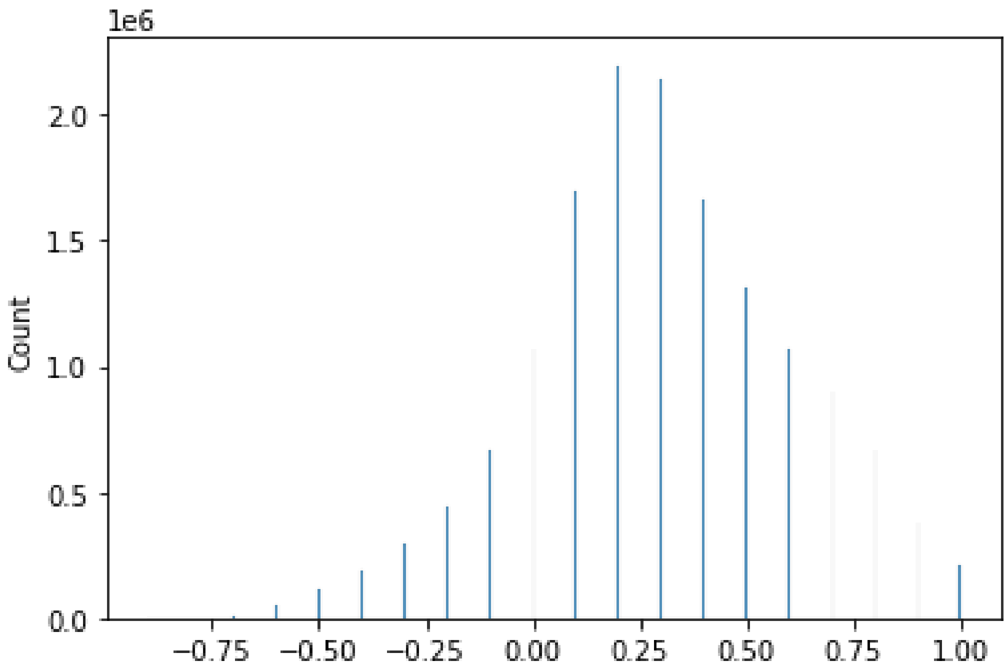
1. item-item cosine similarity
2. user-user cosine similarity

[114]:
```
#item item cosine similarity matrix using raw data
```

```
item_item_raw_cosine =␣
↪compute_cosine_similarity_matrix_sparse(movies['MovieID'],␣
↪sparse_movies_profile, rounding_scale=1)
sns.histplot(x=item_item_raw_cosine.values.flatten())
```

```
Time taken:  0.5298516750335693
```

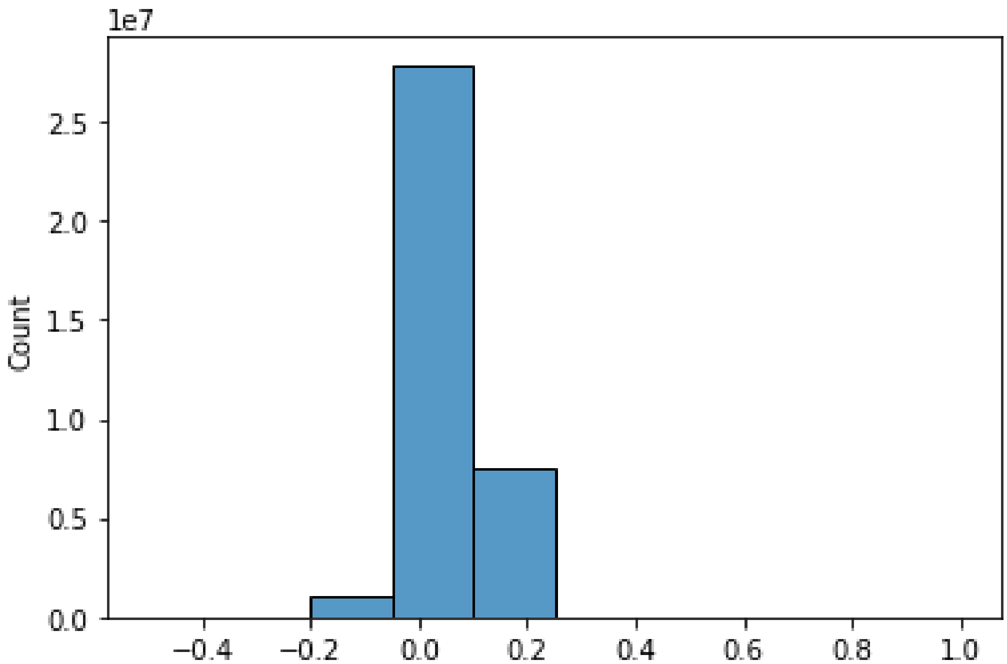
[114]: <Axes: ylabel='Count'>



[157]:
```
#user user cosine similarity matrix using raw data
user_user_raw_cosine = compute_cosine_similarity_matrix_sparse(users['UserID'],␣
↪sparse_utility, rounding_scale=1)
sns.histplot(x=user_user_raw_cosine.values.flatten(), bins=10)
```

```
Time taken:  7.935024738311768
```

[157]: <Axes: ylabel='Count'>



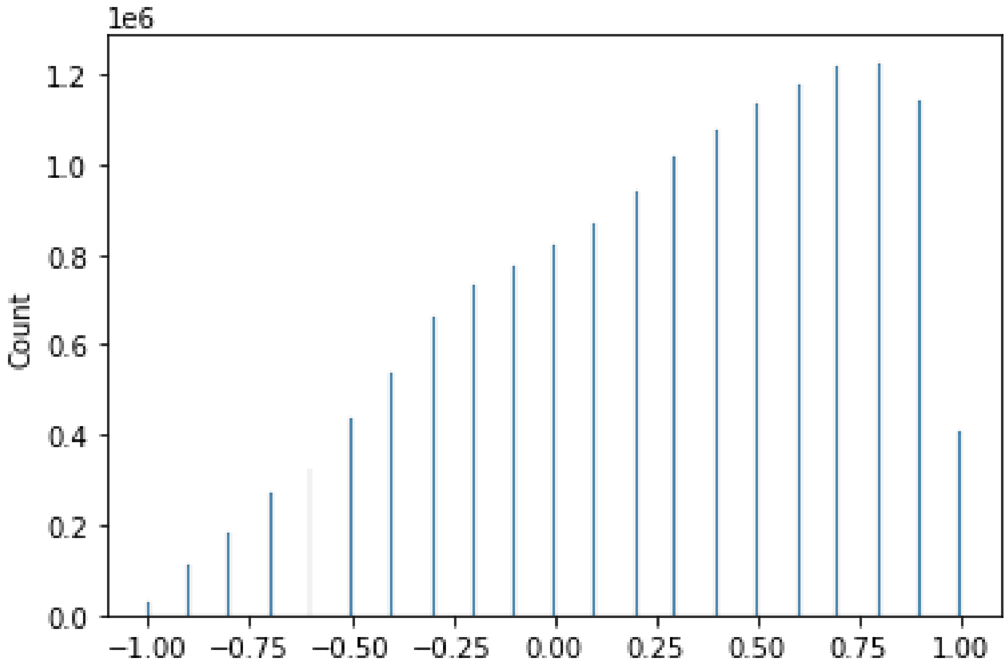
create similarity matrices using *embeddings* We create the following similarity matrices.

1. item-item cosine similarity for d=4
2. user-user cosine similarity for d=4
3. item-item cosine similarity for d=2
4. user-user cosine similarity for d=2

[116]:
```
#item item cosine similarity matrix with d4 embedding
item_item_d4_cosine =␣
 ↪compute_cosine_similarity_matrix_sparse(movies['MovieID'],␣
 ↪item_embedding_d4, rounding_scale=1)
sns.histplot(x=item_item_d4_cosine.values.flatten())
```

```
Time taken:  0.51774001121521
```

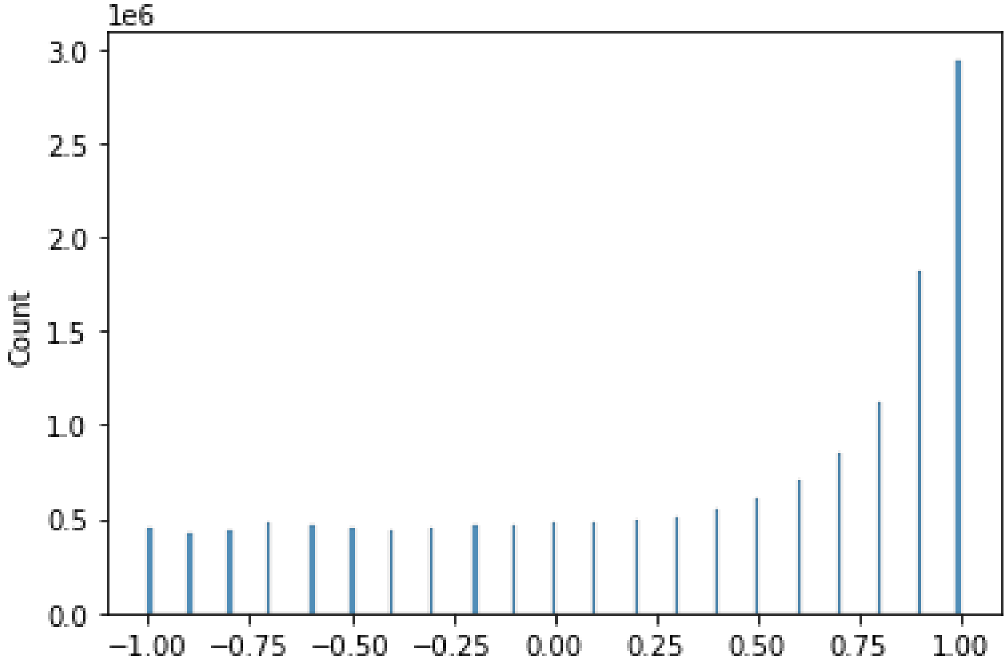
[116]:
```
<Axes: ylabel='Count'>
```



[117]:
```
#item item cosine similarity matrix with d2 embedding
item_item_d2_cosine =␣
 ↪compute_cosine_similarity_matrix_sparse(movies['MovieID'],␣
 ↪item_embedding_d2, rounding_scale=1)
sns.histplot(x=item_item_d2_cosine.values.flatten())
```

```
Time taken:  0.32555556297302246
```

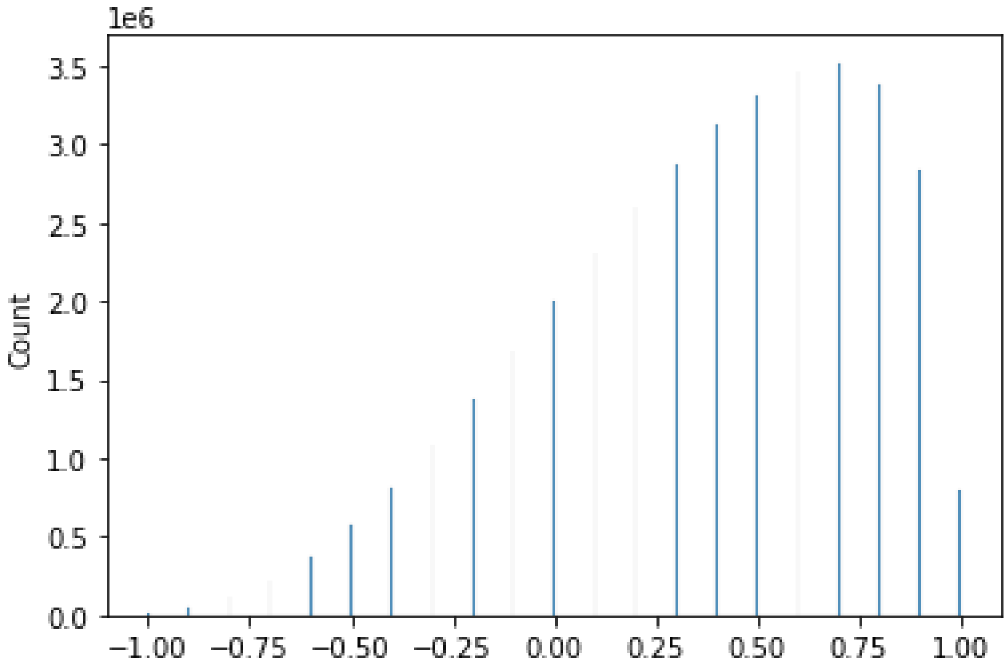
[117]: <Axes: ylabel='Count'>



[118]:
```
#user user cosine similarity matrix with d4 embedding
user_user_d4_cosine = compute_cosine_similarity_matrix_sparse(users['UserID'],␣
    ↪user_embedding_d4, rounding_scale=1)
sns.histplot(x=user_user_d4_cosine.values.flatten())
```

```
Time taken:  0.9482672214508057
```

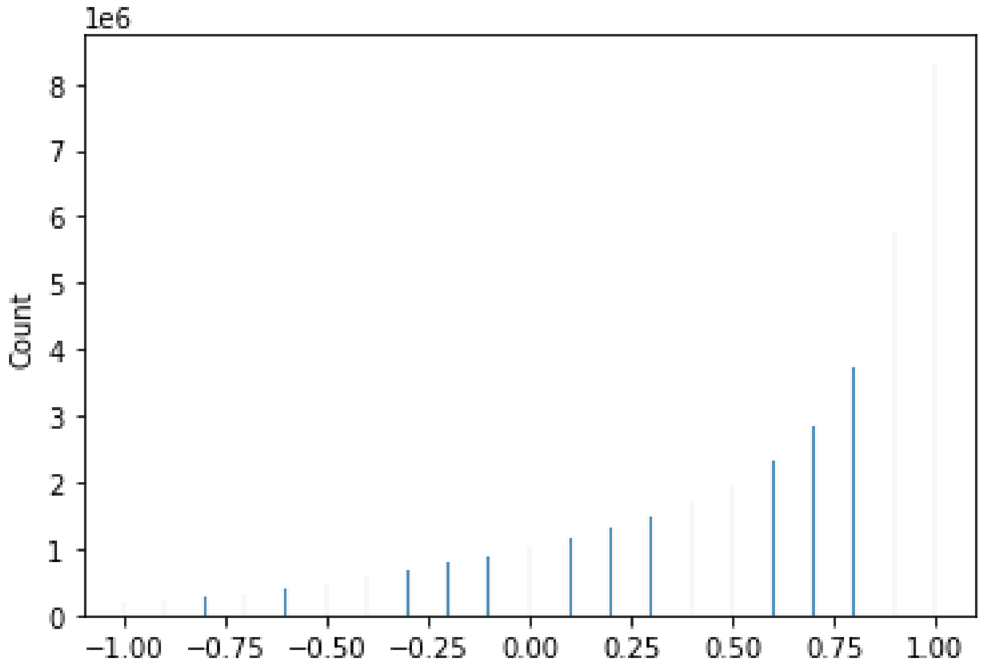
[118]: <Axes: ylabel='Count'>



[119]:
```
#user user cosine similarity matrix with d2 embedding
user_user_d2_cosine = compute_cosine_similarity_matrix_sparse(users['UserID'],␣
    ↪user_embedding_d2, rounding_scale=1)
sns.histplot(x=user_user_d2_cosine.values.flatten())
```

```
Time taken:  0.770803689956665
```

[119]:
```
<Axes: ylabel='Count'>
```



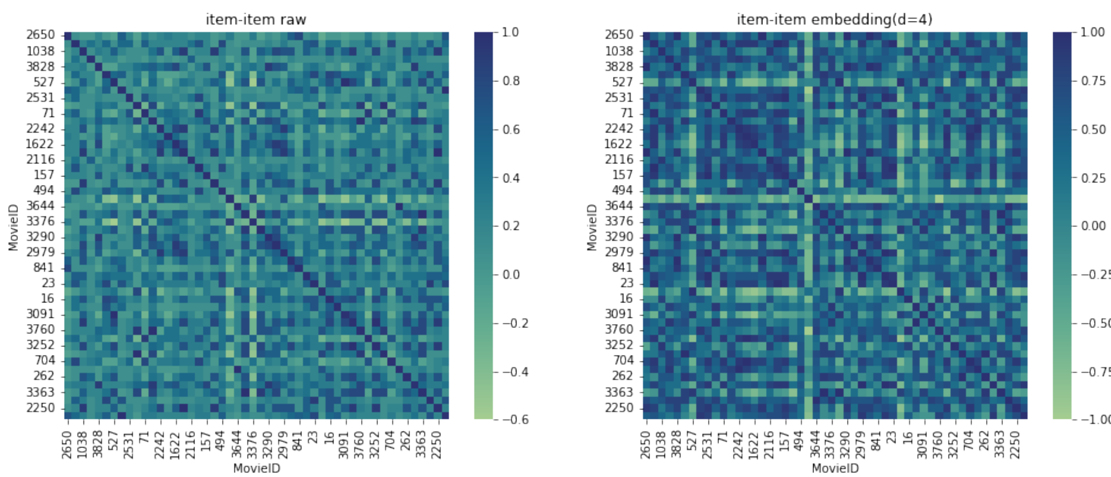
Visualize and compare similarity matrices for raw data and embeddings

[120]:
```
sim_matrices = [
  {
      "sm1": [item_item_raw_cosine, 'item-item raw'],
      "sm2": [item_item_d4_cosine, 'item-item embedding(d=4)']
  },
  {
      "sm1": [item_item_raw_cosine, 'item-item raw'],
      "sm2": [item_item_d2_cosine, 'item-item embedding(d=2)']
  },
  {
      "sm1": [user_user_raw_cosine, 'user-user raw'],
      "sm2": [user_user_d4_cosine, 'user-user embedding(d=4)']
  },
  {
      "sm1": [user_user_raw_cosine, 'user-user raw'],
      "sm2": [user_user_d2_cosine, 'user-user embedding(d=2)']
  }
]
```

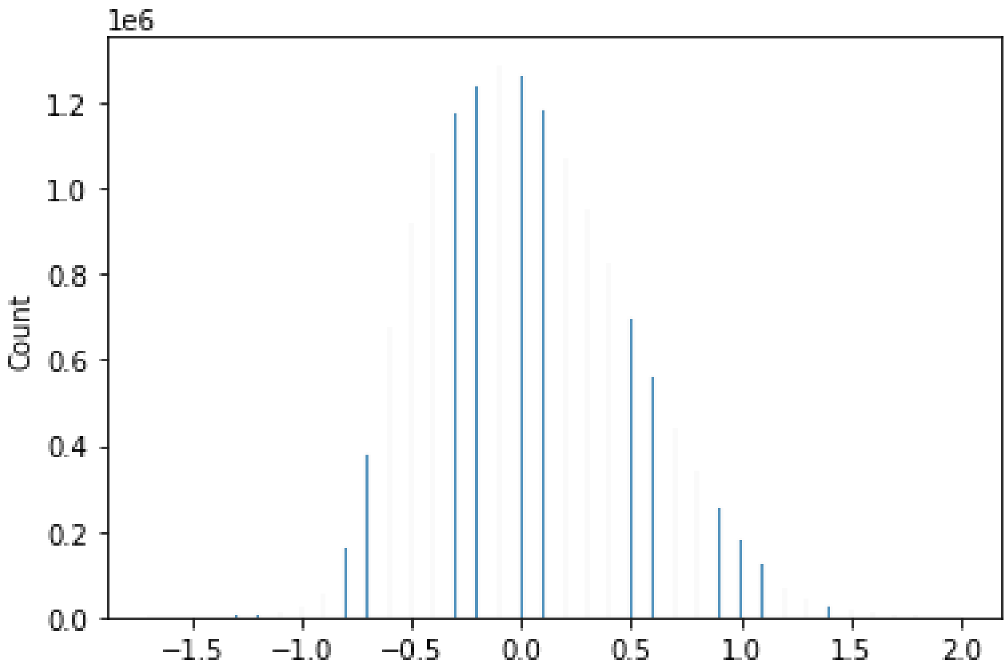
[156]:
```
#visualize original(raw) and embeddings similarity matrices
from IPython.display import Javascript
display(Javascript('''google.colab.output.setIframeHeight(0, true, {maxHeight:␣
 ↪5000})'''))
```

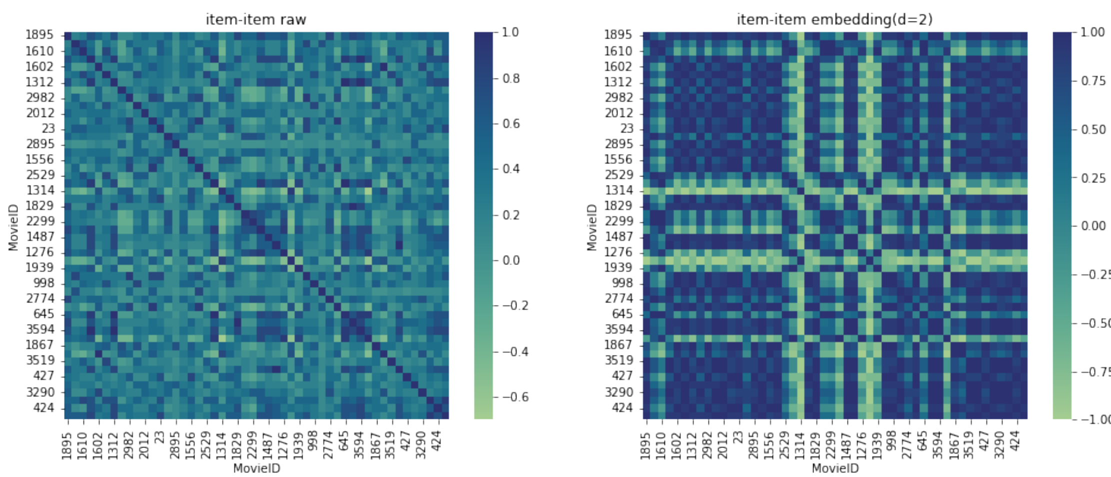
```
n=50 #subset size
for rec in sim_matrices:
  sm1, title1 = rec["sm1"]
  sm2, title2 = rec["sm2"]

  sm1_subset, user_indices = get_similarity_matrix_subset(sm1, n=n)
  sm2_subset, user_indices = get_similarity_matrix_subset(sm2,␣
 ↪ids=user_indices, n=n)

  visualize_similarity_mat(sm1_subset, sm2_subset, title1=title1, title2=title2)

  sim1_values = sm1.values
  sim2_values = sm2.values

  rmse_err, mape_err = compute_error_metrics(sim1_values, sim2_values)
  print(f'\nRMSE between {title1} and {title2}: {rmse_err}')

  print(f'Distribution of {title1} - {title2}')
  sns.histplot(x=(sim1_values.ravel() - sim2_values.ravel()))
  plt.show()
```

```
<IPython.core.display.Javascript object>
```

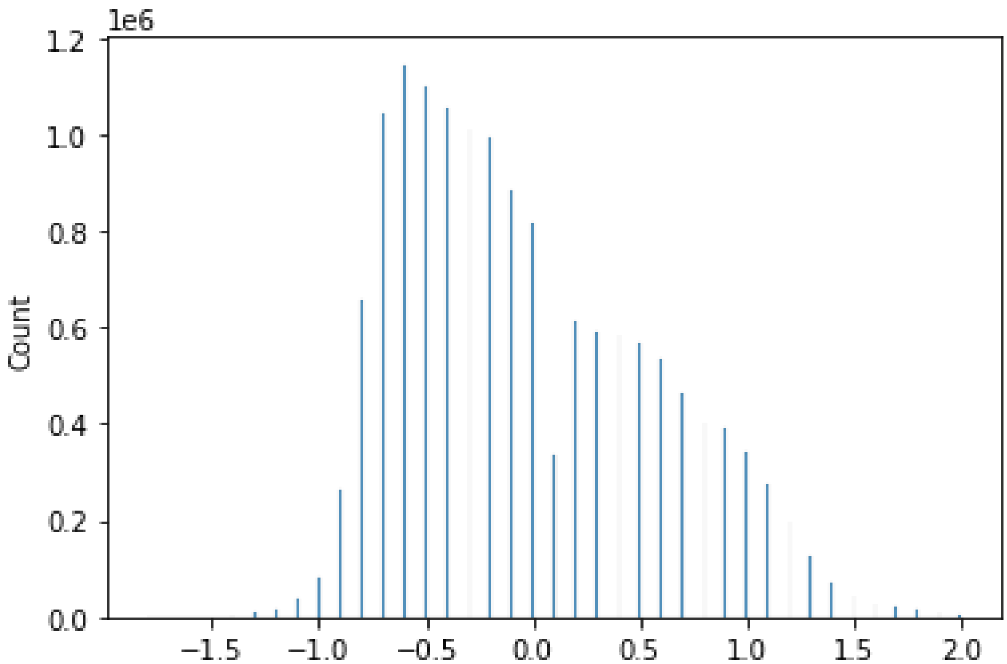


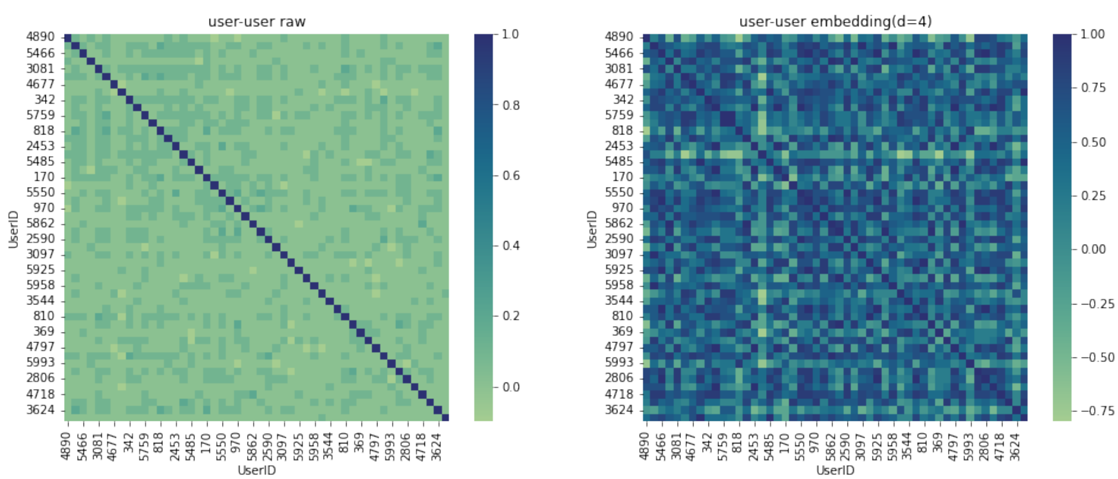

```
RMSE between item-item raw and item-item embedding(d=4): 0.45496289701600207
Distribution of item-item raw - item-item embedding(d=4)
```



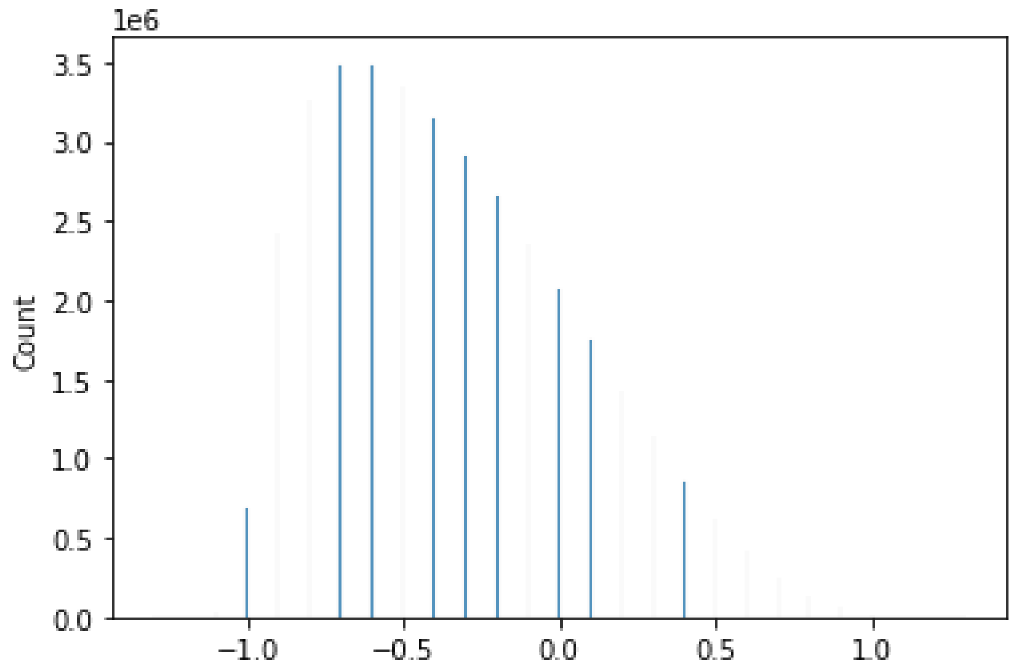


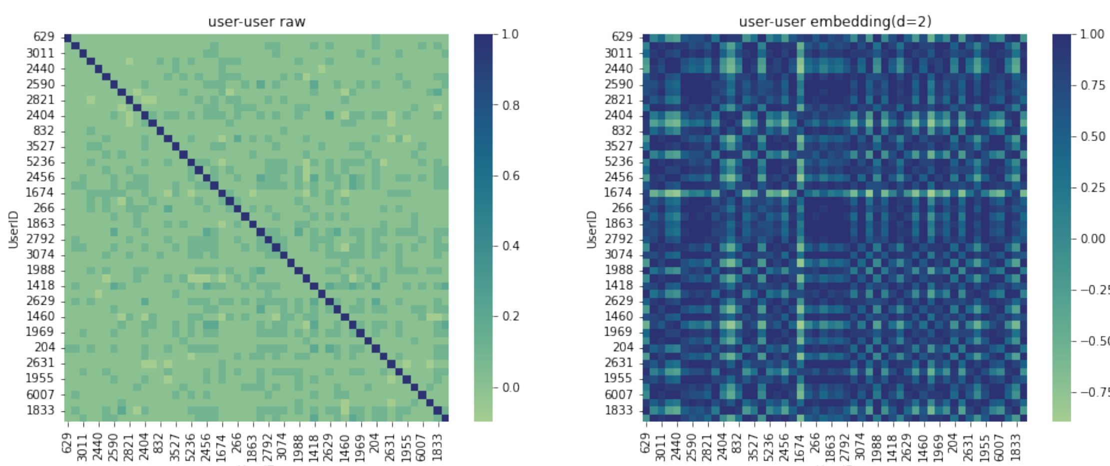

```
RMSE between item-item raw and item-item embedding(d=2): 0.5915489818934705
Distribution of item-item raw - item-item embedding(d=2)
```



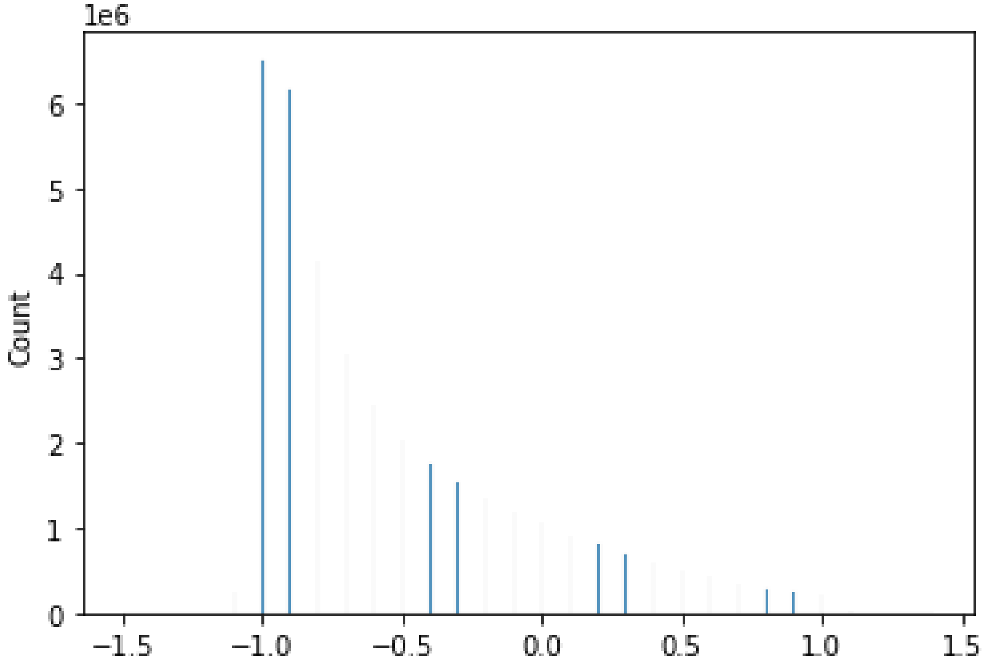


RMSE between user-user raw and user-user embedding(d=4): 0.5321302795059191
Distribution of user-user raw - user-user embedding(d=4)





`RMSE between user-user raw and user-user embedding(d=2): 0.7231652591029766`
`Distribution of user-user raw - user-user embedding(d=2)`



Observations:

1. For a small random subset of 100 items (movies), we can visually observe that the Heatmap pattern for cosine similarity for the item embedding(d=4) is visually relatively similar to the heatmap pattern for original raw data. However, the pattern for item embedding(d=2) looks relatively less similar to the heatmap pattern for the original raw data.

2. This visual observation can be confirmed through RMSE results between the original raw data and embeddings. RMSE score for item embedding(d=4) is 0.45, whereas for item embedding(d=2) is 0.56.

3. Similar observations can be made for user-user similarity matrices for embeddings(d=4) and embeddings(d=2). RMSE for user embedding(d=4) is 0.53, whereas for user embedding(d=2) is 0.72.

4. We also notice that the range of original cosine scores for items data is [-0.75, 1], and for users data is even narrower: [-0.2, ~0.25]. However, the range for all four embeddings; item/user, d4/d2, increases to increases to [-1,1]. The difference between the d=4 and d=2 embeddings is that shape of the distribution for d=4 embedding appears closer to original shape, while for d=2, it appears almost monotonically increasing.

2.5 User based approach to recommendations using Pearson correlation

Approach Highlight:

1. Create query user's profile (in terms of movie ratings)

2. **Candidate generation:** Find other users who've watched the same movies as the new user. Sort the old users by the count of most movies in common with the new user. Take the

top 100 users and calculate a Similarity Score for each user using the Pearson Correlation function.

3. **Scoring:** Get the top 10 users with the highest similarity indices, all the movies for these users, and add Weighted movie Ratings by Multiplying the Rating to the Similarity Index. Calculate the average recommendation score by dividing the Weighted Rating by the Similarity Index and select movies with the highest score i.e., 5.
4. **Recommendation:** Now, recommend 10 movies based on the ratings given by old users who are similar to the new user.

[167]:
```
#create binary utility matrix
utility_binary = (utility != 0).astype('int')
sparse_utility_binary = csr_matrix(utility_binary)
```

[214]:
```
def user_based_recommendations(query_obj, topN=10):

  #candidate generation: find top 100 users sharing maximum rated movies with␣
↪the query_object
  query_obj_binary = (query_obj != 0).astype('int')
  res = sparse_utility_binary.dot(query_obj_binary)
  candidates_df = pd.DataFrame({'dot_sim':res, 'pearson_sim': 0.0},␣
↪index=utility_binary.index).sort_values(by='dot_sim', ascending=False)[:100]

  #find pearson similarity for all candidates
  for i in range(candidates_df.shape[0]):
    candidate = utility.iloc[i].values
    corr, _ = pearsonr(query_obj, candidate)
    candidates_df.loc[candidates_df.index[i], 'pearson_sim'] = corr

  #take top 10 candidates
  candidates_df = candidates_df.sort_values(by=['pearson_sim', 'dot_sim'],␣
↪ascending=[False, False])[:10]
  candidates = candidates_df.index.values

  #find all movies rated by these 10 candidates
  movies_rating_cnt = utility_binary.loc[candidates].sum(axis=0)
  candidate_movies = movies_rating_cnt[movies_rating_cnt > 0].index.values
  candidate_movie_ratings = utility.loc[candidates, candidate_movies]

  sim_vector = candidates_df['pearson_sim'].values
  sim_total = np.sum(sim_vector)

  #compute weighted recommendation score for each movie. Calculated as follow.
  #each movie rating is multiplied by its rater's pearson similarity score.
  #all such ratings are added and finally divided by total of pearson␣
↪similarity scores to get the final movie recommendation score.
  #we then sort movies in descending order by recommendation scores.
```

```
    movie_rec_scores = (candidate_movie_ratings * sim_vector.reshape(-1,1)).
 ↪sum(axis=0) / sim_total
    res = pd.DataFrame({'movie_id': candidate_movies, 'rec_score':␣
 ↪movie_rec_scores}).sort_values(by='rec_score', ascending=False)

    #return top N movies with highest recommendation score
    return res[:topN]
```

Example: Find top 10 movie recommendations for a given user. For calculation purpose, we can consider our new user to have the same rating pattern as the user with userid 2.

[223]:
```
#check profile for userid 2
userobj = utility.loc[2]
#check ratings (mean centered) given by the user
userobj[userobj != 0]
```

[223]:
```
MovieID
21      -2.713178
95      -1.713178
110      1.286822
163      0.286822
165     -0.713178
           …
3678    -0.713178
3699    -1.713178
3735    -0.713178
3809    -0.713178
3893    -2.713178
Name: 2, Length: 129, dtype: float64
```

[219]:
```
#build user query obj
user_query_obj = utility.loc[2].values
#get recommendations
rec_movies = user_based_recommendations(user_query_obj, topN=10)
rec_movies
```

[219]:

	movie_id	rec_score
MovieID		
318	318	1.208846
593	593	1.140816
1196	1196	0.970207
1954	1954	0.964962
1945	1945	0.960524
480	480	0.956470
1784	1784	0.949768
1193	1193	0.948306
1247	1247	0.907990

```
1259        1259   0.898699
```

[227]:
```python
#show recommended movie details
rec_movies.merge(movies, left_index=True, right_on='MovieID')
```

[227]:
```
      movie_id  rec_score  MovieID  \
315        318   1.208846      318
589        593   1.140816      593
1178      1196   0.970207     1196
1885      1954   0.964962     1954
1876      1945   0.960524     1945
476        480   0.956470      480
1726      1784   0.949768     1784
1176      1193   0.948306     1193
1227      1247   0.907990     1247
1239      1259   0.898699     1259

                                                  Title  \
315                    Shawshank Redemption, The (1994)
589                    Silence of the Lambs, The (1991)
1178  Star Wars: Episode V - The Empire Strikes Back…
1885                                       Rocky (1976)
1876                            On the Waterfront (1954)
476                                 Jurassic Park (1993)
1726                             As Good As It Gets (1997)
1176              One Flew Over the Cuckoo's Nest (1975)
1227                               Graduate, The (1967)
1239                                  Stand by Me (1986)

                                  Genres  release_year
315                                Drama          1994
589                       Drama|Thriller          1991
1178  Action|Adventure|Drama|Sci-Fi|War          1980
1885                        Action|Drama          1976
1876                         Crime|Drama          1954
476              Action|Adventure|Sci-Fi          1993
1726                        Comedy|Drama          1997
1176                               Drama          1975
1227                       Drama|Romance          1967
1239             Adventure|Comedy|Drama          1986
```

2.6 Case study Questionnaire:

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

[122]:
```python
df_temp = users.merge(ratings ,on='UserID')
df_temp.groupby('Age')['Rating'].agg(['count', 'mean'])
```

[122]:
```
           count      mean
Age
18-24     183536  3.507573
25-34     395556  3.545235
35-44     199003  3.618162
45-49      83633  3.638062
50-55      72490  3.714512
56+        38780  3.766632
Under 18   27211  3.549520
```

This shows that users in 25-34 group have rated highest number of movies.

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

[123]:
```
df_temp.groupby('Occupation')['Rating'].agg('count').sort_values()
```

[123]:
```
Occupation
farmer                    2706
homemaker                11345
tradesman/craftsman      12086
retired                  13754
unemployed               14904
lawyer                   20563
customer service         21850
scientist                22951
K-12 student             23290
clerical/admin           31623
doctor/health care       37205
self-employed            46021
sales/marketing          49109
artist                   50068
programmer               57214
writer                   60397
technician/engineer      72816
academic/educator        85351
executive/managerial    105425
other                   130499
college/grad student    131032
Name: Rating, dtype: int64
```

college/grad student - 131032

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

[124]:
```
df_temp.groupby('Gender')['Rating'].count()
```

[124]:
```
Gender
0    246440
1    753769
```

```
Name: Rating, dtype: int64
```

[125]:
```
df_temp.groupby('Gender')['UserID'].nunique()
```

[125]:
```
Gender
0    1709
1    4331
Name: UserID, dtype: int64
```

We encoded Male as 1 and Female as 0. Thus the majority of the users who rated movies are Males.

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

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

[126]:
```
m.groupby('release_year')['MovieID'].nunique().sort_values(ascending=False)
```

[126]:
```
release_year
1996    345
1995    342
1998    337
1997    315
1999    283
       …
1923      3
1919      3
1920      2
1922      2
1921      1
Name: MovieID, Length: 81, dtype: int64
```

Maximum movies (345) were released in year 1996.

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

[127]:
```
movie_rating_cnt = ratings.groupby(['MovieID'])['Rating'].count().
 ↪sort_values(ascending=False)
movie_rating_cnt
```

[127]:
```
MovieID
2858    3428
260     2991
1196    2990
1210    2883
480     2672
        …
3237       1
763        1
624        1
```

```
2563       1
3290       1
Name: Rating, Length: 3706, dtype: int64
```

[128]:
```
movies[movies['MovieID'] == movie_rating_cnt.index[0]]
```

[128]:

	MovieID	Title	Genres	release_year
2789	2858	American Beauty (1999)	Comedy|Drama	1999

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

[129]:
```
#find movie id for 'Liar Liar'
movie_id = movies[movies['Title'].str.contains('Liar Liar')]['MovieID'].
↪values[0]
movie_id
```

[129]: 1485

[130]:
```
#similar movies based on pearson correlation
res = find_similar_movies_pearson(query_id=movie_id, topN=3)
print(res)
movies[movies['MovieID'].isin(res['item'].values.tolist())]
```

```
Time taken:  13.497791528701782
      item   corr
2252  2321  0.993
1029  1042  0.989
1572  1614  0.986
```

[130]:

	MovieID	Title	Genres	release_year
1029	1042	That Thing You Do! (1996)	Comedy	1996
1572	1614	In & Out (1997)	Comedy	1997
2252	2321	Pleasantville (1998)	Comedy	1998

[131]:
```
#similar movies based on cosine similarity
res = find_similar_movies_cosine(query_id=movie_id, topN=3)
print(res)
movies[movies['MovieID'].isin(res['item'].values.tolist())]
```

```
Time taken:  0.004807710647583008
      item  similarity
775    785       0.999
102    104       0.999
1029  1042       0.999
```

[131]:

	MovieID	Title	Genres	release_year
102	104	Happy Gilmore (1996)	Comedy	1996
775	785	Kingpin (1996)	Comedy	1996

```
1029     1042  That Thing You Do! (1996)  Comedy          1996
```

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

item-item similarity based and user-user similarity based

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

The range for both Pearson correlation and Cosine similarity is -1 to 1, where -1 indicates completely opposite vectors, 0 indicates orthogonal (uncorrelated) vectors, and 1 indicates identical vectors.

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

[132]:
```python
print(f'Train RMSE: {train_rmse_err}, MAPE: {train_mape_err}')
print(f'Test RMSE: {test_rmse_err}, MAPE: {test_mape_err}')
```

```
Train RMSE: 1.2040033339668108, MAPE: 0.3367440105074651
Test RMSE: 0.9205173609568992, MAPE: 0.24883384329253652
```

10. Give the sparse 'row' matrix representation for the following dense matrix -

[[1 0] [3 7]]

[134]:
```python
dense_mat = np.array([[1, 0], [3, 7]])
sparse_row_mat = csr_matrix(dense_mat)
sparse_row_mat
```

[134]:
```
<2x2 sparse matrix of type '<class 'numpy.int64'>'
        with 3 stored elements in Compressed Sparse Row format>
```