Problem Statement

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

Data Dictionary:

RATINGS FILE DESCRIPTION

==

All ratings are contained in the file "ratings.dat" and are in the following format:

UserID::MovieID::Rating::Timestamp

UserIDs range between 1 and 6040

MovieIDs range between 1 and 3952

Ratings are made on a 5-star scale (whole-star ratings only)

Timestamp is represented in seconds

Each user has at least 20 ratings

USERS FILE DESCRIPTION

==

User information is in the file "users.dat" and is in the following format:

UserID::Gender::Age::Occupation::Zip-code

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

Gender is denoted by a "M" for male and "F" for female

Age is chosen from the following ranges:

1: "Under 18"

18: "18-24"

25: "25-34"

35: "35-44"

45: "45-49"

50: "50-55"

56: "56+"

Occupation is chosen from the following choices:

0: "other" or not specified

1: "academic/educator"

2: "artist"

3: "clerical/admin"

4: "college/grad student"

5: "customer service"

6: "doctor/health care"

7: "executive/managerial"

8: "farmer"

9: "homemaker"

10: "K-12 student"

11: "lawyer"

12: "programmer"

13: "retired"

14: "sales/marketing"

15: "scientist"

16: "self-employed"

17: "technician/engineer"

18: "tradesman/craftsman"

19: "unemployed"

20: "writer"

MOVIES FILE DESCRIPTION

==

Movie information is in the file "movies.dat" and is in the following format:

MovieID::Title::Genres

Titles are identical to titles provided by the IMDB (including year of release)

Genres are pipe-separated and are selected from the following genres:

Action

Adventure

Animation

Children's

Comedy

Crime

Documentary

Drama

Fantasy

Film-Noir

Horror

Musical

Mystery

Romance

Sci-Fi

Thriller

War

Western

In [382…

```
!pip install cmfrec
```

```
Requirement already satisfied: cmfrec in /usr/local/lib/python3.11/dist-package
s (3.5.1.post13)
Requirement already satisfied: cython in /usr/local/lib/python3.11/dist-package
s (from cmfrec) (3.0.12)
Requirement already satisfied: numpy>=1.25 in /usr/local/lib/python3.11/dist-pa
ckages (from cmfrec) (2.0.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages
(from cmfrec) (1.16.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-package
s (from cmfrec) (2.2.2)
Requirement already satisfied: findblas in /usr/local/lib/python3.11/dist-packa
ges (from cmfrec) (0.1.26.post1)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python
3.11/dist-packages (from pandas->cmfrec) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-p
ackages (from pandas->cmfrec) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dis
t-packages (from pandas->cmfrec) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packa
ges (from python-dateutil>=2.8.2->pandas->cmfrec) (1.17.0)
```

In [383…

```python
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")


import matplotlib as mpl

from collections import defaultdict
from scipy import sparse
from scipy.stats import pearsonr
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.neighbors import NearestNeighbors

from cmfrec import CMF
from sklearn.metrics import mean_absolute_percentage_error
from sklearn.metrics import mean_squared_error
```

In [384…

```
!gdown 1Mpk9GBu9sHzMnb7EMSguihWgFSNSvX5W
!gdown 1InRFz7uEnvSh1sTmQ50GqDpnwXwKQmGw
!gdown 1ZmzsWbmr1SVmRczngXyMJ-YeEzsTFU2Y
```

```
Downloading...
From: https://drive.google.com/uc?id=1Mpk9GBu9sHzMnb7EMSguihWgFSNSvX5W
To: /content/zee-users.dat
100% 134k/134k [00:00<00:00, 90.2MB/s]
Downloading...
From: https://drive.google.com/uc?id=1InRFz7uEnvSh1sTmQ50GqDpnwXwKQmGw
To: /content/zee-ratings.dat
100% 24.6M/24.6M [00:00<00:00, 171MB/s]
Downloading...
From: https://drive.google.com/uc?id=1ZmzsWbmr1SVmRczngXyMJ-YeEzsTFU2Y
To: /content/zee-movies.dat
100% 171k/171k [00:00<00:00, 74.3MB/s]
```

In [385…

```
df_users = pd.read_csv("zee-users.dat", delimiter='::', encoding='ISO-8859-1')
df_users.head()
```

Out[385…

	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

In [386…

```
df_ratings = pd.read_csv("zee-ratings.dat", delimiter='::', encoding='ISO-8859
df_ratings.head()
```

Out[386…

	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

In [387…

```
df_movies = pd.read_csv("zee-movies.dat", delimiter='::', encoding='ISO-8859-1
df_movies.head()
```

Out[387…

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

In [388…

```
df_users.shape
print(f"The users dataset has {df_users.shape[0]} rows and {df_users.shape[1]}
```

```
The users dataset has 6040 rows and 5 columns
```

In [389…

```
df_ratings.shape
print(f"The ratings dataset has {df_ratings.shape[0]} rows and {df_ratings.sha
```

```
The ratings dataset has 1000209 rows and 4 columns
```

In [390…

```
df_movies.shape
print(f"The movies dataset has {df_movies.shape[0]} rows and {df_movies.shape[
```

```
The movies dataset has 3883 rows and 3 columns
```

In [391…

```
df_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
```

In [392…

```
df_users.describe()
```

Out[392…

	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

In [393…

```
df_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
```

In [394…

```
df_ratings.describe()
```

Out[394…

	UserID	MovieID	Rating	Timestamp
count	1.000209e+06	1.000209e+06	1.000209e+06	1.000209e+06
mean	3.024512e+03	1.865540e+03	3.581564e+00	9.722437e+08
std	1.728413e+03	1.096041e+03	1.117102e+00	1.215256e+07
min	1.000000e+00	1.000000e+00	1.000000e+00	9.567039e+08
25%	1.506000e+03	1.030000e+03	3.000000e+00	9.653026e+08
50%	3.070000e+03	1.835000e+03	4.000000e+00	9.730180e+08
75%	4.476000e+03	2.770000e+03	4.000000e+00	9.752209e+08
max	6.040000e+03	3.952000e+03	5.000000e+00	1.046455e+09

In [395…

```
df_movies.info()
```

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

In [396…

```
df_movies.describe()
```

Out[396…

	Movie ID
count	3883.000000
mean	1986.049446
std	1146.778349
min	1.000000
25%	982.500000
50%	2010.000000
75%	2980.500000
max	3952.000000

In [397…

```
df_users.isna().sum().sort_values(ascending=False)
```

Out[397…

	0
UserID	0
Gender	0
Age	0
Occupation	0
Zip-code	0

dtype: int64

In [398…

```
df_ratings.isna().sum().sort_values(ascending=False)
```

Out[398…

	0
UserID	0
MovieID	0
Rating	0
Timestamp	0

dtype: int64

In [399…

```
df_movies.isna().sum().sort_values(ascending=False)
```

Out[399…

	0
Movie ID	0
Title	0
Genres	0

dtype: int64

Replace spaces in column names with underscores for consistency

In [400…

```
df_users.columns = df_users.columns.str.replace(' ', '_')
df_ratings.columns = df_ratings.columns.str.replace(' ', '_')
df_movies.columns = df_movies.columns.str.replace(' ', '_')
```

In [401…

```
df_users.nunique().sort_values(ascending=False)
```

Out[401…

	0
UserID	6040
Zip-code	3439
Occupation	21
Age	7
Gender	2

dtype: int64

In [402…

```
df_ratings.nunique().sort_values(ascending=False)
```

Out[402…

	0
Timestamp	458455
UserID	6040
MovieID	3706
Rating	5

dtype: int64

In [403…

```
df_movies.nunique().sort_values(ascending=False)
```

Out[403…

	0
Movie_ID	3883
Title	3883
Genres	301

dtype: int64

In [404…

```
df_users.dtypes
```

Out[404…

	0
UserID	int64
Gender	object
Age	int64
Occupation	int64
Zip-code	object

dtype: object

In [405…

```
df_ratings.dtypes
```

Out[405…

	0
UserID	int64
MovieID	int64
Rating	int64
Timestamp	int64

dtype: object

In [406…

```
df_movies.dtypes
```

Out[406…

	0
Movie_ID	int64
Title	object
Genres	object

dtype: object

> Feature Engineering and Data transformation

In [407…

```
# Split movie genres to the list
df_movies.Genres = df_movies.Genres.apply(lambda x: x.split('|'))

# Extract year from title
df_movies['Year'] = df_movies['Title'].str.extract(r'\((\d{4})\)')

# Remove the years from the 'Title' column
df_movies['Title'] = df_movies['Title'].str.replace(r'\(\d{4}\)', '', regex=Tr

# Strip extra whitespace
df_movies['Title'] = df_movies['Title'].str.strip()


# Rating timestamp conversion to standard format
df_ratings.Timestamp = pd.to_datetime(df_ratings.Timestamp, unit='s')
# Date and Time data as feature of timestamp
df_ratings['RatingYear'] = df_ratings.Timestamp.dt.year
df_ratings['RatingMonth'] = df_ratings.Timestamp.dt.month
df_ratings['RatingDay'] = df_ratings.Timestamp.dt.day
df_ratings['RatingHour'] = df_ratings.Timestamp.dt.hour
df_ratings['Weekday'] = df_ratings.Timestamp.dt.day_name()
```

In [408…

```
df_movies.head()
```

Out[408...

	Movie_ID	Title	Genres	Year
0	1	Toy Story	[Animation, Children's, Comedy]	1995
1	2	Jumanji	[Adventure, Children's, Fantasy]	1995
2	3	Grumpier Old Men	[Comedy, Romance]	1995
3	4	Waiting to Exhale	[Comedy, Drama]	1995
4	5	Father of the Bride Part II	[Comedy]	1995

In [409...

```
df_ratings.head()
```

Out[409...

	UserID	MovieID	Rating	Timestamp	RatingYear	RatingMonth	RatingDay	R
0	1	1193	5	2000-12-31 22:12:40	2000	12	31	
1	1	661	3	2000-12-31 22:35:09	2000	12	31	
2	1	914	3	2000-12-31 22:32:48	2000	12	31	
3	1	3408	4	2000-12-31 22:04:35	2000	12	31	
4	1	2355	5	2001-01-06 23:38:11	2001	1	6	

In [410...

```
df_ratings_copy = df_ratings.copy(deep=True)
df_users_copy = df_users.copy(deep=True)
df_movies_copy = df_movies.copy(deep=True)
```

In [411...

```
df_users.replace({
    'Age': {
        1: "Under 18",
        18: "18-24",
        25: "25-34",
        35: "35-44",
        45: "45-49",
        50: "50-55",
        56: "56 Above"
    }
}, inplace=True)
```

In [412...

```
df_users.replace({'Occupation': {
    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"
}}, inplace=True)
```

In [413…
```
df_users.head()
```

Out[413…

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	Under 18	k-12 student	48067
1	2	M	56 Above	self-employed	70072
2	3	M	25-34	scientist	55117
3	4	M	45-49	executive/managerial	02460
4	5	M	25-34	writer	55455

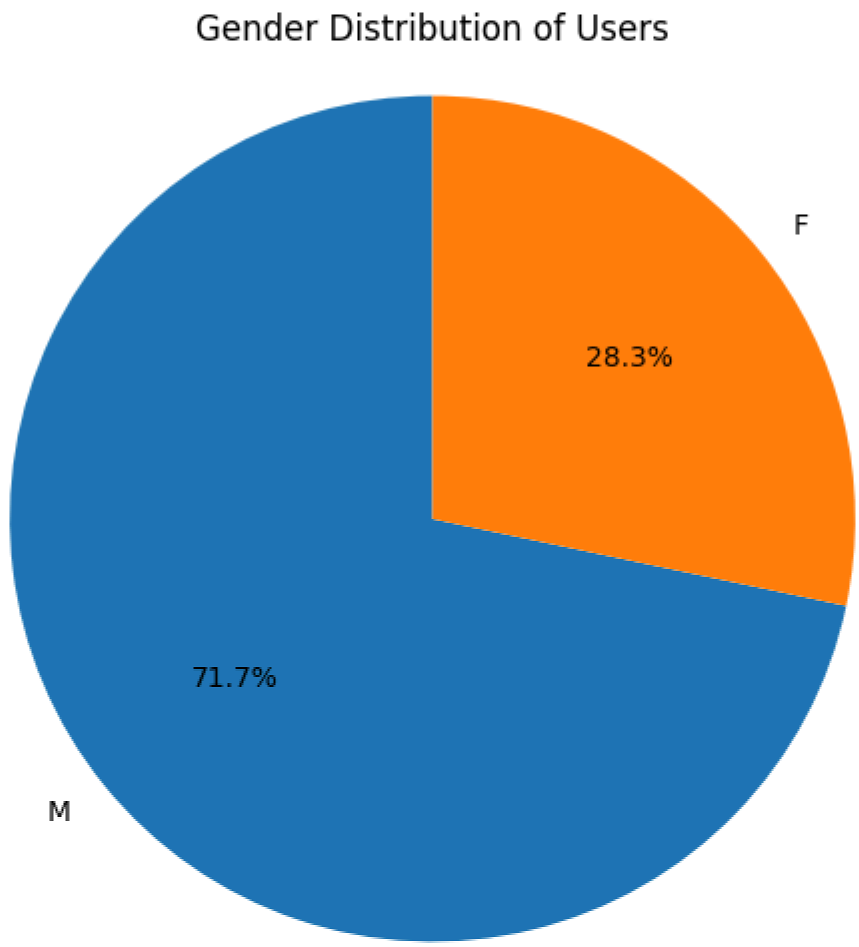
In [414…
```
df_movies.head()
```

Out[414…

	Movie_ID	Title	Genres	Year
0	1	Toy Story	[Animation, Children's, Comedy]	1995
1	2	Jumanji	[Adventure, Children's, Fantasy]	1995
2	3	Grumpier Old Men	[Comedy, Romance]	1995
3	4	Waiting to Exhale	[Comedy, Drama]	1995
4	5	Father of the Bride Part II	[Comedy]	1995

In [415…
```
# Calculate gender distribution
gender_counts = df_users['Gender'].value_counts()

# Plot pie chart
plt.figure(figsize=(6, 6))
plt.pie(
    gender_counts.values,
    labels=gender_counts.index,
    autopct='%1.1f%%',
```

```
    startangle=90
)

# Add title
plt.title('Gender Distribution of Users')

# Ensure pie is a circle
plt.axis('equal')

# Show plot
plt.show()
```



In [416…

```
df_users
```

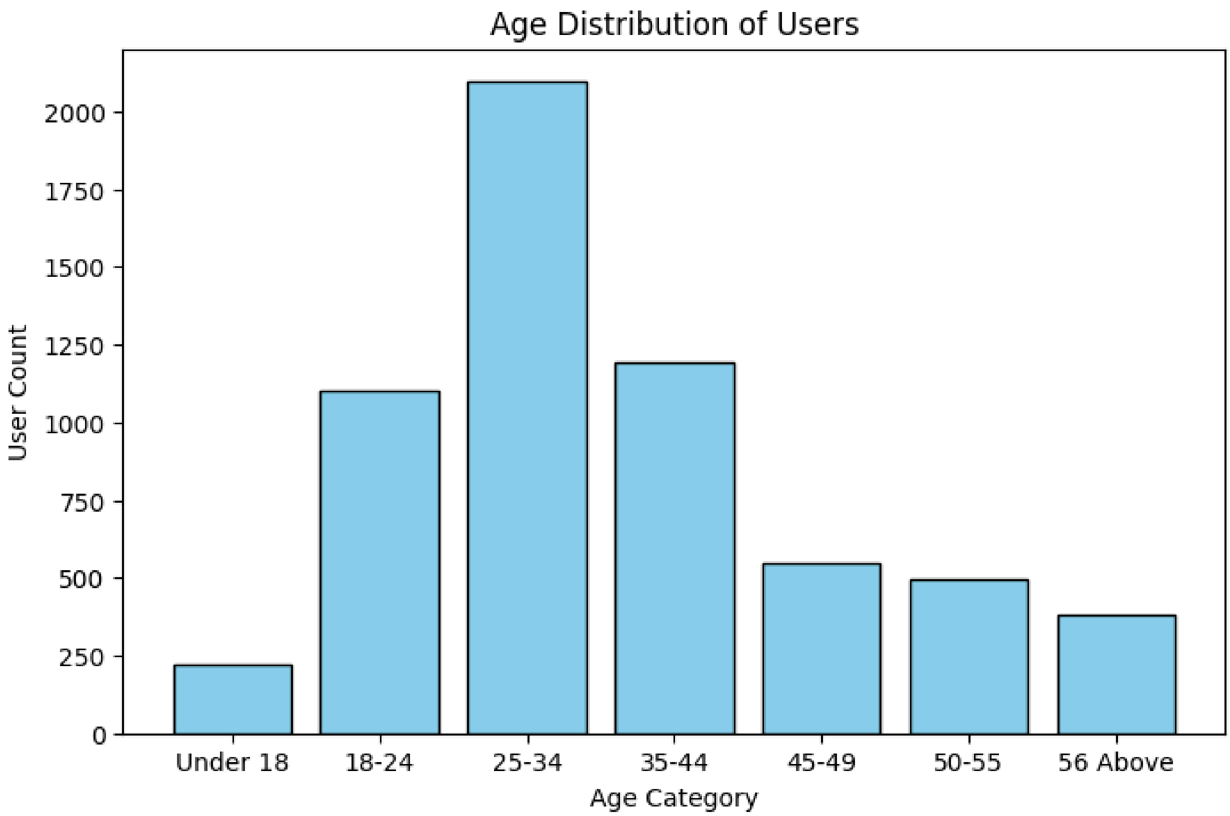
Out[416…

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	Under 18	k-12 student	48067
1	2	M	56 Above	self-employed	70072
2	3	M	25-34	scientist	55117
3	4	M	45-49	executive/managerial	02460
4	5	M	25-34	writer	55455
...	...	...	...	...	...
6035	6036	F	25-34	scientist	32603
6036	6037	F	45-49	academic/educator	76006
6037	6038	F	56 Above	academic/educator	14706
6038	6039	F	45-49	other	01060
6039	6040	M	25-34	doctor/health care	11106

6040 rows × 5 columns

In [417…

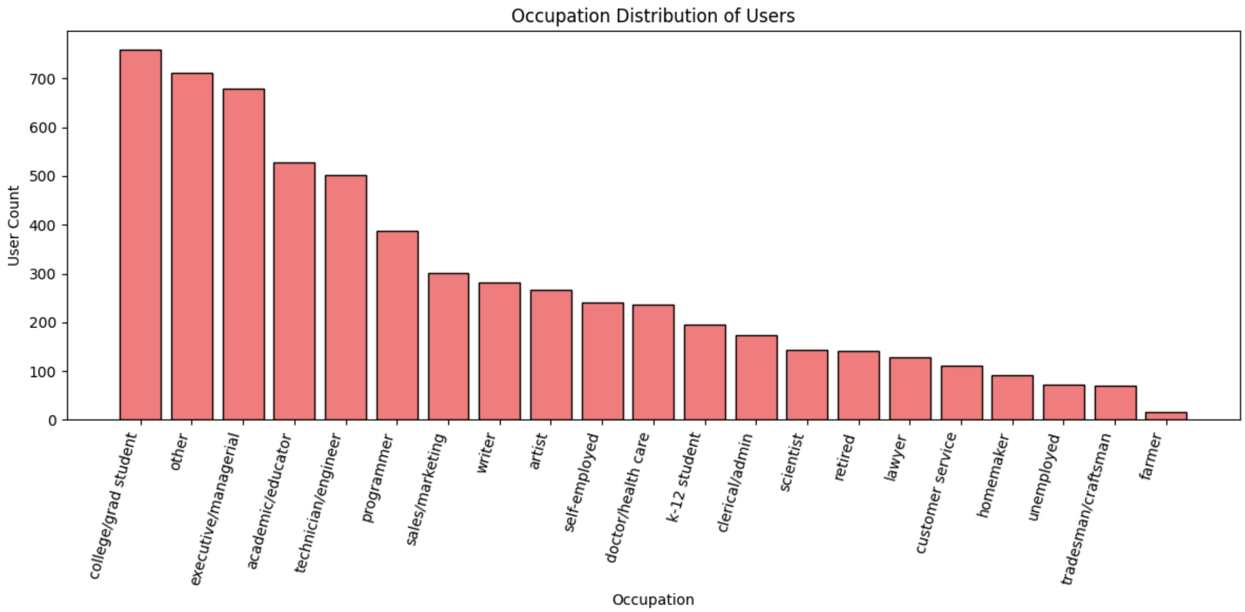
```
# Ensure consistent category order
age_order = ["Under 18", "18-24", "25-34", "35-44", "45-49", "50-55", "56 Abov

age_counts = df_users['Age'].value_counts().reindex(age_order)

plt.figure(figsize=(8, 5))
plt.bar(age_counts.index, age_counts.values, color='skyblue', edgecolor='black
plt.title('Age Distribution of Users')
plt.xlabel('Age Category')
plt.ylabel('User Count')
plt.show()
```



In [418…

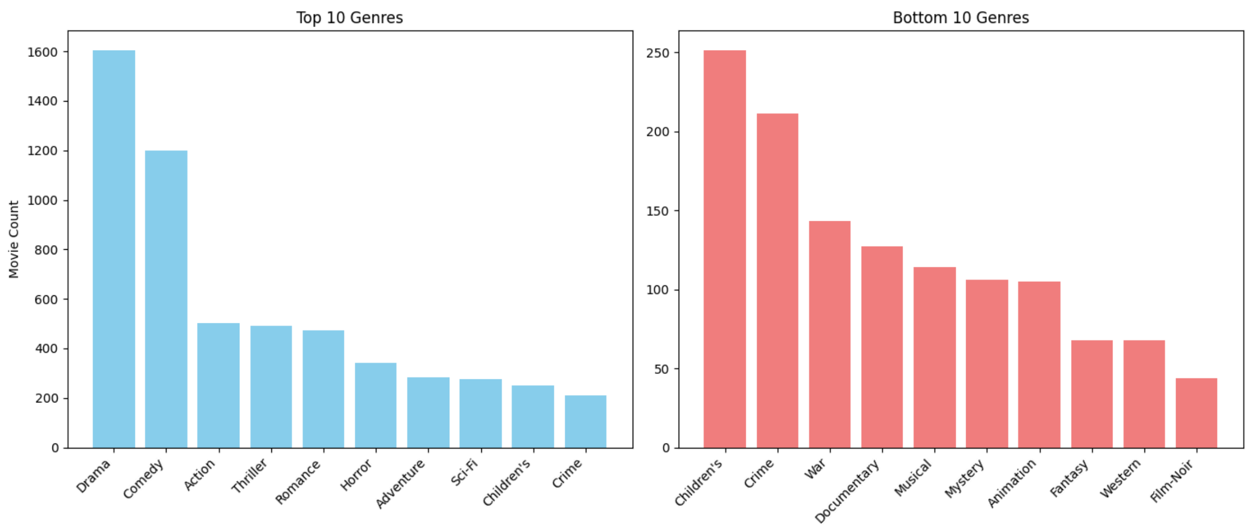
```
## Occupation wise distribution of users


# Occupation code-to-label mapping
occupation_dict = {
    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"
}

# Get occupation counts
occupation_counts = df_users['Occupation'].value_counts()
occupation_counts.rename(index=occupation_dict, inplace=True)

# Plot bar chart
plt.figure(figsize=(12, 6))
plt.bar(occupation_counts.index, occupation_counts.values, color='lightcoral',

# Rotate x-axis labels for readability
plt.xticks(rotation=75, ha='right')

# Labels and title
plt.title('Occupation Distribution of Users')
plt.xlabel('Occupation')
plt.ylabel('User Count')
```

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



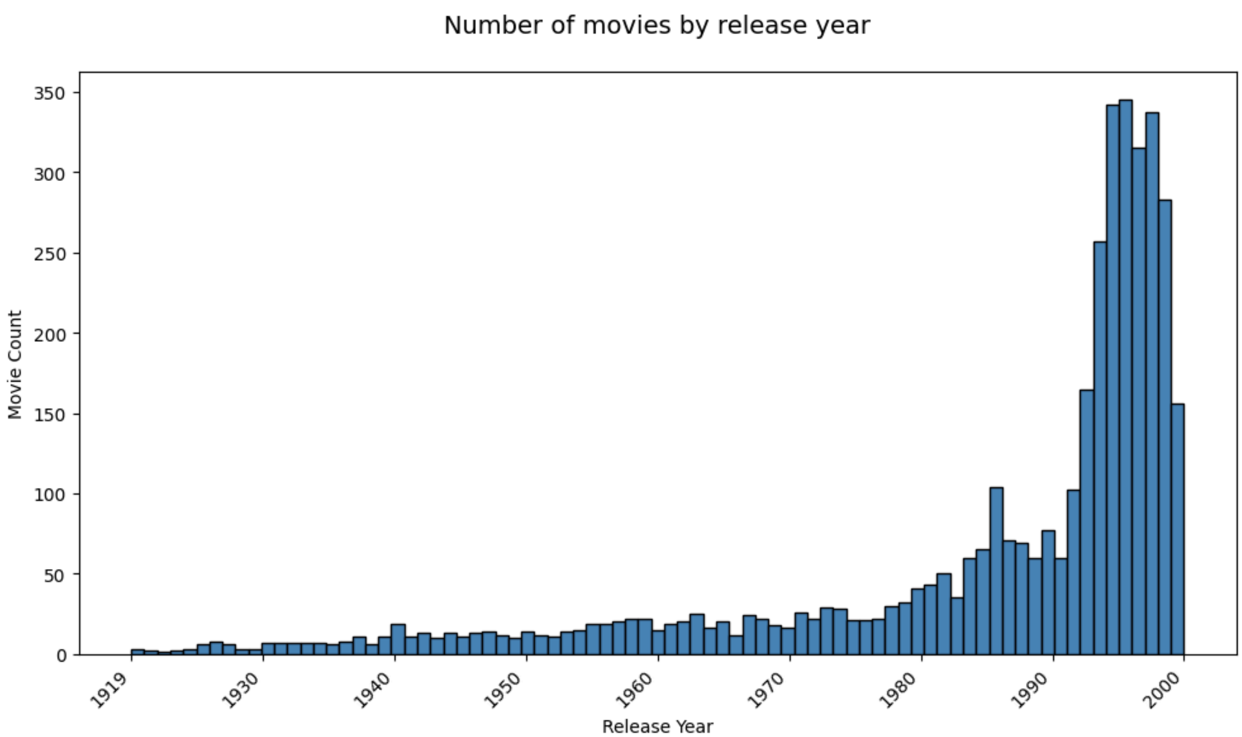
In [419…

```
# Explode genres once to reuse
exploded_genres = df_movies.explode('Genres')

# Get top and bottom 10 genres by count
genre_counts = exploded_genres['Genres'].value_counts()
top_10 = genre_counts.head(10)
bottom_10 = genre_counts.tail(10)

# Create subplots side by side
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Plot top 10 genres
axes[0].bar(top_10.index, top_10.values, color='skyblue')
axes[0].set_title('Top 10 Genres')
axes[0].set_ylabel('Movie Count')
axes[0].set_xticklabels(top_10.index, rotation=45, ha='right')

# Plot bottom 10 genres
axes[1].bar(bottom_10.index, bottom_10.values, color='lightcoral')
axes[1].set_title('Bottom 10 Genres')
axes[1].set_xticklabels(bottom_10.index, rotation=45, ha='right')

# Adjust layout for readability
plt.tight_layout()
plt.show()
```



In [420…

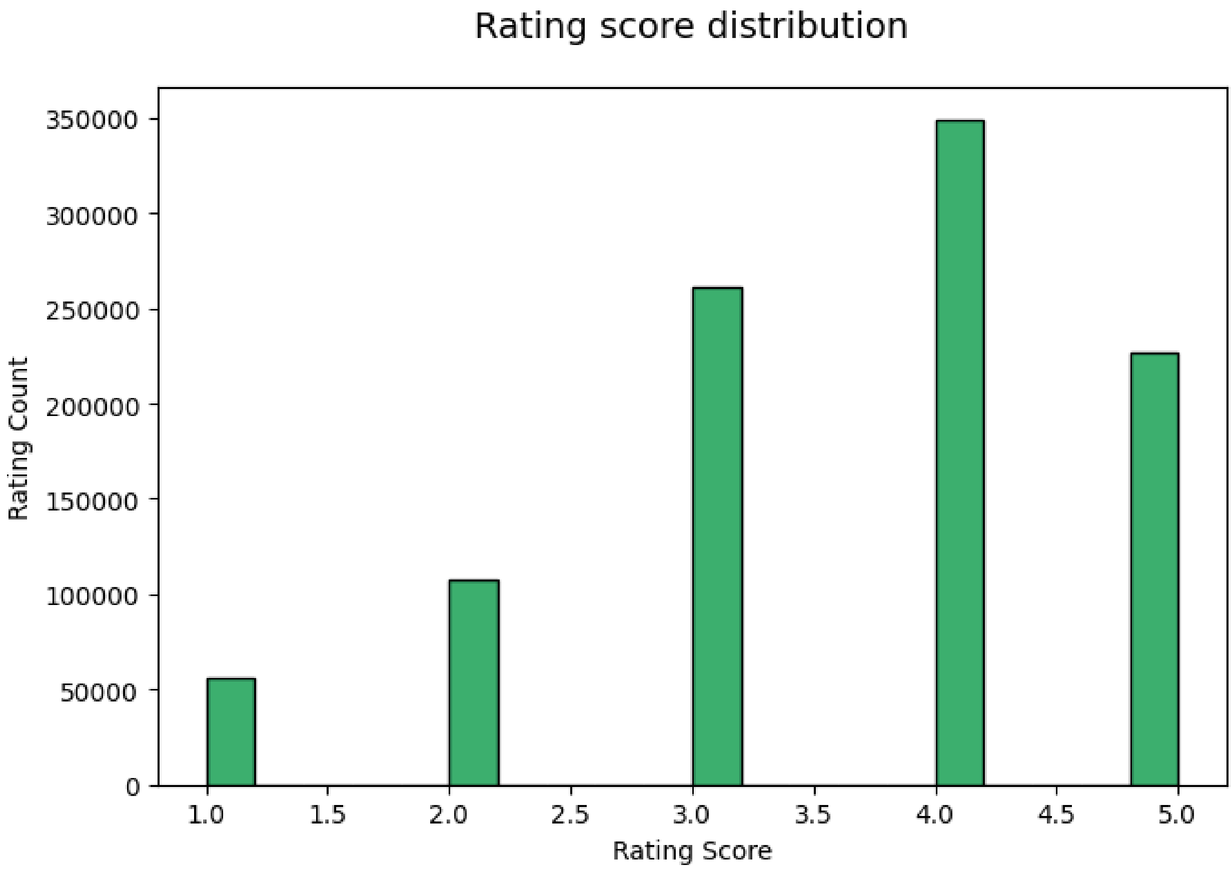
```
## Number of movies by release year

from matplotlib.ticker import MaxNLocator

sorted_years = df_movies['Year'].sort_values()

plt.figure(figsize=(10, 6))
plt.hist(sorted_years, bins=sorted_years.nunique(), color='steelblue', edgecol

plt.title('Number of movies by release year', fontsize=14, y=1.05)
plt.xlabel('Release Year')
plt.ylabel('Movie Count')

ax = plt.gca()
# Limit number of ticks to avoid overcrowding
ax.xaxis.set_major_locator(MaxNLocator(nbins=10))
plt.xticks(rotation=45, ha='right')

plt.tight_layout()
plt.show()
```



In [421…

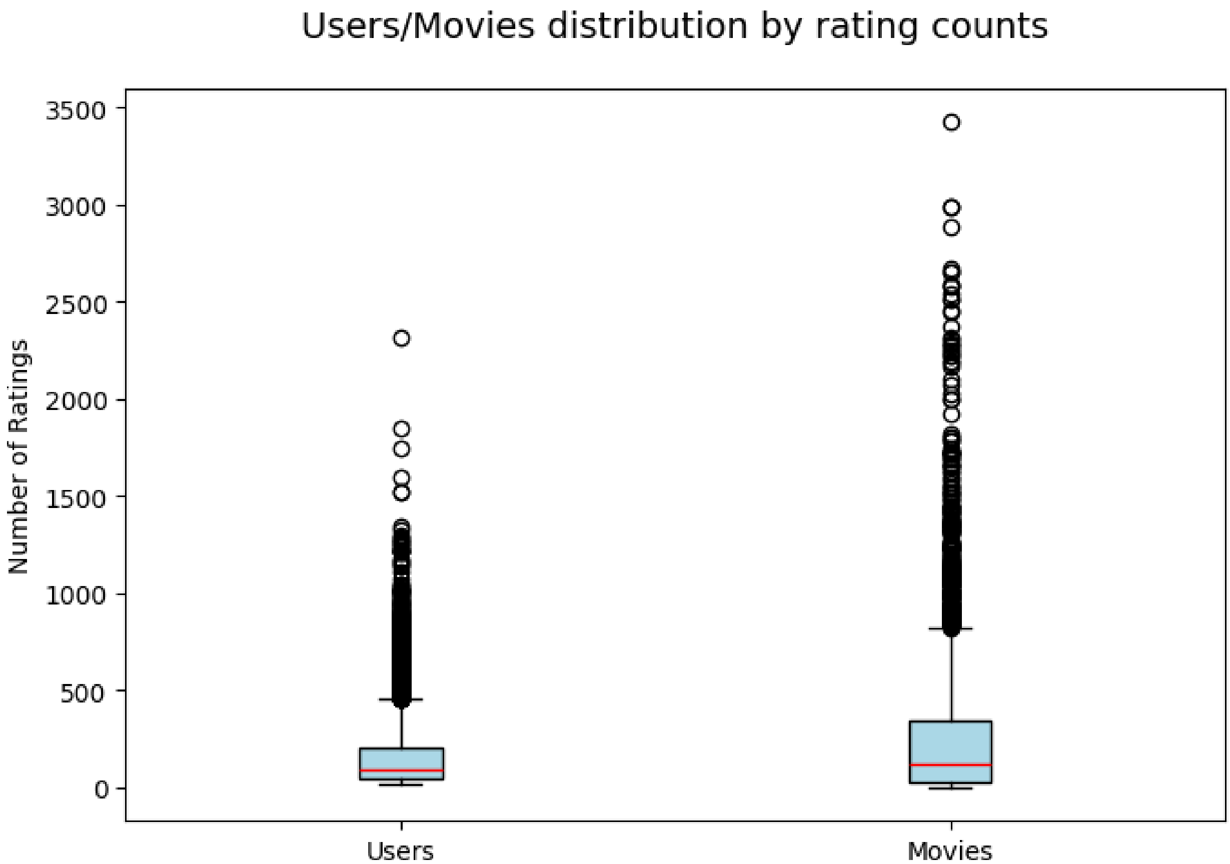
```
# Print mean and median rating
print(f'Mean rating score is {df_ratings.Rating.mean()}')
print(f'Median rating score is {df_ratings.Rating.median()}')

plt.figure(figsize=(7, 5))
plt.hist(df_ratings['Rating'], bins=20, color='mediumseagreen', edgecolor='bla

plt.title('Rating score distribution', fontsize=14, y=1.05)
plt.xlabel('Rating Score')
plt.ylabel('Rating Count')

plt.tight_layout()
plt.show()
```

```
Mean rating score is 3.581564453029317
Median rating score is 4.0
```



In [422…

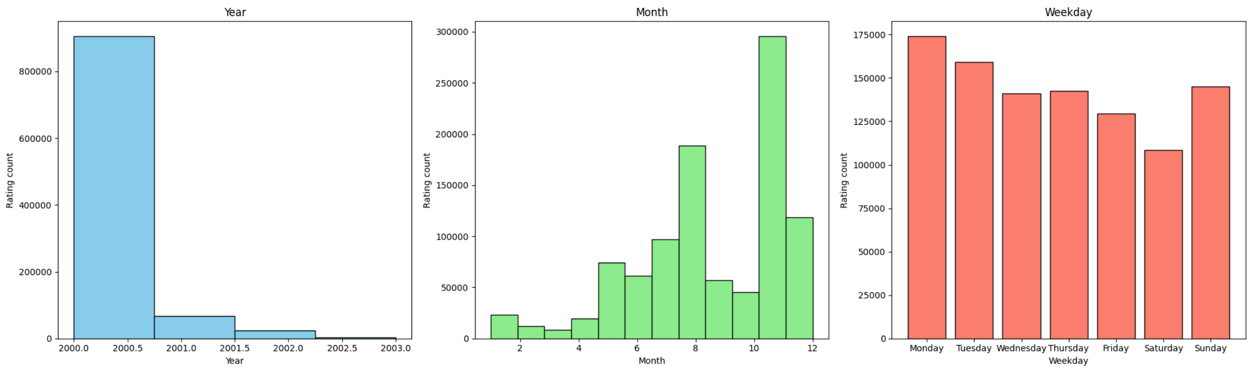
```
## Distribution of users and movies by rating counts

# Calculate rating counts per user and per movie
user_counts = df_ratings['UserID'].value_counts()
movie_counts = df_ratings['MovieID'].value_counts()

plt.figure(figsize=(7, 5))
plt.boxplot([user_counts, movie_counts], labels=['Users', 'Movies'], patch_art
            boxprops=dict(facecolor='lightblue'),
            medianprops=dict(color='red'))

plt.ylabel('Number of Ratings')
plt.title('Users/Movies distribution by rating counts', fontsize=14, y=1.05)

plt.tight_layout()
plt.show()
```



In [423…

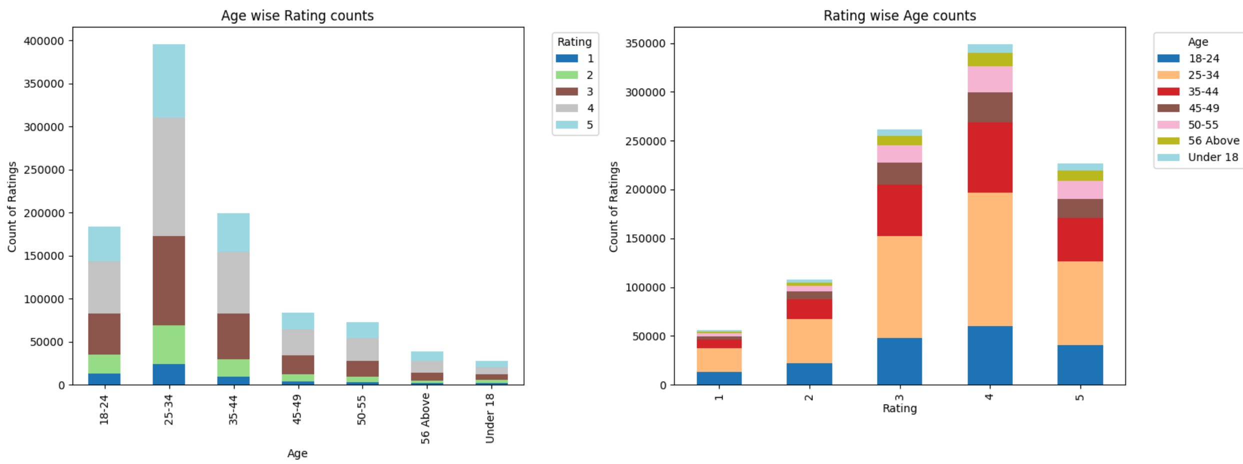
```
## Yearwise ratings given to movies

# Order weekdays properly
ordered_weekdays = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'S
df_ratings['Weekday'] = pd.Categorical(df_ratings['Weekday'], categories=order

fig, axes = plt.subplots(1, 3, figsize=(20, 6))

# Histogram for RatingYear
axes[0].hist(df_ratings['RatingYear'], bins=df_ratings['RatingYear'].nunique()
axes[0].set_title('Year')
axes[0].set_xlabel('Year')
axes[0].set_ylabel('Rating count')

# Histogram for RatingMonth
axes[1].hist(df_ratings['RatingMonth'], bins=12, color='lightgreen', edgecolor
axes[1].set_title('Month')
axes[1].set_xlabel('Month')
axes[1].set_ylabel('Rating count')

# Histogram for Weekday with categorical ordering
# We count values manually to ensure order and then plot as bar chart
weekday_counts = df_ratings['Weekday'].value_counts().reindex(ordered_weekdays
axes[2].bar(weekday_counts.index, weekday_counts.values, color='salmon', edgec
axes[2].set_title('Weekday')
axes[2].set_xlabel('Weekday')
```

```
axes[2].set_ylabel('Rating count')

plt.tight_layout()
plt.show()
```



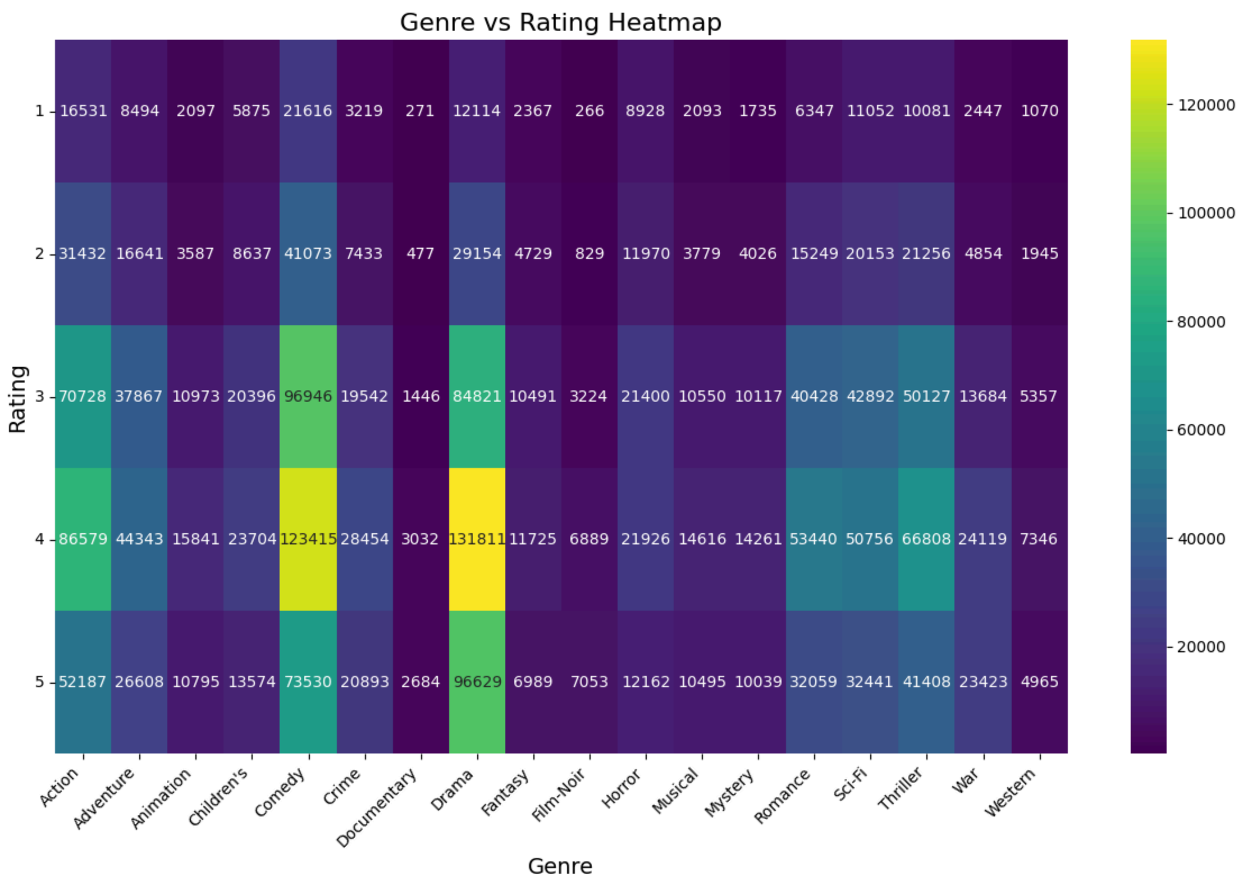
In [424…

```
## Genre wise rating

# Merge and group data
age_rating = pd.merge(df_ratings, df_users, on='UserID', how='left')
grouped = age_rating.groupby(['Age', 'Rating']).size().unstack(fill_value=0)
grouped2 = age_rating.groupby(['Rating', 'Age']).size().unstack(fill_value=0)

fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# 1) Age wise Rating counts (Age on x, ratings stacked)
grouped.plot(kind='bar', stacked=True, ax=axes[0], colormap='tab20')
axes[0].set_title('Age wise Rating counts')
axes[0].set_xlabel('Age')
axes[0].set_ylabel('Count of Ratings')
axes[0].legend(title='Rating', bbox_to_anchor=(1.05, 1), loc='upper left')

# 2) Rating wise Age counts (Rating on x, ages stacked)
grouped2.plot(kind='bar', stacked=True, ax=axes[1], colormap='tab20')
axes[1].set_title('Rating wise Age counts')
axes[1].set_xlabel('Rating')
axes[1].set_ylabel('Count of Ratings')
axes[1].legend(title='Age', bbox_to_anchor=(1.05, 1), loc='upper left')

plt.tight_layout()
plt.show()
```



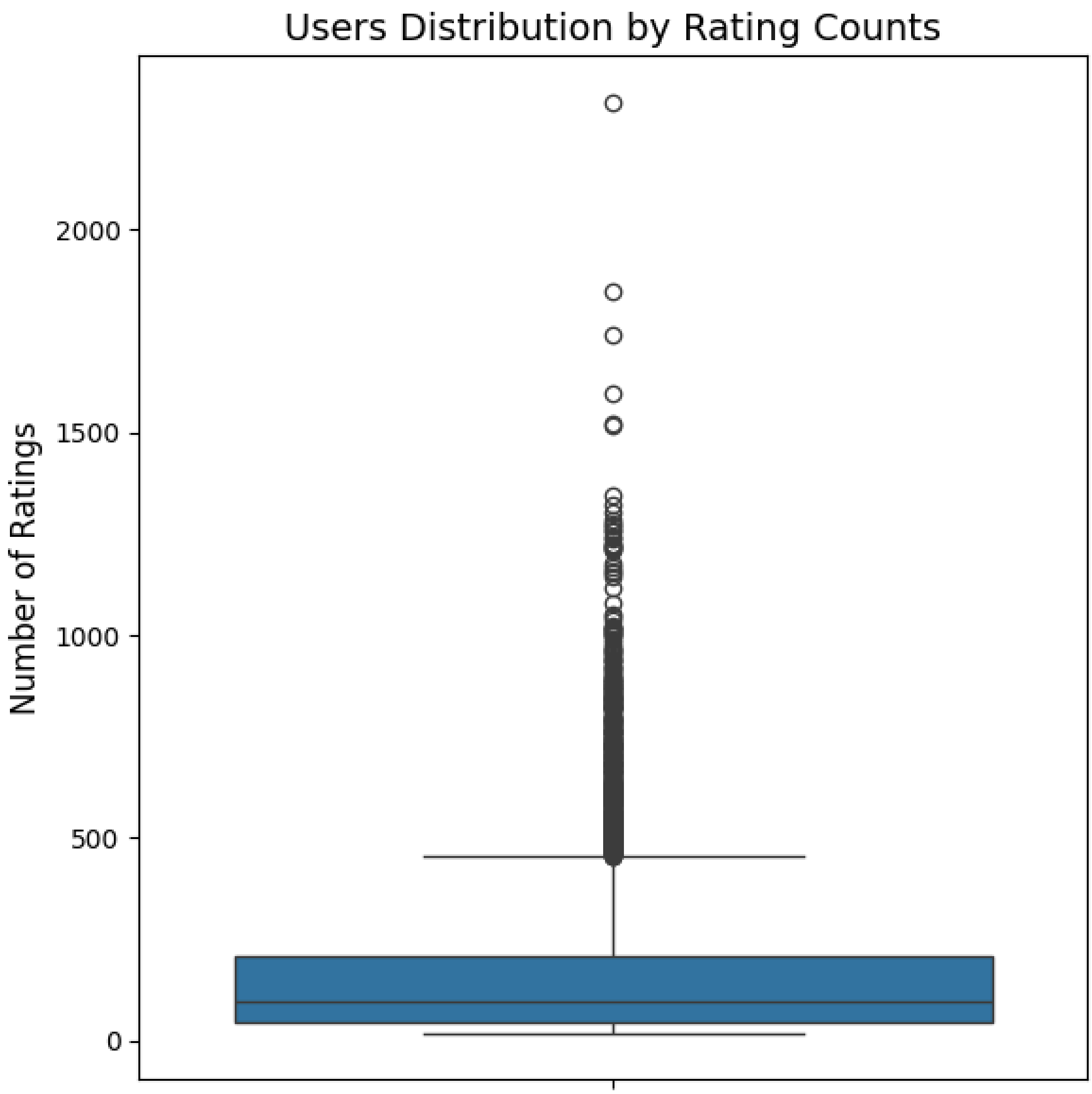
In [425…

```
## Genre v/s Rating Heatmap

# Prepare the data (same as before)
genre_rating = pd.merge(
    df_ratings,
    df_movies.explode('Genres'),
    left_on='MovieID',
    right_on='Movie_ID',
    how='left'
)

genre_rating = (
    genre_rating
    .groupby(['Rating', 'Genres'])
    .size()
    .reset_index(name='count')
    .pivot(index='Rating', columns='Genres', values='count')
    .fillna(0)
)

plt.figure(figsize=(12, 8))
sns.heatmap(genre_rating, cmap='viridis', annot=True, fmt='.0f')

plt.title('Genre vs Rating Heatmap', fontsize=16)
plt.xlabel('Genre', fontsize=14)
plt.ylabel('Rating', fontsize=14)
plt.yticks(rotation=0)  # keep y labels horizontal
plt.xticks(rotation=45, ha='right')  # rotate x labels for readability

plt.tight_layout()
plt.show()
```



In [426…

```
user_rating_counts = df_ratings['UserID'].value_counts()

plt.figure(figsize=(6, 6))
sns.boxplot(y=user_rating_counts)

plt.ylabel('Number of Ratings', fontsize=12)
plt.title('Users Distribution by Rating Counts', fontsize=14)

plt.tight_layout()
plt.show()
```



In [427…

```
df_ratings.rename(columns={
    'MovieID': 'Movie_ID'
}, inplace=True)
```

In [428…

```
df_movies_ratings = pd.merge(df_movies, df_ratings, how='inner', on='Movie_ID'
df_movies_ratings.head()
data = pd.merge(df_movies_ratings, df_users, how='inner', on='UserID')
data.head()
```

Out[428…

	Movie_ID	Title	Genres	Year	UserID	Rating	Timestamp	RatingYear	Ra
0	1	Toy Story	[Animation, Children's, Comedy]	1995	1	5	2001-01-06 23:37:48	2001	
1	1	Toy Story	[Animation, Children's, Comedy]	1995	6	4	2000-12-31 04:30:08	2000	
2	1	Toy Story	[Animation, Children's, Comedy]	1995	8	4	2000-12-31 03:31:36	2000	
3	1	Toy Story	[Animation, Children's, Comedy]	1995	9	5	2000-12-31 01:25:52	2000	
4	1	Toy Story	[Animation, Children's, Comedy]	1995	10	5	2000-12-31 01:34:34	2000	

In [429…

```
missing_value = pd.DataFrame({
    'Missing Value': data.isnull().sum(),
    'Percentage': (data.isnull().sum() / len(data))*100
})
missing_value.sort_values(by='Percentage', ascending=False)
```

Out[429…

	Missing Value	Percentage
Movie_ID	0	0.0
Title	0	0.0
Genres	0	0.0
Year	0	0.0
UserID	0	0.0
Rating	0	0.0
Timestamp	0	0.0
RatingYear	0	0.0
RatingMonth	0	0.0
RatingDay	0	0.0
RatingHour	0	0.0
Weekday	0	0.0
Gender	0	0.0
Age	0	0.0
Occupation	0	0.0
Zip-code	0	0.0

In [430…

```
data['Datetime'] = pd.to_datetime(data['Timestamp'], unit='s') #Change the dat
data['Year']=data['Year'].astype('int32') #Change the datatype from object to
data['Rating']=data['Rating'].astype('int32') #Change the datatype from object
```

In [431…

```
bins = [1919, 1929, 1939, 1949, 1959, 1969, 1979, 1989, 2000]
labels = ['20s', '30s', '40s', '50s', '60s', '70s', '80s', '90s']
data['ReleaseDec'] = pd.cut(data['Year'], bins=bins, labels=labels)
```

In [432…

```
data.head()
```

Out[432…

	Movie_ID	Title	Genres	Year	UserID	Rating	Timestamp	RatingYear	Ra
0	1	Toy Story	[Animation, Children's, Comedy]	1995	1	5	2001-01-06 23:37:48	2001	
1	1	Toy Story	[Animation, Children's, Comedy]	1995	6	4	2000-12-31 04:30:08	2000	
2	1	Toy Story	[Animation, Children's, Comedy]	1995	8	4	2000-12-31 03:31:36	2000	
3	1	Toy Story	[Animation, Children's, Comedy]	1995	9	5	2000-12-31 01:25:52	2000	
4	1	Toy Story	[Animation, Children's, Comedy]	1995	10	5	2000-12-31 01:34:34	2000	

In [433…

```
#@title Recommendations systems
```

In [434…

```
#@title User-Interaction Matrix

matrix = pd.pivot_table(data, index='UserID', columns='Title', values='Rating'
matrix.fillna(0, inplace=True) # Imputing 'NaN' values with Zero rating

print(matrix.shape)

matrix.head(10)
```

```
(6040, 3664)
```

Out[434…

Title	$1,000,000 Duck	'Night Mother	'Til There Was You	'burbs, The	...And Justice for All	1-900	10 Things I Hate About You	101 Dalmatians
UserID								
1	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
3	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
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0

10 rows × 3664 columns

In [435…

```
# Checking data sparsity
n_users = data['UserID'].nunique()
n_movies = data['Movie_ID'].nunique()
sparsity = round(1.0 - data.shape[0] / float( n_users * n_movies), 3)
print('The sparsity level of dataset is ' +  str(sparsity * 100) + '%')
```

```
The sparsity level of dataset is 95.5%
```

In [436…

```
#@title Pearson Correlation
```

Correlation is a measure that tells how closely two variables move in the same or opposite direction. A positive value indicates that they move in the same direction (i.e. if one increases other increases), where as a negative value indicates the opposite.

The most popular correlation measure for numerical data is Pearson’s Correlation. This measures the degree of linear relationship between two numeric variables and lies between -1 to +1. It is represented by ‘r’.

- r=1 means perfect positive correlation
- r=-1 means perfect negative correlation
- r=0 means no linear correlation (note, it does not mean no correlation)

In [437…

```
#@title Item - Based approach
```

In [438…

```
data[data['Title']=='Home Alone']
```

Out[438…

	Movie_ID	Title	Genres	Year	UserID	Rating	Timestamp	RatingYe
156660	586	Home Alone	[Children's, Comedy]	1990	10	3	2000-12-31 02:12:27	20
156661	586	Home Alone	[Children's, Comedy]	1990	11	1	2001-01-07 21:52:36	20
156662	586	Home Alone	[Children's, Comedy]	1990	18	4	2000-12-30 05:47:13	20
156663	586	Home Alone	[Children's, Comedy]	1990	22	3	2000-12-30 05:31:07	20
156664	586	Home Alone	[Children's, Comedy]	1990	26	2	2000-12-30 01:34:09	20
...	...	...	...	...	...	...	...	
157330	586	Home Alone	[Children's, Comedy]	1990	5991	3	2001-09-10 03:33:50	20
157331	586	Home Alone	[Children's, Comedy]	1990	5996	3	2000-08-14 17:57:25	20
157332	586	Home Alone	[Children's, Comedy]	1990	6000	3	2000-04-28 01:18:42	20
157333	586	Home Alone	[Children's, Comedy]	1990	6006	2	2000-04-29 18:37:11	20
157334	586	Home Alone	[Children's, Comedy]	1990	6016	3	2000-04-26 20:02:28	20

675 rows × 18 columns

In [439…

```
#movie_name = input("Enter a movie name: ")
movie_name='Home Alone'
movie_rating = matrix[movie_name] # Taking the ratings of that movie
print(movie_rating)
```

```
UserID
1       0.0
2       0.0
3       0.0
4       0.0
5       0.0
       ...
6036    0.0
6037    0.0
6038    0.0
6039    0.0
6040    0.0
Name: Home Alone, Length: 6040, dtype: float64
```

In [440…

```
similar_movies = matrix.corrwith(movie_rating) #Finding similar movies

sim_df = pd.DataFrame(similar_movies, columns=['Correlation'])
sim_df.sort_values('Correlation', ascending=False, inplace=True) # Sorting the

sim_df.iloc[1: , :].head() #Top 5 correlated movies.
```

Out[440…

Title	Correlation
Home Alone 2: Lost in New York	0.547203
Mrs. Doubtfire	0.468281
Liar Liar	0.455967
Mighty Ducks, The	0.446273
Sister Act	0.444612

In [441…

```
#@title Cosine Similarty
```

Cosine similarity is a measure of similarity between two sequences of numbers. Those sequences are viewed as vectors in a higher dimensional space, and the cosine similarity is defined as the cosine of the angle between them, i.e. the dot product of the vectors divided by the product of their lengths.

The cosine similarity always belongs to the interval [-1,1]. For example, two proportional vectors have a cosine similarity of 1, two orthogonal vectors have a similarity of 0, and two opposite vectors have a similarity of -1.

In [442…

```
item_sim = cosine_similarity(matrix.T) #Finding the similarity values between
item_sim
```

Out[442…
```
array([[1.        , 0.07235746, 0.03701053, ..., 0.        , 0.12024178,
         0.02700277],
        [0.07235746, 1.        , 0.11528952, ..., 0.        , 0.        ,
         0.07780705],
        [0.03701053, 0.11528952, 1.        , ..., 0.        , 0.04752635,
         0.0632837 ],
        ...,
        [0.        , 0.        , 0.        , ..., 1.        , 0.        ,
         0.04564448],
        [0.12024178, 0.        , 0.04752635, ..., 0.        , 1.        ,
         0.04433508],
        [0.02700277, 0.07780705, 0.0632837 , ..., 0.04564448, 0.04433508,
         1.        ]])
```

In [443…
```
item_sim.shape
```

Out[443…
```
(3664, 3664)
```

In [444…
```
#@title Item-Based Similarity
```

In [445…
```
item_sim_matrix = pd.DataFrame(item_sim, index=matrix.columns, columns=matrix.
item_sim_matrix.head() #Item-similarity Matrix
```

Out[445…

Title	$1,000,000 Duck	'Night Mother	'Til There Was You	'burbs, The	...And Justice for All	1-900	1 Things Hat Abou Yo
Title							
$1,000,000 Duck	1.000000	0.072357	0.037011	0.079291	0.060838	0.00000	0.05861
'Night Mother	0.072357	1.000000	0.115290	0.115545	0.159526	0.00000	0.07679
'Til There Was You	0.037011	0.115290	1.000000	0.098756	0.066301	0.08025	0.12789
'burbs, The	0.079291	0.115545	0.098756	1.000000	0.143620	0.00000	0.19219
...And Justice for All	0.060838	0.159526	0.066301	0.143620	1.000000	0.00000	0.07509

5 rows × 3664 columns

In [446…
```
#@title  User-Based Similarity
```

In [447…
```
user_sim = cosine_similarity(matrix) #Finding the similarity values between us
user_sim
```

Out[447…
```
array([[1.        , 0.09638153, 0.12060981, ..., 0.        , 0.17460369,
         0.13359025],
        [0.09638153, 1.        , 0.1514786 , ..., 0.06611767, 0.0664575 ,
         0.21827563],
        [0.12060981, 0.1514786 , 1.        , ..., 0.12023352, 0.09467506,
         0.13314404],
        ...,
        [0.        , 0.06611767, 0.12023352, ..., 1.        , 0.16171426,
         0.09930008],
        [0.17460369, 0.0664575 , 0.09467506, ..., 0.16171426, 1.        ,
         0.22833237],
        [0.13359025, 0.21827563, 0.13314404, ..., 0.09930008, 0.22833237,
         1.        ]])
```

In [448…
```
user_sim_matrix = pd.DataFrame(user_sim, index=matrix.index, columns=matrix.ir
user_sim_matrix.head()
```

Out[448…

UserID	1	2	3	4	5	6	7	
UserID								
1	1.000000	0.096382	0.120610	0.132455	0.090158	0.179222	0.059678	0.1
2	0.096382	1.000000	0.151479	0.171176	0.114394	0.100865	0.305787	0.2
3	0.120610	0.151479	1.000000	0.151227	0.062907	0.074603	0.138332	0.0
4	0.132455	0.171176	0.151227	1.000000	0.045094	0.013529	0.130339	0.1
5	0.090158	0.114394	0.062907	0.045094	1.000000	0.047449	0.126257	0.2

5 rows × 6040 columns

In [449…
```
#@title Nearest Neighbors
```

In [450…
```
model_knn = NearestNeighbors(metric='cosine')
model_knn.fit(matrix.T)
```

Out[450…

▾ NearestNeighbors

NearestNeighbors(metric='cosine')

In [451…
```
##The distances and indices are being calculated with neighbors being 6
distances, indices = model_knn.kneighbors(matrix.T, n_neighbors= 6)
```

In [452…
```
result = pd.DataFrame(indices, columns=['Title1', 'Title2', 'Title3', 'Title4'
result.head()
#The result dataframe consits of the different indices of movies based on the
```

Out[452…

	Title1	Title2	Title3	Title4	Title5	Title6
0	0	737	417	287	585	3266
1	1	809	73	2181	3054	3390
2	2	1637	2544	3340	2603	2012
3	3	1467	2183	1318	1054	3533
4	4	26	728	897	496	947

In [453…

```
##With this for loop replacing the indices in the result dataframe with movie
result2 = result.copy()
for i in range(1, 7):
    mov = pd.DataFrame(matrix.T.index).reset_index()
    mov = mov.rename(columns={'index':f'Title{i}'})
    result2 = pd.merge(result2, mov, on=[f'Title{i}'], how='left')
    result2 = result2.drop(f'Title{i}', axis=1)
    result2 = result2.rename(columns={'Title':f'Title{i}'})
result2.head()
```

Out[453…

	Title1	Title2	Title3	Title4	Title5	Title6
0	$1,000,000 Duck	Computer Wore Tennis Shoes, The	Blackbeard's Ghost	Barefoot Executive, The	Candleshoe	That Darn Cat!
1	'Night Mother	Cry in the Dark, A	Agnes of God	Mommie Dearest	Sophie's Choice	Trip to Bountiful, The
2	'Til There Was You	If Lucy Fell	Picture Perfect	To Gillian on Her 37th Birthday	Practical Magic	Mad Love
3	'burbs, The	Harry and the Hendersons	Money Pit, The	Ghostbusters II	European Vacation	Weekend at Bernie's
4	...And Justice for All	52 Pick-Up	Coma	Deliverance	Boys from Brazil, The	Dog Day Afternoon

In [454…

```
#movie_name = input("Enter a movie name: ")
movie_name = 'Liar Liar'
result2.loc[result2['Title1']==movie_name] #5 nearest movies for the movie pre
```

Out[454…

	Title1	Title2	Title3	Title4	Title5	Title6
1899	Liar Liar	Mrs. Doubtfire	Ace Ventura: Pet Detective	Dumb & Dumber	Home Alone	Wayne's World

In [455…

```
#@title Matrix Factorization
```

Creating a pivot table of movie titles and userid and ratings are taken as values

In [456…
```
rm = data.pivot(index = 'UserID', columns ='Movie_ID', values = 'Rating').fill
rm.head()
```

Out[456…

Movie_ID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	39
UserID															
1	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
5	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	

5 rows × 3706 columns

In [457…
```
#@title Using Cmfrec Library
```

In [458…
```
user_itm = data[['UserID', 'Movie_ID', 'Rating']].copy()
user_itm.columns = ['UserId', 'ItemId', 'Rating']  # Lib requires specific col
user_itm.head(2)
```

Out[458…

	UserId	ItemId	Rating
0	1	1	5
1	6	1	4

In [459…
```
print(user_itm.shape)
print("No.of Users:",len(user_itm['UserId'].unique()))
print("No.of Items:",len(user_itm['ItemId'].unique()))
```

```
(1000209, 3)
No.of Users: 6040
No.of Items: 3706
```

In [460…
```
model = CMF(method="als", k=4, lambda_=0.1, user_bias=False, item_bias=False,
model.fit(user_itm) #Fitting the model
```

Out[460…
```
Collective matrix factorization model
(explicit-feedback variant)
```

In [461…
```
model.A_.shape, model.B_.shape #model.A_ gives the embeddings of Users and moc
```

Out[461…
```
((6040, 4), (3706, 4))
```

In [462…
```
user_itm.Rating.mean(), model.glob_mean_  # Average rating and Global Mean
```

Out[462… (np.float64(3.581564453029317), 3.581564426422119)

In [463…
```
rm__ = np.dot(model.A_, model.B_.T) + model.glob_mean_ #Calculating the predic
rmse = mean_squared_error(rm.values[rm > 0], rm__[rm > 0]) # calculating rmse
print('Root Mean Squared Error: {:.3f}'.format(rmse))
mape =  mean_absolute_percentage_error(rm.values[rm > 0], rm__[rm > 0]) #calcu
print('Mean Absolute Percentage Error: {:.3f}'.format(mape))
```

```
Root Mean Squared Error: 1.365
Mean Absolute Percentage Error: 0.346
```

Embeddings for user-user similarity.

In [464…
```
user=cosine_similarity(model.A_)

user_sim_matrix = pd.DataFrame(user, index=matrix.index, columns=matrix.index)
user_sim_matrix.head()  #User similarity matrix using the embeddings from matr
```

Out[464…

UserID	1	2	3	4	5	6	7
UserID							
1	1.000000	-0.001556	0.330752	-0.243099	0.781295	0.385959	0.017011
2	-0.001556	1.000000	-0.515879	0.039806	0.602824	0.313755	0.059894
3	0.330752	-0.515879	1.000000	0.663703	-0.033458	0.533339	0.719866
4	-0.243099	0.039806	0.663703	1.000000	-0.152643	0.580663	0.931329
5	0.781295	0.602824	-0.033458	-0.152643	1.000000	0.584601	0.021669

5 rows × 6040 columns

In [465…
```
itm=cosine_similarity(model.B_)

itm_sim_matrix = pd.DataFrame(itm, index=user_itm['ItemId'].unique(), columns=
itm_sim_matrix.head()#Item similarity matrix using the embeddings from matrix
```

Out[465…

	1	2	3	4	5	6	7	
1	1.000000	0.281080	-0.048290	-0.108233	0.067749	0.659104	0.324720	0.1033
2	0.281080	1.000000	0.919790	0.823825	0.954888	0.168801	0.955233	0.952ε
3	-0.048290	0.919790	1.000000	0.770813	0.959750	0.036122	0.892197	0.8754
4	-0.108233	0.823825	0.770813	1.000000	0.841995	-0.281402	0.715735	0.9514
5	0.067749	0.954888	0.959750	0.841995	1.000000	-0.079447	0.959800	0.9202

5 rows × 3706 columns

In [466…
```
movie_name=586
```

```
movie_rating = itm_sim_matrix[movie_name] # Taking the ratings of that movie
print(movie_rating)
```

```
1       0.265839
2       0.966962
3       0.935898
4       0.720481
5       0.970005
          ...
3948    0.534284
3949   -0.391499
3950    0.484258
3951    0.163836
3952    0.451043
Name: 586, Length: 3706, dtype: float32
```

In [467…

```
similar_movies = itm_sim_matrix.corrwith(movie_rating) #Finding similar movies

sim_df = pd.DataFrame(similar_movies, columns=['Correlation'])
sim_df.sort_values('Correlation', ascending=False, inplace=True) # Sorting the

sim_df.iloc[1: , :].head() #Top 5 correlated movies.
```

Out[467…

	Correlation
3482	0.998459
3594	0.997291
653	0.995545
2875	0.995394
3565	0.994582

In [468…

```
item_mov = data[['Movie_ID', 'Title']].copy()
item_mov.drop_duplicates(inplace=True)
item_mov.reset_index(drop=True,inplace=True)

sim_df1= sim_df.copy()
sim_df1.reset_index(inplace=True)
sim_df1.rename(columns = {'index':'Movie_ID'}, inplace = True)
sim_mov = pd.merge(sim_df1,item_mov,on='Movie_ID',how='inner')
sim_mov.head(6)
```

Out[468…

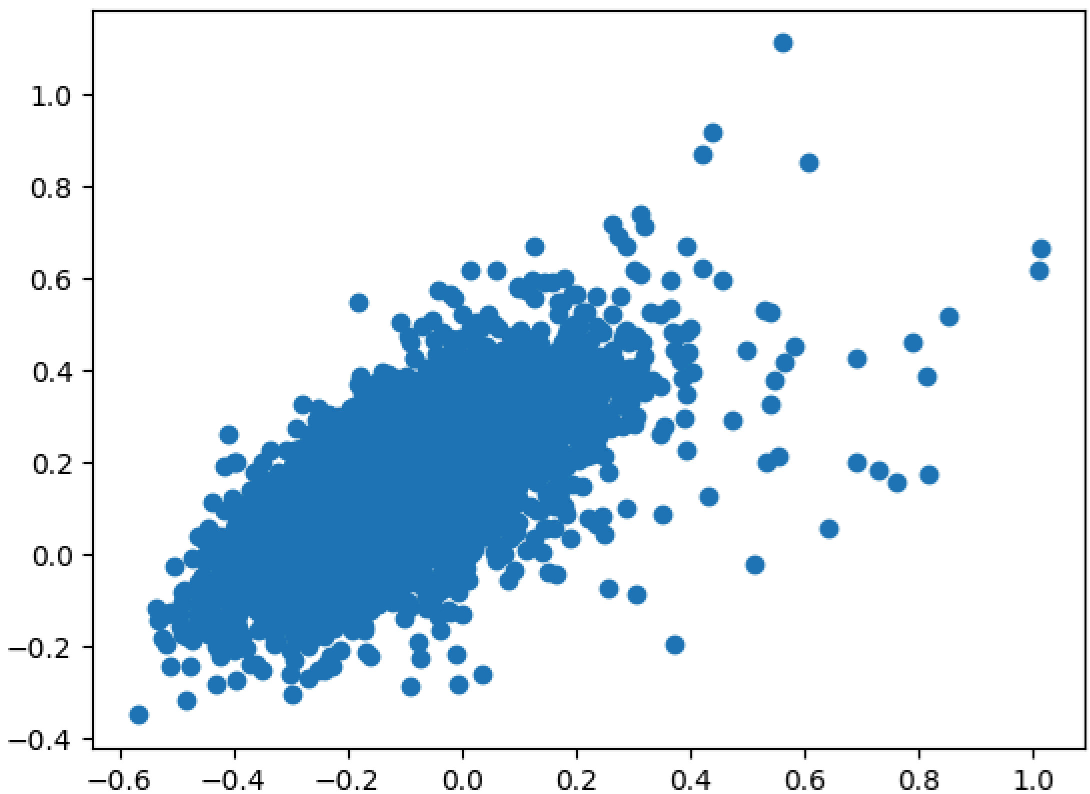
	Movie_ID	Correlation	Title
0	586	1.000000	Home Alone
1	3482	0.998459	Price of Glory
2	3594	0.997291	Center Stage
3	653	0.995545	Dragonheart
4	2875	0.995394	Sommersby
5	3565	0.994582	Where the Heart Is

In [469…
```
model1 = CMF(method="als", k=2, lambda_=0.1, user_bias=False, item_bias=False,
model1.fit(user_itm)
```

Out[469…
```
Collective matrix factorization model
(explicit-feedback variant)
```

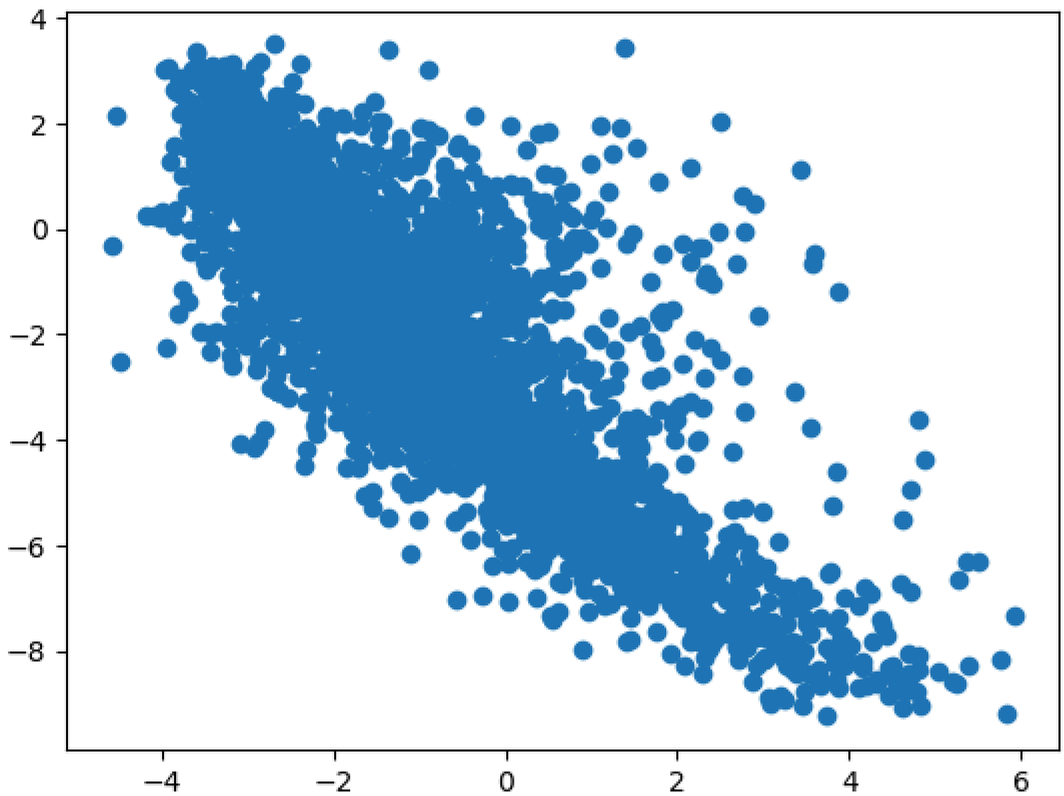
In [470…
```
plt.scatter(model1.A_[:, 0], model1.A_[:, 1], cmap = 'hot')
```

Out[470…
```
<matplotlib.collections.PathCollection at 0x7b3c371ea990>
```



In [471…
```
plt.scatter(model1.B_[:, 0], model1.B_[:, 1], cmap='hot')
```

Out[471…
```
<matplotlib.collections.PathCollection at 0x7b3c37179e50>
```



User-Based Approach(optional)

In [472…
```
#Taking 6 movies names in random
mov_name = ['Hamlet', 'Dumb & Dumber', 'Ace Ventura: Pet Detective', 'Home Alc
```

In [473…
```
#Finding the MovieID's for the above movies
mov_id = []
for mov in mov_name:
    id = data[data['Title'] == mov]['Movie_ID'].iloc[0]
    mov_id.append(id)
```

In [474…
```
#mov_rating = list(map(int, input("Rate these movies respectively: ").split())
mov_rating = [5,3,2,1,4,3]#Give the random user rating for the movies
```

In [475…
```
user_choices = pd.DataFrame({'Movie_ID': mov_id, 'Title': mov_name, 'Rating':
user_choices.sort_values(by='Movie_ID') #User choices
```

Out[475…

	Movie_ID	Title	Rating
1	231	Dumb & Dumber	3
2	344	Ace Ventura: Pet Detective	2
3	586	Home Alone	1
5	905	It Happened One Night	3
0	1411	Hamlet	5
4	3034	Robin Hood	4

In [476…

```
other_users = data[data['Movie_ID'].isin(user_choices['Movie_ID'].values)] #Fi
other_users = other_users[['UserID', 'Movie_ID', 'Rating']]
other_users['UserID'].nunique()
```

Out[476… 1810

In [477…

```
common_movies = other_users.groupby(['UserID']) #Grouping the data based on Us
common_movies = sorted(common_movies, key=lambda x: len(x[1]), reverse=True) #
common_movies[0]
```

Out[477…

```
((1605,),
         UserID  Movie_ID  Rating
 60910     1605       231       2
 92310     1605       344       3
 156847    1605       586       3
 216150    1605       905       4
 418869    1605      1411       3
 814313    1605      3034       4)
```

In [478…

```
top_users = common_movies[:100] #Taking top 100 users who watched same movies
```

In [479…

```
#Calculating pearson correlation
pearson_corr = {}

for user_id, movies in top_users:
    movies = movies.sort_values(by='Movie_ID')
    movie_list = movies['Movie_ID'].values #Taking list of movieid's

    new_user_ratings = user_choices[user_choices['Movie_ID'].isin(movie_list)]
    user_ratings = movies[movies['Movie_ID'].isin(movie_list)]['Rating'].value

    corr = pearsonr(new_user_ratings, user_ratings) # Calculating the correlat
    pearson_corr[user_id] = corr[0] #Correlation value for each UserID
```

In [480…

```
pearson_df = pd.DataFrame(columns=['UserID', 'Similarity Index'], data=pearsor
pearson_df = pearson_df.sort_values(by='Similarity Index', ascending=False)[:1
pearson_df
```

Out[480…

	UserID	Similarity Index
98	(3224,)	0.943880
7	(424,)	0.943456
73	(1943,)	0.923381
35	(5795,)	0.880705
43	(524,)	0.870388
53	(1019,)	0.870388
82	(2507,)	0.852803
56	(1112,)	0.774597
42	(438,)	0.774597
89	(2896,)	0.774597

In [481…

```
pearson_df['UserID'] = pearson_df['UserID'].apply(lambda x: x[0] if isinstance
pearson_df['UserID'] = pearson_df['UserID'].astype(int)
```

In [482…

```
users_rating = pearson_df.merge(data, on='UserID', how='inner') #Merging the c
users_rating['Weighted Rating'] = users_rating['Rating'] * users_rating['Simil
users_rating = users_rating[['UserID', 'Movie_ID', 'Rating', 'Similarity Index
users_rating
```

Out[482…

	UserID	Movie_ID	Rating	Similarity Index	Weighted Rating
0	3224	2	3	0.943880	2.831639
1	3224	3	4	0.943880	3.775519
2	3224	6	4	0.943880	3.775519
3	3224	7	3	0.943880	2.831639
4	3224	10	3	0.943880	2.831639
...	...	...	...	...	...
8697	2896	3826	3	0.774597	2.323790
8698	2896	3861	3	0.774597	2.323790
8699	2896	3863	3	0.774597	2.323790
8700	2896	3869	3	0.774597	2.323790
8701	2896	3948	4	0.774597	3.098387

8702 rows × 5 columns

In [483…

```
# Calculate sum of similarity index and weighted rating for each movie
```

```
grouped_ratings = users_rating.groupby('Movie_ID').sum()[['Similarity Index',

recommend_movies = pd.DataFrame()

# Add average recommendation score.
# We're calculating average recommendation score by dividing the Weighted Rati
recommend_movies['avg_reccomend_score'] = grouped_ratings['Weighted Rating']/g
recommend_movies['Movie_ID'] = grouped_ratings.index
recommend_movies = recommend_movies.reset_index(drop=True)

# Select movies with the highest score i.e. 5
recommend_movies = recommend_movies[(recommend_movies['avg_reccomend_score'] =
```

In [484…

```
recommendations = data[data['Movie_ID'].isin(recommend_movies['Movie_ID'])][['
recommendations
```

Out[484…

	Movie_ID	Title
217354	908	North by Northwest
304323	1199	Brazil
235691	950	Thin Man, The
518003	1938	Lost Weekend, The
304893	1199	Brazil
487227	1734	My Life in Pink (Ma vie en rose)
627960	2325	Orgazmo
736435	2721	Trick
354248	1264	Diva
86952	319	Shallow Grave

In [485…

```
#@title Regression Based Rec Sys
```

In [486…

```
from sklearn.preprocessing import StandardScaler
```

In [487…

```
df_movies_copy.head()
```

Out[487…

	Movie_ID	Title	Genres	Year
0	1	Toy Story	[Animation, Children's, Comedy]	1995
1	2	Jumanji	[Adventure, Children's, Fantasy]	1995
2	3	Grumpier Old Men	[Comedy, Romance]	1995
3	4	Waiting to Exhale	[Comedy, Drama]	1995
4	5	Father of the Bride Part II	[Comedy]	1995

In [488…

```
df_ratings_copy.head()
```

Out[488…

	UserID	MovieID	Rating	Timestamp	RatingYear	RatingMonth	RatingDay	R
0	1	1193	5	2000-12-31 22:12:40	2000	12	31	
1	1	661	3	2000-12-31 22:35:09	2000	12	31	
2	1	914	3	2000-12-31 22:32:48	2000	12	31	
3	1	3408	4	2000-12-31 22:04:35	2000	12	31	
4	1	2355	5	2001-01-06 23:38:11	2001	1	6	

In [489…

```
df_users_copy.head()
```

Out[489…

	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

In [490…

```
genres_df = pd.get_dummies(df_movies_copy['Genres'].apply(pd.Series).stack()).
genres_df.head()
```

Out[490…

	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Dra
0	0	0	1	1	1	0	0	
1	0	1	0	1	0	0	0	
2	0	0	0	0	1	0	0	
3	0	0	0	0	1	0	0	
4	0	0	0	0	1	0	0	

In [491…

```
m = pd.concat([df_movies_copy['Movie_ID'],genres_df.iloc[:,1:]],axis=1)
m.head()
```

Out[491…

	Movie_ID	Adventure	Animation	Children's	Comedy	Crime	Documentary	D
0	1	0	1	1	1	0	0	
1	2	1	0	1	0	0	0	
2	3	0	0	0	1	0	0	
3	4	0	0	0	1	0	0	
4	5	0	0	0	1	0	0	

In [492…

```
from datetime import datetime
r = df_ratings_copy.copy()

# Convert 'Timestamp' to datetime dtype
r['Timestamp'] = pd.to_datetime(r['Timestamp'])

# Extract hour
r['hour'] = r['Timestamp'].dt.hour

# You can keep 'Rating' as int
r['Rating'] = r['Rating'].astype(int)

r.head()
```

Out[492…

	UserID	MovieID	Rating	Timestamp	RatingYear	RatingMonth	RatingDay	R
0	1	1193	5	2000-12-31 22:12:40	2000	12	31	
1	1	661	3	2000-12-31 22:35:09	2000	12	31	
2	1	914	3	2000-12-31 22:32:48	2000	12	31	
3	1	3408	4	2000-12-31 22:04:35	2000	12	31	
4	1	2355	5	2001-01-06 23:38:11	2001	1	6	

In [493…

```
df_users2 = df_users_copy.merge(r.groupby('UserID').Rating.mean().reset_index(
df_users2 = df_users2.merge(r.groupby('UserID').hour.mean().reset_index(), on=
df_users2.head(2)
```

Out[493…

	UserID	Gender	Age	Occupation	Zip-code	Rating	hour
0	1	F	1	10	48067	4.188679	22.245283
1	2	M	56	16	70072	3.713178	21.155039

In [494…

```
u = df_users2[['UserID','Age', 'Rating', 'hour']].copy()
u = u.set_index('UserID')
u .columns = ['Age', 'User_avg_rating', 'hour']

scaler = StandardScaler()
u = pd.DataFrame(scaler.fit_transform(u), columns=u.columns, index=u.index)
u.head(2)
```

Out[494…

UserID	Age	User_avg_rating	hour
1	-2.298525	1.131261	1.414540
2	1.966729	0.024380	1.261846

In [495…

```
df_cat = df_users2[['Gender','Occupation']]
df_cat['Gender']=pd.get_dummies(df_cat['Gender'], columns=['Gender'],drop_firs
df_cat = pd.concat([df_users_copy['UserID'],df_cat],axis=1)
df_cat.head()
```

Out[495…

	UserID	Gender	Occupation
0	1	False	10
1	2	True	16
2	3	True	15
3	4	True	7
4	5	True	20

In [496…

```
print(u.columns)
```

```
Index(['Age', 'User_avg_rating', 'hour'], dtype='object')
```

In [497…

```
X = df_ratings_copy[['MovieID', 'UserID', 'Rating']].copy()
X = X.merge(u.reset_index(), on='UserID', how='right')
X = X.merge(m.reset_index(), left_on='MovieID', right_on='Movie_ID', how='righ
X = X.merge(df_cat, on='UserID', how='right')
X.drop(columns=['index'], axis=1, inplace=True)
X.dropna(inplace=True)
X.reset_index(inplace=True,drop=True)
X1=X.copy()
X.head()
```

Out[497…

	MovieID	UserID	Rating	Age	User_avg_rating	hour	Movie_ID	Adve
0	1.0	1.0	5.0	-2.298525	1.131261	1.41454	1	
1	48.0	1.0	5.0	-2.298525	1.131261	1.41454	48	
2	150.0	1.0	5.0	-2.298525	1.131261	1.41454	150	
3	260.0	1.0	4.0	-2.298525	1.131261	1.41454	260	
4	527.0	1.0	5.0	-2.298525	1.131261	1.41454	527	

5 rows × 26 columns

In [498…

```
X = X.drop(columns = ['MovieID', 'UserID'])
y = X.pop('Rating')
```

In [499…

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
```

In [500…

```
from sklearn.ensemble import GradientBoostingRegressor

model = GradientBoostingRegressor()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

In [501…

```
rmse = mean_squared_error(y_test, y_pred) # calculating rmse value
print('Root Mean Squared Error: {:.3f}'.format(rmse))
```

```
Root Mean Squared Error: 0.983
```

In [502…

```
mape =  mean_absolute_percentage_error(y_test, y_pred) #calculating mape value
print('Mean Absolute Percentage Error: {:.3f}'.format(mape))
```

```
Mean Absolute Percentage Error: 0.319
```

In [503…

```
#@title Ensemble Recommender System
```

In [504…

```
X1.head()
```

Out[504…

	MovieID	UserID	Rating	Age	User_avg_rating	hour	Movie_ID	Adve
0	1.0	1.0	5.0	-2.298525	1.131261	1.41454	1	
1	48.0	1.0	5.0	-2.298525	1.131261	1.41454	48	
2	150.0	1.0	5.0	-2.298525	1.131261	1.41454	150	
3	260.0	1.0	4.0	-2.298525	1.131261	1.41454	260	
4	527.0	1.0	5.0	-2.298525	1.131261	1.41454	527	

5 rows × 26 columns

In [505…
```
y = X1.pop('Rating')
```

In [506…
```
X_train, X_test, y_train, y_test = train_test_split(X1, y, test_size=0.2, ranc
```

In [507…
```
X_train1 = X_train[['Movie_ID', 'UserID']].copy()
X_train = X_train.drop(columns = ['Movie_ID', 'UserID'])
user_item_train=pd.concat([X_train1,y_train],axis=1)
```

In [508…
```
X_test1 = X_test[['Movie_ID', 'UserID']].copy()
X_test = X_test.drop(columns = ['Movie_ID', 'UserID'])
user_item_test=pd.concat([X_test1,y_test],axis=1)
```

In [509…
```
model = GradientBoostingRegressor()
model.fit(X_train, y_train)
y_pred_reg = model.predict(X_test)
```

In [510…
```
user_item_test.columns = ['UserId', 'ItemId', 'Rating']  # Lib requires specif
user_item_test.head(2)
```

Out[510…

	UserId	ItemId	Rating
511275	858	3154.0	2.0
467574	3863	2881.0	3.0

In [511…
```
model = CMF(method="als", k=4, lambda_=0.1, user_bias=False, item_bias=False,
model.fit(user_item_test)
```

Out[511…
```
Collective matrix factorization model
(explicit-feedback variant)
```

In [512…
```
y_pred_mf = np.dot(model.A_, model.B_.T) + model.glob_mean_
```

In [513…
```
df = pd.DataFrame(y_pred_mf,columns =list(model.item_mapping_),index=list(mode
df.head()
```

Out[513…

	3154.0	2881.0	5926.0	5232.0	5319.0	1584.0	4972.0	60
858	4.061112	4.424901	3.526924	4.973579	4.171535	4.646420	4.902835	4.20
3863	3.953694	3.307842	4.051600	3.182384	3.715579	2.934999	3.452144	2.58
1953	4.337581	3.833681	3.391613	4.681539	4.126843	3.827811	4.520000	3.66
1396	3.347122	4.162496	4.510985	3.078121	3.760908	3.529122	3.966618	2.84
2054	3.844099	3.048064	3.921417	2.870862	3.597624	2.436075	3.200737	2.42

5 rows × 6031 columns

In [514…

```
df1=df.unstack().reset_index()
df1.rename(columns={'level_0': 'ItemId', 'level_1': 'UserId',0:'Rating'}, inpl
df1.tail()
```

Out[514…

	ItemId	UserId	Rating
20957720	4527.0	2765	3.821465
20957721	4527.0	3899	3.043348
20957722	4527.0	2914	3.676330
20957723	4527.0	545	4.324425
20957724	4527.0	503	3.544468

In [515…

```
df_mf = pd.merge(user_item_test, df1, on=['UserId','ItemId'], how='inner')
df_mf.rename(columns={'Rating_x': 'True_rating', 'Rating_y': 'Mf_pred_ratings'
df_mf.head()
```

Out[515…

	UserId	ItemId	True_rating	Mf_pred_ratings
0	858	3154.0	2.0	4.061112
1	3863	2881.0	3.0	3.307842
2	1953	5926.0	3.0	3.391613
3	1396	5232.0	5.0	3.078121
4	2054	5319.0	3.0	3.597624

In [516…

```
df_gb=pd.DataFrame(y_pred_reg,columns =['reg_pred_ratings'])
df_reg= pd.concat([df_gb,df_mf['Mf_pred_ratings']],axis=1)
df_reg.head()
```

Out[516…

	reg_pred_ratings	Mf_pred_ratings
0	4.196260	4.061112
1	3.528049	3.307842
2	3.921376	3.391613
3	3.496896	3.078121
4	3.398280	3.597624

In [517…
```
y = df_mf['True_rating']
X_train, X_test, y_train, y_test = train_test_split(df_reg, y, test_size=0.2,
```

In [518…
```
from sklearn.linear_model import LinearRegression
```

In [519…
```
model = LinearRegression().fit(X_train, y_train)
```

In [520…
```
y_pred_en=model.predict(X_test)
```

In [521…
```
rmse = mean_squared_error(y_test, y_pred_en) # calculating rmse value
print('Root Mean Squared Error: {:.3f}'.format(rmse))
```

```
Root Mean Squared Error: 0.581
```

In [522…
```
mape =  mean_absolute_percentage_error(y_test, y_pred_en) #calculating mape va
print('Mean Absolute Percentage Error: {:.3f}'.format(mape))
```

```
Mean Absolute Percentage Error: 0.218
```

Questionnaire

1. Users of which age group have watched and rated the most number of movies? :- **25-34 age group**
2. Users belonging to which profession have watched and rated the most movies? :- **college/grad student**
3. Most of the users in our dataset who've rated the movies are Male. (T/F):- **True**
4. Most of the movies present on our dataset were released in which decade? :- **b.90s** a.70s b. 90s c. 50s d.80s
5. The movie with maximum no. of ratings is ___ :- **American Beauty**
6. Name the top 3 movies similar to 'Liar Liar' on the item-based

approach. :- **Mrs. Doubtfire, Ace Ventura: Pet, Detective Dumb & Dumber**

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

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

9. Mention the RMSE and MAPE that you got while evaluating the Matrix Factorization model.:- **RMSE:0.701 and MAPE: 0.54**

In [523…

```
from scipy.sparse import csr_matrix
# create dense matrix
A = np.array([[1,0],[3,7]])
# convert to sparse matrix (CSR method)
S = csr_matrix(A)
print(S)
```

```
<Compressed Sparse Row sparse matrix of dtype 'int64'
	with 3 stored elements and shape (2, 2)>
  Coords	Values
  (0, 0)	1
  (1, 0)	3
  (1, 1)	7
```

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