Movie Recommendation System

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Github Link: https://github.com/gautamnaik1994/MovieRecommendationMLCaseStudy

render nbviewer Open in Colab

About Zee Entertainment

Zee Entertainment Enterprises is an Indian media conglomerate, headquartered in Mumbai, India. It has interests in television, print, internet, film, and businesses related to mobile content, and operates 45 channels worldwide.

Business Problem
Zee Entertainement want to enhance user experience on their OTT platform by recommending movies to users based on their past viewing history and preferences. They want to build a recommendation system that can predict the movies that a user is likely to watch based on their past viewing history and preferences.
The insights gained from this system are expected to drive user engagement, increase satisfaction, and foster a more intuitive user experience.

Solution

We will build a recommendation system that will predict the movies that a user is likely to watch based on their past viewing history and preferences. We will use the following approaches to build the recommendation system:

- Pearson Correlation
- Cosine Similarity
- Matrix Factorization

Metrics used

We will use RMSE and MAPE for evaluating the performance of the recommendation system.

Dataset

1.Rating Data

Contains user ratings for movies on a 5-star scale. Includes a timestamp representing when the rating was given. Each user has rated at least 20 movies.

Column	Explanation
UserID	Unique identifier for each user
MovieID	Unique identifier for each movie
Rating	User's rating for the movie on a 5-star scale
Timestamp	The time when the rating was given, represented as a Unix timestamp

2.User Data

Demographic data is voluntarily provided by users and varies in accuracy and completeness.

Column	Explanation
UserID	Unique identifier for each user
Gender	Gender of the user (e.g., M for male, F for female)
Age	Age group of the user
Occupation	Occupation of the user
Zip-code	Zip code of the user's location

3.Movie Data

Column	Explanation
MovieID	Unique identifier for each movie
Title	Title of the movie
Genres	Genres of the movie, categorized into multiple types and pipe-separated

In [233…
```
import polars as pl
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
sns.set_theme(style="whitegrid")
import duckdb as db
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler
import numpy as np
import pickle
from sklearn.model_selection import train_test_split

from sklearn.metrics import mean_squared_error, mean_absolute_percentage_error
from sklearn.decomposition import TruncatedSVD
```

Data Loading and Preprocessing

In [3]:
```
movies = pd.read_csv("../data/raw/zee-movies.dat", sep="::", encoding='ISO-8859-1', engine="python").to_parquet("../data/raw/movies.parquet")
ratings = pd.read_csv("../data/raw/zee-ratings.dat", sep="::", encoding='ISO-8859-1', engine="python").to_parquet("../data/raw/ratings.parquet")
users = pd.read_csv("../data/raw/zee-users.dat", sep="::", encoding='ISO-8859-1', engine="python").to_parquet("../data/raw/users.parquet")
```

In [234…
```
movies = pl.read_parquet("../data/raw/movies.parquet")
ratings = pl.read_parquet("../data/raw/ratings.parquet")
users = pl.read_parquet("../data/raw/users.parquet")
```

In [235…
```
movies.null_count()
```

Out[235… shape: (1, 3)

Movie ID	Title	Genres
u32	u32	u32
0	0	0

In [236…
```
users.null_count()
```

Out[236… shape: (1, 5)

UserID	Gender	Age	Occupation	Zip-code
u32	u32	u32	u32	u32
0	0	0	0	0

In [237…
```
movies.null_count()
```

Out[237…

shape: (1, 3)

Movie ID	Title	Genres
u32	u32	u32
0	0	0

Movies

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

Out[3]:

shape: (5, 3)

Movie ID	Title	Genres
i64	str	str
1	"Toy Story (1995)"	"Animation|Children's|Comedy"
2	"Jumanji (1995)"	"Adventure|Children's|Fantasy"
3	"Grumpier Old Men (1995)"	"Comedy|Romance"
4	"Waiting to Exhale (1995)"	"Comedy|Drama"
5	"Father of the Bride Part II (1…	"Comedy"

In [4]:
```
movies.shape
```

Out[4]:
```
(3883, 3)
```

In [5]:
```
movies=movies.with_columns(
    pl.col("Title").str.extract(r"\((\d{4})\)", group_index=1).alias("ReleaseYear")
)
movies=movies.rename({"Movie ID":"MovieID"})
movies.head()
```

Out[5]:

shape: (5, 4)

MovieID	Title	Genres	ReleaseYear
i64	str	str	str
1	"Toy Story (1995)"	"Animation|Children's|Comedy"	"1995"
2	"Jumanji (1995)"	"Adventure|Children's|Fantasy"	"1995"
3	"Grumpier Old Men (1995)"	"Comedy|Romance"	"1995"
4	"Waiting to Exhale (1995)"	"Comedy|Drama"	"1995"
5	"Father of the Bride Part II (1…	"Comedy"	"1995"

In [6]:
```
movies_expanded=movies.with_columns(
    pl.col("Genres").str.split("|").alias("Genres")
).explode("Genres").to_pandas()


movies_expanded = movies_expanded.pivot_table(index="MovieID", columns="Genres", aggfunc='size', fill_value=0)
movies_expanded
```

Out[6]:

Genres	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
MovieID																		
1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0
4	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
3948	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
3949	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3950	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3951	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3952	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0

3883 rows × 18 columns

In [7]:
```
movies_expanded.to_parquet("../data/processed/movies_expanded.parquet")
```

Users

In [8]:
```
users.head()
```

Out[8]:

shape: (5, 5)

UserID	Gender	Age	Occupation	Zip-code
i64	str	i64	i64	str
1	"F"	1	10	"48067"
2	"M"	56	16	"70072"
3	"M"	25	15	"55117"
4	"M"	45	7	"02460"
5	"M"	25	20	"55455"

In [9]:
```
users.shape
```

Out[9]:
```
(6040, 5)
```

In [10]:
```
users=users.rename({"Zip-code":"ZipCode"})
occupations = pl.read_csv("../data/processed/occupations.csv")
ages = pl.read_csv("../data/processed/ages.csv")
users=users.join(occupations, on="Occupation", how="left").join(ages, on="Age", how="left").drop("Occupation")
users.head()
```

Out[10]:

shape: (5, 6)

UserID	Gender	Age	ZipCode	OccupationName	AgeCategory
i64	str	i64	str	str	str
1	"F"	1	"48067"	"K-12 student"	"Under-18"
2	"M"	56	"70072"	"self-employed"	"56+"
3	"M"	25	"55117"	"scientist"	"25-34"
4	"M"	45	"02460"	"executive/managerial"	"45-49"
5	"M"	25	"55455"	"writer"	"25-34"

In [11]:
```
users.describe()
```

Out[11]: shape: (9, 7)

statistic	UserID	Gender	Age	ZipCode	OccupationName	AgeCategory
str	f64	str	f64	str	str	str
"count"	6040.0	"6040"	6040.0	"6040"	"6040"	"6040"
"null_count"	0.0	"0"	0.0	"0"	"0"	"0"
"mean"	3020.5	null	30.639238	null	null	null
"std"	1743.742145	null	12.895962	null	null	null
"min"	1.0	"F"	1.0	"00231"	"K-12 student"	"18-24"
"25%"	1511.0	null	25.0	null	null	null
"50%"	3021.0	null	25.0	null	null	null
"75%"	4530.0	null	35.0	null	null	null
"max"	6040.0	"M"	56.0	"99945"	"writer"	"Under-18"

Ratings

In [12]:
```
ratings.head()
```

Out[12]: shape: (5, 4)

UserID	MovieID	Rating	Timestamp
i64	i64	i64	i64
1	1193	5	978300760
1	661	3	978302109
1	914	3	978301968
1	3408	4	978300275
1	2355	5	978824291

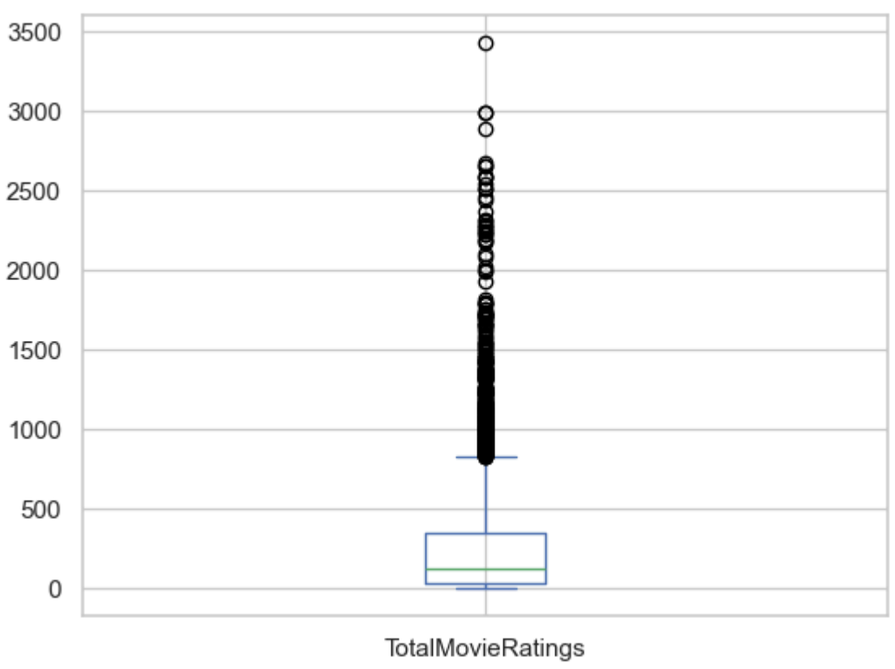
In [13]:
```
ratings.shape, ratings["MovieID"].n_unique()
```

Out[13]: ((1000209, 4), 3706)

In [14]:
```
ratings=ratings.join(movies, on="MovieID", how="left")
ratings=ratings.with_columns(
       pl.from_epoch("Timestamp", time_unit="s")
)
ratings = ratings.with_columns([
    pl.col("Timestamp").dt.year().alias("Year"),
    pl.col("Timestamp").dt.month().alias("Month"),
    pl.col("Timestamp").dt.day().alias("Day"),
    pl.col("Timestamp").dt.weekday().alias("Weekday"),
    pl.col("Timestamp").dt.hour().alias("Hour"),
    pl.col("Timestamp").dt.strftime('%A').alias("WeekdayName"),
    (pl.col("Timestamp").dt.weekday() >= 5).alias("IsWeekend"),
])

ratings=db.sql("""
    select *,
        round(avg(Rating) over(partition by MovieID),3) AvgMovieRating,
        count(*) over(partition by MovieID) TotalMovieRatings,
        round(avg(Rating) over(partition by UserID),3) AvgUserRating,
        count(*) over(partition by UserID) TotalUserRatings
        from ratings
""").pl()
```

In [14]:
```
ratings.select("MovieID", "TotalMovieRatings").unique().to_pandas()["TotalMovieRatings"].plot(kind="box")
```

Out[14]: <Axes: >



In [15]:
```
ratings.describe()
```

Out[15]: shape: (9, 19)

statistic	UserID	MovieID	Rating	Timestamp	Title	Genres	ReleaseYear	Year	Month	Day	Weekday	Hour	WeekdayName	IsWeekend	AvgMovieRat
str	f64	f64	f64	str	str	str	str	f64	f64	f64	f64	f64	str	f64	
"count"	1.000209e6	1.000209e6	1.000209e6	"1000209"	"1000209"	"1000209"	"1000209"	1.000209e6	1.000209e6	1.000209e6	1.000209e6	1.000209e6	"1000209"	1.000209e6	1.000209
"null_count"	0.0	0.0	0.0	"0"	"0"	"0"	"0"	0.0	0.0	0.0	0.0	0.0	"0"	0.0	
"mean"	3024.512348	1865.539898	3.581564	"2000-10-22 19:41:35.404665"	null	null	null	2000.126168	8.710371	15.440691	3.800285	11.9162	null	0.383028	3.581
"std"	1728.412695	1096.040689	1.117102	null	null	null	null	0.422392	2.71747	8.888445	2.04252	7.894465	null	null	0.545
"min"	1.0	1.0	1.0	"2000-04-25 23:05:32"	"$1,000,000 Duck (1971)"	"Action"	"1919"	2000.0	1.0	1.0	1.0	0.0	"Friday"	0.0	
"25%"	1506.0	1030.0	3.0	"2000-08-03 11:37:17"	null	null	null	2000.0	7.0	7.0	2.0	4.0	null	null	3.2
"50%"	3070.0	1835.0	4.0	"2000-10-31 18:46:46"	null	null	null	2000.0	9.0	17.0	4.0	14.0	null	null	3
"75%"	4476.0	2770.0	4.0	"2000-11-26 06:42:19"	null	null	null	2000.0	11.0	22.0	6.0	19.0	null	null	3.9
"max"	6040.0	3952.0	5.0	"2003-02-28 17:49:50"	"eXistenZ (1999)"	"Western"	"2000"	2003.0	12.0	31.0	7.0	23.0	"Wednesday"	1.0	

In [16]:
```
weighted_ratings=ratings.select("MovieID", "TotalMovieRatings", "AvgMovieRating").unique().with_columns(
    WeightedAverageMovieRating=(((pl.col("TotalMovieRatings") * pl.col("AvgMovieRating")
```

```
                    ) + pl.lit(350))/(pl.lit(100)+pl.col("TotalMovieRatings")))
)
weighted_ratings
```

Out[16]: shape: (3_706, 4)

MovieID	TotalMovieRatings	AvgMovieRating	WeightedAverageMovieRating
i64	i64	f64	f64
3742	234	3.97	3.829281
245	11	3.0	3.45045
3077	88	4.227	3.840298
2368	58	1.69	2.83557
1306	136	3.603	3.559356
…	…	…	…
1009	291	3.186	3.266307
3068	379	3.865	3.7888
1224	426	4.286	4.13657
888	48	2.208	3.080973
92	88	2.341	2.957489

In [17]:
```
weighted_ratings.describe()
```

Out[17]: shape: (9, 5)

statistic	MovieID	TotalMovieRatings	AvgMovieRating	WeightedAverageMovieRating
str	f64	f64	f64	f64
"count"	3706.0	3706.0	3706.0	3706.0
"null_count"	0.0	0.0	0.0	0.0
"mean"	1995.573125	269.889099	3.23889	3.434259
"std"	1151.148045	384.047838	0.672922	0.332625
"min"	1.0	1.0	1.0	2.038376
"25%"	989.0	33.0	2.822	3.263614
"50%"	2034.0	124.0	3.332	3.466667
"75%"	2991.0	350.0	3.741	3.595861
"max"	3952.0	3428.0	5.0	4.509663

In [18]:
```
ratings=ratings.join(weighted_ratings.select("MovieID", "WeightedAverageMovieRating"), on="MovieID", how="left")
ratings.head()
```

Out[18]: shape: (5, 19)

UserID	MovieID	Rating	Timestamp	Title	Genres	ReleaseYear	Year	Month	Day	Weekday	Hour	WeekdayName	IsWeekend	AvgMovieRating	TotalMovieRatings	AvgUserRating	Tot
i64	i64	i64	datetime[µs]	str	str	str	i32	i8	i8	i8	i8	str	bool	f64	i64	f64	
4	1097	4	2000-12-31 20:19:24	"E.T. the Extra-Terrestrial (19…	"Children's|Drama|Fantasy|Sci-F…	"1982"	2000	12	31	7	20	"Sunday"	true	3.965	2269	4.19	
4	2951	4	2000-12-31 20:24:42	"Fistful of Dollars, A (1964)"	"Action|Western"	"1964"	2000	12	31	7	20	"Sunday"	true	3.994	522	4.19	
4	3418	4	2000-12-31 20:24:20	"Thelma & Louise (1991)"	"Action|Drama"	"1991"	2000	12	31	7	20	"Sunday"	true	3.68	1417	4.19	
4	2366	4	2000-12-31 20:23:50	"King Kong (1933)"	"Action|Adventure|Horror"	"1933"	2000	12	31	7	20	"Sunday"	true	3.656	756	4.19	
4	1198	5	2000-12-31 20:23:19	"Raiders of the Lost Ark (1981)"	"Action|Adventure"	"1981"	2000	12	31	7	20	"Sunday"	true	4.478	2514	4.19	

In [19]:
```
combined = ratings.join(users, on="UserID")
combined.head()
```

Out[19]: shape: (5, 24)

UserID	MovieID	Rating	Timestamp	Title	Genres	ReleaseYear	Year	Month	Day	Weekday	Hour	WeekdayName	IsWeekend	AvgMovieRating	TotalMovieRatings	AvgUserRating	Tot
i64	i64	i64	datetime[µs]	str	str	str	i32	i8	i8	i8	i8	str	bool	f64	i64	f64	
4	1097	4	2000-12-31 20:19:24	"E.T. the Extra-Terrestrial (19…	"Children's|Drama|Fantasy|Sci-F…	"1982"	2000	12	31	7	20	"Sunday"	true	3.965	2269	4.19	
4	2951	4	2000-12-31 20:24:42	"Fistful of Dollars, A (1964)"	"Action|Western"	"1964"	2000	12	31	7	20	"Sunday"	true	3.994	522	4.19	
4	3418	4	2000-12-31 20:24:20	"Thelma & Louise (1991)"	"Action|Drama"	"1991"	2000	12	31	7	20	"Sunday"	true	3.68	1417	4.19	
4	2366	4	2000-12-31 20:23:50	"King Kong (1933)"	"Action|Adventure|Horror"	"1933"	2000	12	31	7	20	"Sunday"	true	3.656	756	4.19	
4	1198	5	2000-12-31 20:23:19	"Raiders of the Lost Ark (1981)"	"Action|Adventure"	"1981"	2000	12	31	7	20	"Sunday"	true	4.478	2514	4.19	

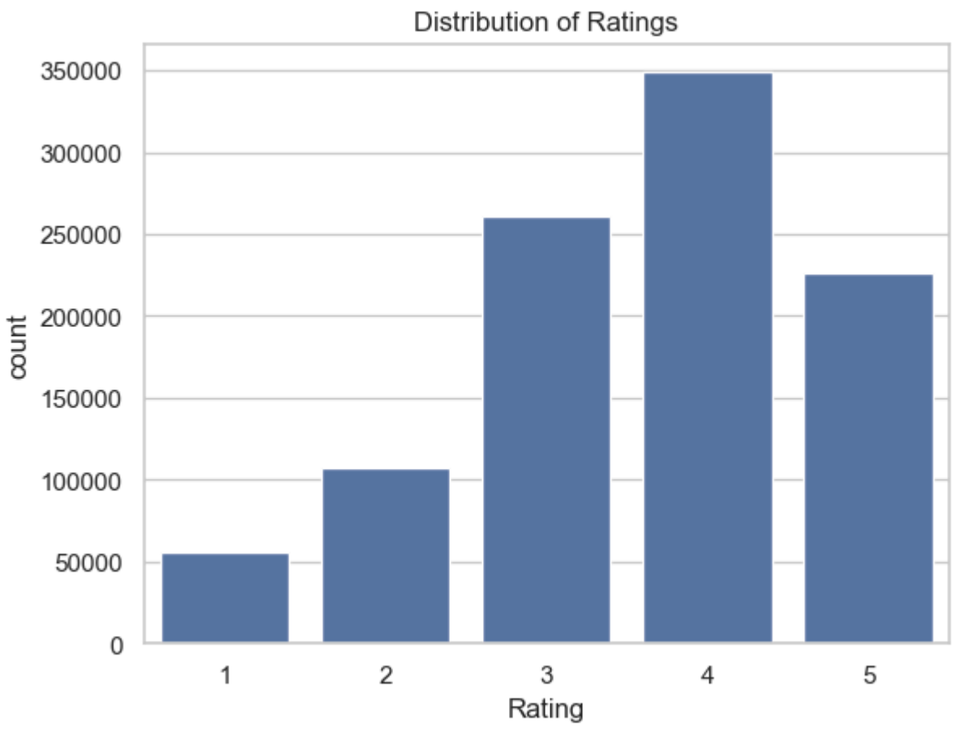
In [20]:
```
combined=db.sql("""
select *,
       case
        when AvgMovieRating >=4.0 then 'Good'
        when AvgMovieRating < 3.0 then 'Bad'
       else 'Average'
       end as MovieClass,
        case
        when TotalMovieRatings >=1000 then 'Very Popular'
        when TotalMovieRatings < 100 then 'Not Popular'
       else 'Popular'
       end as MoviePopularity
    from  combined
""").pl()
```

In [21]:
```
combined.write_parquet("../data/processed/combined.parquet")
ratings.write_parquet("../data/processed/ratings.parquet")
users.write_parquet("../data/processed/users.parquet")
movies.write_parquet("../data/processed/movies.parquet")
```

EDA

In [226…
```
ratings = pl.read_parquet("../data/processed/ratings.parquet")
users = pl.read_parquet("../data/processed/users.parquet")
combined = pl.read_parquet("../data/processed/combined.parquet")
```

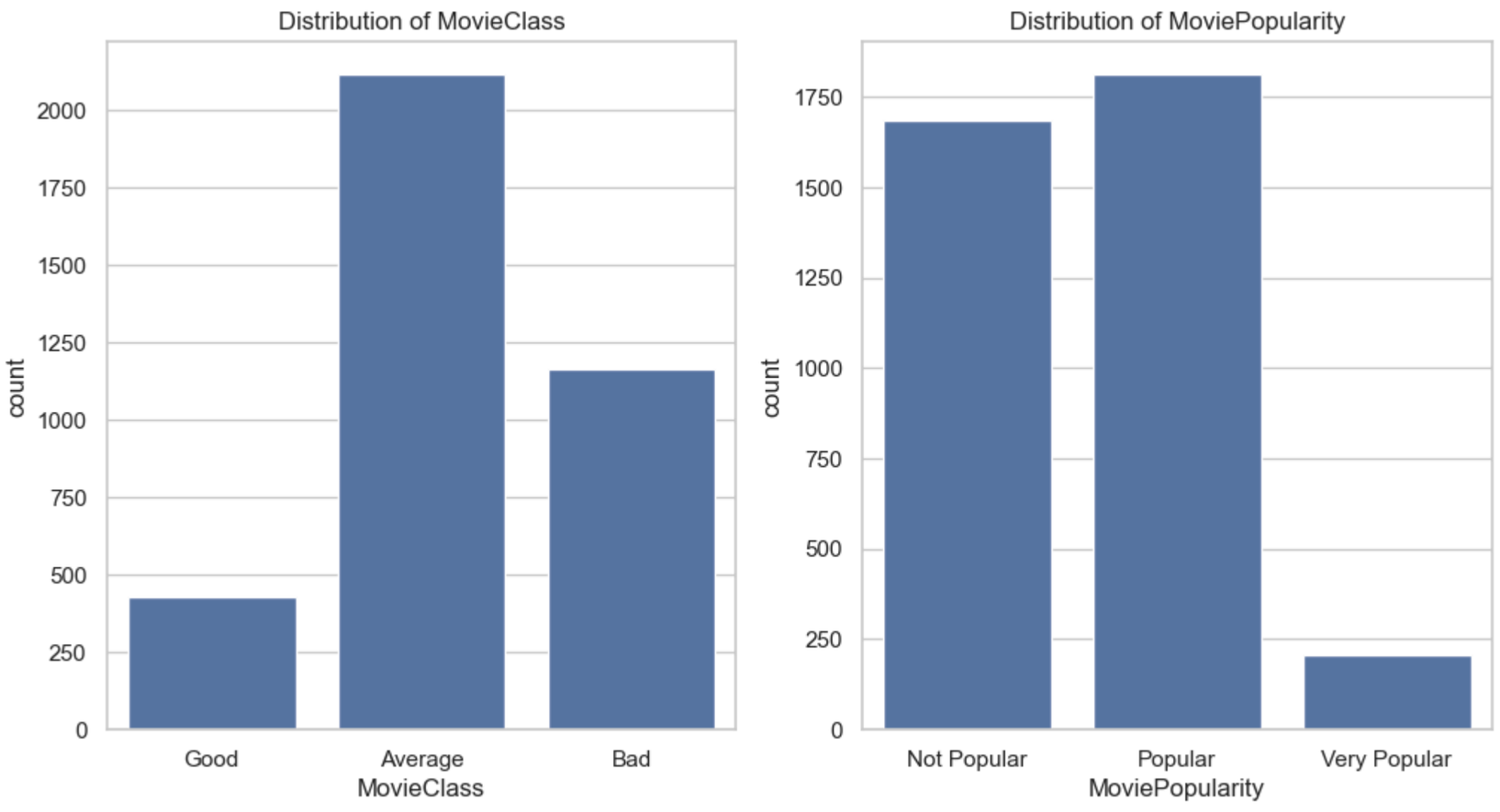
In [23]:
```
sns.countplot(data=combined, x="Rating")
plt.title("Distribution of Ratings");
```



Observations

- Above plot shows distribution of ratings given by users.

In [29]:
```
fig, ax = plt.subplots(1, 2, figsize=(12, 6))

sns.countplot(data=combined.select("MovieID", "MovieClass").unique(), x="MovieClass" , ax=ax[0])
ax[0].set_title("Distribution of MovieClass");

sns.countplot(data=combined.select("MovieID", "MoviePopularity").unique(), x="MoviePopularity" , ax=ax[1])
ax[1].set_title("Distribution of MoviePopularity");
```



Observations

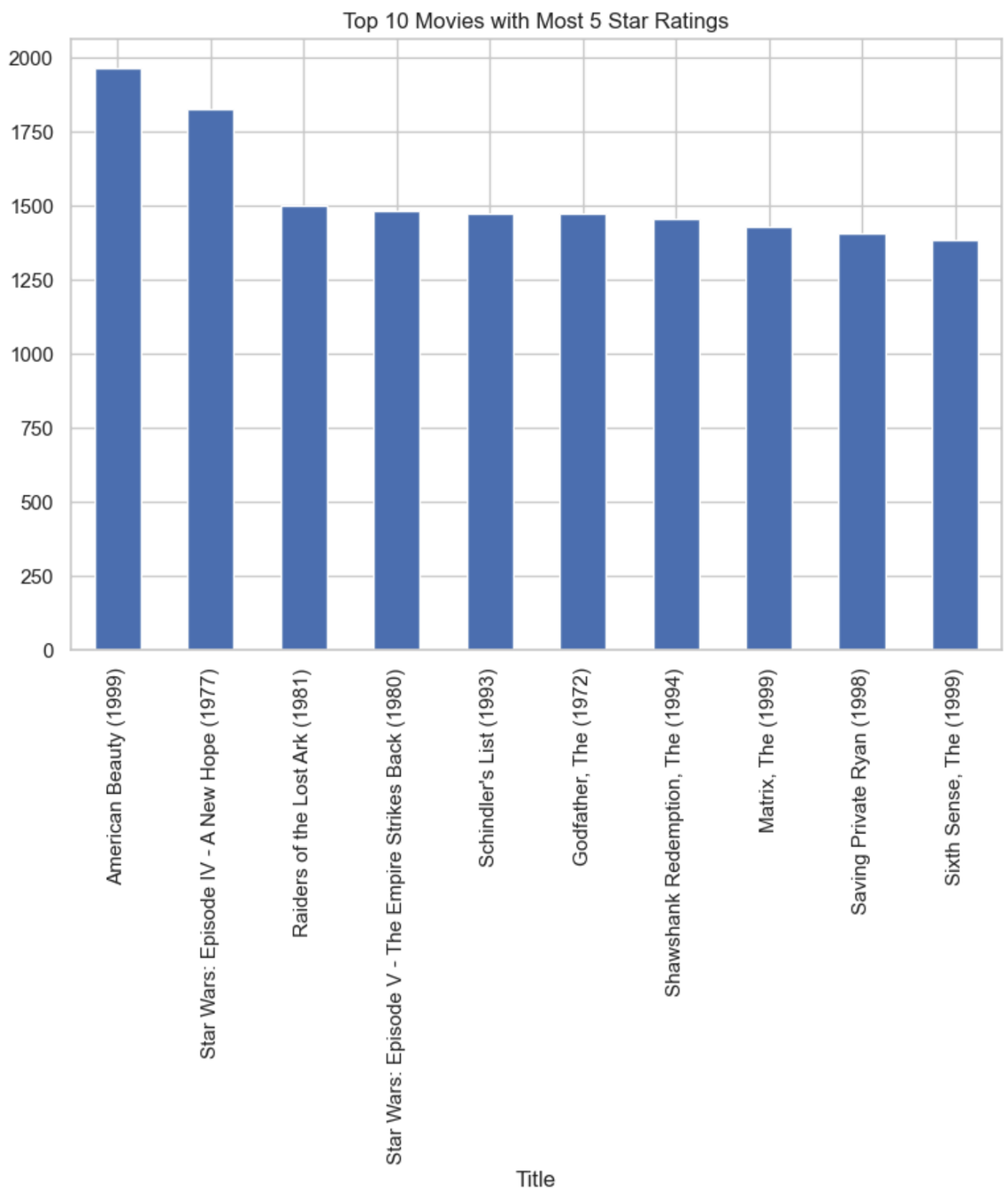
- We can see that majority of the movies are rated as average
- We can see that majority of the movies are in "Popular" category, but very few in "Very Popular" category.

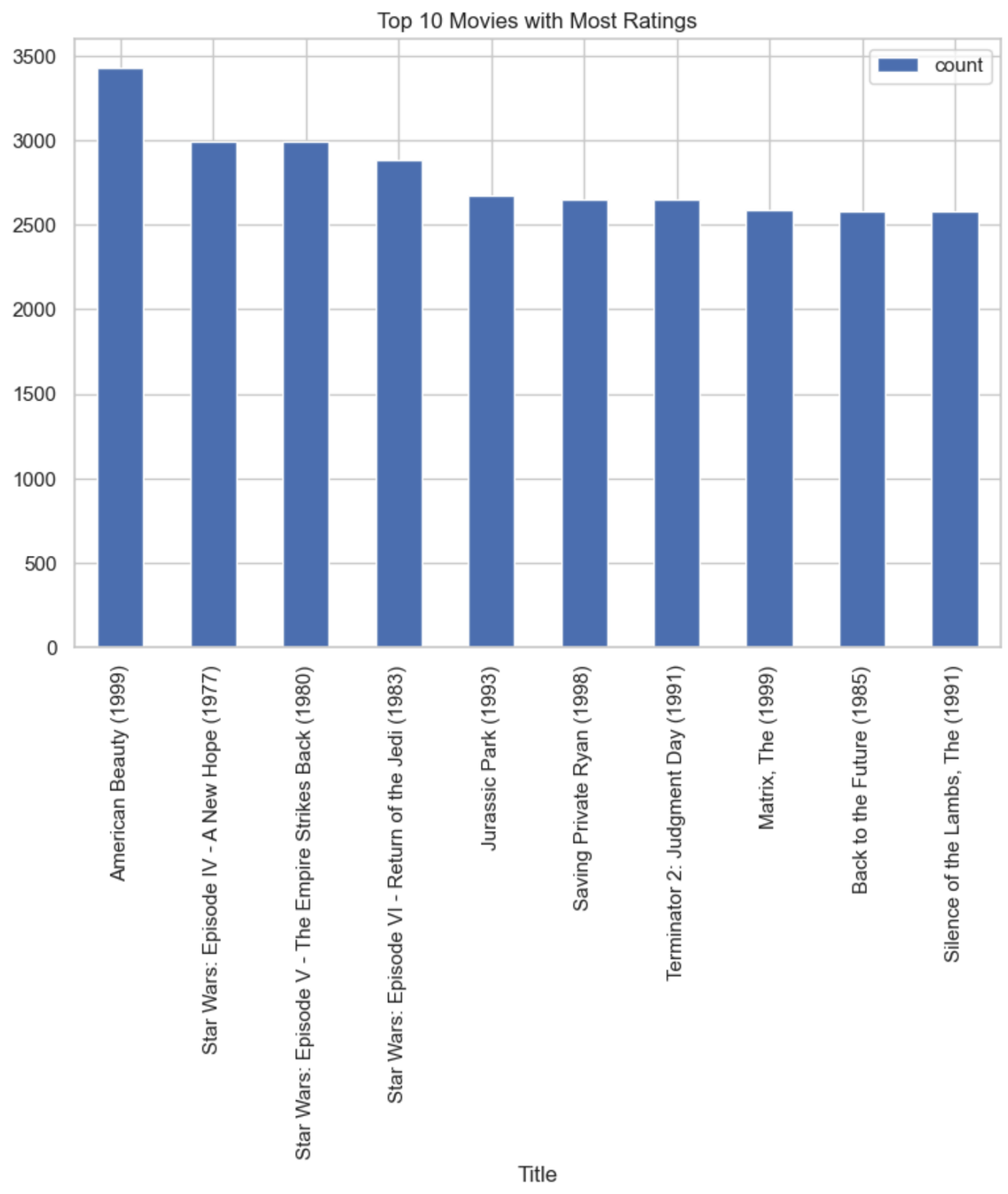
In [74]:
```
combined["Title"].value_counts().sort("count",  descending=True).head(10)
```

Out[74]: shape: (10, 2)

Title	count
str	u32
"American Beauty (1999)"	3428
"Star Wars: Episode IV - A New …	2991
"Star Wars: Episode V - The Emp…	2990
"Star Wars: Episode VI - Return…	2883
"Jurassic Park (1993)"	2672
"Saving Private Ryan (1998)"	2653
"Terminator 2: Judgment Day (19…	2649
"Matrix, The (1999)"	2590
"Back to the Future (1985)"	2583
"Silence of the Lambs, The (199…	2578

In [75]:
```
fig, ax = plt.subplots(1, 2, figsize=(20, 6))

combined.filter(pl.col("Rating") == 5).group_by("Title").agg(pl.count("Rating").alias("Count")).sort("Count", descending=True).head(10).to_pandas().plot(kind="bar", x="Title", y="Count",
ax[0].set_title("Top 10 Movies with Most 5 Star Ratings");

combined["Title"].value_counts().sort("count",  descending=True).head(10).to_pandas().plot(kind="bar", x="Title", y="count", ax=ax[1])
ax[1].set_title("Top 10 Movies with Most Ratings");
```





Observations

- Above plot shows the top 10 5 star rated movies.

In [77]:
```
users["Gender"].value_counts()
```

Out[77]: shape: (2, 2)

Gender	count
str	u32
"F"	1709
"M"	4331

Observations

- We can see that there are more Male users then Female users

In [228…]:
```
combined["Gender"].value_counts(normalize=True)
```

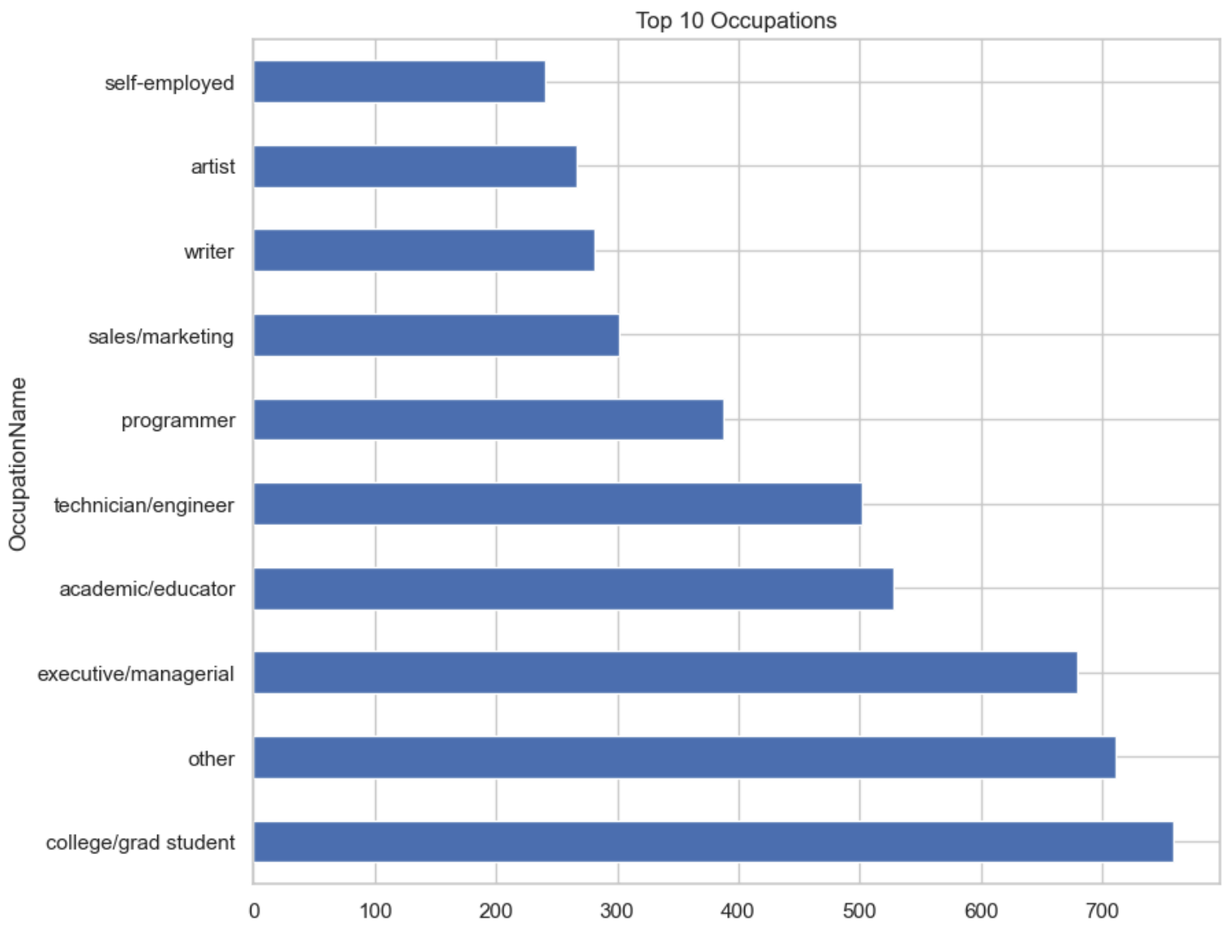
Out[228…] shape: (2, 2)

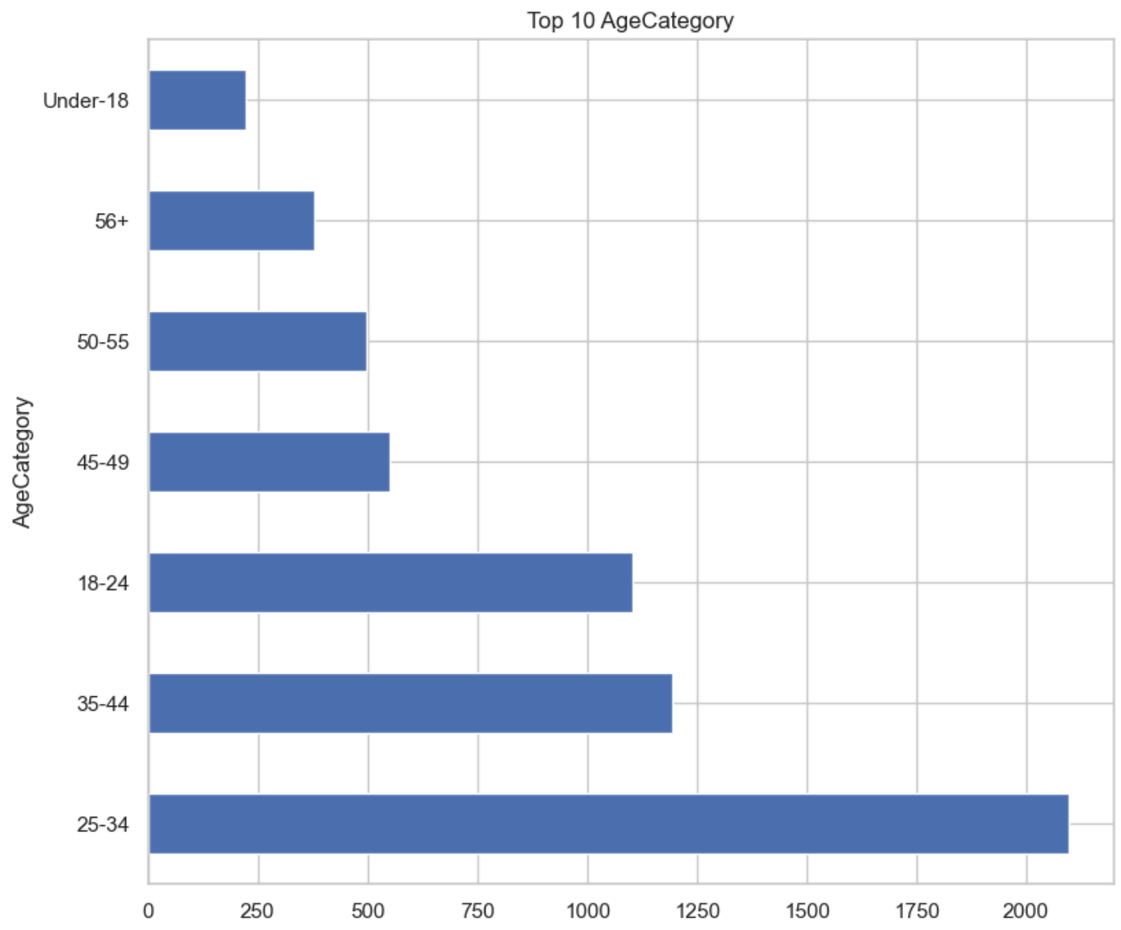
Gender	proportion
str	f64
"F"	0.246389
"M"	0.753611

Observations

- We can see that majority of ratings are given by male users.

In [78]:
```
fig, ax = plt.subplots(1, 2, figsize=(20,8))
users["OccupationName"].value_counts().sort("count", descending=True).head(10).to_pandas().plot(kind="barh", x="OccupationName", y="count", legend=False, ax=ax[0] );
ax[0].set_title("Top 10 Occupations");
users["AgeCategory"].value_counts().sort("count", descending=True).head(10).to_pandas().plot(kind="barh", x="AgeCategory", y="count", legend=False, ax=ax[1] );
ax[1].set_title("Top 10 AgeCategory");
```



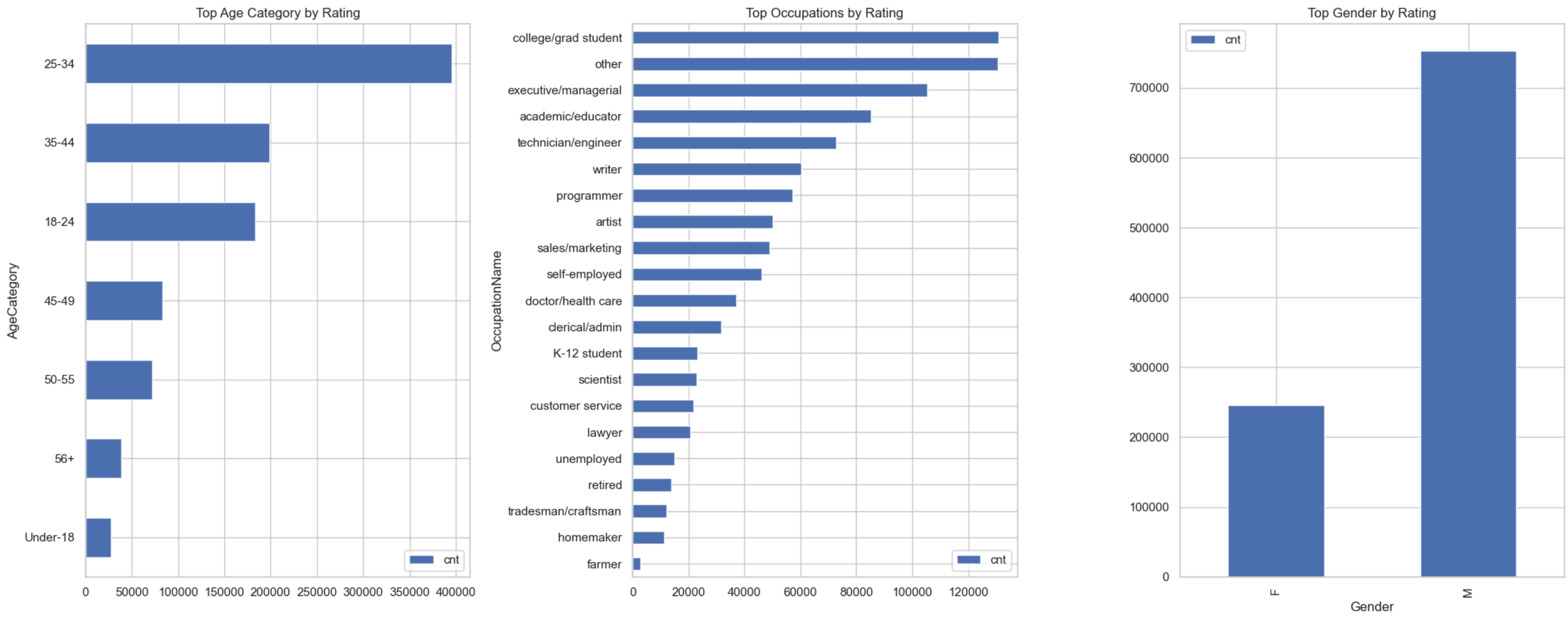


Observations

- We can see that most of the users are from College/Grad students category
- we can also see that most of the users belong to 25-34 age group

Examine user demographics and their potential influence on movie preferences

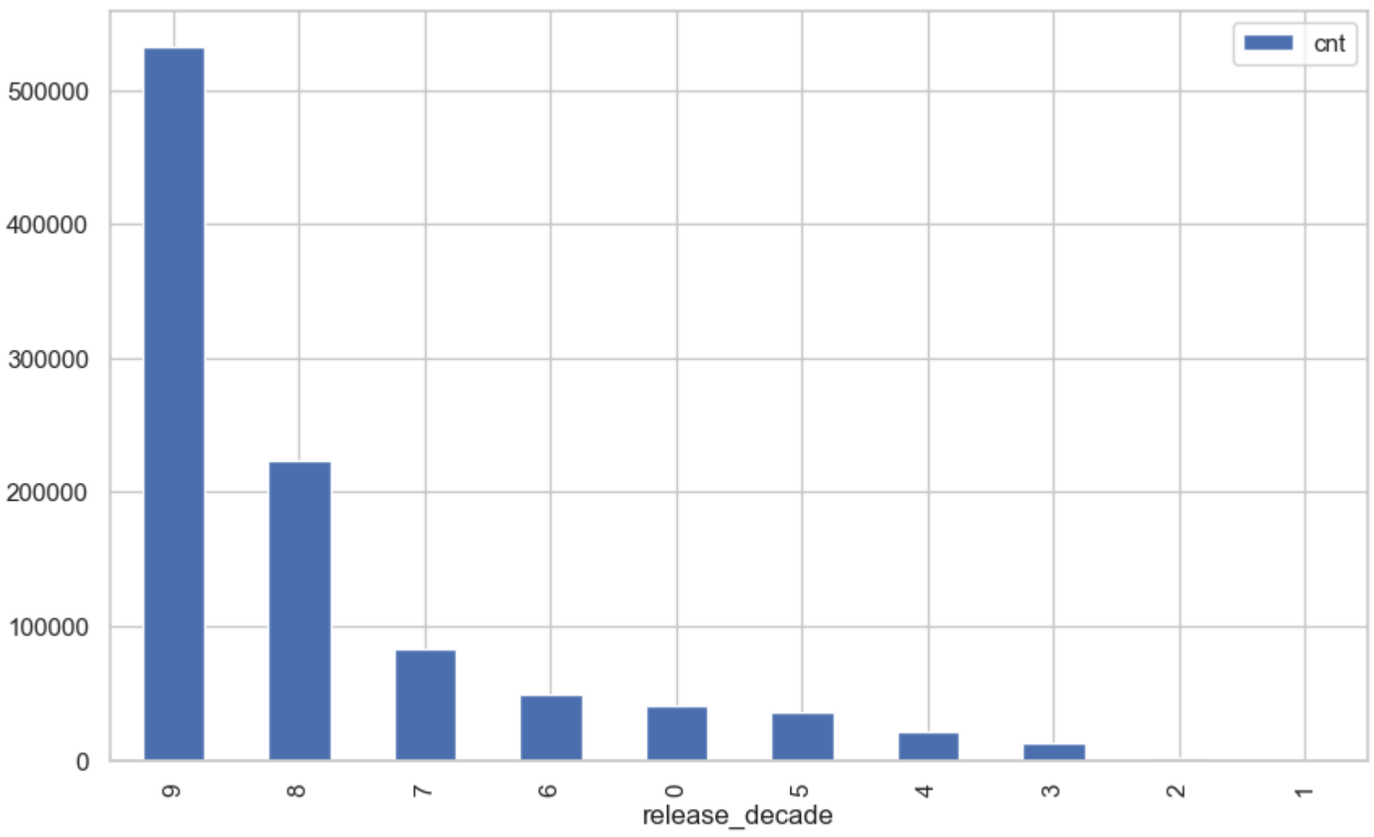
In [79]:
```
fig, ax = plt.subplots(1, 3, figsize=(20, 8))

db.sql("""
select AgeCategory, count(*) cnt from combined group by AgeCategory order by cnt
""").to_df().plot(kind="barh", x="AgeCategory", y="cnt", ax=ax[0] );
ax[0].set_title("Top Age Category by Rating");

db.sql("""
select OccupationName, count(*) cnt from combined group by OccupationName order by cnt
""").to_df().plot(kind="barh", x="OccupationName", y="cnt", ax=ax[1] );
ax[1].set_title("Top Occupations by Rating");

db.sql("""
select Gender, count(*) cnt from combined group by Gender order by cnt
""").to_df().plot(kind="bar", x="Gender", y="cnt", ax=ax[2] );
ax[2].set_title("Top Gender by Rating");
plt.tight_layout()
```



Observations

- We can see that users with ages between 25-35 have rated the highest movies
- We can see that college/grad students have highest rated movies
- Most the users who have rated the movies are male

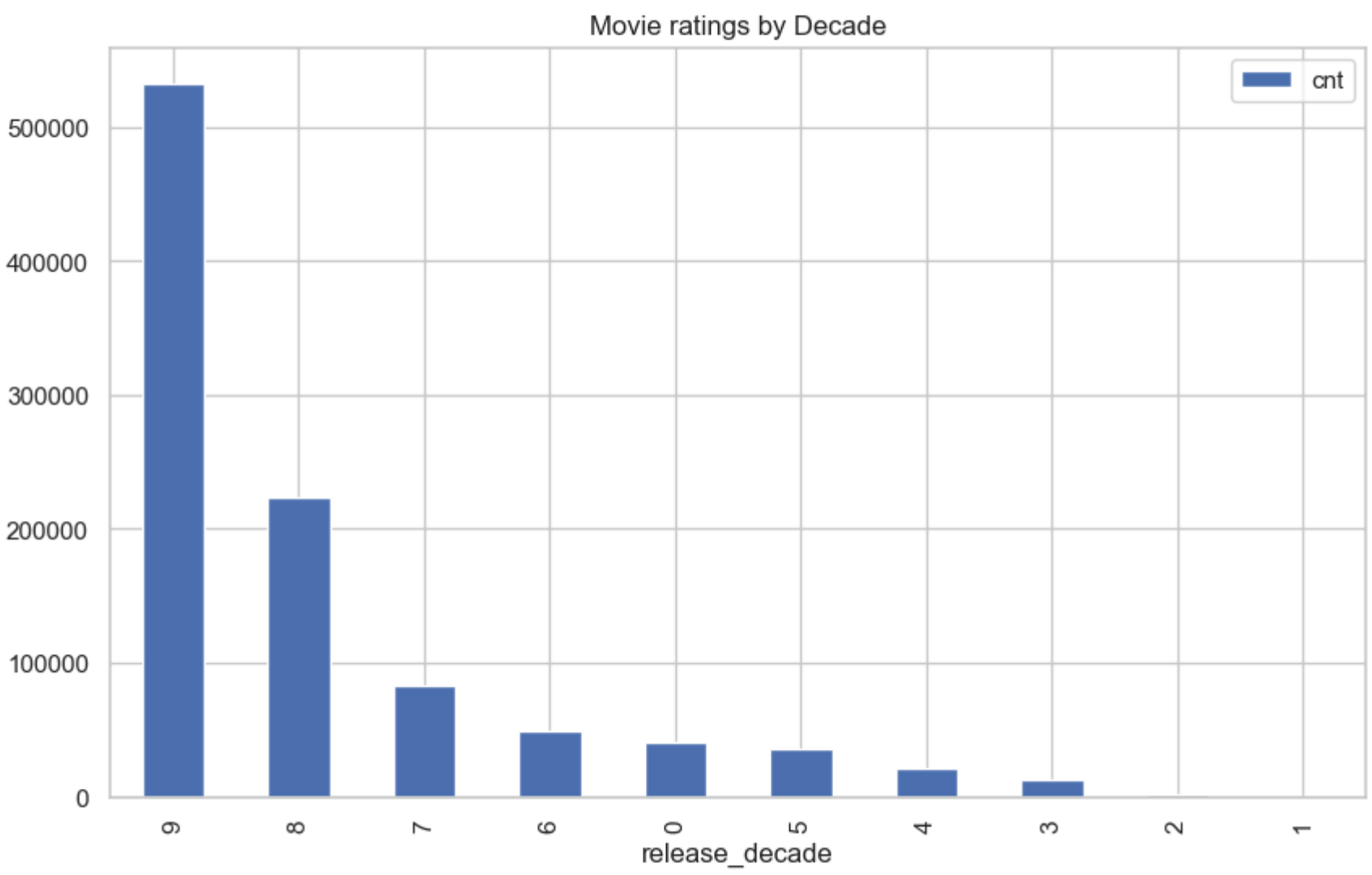
In [ ]:
```
db.sql("""
       select
       substring(ReleaseYear, 3,1) release_decade,
       count(*) cnt from movies
       group by release_decade order by cnt desc""").to_df().plot(kind="bar", x="release_decade", y="cnt", figsize=(10, 6));
```



Observations

- From above plot we can see that most odf the movies were released in 90's decade

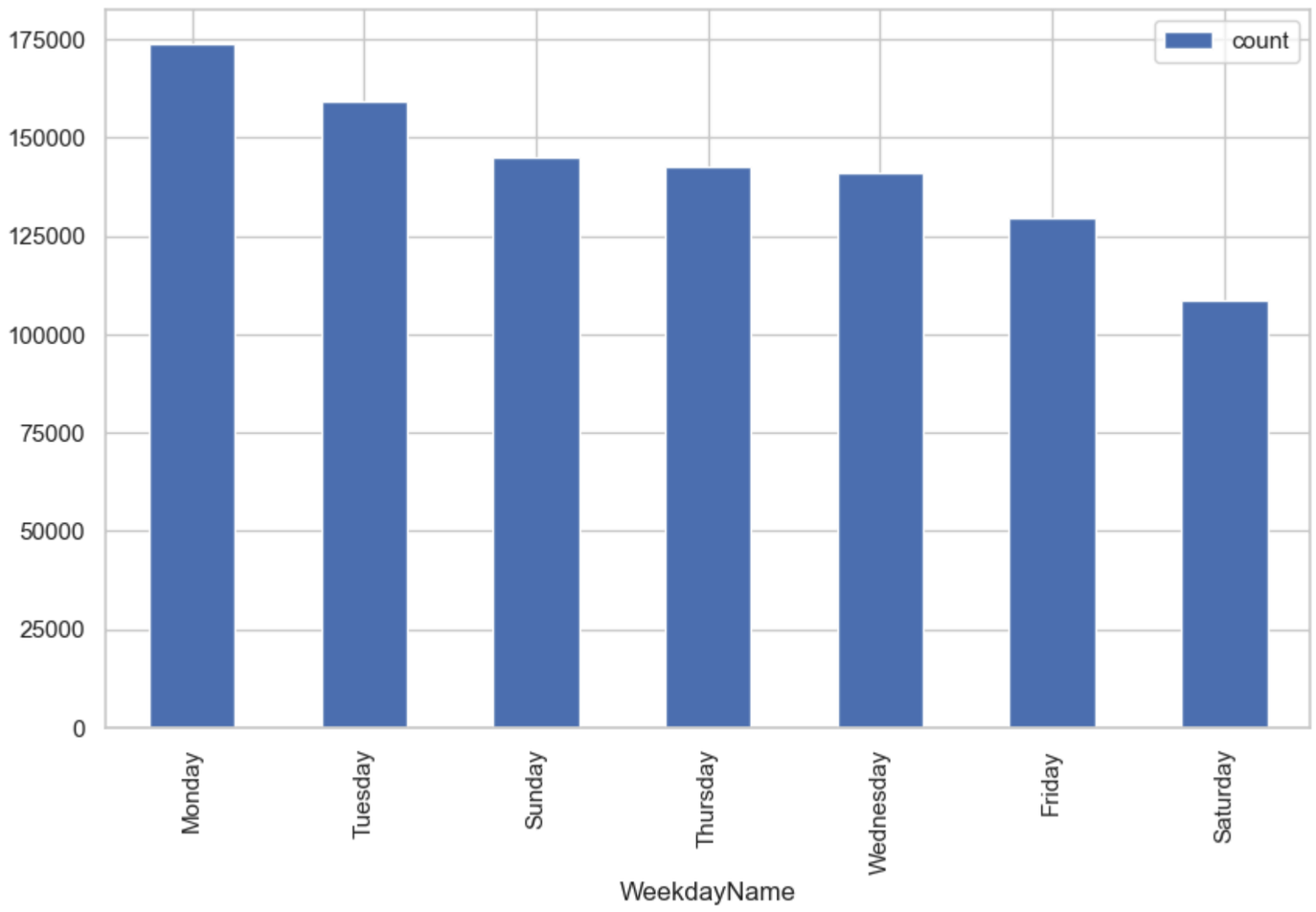
In [232…
```
db.sql("""
       select
       substring(ReleaseYear, 3,1) release_decade,
       count(*) cnt from combined
       group by release_decade order by cnt desc""").to_df().plot(kind="bar", x="release_decade", y="cnt", figsize=(10, 6));
plt.title("Movie ratings by Decade");
```



Observations

- We can see that people have rated movies from from 90's decade the most

In [17]:
```
combined["WeekdayName"].value_counts().sort("count",  descending=True).to_pandas().plot(kind="bar", x="WeekdayName", y="count", figsize=(10, 6));
```



Observations

- We can see that most of the ratings are given on Monday

In [229…
```
combined
```

Out[229… shape: (1_000_209, 26)

UserID	MovieID	Rating	Timestamp	Title	Genres	ReleaseYear	Year	Month	Day	Weekday	Hour	WeekdayName	IsWeekend	AvgMovieRating	TotalMovieRatings	AvgUserRating	Tot
i64	i64	i64	datetime[μs]	str	str	str	i32	i8	i8	i8	i8	str	bool	f64	i64	f64	
4	1097	4	2000-12-31 20:19:24	"E.T. the Extra-Terrestrial (19…	"Children's|Drama|Fantasy|Sci-F…	"1982"	2000	12	31	7	20	"Sunday"	true	3.965	2269	4.19	
4	2951	4	2000-12-31 20:24:42	"Fistful of Dollars, A (1964)"	"Action|Western"	"1964"	2000	12	31	7	20	"Sunday"	true	3.994	522	4.19	
4	3418	4	2000-12-31 20:24:20	"Thelma & Louise (1991)"	"Action|Drama"	"1991"	2000	12	31	7	20	"Sunday"	true	3.68	1417	4.19	
4	2366	4	2000-12-31 20:23:50	"King Kong (1933)"	"Action|Adventure|Horror"	"1933"	2000	12	31	7	20	"Sunday"	true	3.656	756	4.19	
4	1198	5	2000-12-31 20:23:19	"Raiders of the Lost Ark (1981)"	"Action|Adventure"	"1981"	2000	12	31	7	20	"Sunday"	true	4.478	2514	4.19	
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	
6038	1223	5	2000-04-26 00:08:54	"Grand Day Out, A (1992)"	"Animation|Comedy"	"1992"	2000	4	26	3	0	"Wednesday"	false	4.362	473	3.8	
6038	1276	3	2000-04-26 00:06:44	"Cool Hand Luke (1967)"	"Comedy|Drama"	"1967"	2000	4	26	3	0	"Wednesday"	false	4.254	930	3.8	
6038	1387	2	2000-04-25 23:56:45	"Jaws (1975)"	"Action|Horror"	"1975"	2000	4	25	2	23	"Tuesday"	false	4.09	1697	3.8	
6038	1136	4	2000-04-26 00:08:28	"Monty Python and the Holy Grai…	"Comedy"	"1974"	2000	4	26	3	0	"Wednesday"	false	4.335	1599	3.8	
6038	2700	1	2000-04-26 02:10:51	"South Park: Bigger, Longer and…	"Animation|Comedy"	"1999"	2000	4	26	3	2	"Wednesday"	false	3.76	1269	3.8	

https://builtin.com/data-science/recommender-systems

Pearson Correlation Recommender

Item-Item Similarity Based Collaborative Filtering

In [184…
```
movies = pd.read_parquet("../data/processed/movies.parquet")
ratings = pd.read_parquet("../data/processed/ratings.parquet", engine ='fastparquet')
users = pd.read_parquet("../data/processed/users.parquet")
```

Pivot Table

In [185…
```
rating_pivot = ratings.pivot_table(values="Rating", index="UserID", columns="MovieID").fillna(0)
rating_pivot.head()
```

Out[185…

MovieID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948	3949	3950	3951	3952
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	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	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	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	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	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 3706 columns

Correlation Matrix

In [186…
```
movie_corr = rating_pivot.corr()
movie_corr.head()
```

Out[186…

MovieID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948	3949	3950	395
MovieID																				
1	1.000000	0.262649	0.146536	0.109375	0.170156	0.168087	0.189333	0.082963	0.045705	0.215653	...	0.039913	0.002483	0.054038	0.018530	-0.007335	0.132009	0.076941	0.050559	-0.00284
2	0.262649	1.000000	0.169586	0.111616	0.196561	0.137334	0.193658	0.173878	0.126871	0.302042	...	0.025345	0.004734	0.055814	0.061466	0.047608	0.108027	0.075658	0.060941	0.00048
3	0.146536	0.169586	1.000000	0.158659	0.268062	0.095834	0.238816	0.068058	0.100622	0.164252	...	0.007877	0.058906	0.032291	0.059063	0.028135	0.104775	0.050016	0.039715	-0.01120
4	0.109375	0.111616	0.158659	1.000000	0.247529	0.071081	0.187311	0.034228	0.042133	0.082035	...	0.037847	0.048747	-0.008854	0.007128	0.011165	0.067022	0.064363	0.008411	0.01259
5	0.170156	0.196561	0.268062	0.247529	1.000000	0.075012	0.264749	0.076378	0.116465	0.176002	...	0.002233	0.078781	0.032615	0.023873	-0.002865	0.107924	0.048976	0.033442	-0.00587

5 rows × 3706 columns

In [82]:
```
with open("../models/movie_corr.pkl", "wb") as f:
    pickle.dump(movie_corr, f)
```

In [2]:
```
with open("../models/movie_corr.pkl", "rb") as f:
    movie_corr = pickle.load(f)
```

Recommendation based only on movie id

In [187…
```
movies
```

Out[187…

	MovieID	Title	Genres	ReleaseYear
0	1	Toy Story (1995)	Animation|Children's|Comedy	1995
1	2	Jumanji (1995)	Adventure|Children's|Fantasy	1995
2	3	Grumpier Old Men (1995)	Comedy|Romance	1995
3	4	Waiting to Exhale (1995)	Comedy|Drama	1995
4	5	Father of the Bride Part II (1995)	Comedy	1995
...	...	...	...	...
3878	3948	Meet the Parents (2000)	Comedy	2000
3879	3949	Requiem for a Dream (2000)	Drama	2000
3880	3950	Tigerland (2000)	Drama	2000
3881	3951	Two Family House (2000)	Drama	2000
3882	3952	Contender, The (2000)	Drama|Thriller	2000

3883 rows × 4 columns

In [108…
```
random_movie = movies.sample(1)
random_movie_id = random_movie["MovieID"].values[0]
random_movie
```

Out[108…

	MovieID	Title	Genres	ReleaseYear
1736	1796	In God's Hands (1998)	Action|Drama	1998

In [112…
```
top_n_movies=movie_corr.loc[648].sort_values(ascending=False)
top_n_movies = top_n_movies[top_n_movies.index != random_movie_id]
top_n_movies=top_n_movies[:10]
top_n_movies
```

Out[112…
```
MovieID
648     1.000000
380     0.492173
733     0.487349
10      0.468448
1552    0.465473
1370    0.456723
1377    0.448973
349     0.448161
165     0.442651
1608    0.441444
Name: 648, dtype: float64
```

In [113…
```
pd.DataFrame(top_n_movies.index).merge(movies, on="MovieID")
```

Out[113…

	MovieID	Title	Genres	ReleaseYear
0	648	Mission: Impossible (1996)	Action|Adventure|Mystery	1996
1	380	True Lies (1994)	Action|Adventure|Comedy|Romance	1994
2	733	Rock, The (1996)	Action|Adventure|Thriller	1996
3	10	GoldenEye (1995)	Action|Adventure|Thriller	1995
4	1552	Con Air (1997)	Action|Adventure|Thriller	1997
5	1370	Die Hard 2 (1990)	Action|Thriller	1990
6	1377	Batman Returns (1992)	Action|Adventure|Comedy|Crime	1992
7	349	Clear and Present Danger (1994)	Action|Adventure|Thriller	1994
8	165	Die Hard: With a Vengeance (1995)	Action|Thriller	1995
9	1608	Air Force One (1997)	Action|Thriller	1997

Combining above code into a function

In [190…

```
def recommend_movies_by_movie_id(movie_id, n=5):
    print(f"Recommendation for movie: {movies[movies['MovieID'] == movie_id]['Title'].values[0]}")
    top_n_movies=movie_corr.loc[movie_id].sort_values(ascending=False)
    top_n_movies = top_n_movies[top_n_movies.index != movie_id]
    top_n_movies=top_n_movies[:n]
    return pd.DataFrame(top_n_movies.index).merge(movies, on="MovieID")
```

In [189…

```
recommend_movies_by_movie_id(1485)
```

```
Recommendation for movie: Liar Liar (1997)
```

Out[189…

	MovieID	Title	Genres	ReleaseYear
0	500	Mrs. Doubtfire (1993)	Comedy	1993
1	231	Dumb & Dumber (1994)	Comedy	1994
2	344	Ace Ventura: Pet Detective (1994)	Comedy	1994
3	586	Home Alone (1990)	Children's|Comedy	1990
4	1777	Wedding Singer, The (1998)	Comedy|Romance	1998
5	3253	Wayne's World (1992)	Comedy	1992
6	784	Cable Guy, The (1996)	Comedy	1996
7	333	Tommy Boy (1995)	Comedy	1995
8	1517	Austin Powers: International Man of Mystery (1...	Comedy	1997
9	585	Brady Bunch Movie, The (1995)	Comedy	1995

Recommendation based user id

This will recommend movies to a user based on the movies that the user has already watched. It will only recommend movies that have a high correlation with the movies that the user has rated highly.

In [89]:

```
# source chatgpt
def calculate_dynamic_threshold(similarity_row):
    """
    Calculates a dynamic threshold based on the similarity distribution for a movie.
    Ignores NaN and negative values, and uses the 25th percentile as the threshold.

    Args:
        similarity_row (np.ndarray): Row of similarity scores for a movie.

    Returns:
        float: Dynamic threshold for the movie.
    """
    valid_similarities = similarity_row[~np.isnan(similarity_row) & (similarity_row > 0)]
    if len(valid_similarities) == 0:
        return 0  # No valid similarities, set threshold to 0
    return np.percentile(valid_similarities, 25)  # 25th percentile
```

In [142…

```
def recommend_movies_by_user_id(user_id, n=10):
    user_rated_movies = rating_pivot.loc[user_id][rating_pivot.loc[user_id] > 0].index
    movie_ratings = rating_pivot.loc[user_id].to_dict()
    unrated_movies = rating_pivot.loc[user_id][rating_pivot.loc[user_id] == 0].index

    similarity_score={}
    for movie_id in unrated_movies:
        numerator = 0
        denominator = 0
        threshold = calculate_dynamic_threshold(movie_corr[movie_id])
        for rated_movie in user_rated_movies:
            sim=movie_corr.loc[movie_id, rated_movie]
            if sim > threshold:
                numerator += sim * movie_ratings[rated_movie]
                denominator += abs(sim)
        similarity_score[movie_id] = numerator / denominator if denominator != 0 else 0
    return pd.DataFrame(similarity_score.items(), columns=["MovieID", "PredictedRating"]).sort_values("PredictedRating", ascending=False).merge(movies, on="MovieID").head(10)
```

In [143…

```
recommend_movies_by_user_id(1)
```

Out[143…

	MovieID	PredictedRating	Title	Genres	ReleaseYear
0	1915	5.000000	Voyage to the Beginning of the World (1997)	Drama	1997
1	3216	4.751446	Vampyros Lesbos (Las Vampiras) (1970)	Horror	1970
2	3621	4.671628	Possession (1981)	Drama|Horror	1981
3	878	4.591584	Bye-Bye (1995)	Drama	1995
4	1433	4.581080	Machine, The (1994)	Comedy|Horror	1994
5	2740	4.550616	Kindred, The (1986)	Horror	1986
6	1787	4.549433	Paralyzing Fear: The Story of Polio in America...	Documentary	1998
7	989	4.533011	Schlafes Bruder (Brother of Sleep) (1995)	Drama	1995
8	3881	4.532808	Bittersweet Motel (2000)	Documentary	2000
9	3123	4.528056	Spring Fever USA (a.k.a. Lauderdale) (1989)	Comedy	1989

Cosine Similarity

Item-Item Similarity Based Collaborative Filtering

In [191…

```
movies = pl.read_parquet('../data/processed/movies.parquet')
ratings = pd.read_parquet('../data/processed/ratings.parquet', engine='fastparquet')
users = pd.read_parquet("../data/processed/users.parquet")
```

Pivot Table

In [192…

```
rating_pivot = ratings.pivot_table(values="Rating", index="MovieID", columns="UserID").fillna(0)
```

```
rating_pivot.head()
```

Out[192…

UserID	1	2	3	4	5	6	7	8	9	10	...	6031	6032	6033	6034	6035	6036	6037	6038	6039	6040
MovieID																					
1	5.0	0.0	0.0	0.0	0.0	4.0	0.0	4.0	5.0	5.0	...	0.0	4.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	3.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
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	0.0	1.0	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	3.0	0.0	0.0	...	0.0	0.0	0.0	0.0	2.0	2.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0

5 rows × 6040 columns

Ratings based similarity matrix

In [193…

```
cos_similarity = cosine_similarity(rating_pivot)
rating_based_movie_similarity_df = pd.DataFrame(cos_similarity, index=rating_pivot.index, columns=rating_pivot.index)
rating_based_movie_similarity_df.head()
```

Out[193…

MovieID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948	3949	3950	3951
MovieID																				
1	1.000000	0.390349	0.267943	0.178789	0.256569	0.347373	0.301490	0.125709	0.106620	0.377459	...	0.099502	0.020966	0.084105	0.081826	0.045949	0.309676	0.186633	0.093479	0.042829
2	0.390349	1.000000	0.240946	0.155457	0.249970	0.244827	0.262772	0.196521	0.158469	0.386200	...	0.061819	0.015209	0.075310	0.095573	0.074271	0.213650	0.140781	0.087013	0.026063
3	0.267943	0.240946	1.000000	0.192788	0.308290	0.187020	0.292230	0.092122	0.128378	0.245601	...	0.038492	0.065507	0.049512	0.087377	0.050985	0.190575	0.104837	0.062258	0.010073
4	0.178789	0.155457	0.192788	1.000000	0.271990	0.125170	0.220024	0.049554	0.060334	0.133707	...	0.055486	0.053300	0.002227	0.025278	0.025204	0.118902	0.096318	0.022588	0.024769
5	0.256569	0.249970	0.308290	0.271990	1.000000	0.148114	0.305107	0.095512	0.138392	0.237681	...	0.026632	0.083898	0.046399	0.047542	0.016156	0.174554	0.092403	0.051633	0.010750

5 rows × 3706 columns

In [194…

```
ratings.head()
```

Out[194…

	UserID	MovieID	Rating	Timestamp	Title	Genres	ReleaseYear	Year	Month	Day	Weekday	Hour	WeekdayName	IsWeekend	AvgMovieRating	TotalMovieRatings	AvgUserRating	To
0	4	1097	4	2000-12-31 20:19:24	E.T. the Extra-Terrestrial (1982)	Children's|Drama|Fantasy|Sci-Fi	1982	2000	12	31	7	20	Sunday	True	3.965	2269	4.19	
1	4	2951	4	2000-12-31 20:24:42	Fistful of Dollars, A (1964)	Action|Western	1964	2000	12	31	7	20	Sunday	True	3.994	522	4.19	
2	4	3418	4	2000-12-31 20:24:20	Thelma & Louise (1991)	Action|Drama	1991	2000	12	31	7	20	Sunday	True	3.680	1417	4.19	
3	4	2366	4	2000-12-31 20:23:50	King Kong (1933)	Action|Adventure|Horror	1933	2000	12	31	7	20	Sunday	True	3.656	756	4.19	
4	4	1198	5	2000-12-31 20:23:19	Raiders of the Lost Ark (1981)	Action|Adventure	1981	2000	12	31	7	20	Sunday	True	4.478	2514	4.19	

In [195…

```
ratings=ratings[["MovieID", "AvgMovieRating", "TotalMovieRatings"]].drop_duplicates()
ratings.shape
```

Out[195… (3706, 3)

In [196…

```
movies.head()
```

Out[196… shape: (5, 4)

MovieID	Title	Genres	ReleaseYear
i64	str	str	str
1	"Toy Story (1995)"	"Animation|Children's|Comedy"	"1995"
2	"Jumanji (1995)"	"Adventure|Children's|Fantasy"	"1995"
3	"Grumpier Old Men (1995)"	"Comedy|Romance"	"1995"
4	"Waiting to Exhale (1995)"	"Comedy|Drama"	"1995"
5	"Father of the Bride Part II (1…	"Comedy"	"1995"

In [197…

```
movies=movies.with_columns(
    pl.col("Genres").str.split("|").alias("Genres")
).explode("Genres").to_pandas()
movies.head()
```

Out[197…

	MovieID	Title	Genres	ReleaseYear
0	1	Toy Story (1995)	Animation	1995
1	1	Toy Story (1995)	Children's	1995
2	1	Toy Story (1995)	Comedy	1995
3	2	Jumanji (1995)	Adventure	1995
4	2	Jumanji (1995)	Children's	1995

In [198…

```
movies_pivot = movies.pivot_table(index="MovieID", columns="Genres", aggfunc='size', fill_value=0)
movies_pivot
```

Out[198…

Genres	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western
MovieID																		
1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0
4	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
3948	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
3949	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3950	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3951	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3952	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0

3883 rows × 18 columns

In [199…
```
movies_pivot=movies_pivot.reset_index()
```

In [200…
```
movies_df=movies_pivot.merge(ratings, on="MovieID", how="left").fillna(0)
movies_df = movies_df.set_index("MovieID")
movies_df.head()
```

Out[200…

MovieID	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thriller	War	Western	AvgMovieRating	TotalMovieRatings
1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	4.147	2077.0
2	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3.201	701.0
3	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	3.017	478.0
4	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	2.729	170.0
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3.007	296.0

In [201…
```
sc=StandardScaler()
movies_df_scaled=sc.fit_transform(movies_df)
movies_df_scaled
```

Out[201…
```
array([[-0.38576751, -0.28037673,  5.99841249, ..., -0.13350797,
         1.12006327,  4.79623255],
       [-0.38576751,  3.56662979, -0.16671078, ..., -0.13350797,
         0.11643486,  1.16890068],
       [-0.38576751, -0.28037673, -0.16671078, ..., -0.13350797,
        -0.07877405,  0.58104094],
       ...,
       [-0.38576751, -0.28037673, -0.16671078, ..., -0.13350797,
         0.61082264, -0.53668342],
       [-0.38576751, -0.28037673, -0.16671078, ..., -0.13350797,
         0.85801653, -0.57358941],
       [-0.38576751, -0.28037673, -0.16671078, ..., -0.13350797,
         0.73176729,  0.34378813]])
```

In [202…
```
movies_df_scaled=pd.DataFrame(movies_df_scaled, columns=movies_df.columns, index=movies_df.index)
```

In [203…
```
movies_df_scaled.to_parquet("../data/processed/movies_df_scaled.parquet")
```

Movies features based similarity matrix

In [204…
```
cos_similarity_matrix = cosine_similarity(movies_df_scaled)
features_based_movie_similarity_df = pd.DataFrame(cos_similarity_matrix , index=movies_pivot["MovieID"], columns=movies_pivot["MovieID"])
```

In [205…
```
features_based_movie_similarity_df
```

Out[205…

MovieID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948	3949	3
1	1.000000	0.214883	0.114197	-0.070673	0.126977	0.089959	0.121087	0.218764	-0.187190	0.075936	...	-0.012860	-0.188402	0.619093	-0.227593	-0.170745	0.438119	-0.071367	-0.29
2	0.214883	1.000000	-0.092706	-0.217185	-0.126030	-0.038100	-0.092920	0.546101	-0.095381	0.239267	...	-0.155741	-0.217542	0.341691	-0.144834	-0.095539	-0.021251	-0.129380	-0.185
3	0.114197	-0.092706	1.000000	0.135416	0.428231	-0.136309	0.992276	-0.155519	-0.173579	-0.152016	...	0.374468	0.097010	-0.135699	-0.328026	-0.184498	0.418960	-0.313237	-0.390
4	-0.070673	-0.217185	0.135416	1.000000	0.514122	-0.378870	0.115308	-0.249094	-0.279179	-0.399782	...	0.526790	0.951543	-0.184879	-0.046030	-0.319962	0.288021	0.222536	0.31
5	0.126977	-0.126030	0.428231	0.514122	1.000000	-0.208928	0.420986	-0.136069	-0.071495	-0.227369	...	0.965647	0.459594	-0.143302	-0.392635	-0.084687	0.780391	-0.265488	-0.29
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
3948	0.438119	-0.021251	0.418960	0.288021	0.780391	0.045243	0.435800	-0.160179	-0.171070	0.018524	...	0.611824	0.093331	-0.200913	-0.411170	-0.130462	1.000000	-0.030609	-0.302
3949	-0.071367	-0.129380	-0.313237	0.222536	-0.265488	-0.143745	-0.247259	-0.167237	-0.202703	-0.194180	...	-0.263223	0.045474	-0.277147	-0.049866	-0.049751	-0.030609	1.000000	0.915
3950	-0.297797	-0.185864	-0.390295	0.319213	-0.291218	-0.292791	-0.345050	-0.143393	-0.131373	-0.334119	...	-0.203880	0.246525	-0.221407	0.035355	-0.025689	-0.302047	0.915673	1.000
3951	-0.276489	-0.176879	-0.375893	0.282743	-0.282444	-0.265781	-0.317401	-0.136006	-0.140927	-0.311465	...	-0.191830	0.186464	-0.234091	0.008879	-0.004637	-0.269999	0.933331	0.99
3952	-0.061829	-0.112546	-0.288543	-0.009541	-0.337866	0.320571	-0.261479	-0.175810	-0.238426	0.329971	...	-0.353492	-0.086916	-0.199722	0.579342	0.746216	-0.138255	0.397815	0.33

3883 rows × 3883 columns

In [206…
```
user_rating_pivot=rating_pivot.T
user_rating_pivot
```

Out[206…

MovieID	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948	3949	3950	3951	3952
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	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	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	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	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	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
6036	0.0	0.0	0.0	2.0	0.0	3.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6037	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6038	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6039	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6040	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

6040 rows × 3706 columns

User Ratings based similarity matrix

In [207…
```
cos_similarity_matrix = cosine_similarity(user_rating_pivot)
user_rating_based_similarity_df = pd.DataFrame(cos_similarity_matrix, index=user_rating_pivot.index, columns=user_rating_pivot.index)
user_rating_based_similarity_df
```

Out[207…

UserID	1	2	3	4	5	6	7	8	9	10	...	6031	6032	6033	6034	6035	6036	6037	6038	6039
UserID																				
1	1.000000	0.096382	0.120610	0.132455	0.090158	0.179222	0.059678	0.138241	0.226148	0.255288	...	0.170588	0.082006	0.069807	0.033663	0.114877	0.186329	0.135979	0.000000	0.174604
2	0.096382	1.000000	0.151479	0.171176	0.114394	0.100865	0.305787	0.203337	0.190198	0.226861	...	0.112503	0.091222	0.268565	0.014286	0.183384	0.228241	0.206274	0.066118	0.066457
3	0.120610	0.151479	1.000000	0.151227	0.062907	0.074603	0.138332	0.077656	0.126457	0.213655	...	0.092960	0.125864	0.161507	0.000000	0.097308	0.143264	0.107744	0.120234	0.094675
4	0.132455	0.171176	0.151227	1.000000	0.045094	0.013529	0.130339	0.100856	0.093651	0.120738	...	0.163629	0.093041	0.382803	0.000000	0.082097	0.170583	0.127464	0.062907	0.064634
5	0.090158	0.114394	0.062907	0.045094	1.000000	0.047449	0.126257	0.220817	0.261330	0.117052	...	0.100652	0.035732	0.061806	0.054151	0.179083	0.293365	0.172686	0.020459	0.027689
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
6036	0.186329	0.228241	0.143264	0.170583	0.293365	0.093583	0.122441	0.227400	0.239607	0.338072	...	0.131294	0.209843	0.186426	0.103431	0.267405	1.000000	0.341462	0.124174	0.219115
6037	0.135979	0.206274	0.107744	0.127464	0.172686	0.065788	0.111673	0.144395	0.225055	0.246902	...	0.142309	0.276134	0.129985	0.118749	0.141676	0.341462	1.000000	0.049015	0.252146
6038	0.000000	0.066118	0.120234	0.062907	0.020459	0.065711	0.000000	0.019242	0.093470	0.113789	...	0.108837	0.106897	0.040689	0.000000	0.063967	0.124174	0.049015	1.000000	0.161714
6039	0.174604	0.066457	0.094675	0.064634	0.027689	0.167303	0.014977	0.044660	0.046434	0.296776	...	0.118776	0.250994	0.053750	0.102168	0.068399	0.219115	0.252146	0.161714	1.000000
6040	0.133590	0.218276	0.133144	0.137968	0.241437	0.083436	0.080680	0.148123	0.215819	0.255793	...	0.154574	0.291988	0.115540	0.118840	0.168997	0.411891	0.428240	0.099300	0.228332

6040 rows × 6040 columns

In [208…
```
users=users.drop([ "AgeCategory"], axis=1)
```

In [209…
```
users["Gender"]=users["Gender"].map({
    "M":1,
    "F":0
})
```

In [210…
```
users["ZipCode"]=users["ZipCode"].astype(str).str.extract(r"(\d{1})").astype(int)
```

In [211…
```
users.head()
```

Out[211…

	UserID	Gender	Age	ZipCode	OccupationName
0	1	0	1	4	K-12 student
1	2	1	56	7	self-employed
2	3	1	25	5	scientist
3	4	1	45	0	executive/managerial
4	5	1	25	5	writer

In [212…
```
users
```

Out[212…

	UserID	Gender	Age	ZipCode	OccupationName
0	1	0	1	4	K-12 student
1	2	1	56	7	self-employed
2	3	1	25	5	scientist
3	4	1	45	0	executive/managerial
4	5	1	25	5	writer
...	...	...	...	...	...
6035	6036	0	25	3	scientist
6036	6037	0	45	7	academic/educator
6037	6038	0	56	1	academic/educator
6038	6039	0	45	0	other
6039	6040	1	25	1	doctor/health care

6040 rows × 5 columns

In [213…
```
encoder = OneHotEncoder(sparse_output=False)
occupation_one_hot = encoder.fit_transform(users["OccupationName"].values.reshape(-1, 1))
occupation_one_hot_df = pd.DataFrame(occupation_one_hot, columns=encoder.get_feature_names_out(["Occupation"]))
occupation_one_hot_df.head()
```

Out[213…

	Occupation_K-12 student	Occupation_academic/educator	Occupation_artist	Occupation_clerical/admin	Occupation_college/grad student	Occupation_customer service	Occupation_doctor/health care	Occupation_executive/managerial	Occupa
0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
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	1.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 21 columns

In [214…
```
encoder = OneHotEncoder(sparse_output=False)
zipCode_one_hot = encoder.fit_transform(users["ZipCode"].values.reshape(-1, 1))
zipCode_one_hot_df = pd.DataFrame(zipCode_one_hot, columns=encoder.get_feature_names_out(["ZipCode"]))
zipCode_one_hot_df.head()
```

Out[214…

	ZipCode_0	ZipCode_1	ZipCode_2	ZipCode_3	ZipCode_4	ZipCode_5	ZipCode_6	ZipCode_7	ZipCode_8	ZipCode_9
0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
3	1.0	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	1.0	0.0	0.0	0.0	0.0

In [215…
```
users = pd.concat([users, occupation_one_hot_df, zipCode_one_hot_df], axis=1)
users = users.drop(["OccupationName", "ZipCode"], axis=1)
users.head()
```

Out[215…

	UserID	Gender	Age	Occupation_K-12 student	Occupation_academic/educator	Occupation_artist	Occupation_clerical/admin	Occupation_college/grad student	Occupation_customer service	Occupation_doctor/health care	...	ZipCode_0	Zi
0	1	0	1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	
1	2	1	56	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	
2	3	1	25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	
3	4	1	45	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	1.0	
4	5	1	25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	

5 rows × 34 columns

In [216…
```
users=users.set_index("UserID")
```

In [217…
```
users
```

Out[217…

UserID	Gender	Age	Occupation_K-12 student	Occupation_academic/educator	Occupation_artist	Occupation_clerical/admin	Occupation_college/grad student	Occupation_customer service	Occupation_doctor/health care	Occupation_executive
1	0	1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	1	56	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	1	25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	1	45	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
5	1	25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	
6036	0	25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6037	0	45	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
6038	0	56	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
6039	0	45	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6040	1	25	0.0	0.0	0.0	0.0	0.0	0.0	1.0	

6040 rows × 33 columns

In [218…
```
sc = StandardScaler()
users_scaled = sc.fit_transform(users)
users_scaled = pd.DataFrame(users_scaled, columns=users.columns)
users_scaled.head()
```

Out[218…

	Gender	Age	Occupation_K-12 student	Occupation_academic/educator	Occupation_artist	Occupation_clerical/admin	Occupation_college/grad student	Occupation_customer service	Occupation_doctor/health care	Occupation_execut
0	-1.591927	-2.298525	5.474884	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
1	0.628170	1.966729	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
2	0.628170	-0.437323	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
3	0.628170	1.113678	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
4	0.628170	-0.437323	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	

5 rows × 33 columns

In [220…
```
users_scaled["UserID"] = users.index
users_scaled=users_scaled.set_index("UserID")
```

In [221…
```
users_scaled
```

Out[221…

UserID	Gender	Age	Occupation_K-12 student	Occupation_academic/educator	Occupation_artist	Occupation_clerical/admin	Occupation_college/grad student	Occupation_customer service	Occupation_doctor/health care	Occupation_e
1	-1.591927	-2.298525	5.474884	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
2	0.628170	1.966729	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
3	0.628170	-0.437323	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
4	0.628170	1.113678	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
5	0.628170	-0.437323	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
...	...	...	...	...	...	...	...	...	...	
6036	-1.591927	-0.437323	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
6037	-1.591927	1.113678	-0.182652	3.231005	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
6038	-1.591927	1.966729	-0.182652	3.231005	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
6039	-1.591927	1.113678	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	-0.201647	
6040	0.628170	-0.437323	-0.182652	-0.309501	-0.215058	-0.171718	-0.379108	-0.137453	4.959155	

6040 rows × 33 columns

In [222…
```
users_scaled.to_parquet("../data/processed/users_scaled.parquet")
```

User features based similarity matrix

In [223…
```
cos_similarity_matrix = cosine_similarity(users_scaled)
```

In [224…
```
user_feature_based_similarity_df = pd.DataFrame(cos_similarity_matrix, index=users_scaled.index, columns=users_scaled.index)
user_feature_based_similarity_df
```

Out[224…

UserID	1	2	3	4	5	6	7	8	9	10	...	6031	6032	6033	6034	6035	6036	6037	6(
1	1.000000	-0.163047	-0.040782	-0.184655	-0.053070	-0.047508	-0.121693	-0.059596	-0.057325	-0.019182	...	0.418483	-0.184437	-0.119584	-0.065764	0.039036	0.028298	-0.055279	-0.113
2	-0.163047	1.000000	-0.052300	0.015504	-0.067918	-0.001102	-0.034173	-0.076139	-0.073387	-0.093613	...	-0.162923	0.015508	0.329356	-0.082850	0.326675	-0.074432	0.405378	0.022
3	-0.040782	-0.052300	1.000000	-0.070649	0.218332	0.102457	-0.056982	-0.041888	-0.040110	-0.113774	...	-0.080931	0.251690	-0.040841	-0.047632	-0.075035	0.717658	-0.090995	-0.106
4	-0.184655	0.015504	-0.070649	1.000000	-0.091840	-0.037396	0.431679	-0.103045	-0.099220	-0.162331	...	-0.209619	0.477791	-0.001334	-0.112908	-0.154773	-0.104281	-0.080490	-0.045
5	-0.053070	-0.067918	0.218332	-0.091840	1.000000	0.131277	-0.074230	-0.054735	-0.052425	-0.147344	...	-0.105011	0.322702	-0.053087	-0.062135	-0.097312	-0.065198	-0.117823	-0.138
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
6036	0.028298	-0.074432	0.717658	-0.104281	-0.065198	-0.001686	-0.090273	-0.073024	-0.070461	0.003416	...	0.023645	-0.104151	-0.060101	-0.078865	0.016783	1.000000	0.000476	-0.009
6037	-0.055279	0.405378	-0.090995	-0.080490	-0.117823	0.043866	0.389955	-0.131766	-0.127371	0.566061	...	-0.028874	-0.080378	0.335466	-0.140523	0.958921	0.000476	1.000000	0.533
6038	-0.113344	0.022354	-0.106738	-0.045279	-0.138108	0.072589	0.419142	0.237665	-0.149318	0.604709	...	-0.066659	-0.045203	-0.003204	-0.163793	0.433644	-0.009940	0.533680	1.000
6039	-0.067826	-0.030908	-0.109848	0.401055	-0.142211	0.049617	0.347807	-0.159019	-0.153740	0.024123	...	0.406711	-0.098944	-0.040498	-0.169398	-0.005807	-0.001837	0.062862	0.103
6040	-0.049748	-0.063706	-0.034785	-0.086118	-0.045467	-0.070101	-0.069561	0.291134	-0.049077	-0.138324	...	-0.098524	-0.086002	-0.049781	-0.058202	-0.091315	-0.061176	-0.110616	0.201

6040 rows × 6040 columns

Recommend movies based on movie id

In [108…
```
def recommend_movies_by_movie_id(movie_id, n=10):
    print(f"Recommendation for movie: {movies[movies['MovieID'] == movie_id]['Title'].values[0]}")
    top_n_movies=rating_based_movie_similarity_df.loc[movie_id].sort_values(ascending=False)
    top_n_movies = top_n_movies[top_n_movies.index != movie_id]
    top_n_movies=top_n_movies[:n]
    return pd.DataFrame(top_n_movies.index).merge(movies, on="MovieID")
```

In [225…
```
recommend_movies_by_movie_id(1485, 10)
```

```
Recommendation for movie: Liar Liar (1997)
```

Out[225…

	MovieID	Title	Genres	ReleaseYear
0	500	Mrs. Doubtfire (1993)	Comedy	1993
1	231	Dumb & Dumber (1994)	Comedy	1994
2	344	Ace Ventura: Pet Detective (1994)	Comedy	1994
3	586	Home Alone (1990)	Children's	1990
4	586	Home Alone (1990)	Comedy	1990
5	1777	Wedding Singer, The (1998)	Comedy	1998
6	1777	Wedding Singer, The (1998)	Romance	1998
7	3253	Wayne's World (1992)	Comedy	1992
8	784	Cable Guy, The (1996)	Comedy	1996
9	333	Tommy Boy (1995)	Comedy	1995
10	1517	Austin Powers: International Man of Mystery (1...	Comedy	1997
11	585	Brady Bunch Movie, The (1995)	Comedy	1995

Matrix Factorization

In [128…
```
from cmfrec import CMF
```

In [135…
```
users_scaled = pd.read_parquet("../data/processed/users_scaled.parquet")
movies_df_scaled = pd.read_parquet("../data/processed/movies_df_scaled.parquet")
ratings = pd.read_parquet("../data/processed/ratings.parquet", engine='fastparquet')
movies_expanded = pd.read_parquet("../data/processed/movies_expanded.parquet")
```

In [137…
```
ratings=ratings[["UserID", "MovieID", "Rating"]]
ratings= ratings.rename(columns={"MovieID":"ItemId", "UserID":"UserId"})
users_scaled=users_scaled.reset_index().rename(columns={"UserID":"UserId"})
movies_df_scaled=movies_df_scaled.reset_index().rename(columns={"MovieID":"ItemId"})
```

In [138…
```
model = CMF(method="als", k=4, lambda_=1e+1)

model.fit(
    X=ratings,
    U=users_scaled,
    I=movies_df_scaled,
)
```

```
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
```

Out[138… Collective matrix factorization model
(explicit-feedback variant)

In [139…
```
predicted_rating = model.predict(user=12, item=1641)
print(f"Predicted rating for user 12 and movie 1642: {predicted_rating}")
```

```
Predicted rating for user 12 and movie 1642: 3.654609441757202
```

Using MF to create new User and Item embeddings

In [140…
```
new_A = model.A_
new_B = model.B_

new_A.shape, new_B.shape
```

Out[140… ((6040, 4), (3883, 4))

Train Test Split

In [141…
```
rating_train, rating_test = train_test_split(ratings, test_size=0.2)
```

In [142…
```
model = CMF(method="als", lambda_=1e+1, n_jobs=-1, k=4)

model.fit(
    X=rating_train,
    U=users_scaled,
    I=movies_df_scaled,
);
```

```
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
```

In [143…
```
rating_test["PredictedRating"]=model.predict(user=rating_test["UserId"], item=rating_test["ItemId"])
```

In [144…
```
rmse = np.sqrt(mean_squared_error(rating_test['Rating'], rating_test['PredictedRating']))
mape = mean_absolute_percentage_error(rating_test['Rating'], rating_test['PredictedRating'])
print(f"RMSE: {rmse}, MAPE: {mape}")
```

```
RMSE: 0.8633580280856977, MAPE: 0.2643586531079951
```

Hyperparameter Tuning

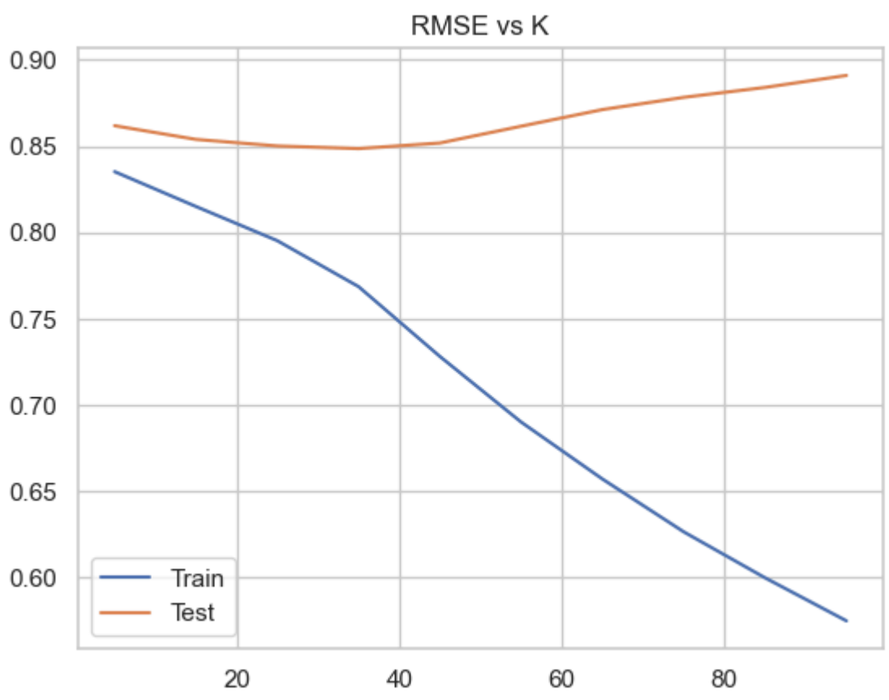
In [145…
```
vals =np.arange(5, 103, 10).tolist()
vals
```

Out[145… [5, 15, 25, 35, 45, 55, 65, 75, 85, 95]

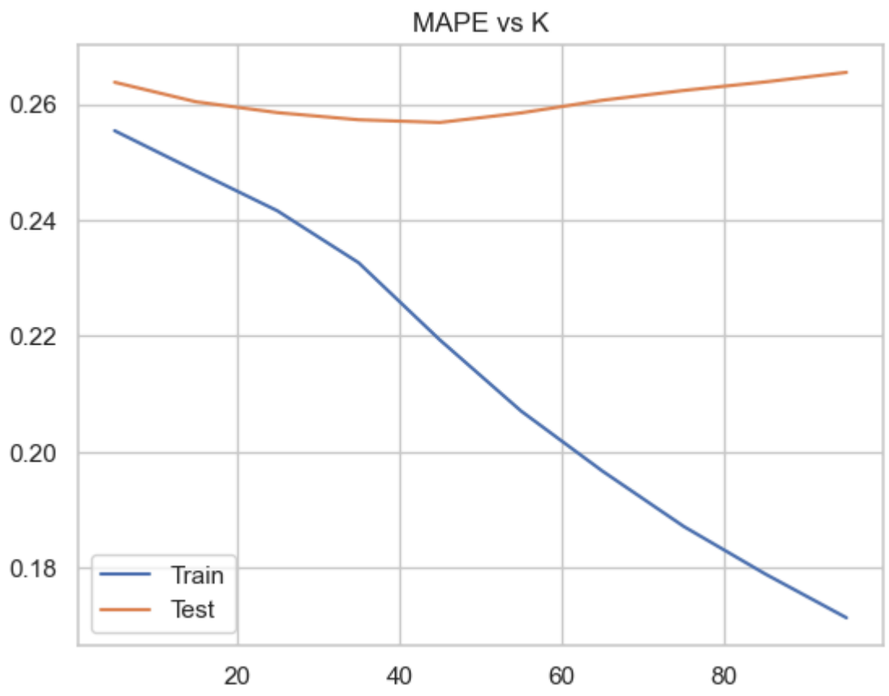
In [146…
```
rmse_scores_train=[]
mape_scores_train=[]
rmse_scores_test=[]
mape_scores_test=[]

for n in vals:
    print(f"Training model with k={n}")
    model = CMF(method="als", lambda_=1e+1, n_jobs=-1, k=n)

    model.fit(
        X=rating_train,
        U=users_scaled,
        I=movies_df_scaled,
    );


    rating_test["PredictedRating"]=model.predict(user=rating_test["UserId"], item=rating_test["ItemId"])
    rmse = np.sqrt(mean_squared_error(rating_test['Rating'], rating_test['PredictedRating']))
    mape = mean_absolute_percentage_error(rating_test['Rating'], rating_test['PredictedRating'])
    rmse_scores_test.append(rmse)
    mape_scores_test.append(mape)

    rating_train["PredictedRating"]=model.predict(user=rating_train["UserId"], item=rating_train["ItemId"])
    rmse = np.sqrt(mean_squared_error(rating_train['Rating'], rating_train['PredictedRating']))
    mape = mean_absolute_percentage_error(rating_train['Rating'], rating_train['PredictedRating'])

    rmse_scores_train.append(rmse)
    mape_scores_train.append(mape)

    rating_train=rating_train.drop("PredictedRating", axis=1);
```

```
Training model with k=5
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=15
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=25
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=35
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=45
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=55
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=65
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=75
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=85
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
Training model with k=95
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
```

In [147…
```
sns.lineplot(x=vals, y=rmse_scores_train, label="Train")
sns.lineplot(x=vals, y=rmse_scores_test, label="Test")
plt.title("RMSE vs K");
```



In [148…
```
sns.lineplot(x=vals, y=mape_scores_train, label="Train")
sns.lineplot(x=vals, y=mape_scores_test, label="Test")
plt.title("MAPE vs K");
```



Observations

- We can see that the RMSE and MAPE is lowest for 40 latent features

Visualizing the latent features

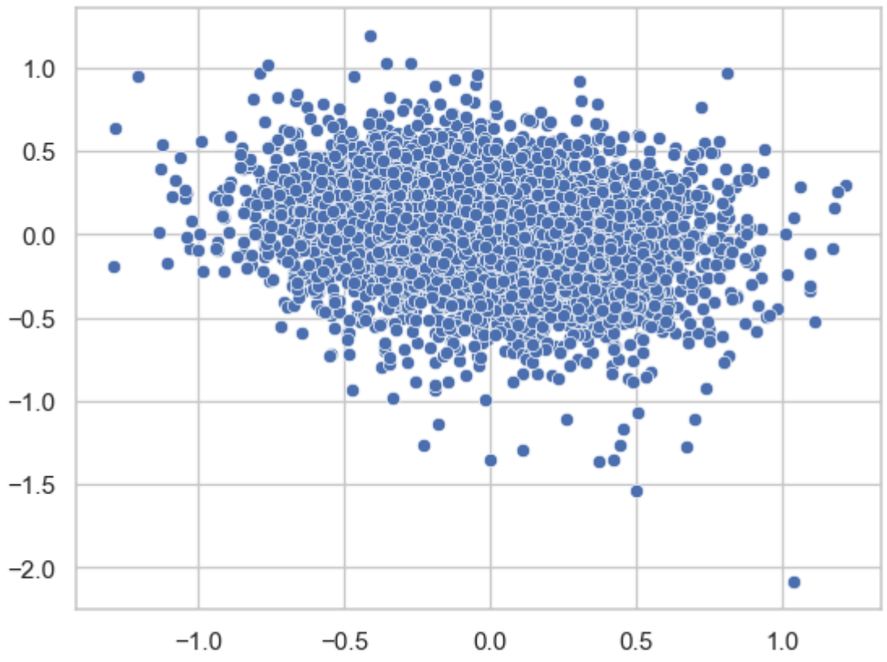
In [149…
```
model = CMF(method="als", k=2, lambda_=1e+1)

model.fit(
    X=ratings,
    U=users_scaled,
    I=movies_df_scaled,
)
```

```
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
```

Out[149…
```
Collective matrix factorization model
(explicit-feedback variant)
```

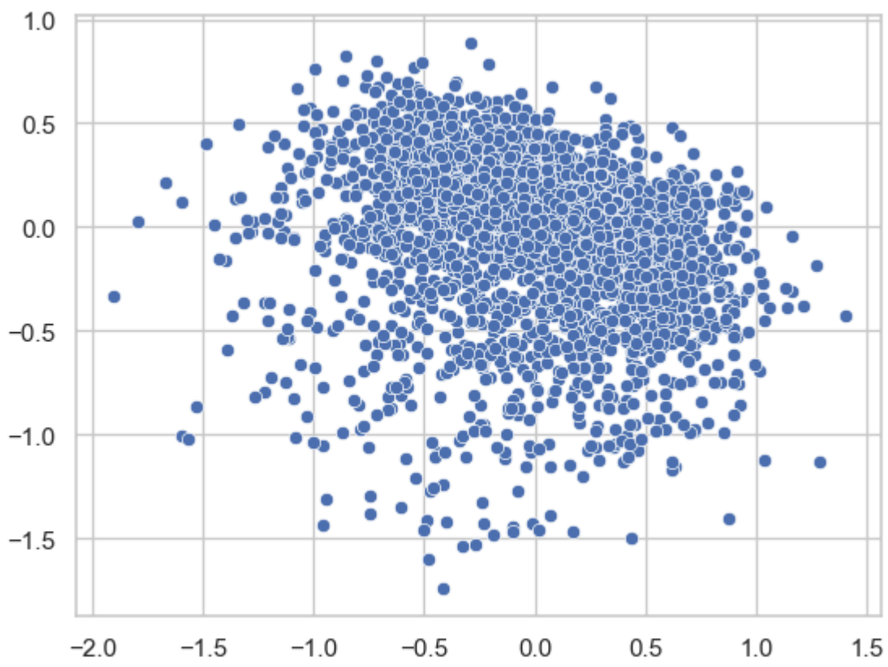
In [150…
```
sns.scatterplot(x=model.A_[:, 0], y=model.A_[:, 1])
```

Out[150…
```
<Axes: >
```



In [151…
```
sns.scatterplot(x=model.B_[:, 0], y=model.B_[:, 1])
```

Out[151…
```
<Axes: >
```



Observations

- From above plots there is uniform circular distribution of latent features

Using latent features to recommend movies

In [152…
```
model = CMF(method="als", k=4, lambda_=0.1, n_jobs=-1, user_bias=False, item_bias=False)

model.fit(
    X=ratings,
    U=users_scaled,
    I=movies_df_scaled,
)
```

```
/opt/homebrew/Caskroom/miniforge/base/lib/python3.10/site-packages/cmfrec/__init__.py:138: UserWarning: Attempting to use more than 1 thread, but package was built without multi-threading
support - see the project's GitHub page for more information.
  warnings.warn(msg_omp)
```

Out[152…
```
Collective matrix factorization model
(explicit-feedback variant)
```

In [153…
```
model.A_.shape, model.B_.shape
```

Out[153…
```
((6040, 4), (3883, 4))
```

In [154…
```
user_latent = pd.DataFrame(model.A_, index=users_scaled["UserId"])
movie_latent = pd.DataFrame(model.B_, index=movies_df_scaled["ItemId"])
```

In [ ]:
```
user_latent_cosine = cosine_similarity(user_latent)
movie_latent_cosine = cosine_similarity(movie_latent)

user_latent_cosine_df = pd.DataFrame(user_latent_cosine, index=user_latent.index, columns=user_latent.index)
movie_latent_cosine_df = pd.DataFrame(movie_latent_cosine, index=movie_latent.index, columns=movie_latent.index)
```

In [159…
```
movie_latent_cosine_df
```

Out[159…

ItemId	1	2	3	4	5	6	7	8	9	10	...	3943	3944	3945	3946	3947	3948	3949	395
ItemId																			
1	1.000000	0.128640	-0.236907	-0.425389	-0.167614	0.850026	0.133287	-0.192980	-0.513168	0.558419	...	-0.439041	-0.439041	-0.439041	-0.950027	-0.950027	-0.950027	-0.439041	-0.75078
2	0.128640	1.000000	0.928556	0.740851	0.917736	0.046734	0.908123	0.932466	0.683385	0.601534	...	-0.594867	-0.594867	-0.594867	-0.219299	-0.219299	-0.219299	-0.594867	0.18896
3	-0.236907	0.928556	1.000000	0.853322	0.966422	-0.274106	0.848517	0.962935	0.857257	0.406098	...	-0.358777	-0.358777	-0.358777	0.146232	0.146232	0.146232	-0.358777	0.50512
4	-0.425389	0.740851	0.853322	1.000000	0.885579	-0.551441	0.768426	0.905383	0.675786	-0.065902	...	-0.330329	-0.330329	-0.330329	0.201478	0.201478	0.201478	-0.330329	0.51318
5	-0.167614	0.917736	0.966422	0.885579	1.000000	-0.342612	0.941877	0.930159	0.707797	0.293228	...	-0.300162	-0.300162	-0.300162	0.026009	0.026009	0.026009	-0.300162	0.52847
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	.
3948	-0.950027	-0.219299	0.146232	0.201478	0.026009	-0.699544	-0.291202	0.055348	0.520411	-0.399748	...	0.522211	0.522211	0.522211	1.000000	1.000000	1.000000	0.522211	0.70648
3949	-0.439041	-0.594867	-0.358777	-0.330329	-0.300162	-0.552383	-0.363247	-0.552712	-0.252763	-0.528609	...	1.000000	1.000000	1.000000	0.522211	0.522211	0.522211	1.000000	0.59554
3950	-0.750782	0.188965	0.505122	0.513188	0.528476	-0.864218	0.334081	0.335128	0.517531	-0.307315	...	0.595543	0.595543	0.595543	0.706484	0.706484	0.706484	0.595543	1.00000
3951	-0.439041	-0.594867	-0.358777	-0.330329	-0.300162	-0.552383	-0.363247	-0.552712	-0.252763	-0.528609	...	1.000000	1.000000	1.000000	0.522211	0.522211	0.522211	1.000000	0.59554
3952	-0.439041	-0.594867	-0.358777	-0.330329	-0.300162	-0.552383	-0.363247	-0.552712	-0.252763	-0.528609	...	1.000000	1.000000	1.000000	0.522211	0.522211	0.522211	1.000000	0.59554

3883 rows × 3883 columns

In [172…
```
movies = pd.read_parquet("../data/processed/movies.parquet")
```

In [181…
```
db.sql("""
    select * from movies where Title like '%Liar Liar%'
""")
```

Out[181…

MovieID int64	Title varchar	Genres varchar	ReleaseYear varchar
1485	Liar Liar (1997)	Comedy	1997

In [183…
```
def recommend_movies_by_movie_id(movie_id, n=10):
    print(f"Recommendation for movie: {movies[movies['MovieID'] == movie_id]['Title'].values[0]}")
    top_n_movies=movie_latent_cosine_df.loc[movie_id].sort_values(ascending=False)
    top_n_movies = top_n_movies[top_n_movies.index != movie_id]
    top_n_movies=top_n_movies[:n]
    return pd.DataFrame(top_n_movies.index).merge(movies, left_on="ItemId", right_on="MovieID")

recommend_movies_by_movie_id(1485, 5)
```

```
Recommendation for movie: Liar Liar (1997)
```

Out[183…

	ItemId	MovieID	Title	Genres	ReleaseYear
0	909	909	Apartment, The (1960)	Comedy|Drama	1960
1	2142	2142	American Tail: Fievel Goes West, An (1991)	Animation|Children's|Comedy	1991
2	2539	2539	Analyze This (1999)	Comedy	1999
3	3632	3632	Monsieur Verdoux (1947)	Comedy	1947
4	2434	2434	Down in the Delta (1998)	Drama	1998

Insights and Recommendations

Model Comparison

- We can see that all the methods provide similar quality of results.
- But, matrix factorization provides better results as it learns latent features of users and movies. Using this we got a MAPE of 0.26 and RMSE of 0.85
- Pearson and Cosine similarity based collaborative filtering methods are not able to provide good recommendations they are based on raw data and cannot handle sparse data

Recommendations

- In order to imporve the recommendation system we can use both content based features and ratings as input to the model
- We can also use deep learning model to better understand the user preferences and find out deeper insights
- In terms of content, we can add more movies from 90's decade as most of the users have rated movies from that decade

Insights

- From above analysis we can see that American Beauty(1999) has the most number of ratings and is the most popular movie at 3448
- Majority of the users have rated movies with 4 followed by 3
- Around 2000 of the movies have been classified as Average, 400 as Good and 1000 as Bad
- Most of the users are from College/Grad students category followed by Executive/Managerial
- Most of the users belong to 25-34 age group followed by 35-44
- We can see that users with ages between 25-35 have rated the highest movies
- We can see that college/grad students have highest rated movies
- Most the users who have rated the movies are male
- From above plot we can see that most odf the movies were released in 90's decade
- We can see that most of the ratings are given on Monday

Additional Insights

Pearson Correlation vs Cosine Similarity

- The Pearson Correlation coefficient ranges from -1 to 1.
- Cosine Similarity belongs to the interval between 0 and 1, where 1 indicates identical vectors, and 0 indicates orthogonal (completely dissimilar) vectors.

Collaborative Filtering

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

Similar to Liar Liar

- Pearson Correlation Recommender: Mrs. Doubtfire (1993), Dumb & Dumber (1994), Ace Ventura: Pet Detective (1994), Home Alone (1990), Wedding Singer, The (1998)
- Cosine Similarity Recommender: Mrs. Doubtfire (1993), Dumb & Dumber (1994), Ace Ventura: Pet Detective (1994), Home Alone (1990), Wedding Singer, The (1998)
- Matrix Factorization Recommender using Item latent feature: Apartment, The (1960), American Tail: Fievel Goes West, An (1991), Analyze This (1999), Monsieur Verdoux (1947), Down in the Delta

Gender Rating Distribution

- 75% of the ratings are given by male users

Movie release year distribution

- Majority of the movies in the dataset have released in the 90's decade

Sparse Matrix Representation

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

In [16]:
```
from scipy.sparse import csr_matrix
A = np.array([[1,0],[3,7]])
S = csr_matrix(A)
print(S)
```

```
  (0, 0)        1
  (1, 0)        3
  (1, 1)        7
```