Movie recommendations.

Introduction:

For this project, we will use the "small" dataset from GroupLens. This dataset includes four main files:

- **movies.csv**: Contains information about each movie, including its ID, title, and genres.
- **ratings.csv**: Records user ratings, with fields for user ID, movie ID, rating, and timestamp.
- **tags.csv**: Aggregates user-generated keywords associated with movies.
- **links.csv**: Provides mappings between MovieLens IDs and external databases such as IMDb and TMDB.

Since good recommendations play an important role in client satisfaction we will make of Our objective to develop a recommendation system that can automatically suggest the top 5 movies to a given user. These recommendations will be based on the user's past ratings and those of similar users.

Methodology

Exploratory data Analysis

- dataset overview & cleaning
- dataset description
- data/ business understanding

Major questions

this part will sharpen our understanding of the data and the business task. Major questions will be answered. they will help us grasp the data.

Modelisation

- data preparation for modelisation
- building Matrix
- collaborative filtering
- training/ optimisation of SVD model

Contact information

- name
- email
- phone number
- LinkedIn

Exploratory data Analysis

Dataset overview & cleaning

In [1]:
```
# importing library
import pandas as pd
import numpy as np

# Vizualisation
import matplotlib.pyplot as plt
import seaborn as sns

# Modelisation & Machine Learning
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error

# Collaborative Filtering & Recommendation
from surprise import Dataset, Reader, SVD, KNNBasic, accuracy
from surprise.model_selection import cross_validate, train_test_split as surpris

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

we will load the necessary files

In [2]:
```
movies_df = pd.read_csv('movies.csv')
movies_df.head()
```

Out[2]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

In [3]:
```
movies_df.shape
```

Out[3]: (9742, 3)

In [4]:
```
movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   movieId  9742 non-null   int64 
 1   title    9742 non-null   object
 2   genres   9742 non-null   object
dtypes: int64(1), object(2)
memory usage: 228.5+ KB
```

In [5]:
```
movies_df.describe()
```

Out[5]:

	movieId
count	9742.000000
mean	42200.353623
std	52160.494854
min	1.000000
25%	3248.250000
50%	7300.000000
75%	76232.000000
max	193609.000000

In [6]:
```
# let's check for duplicates
duplicates = movies_df.duplicated()
print("duplicates :", duplicates.sum())
```

```
duplicates : 0
```

In [7]:
```
ratings_df = pd.read_csv('ratings.csv')
ratings_df.head()
```

Out[7]:

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931

In [8]:
```
ratings_df.shape
```

Out[8]: (100836, 4)

In [9]:
```
ratings_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100836 entries, 0 to 100835
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   userId     100836 non-null  int64  
 1   movieId    100836 non-null  int64  
 2   rating     100836 non-null  float64
 3   timestamp  100836 non-null  int64  
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
```

In [10]:
```
ratings_df.describe()
```

Out[10]:

	userId	movieId	rating	timestamp
count	100836.000000	100836.000000	100836.000000	1.008360e+05
mean	326.127564	19435.295718	3.501557	1.205946e+09
std	182.618491	35530.987199	1.042529	2.162610e+08
min	1.000000	1.000000	0.500000	8.281246e+08
25%	177.000000	1199.000000	3.000000	1.019124e+09
50%	325.000000	2991.000000	3.500000	1.186087e+09
75%	477.000000	8122.000000	4.000000	1.435994e+09
max	610.000000	193609.000000	5.000000	1.537799e+09

In [11]:
```
ratings_df['userId'].nunique()
```

Out[11]: 610

Comment

The **movies.csv** file contains **9,742 movies** with three main columns: **movieId**, **title**, and **genres**.

- No missing values;

The **ratings.csv** file contains **100,836 ratings** made by **610 users** across various movies.

- Ratings range from **0.5 to 5**, typical of the **MovieLens 100k** dataset.

These two files are clean and complete , which simplifies the preparation phase.

Dataset Description

Some description have been provided in the introduction of this project. For more description of the data you may wanna read this:

The dataset is composed of four main files:

movies.csv: contains information about the movies (ID, title, genres). ratings.csv: contains user ratings (userId, movieId, rating, timestamp). tags.csv: gathers keywords associated with movies by users. links.csv: provides mappings between MovieLens IDs, IMDb, and TMDB.

For this project, we will focus on movies.csv and ratings.csv, as they form the foundation of collaborative filtering:

ratings.csv allows us to build the user–movie matrix based on the ratings given.

business understanding

Video streaming platforms face a major challenge: delivering relevant content to each user from an immense catalog. Without personalized recommendations, users may feel lost and leave the platform, leading to lower retention.

Our goal is to build a recommendation system capable of automatically suggesting the top 5 movies to a user, based on their past ratings and those of similar users.

This collaborative filtering model will analyze shared behaviors among users to predict future preferences. By integrating such a solution, a streaming company can enhance the user experience, increase engagement, and reduce churn.

The key idea behind collaborative filtering is that similar users share similar interests, and users tend to like items that others with similar tastes also enjoy.

Merging the two datasets on the common key movieId.

In [12]:
```
# Merging the datasets on 'movieId'
merged_df = pd.merge(ratings_df, movies_df, on='movieId')

# preview
merged_df.head()
```

Out[12]:

	userId	movieId	rating	timestamp	title	ge
0	1	1	4.0	964982703	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fa
1	1	3	4.0	964981247	Grumpier Old Men (1995)	Comedy|Rom
2	1	6	4.0	964982224	Heat (1995)	Action|Crime|Th
3	1	47	5.0	964983815	Seven (a.k.a. Se7en) (1995)	Mystery|Th
4	1	50	5.0	964982931	Usual Suspects, The (1995)	Crime|Mystery|Th

In [13]:

```
# shape
merged_df.shape
```

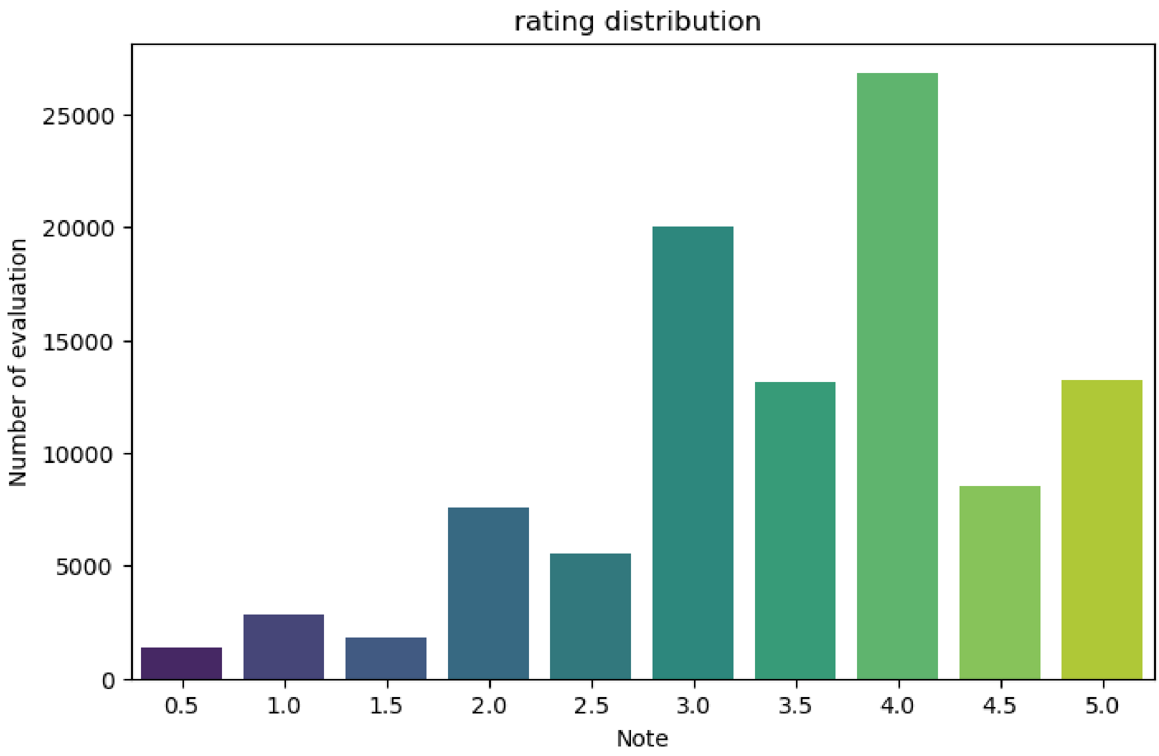
Out[13]: (100836, 6)

Major Questions

What does the distribution of ratings reveal?

In [14]:

```
plt.figure(figsize=(8,5))
sns.countplot(x='rating', data=ratings_df, palette='viridis')
plt.title("rating distribution ")
plt.xlabel("Note")
plt.ylabel("Number of evaluation")
plt.show()
```

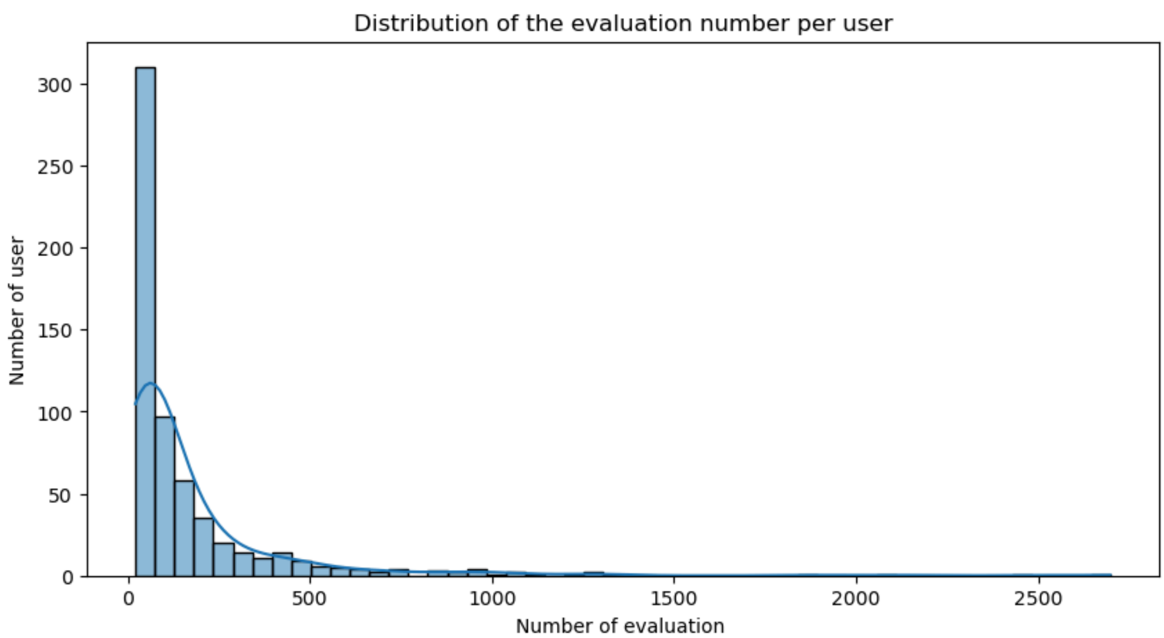


Answer

most ratings fall between 3 and 5, suggesting a generally positive trend.

What does the distribution of ratings per user reveal about user activity levels?

In [15]:
```
ratings_per_user = ratings_df.groupby('userId')['rating'].count()
plt.figure(figsize=(10,5))
sns.histplot(ratings_per_user, bins=50, kde=True)
plt.title("Distribution of the evaluation number per user")
plt.xlabel("Number of evaluation ")
plt.ylabel("Number of user")
plt.show()
```

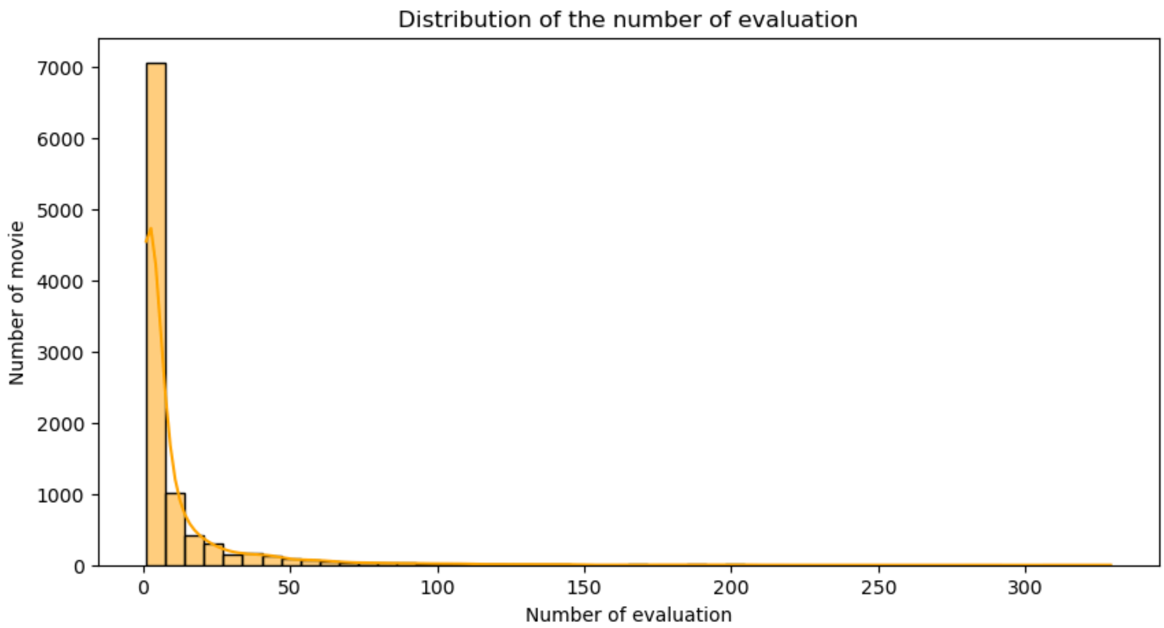


Answer

some users are highly active while others contribute very few ratings, highlighting the imbalance.

What does the number of ratings per movie reveal about the dataset's structure?

In [22]:
```
ratings_per_movie = ratings_df.groupby('movieId')['rating'].count()
plt.figure(figsize=(10,5))
sns.histplot(ratings_per_movie, bins=50, kde=True, color='orange')
plt.title("Distribution of the number of evaluation")
plt.xlabel("Number of evaluation")
plt.ylabel("Number of movie")
plt.show()
```

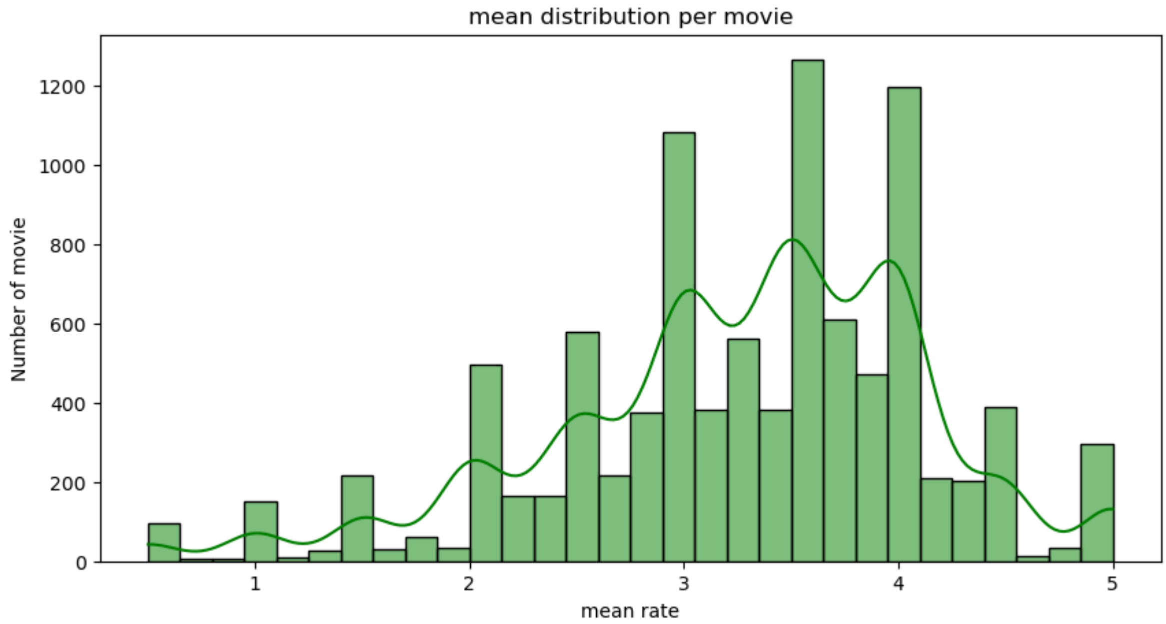


Answer

some movies have far more ratings thatn others.

What does the average rating per movie suggest about overall film reception?

In [17]:
```
mean_ratings = ratings_df.groupby('movieId')['rating'].mean()
plt.figure(figsize=(10,5))
sns.histplot(mean_ratings, bins=30, kde=True, color='green')
plt.title("mean distribution per movie")
plt.xlabel("mean rate")
plt.ylabel("Number of movie")
plt.show()
```



Answer

It reflects the observation that most movies are rated between 3 and 4.5, with few receiving very low scores.

How are average ratings affected by the number of votes?

In [23]:
```
# Calcul du nombre de notes et de la moyenne des notes par film
ratings_summary = ratings_df.groupby('movieId')['rating'].agg(['mean', 'count'])
ratings_summary = ratings_summary.merge(movies_df[['movieId', 'title']], on='mov

# Nuage de points : note moyenne vs nombre de notations
plt.figure(figsize=(10,6))
sns.scatterplot(data=ratings_summary, x='count', y='mean', alpha=0.6)
plt.title("Relation between th mean and the numbe of rating per movie")
plt.xlabel("number of ratings ")
plt.ylabel("Mean rating")
plt.show()
```

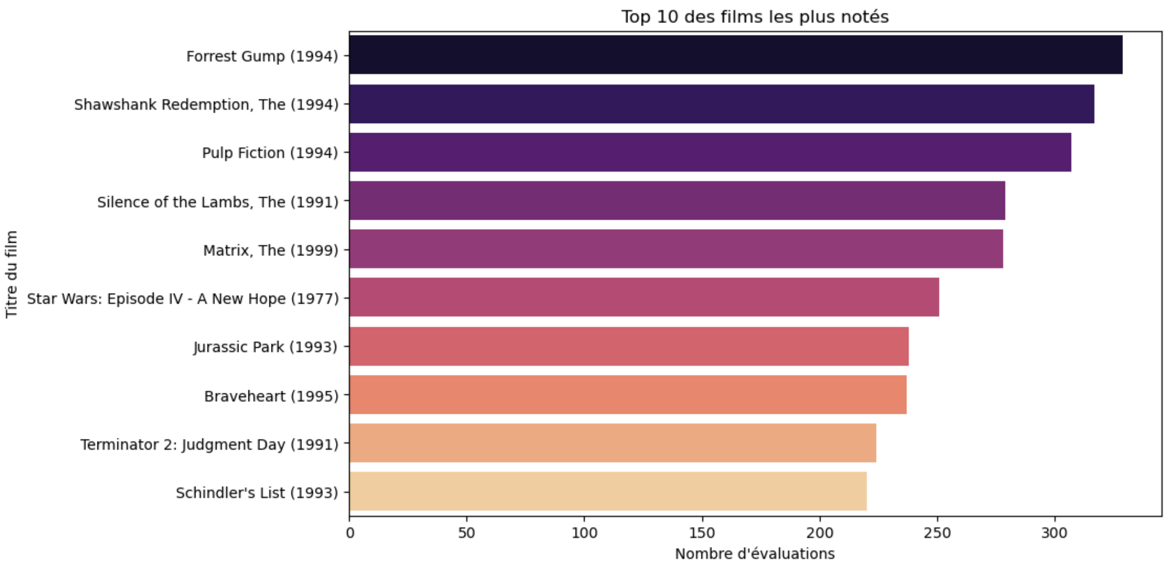
Answer

Movies with only a handful of ratings often show extreme values—either very high or very low—whereas those with many ratings tend to stabilize around an average of 3.5. This highlights the importance of having enough ratings to reliably gauge a film's actual popularity.

Top 10 Most Rated Movies

In [19]:
```
top_movies = (merged_df.groupby('title')['rating']
              .count()
              .sort_values(ascending=False)
              .head(10))

plt.figure(figsize=(10,6))
sns.barplot(x=top_movies.values, y=top_movies.index, palette='magma')
plt.title("Top 10 des films les plus notés")
plt.xlabel("Nombre d'évaluations")
plt.ylabel("Titre du film")
plt.show()
```



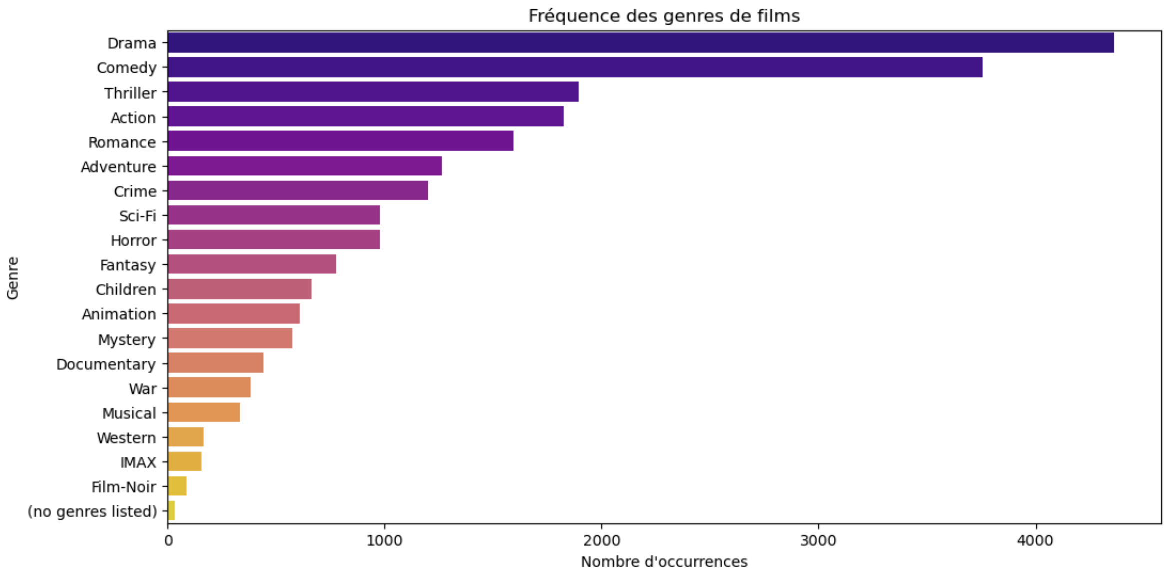
What are the most common genres ?

In [20]:
```
from collections import Counter

all_genres = []
for g in movies_df['genres']:
    all_genres.extend(g.split('|'))

genre_counts = Counter(all_genres)
genre_df = pd.DataFrame(genre_counts.items(), columns=['Genre', 'Count']).sort_v

plt.figure(figsize=(12,6))
sns.barplot(x='Count', y='Genre', data=genre_df, palette='plasma')
plt.title("Fréquence des genres de films")
plt.xlabel("Nombre d'occurrences")
plt.ylabel("Genre")
plt.show()
```



Answer

Drama, comedy and thriller are the most common genre in this dataset.

Modelisation

Data Preparation for modelisation

Remarque

Some users have rated very few movies, and some films have received very few ratings. To improve the quality of collaborative filtering, we will filter out users or movies with fewer than 5 ratings.

In [24]:
```
min_ratings_user = 5
min_ratings_movie = 5

filtered_df = merged_df[
    merged_df['userId'].map(ratings_per_user) >= min_ratings_user
]
filtered_df = filtered_df[
    filtered_df['movieId'].map(ratings_per_movie) >= min_ratings_movie
]

print("shape after filtering :", filtered_df.shape)
```

```
shape after filtering : (90274, 6)
```

Building the matrix User × Movie

In [25]:
```
# Création de la matrice user-item
user_item_matrix = filtered_df.pivot(index='userId', columns='movieId', values='

print("user x film matrix:")
user_item_matrix.head()
```

```
user x film matrix:
```

Out[25]:

movieId	1	2	3	4	5	6	7	8	9	10	...	176371	17775
userId													
1	4.0	NaN	4.0	NaN	NaN	4.0	NaN	NaN	NaN	NaN	...	NaN	Na
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	Na
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	Na
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	Na
5	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	Na

5 rows × 3650 columns

Preparation for Surprise

In [26]:
```
# Définir le Reader
reader = Reader(rating_scale=(0.5, 5.0))
```

```
# Charger le dataset
data = Dataset.load_from_df(filtered_df[['userId', 'movieId', 'rating']], reader
```

Modelisation (filtrage collaboratif)

Train/test split

In [27]:
```
# Split : 80% train, 20% test
trainset, testset = surprise_train_test_split(data, test_size=0.2, random_state=
```

training an SVD Model

In [28]:
```
# SVD model
model_svd = SVD()
model_svd.fit(trainset)
```

Out[28]: <surprise.prediction_algorithms.matrix_factorization.SVD at 0x1e0b37d27e0>

prediction on the test-set

In [29]:
```
predictions_svd = model_svd.test(testset)
```

Model evaluation

In [30]:
```
# Évaluating model performance
rmse_svd = accuracy.rmse(predictions_svd)
print("RMSE SVD :", rmse_svd)
```

```
RMSE: 0.8530
RMSE SVD : 0.8530272671147646
```

Optimisation of the SVD Model with GridSearchCV

In [31]:
```
from surprise.model_selection import GridSearchCV
# Définir la grille d'hyperparamètres à tester
param_grid = {
    'n_factors': [50, 100, 150],        # nombre de facteurs latents
    'n_epochs': [20, 30, 40],           # nombre d'itérations
    'lr_all': [0.002, 0.005, 0.01],     # taux d'apprentissage
    'reg_all': [0.02, 0.05, 0.1]        # régularisation
}

# Création du grid search
gs = GridSearchCV(SVD, param_grid, measures=['rmse', 'mae'], cv=3, n_jobs=-1)

# Exécution du grid search
gs.fit(data)

# Meilleurs paramètres
print("Best SVD parameters : ", gs.best_params['rmse'])
print(" Best RMSE score  : ", gs.best_score['rmse'])
```

```
Best SVD parameters :  {'n_factors': 100, 'n_epochs': 40, 'lr_all': 0.01, 'reg_al
l': 0.1}
 Best RMSE score  :  0.8428036388460759
```

Remarque:

n_factors=150 → the model learns 150 latent dimensions (more complexity, greater ability to capture subtle preferences).

n_epochs=40 → more training iterations.

lr_all=0.01 → a faster learning rate.

reg_all=0.1 → stronger regularization to prevent overfitting.

Best model found

In [32]:
```python
best_svd = gs.best_estimator['rmse']
```

Model training

In [33]:
```python
trainset = data.build_full_trainset()
best_svd.fit(trainset)
```

Out[33]:
```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x1e0b6022360>
```

predictions

In [34]:
```python
user_id = 1
movieId = 50

# prediction of the rating that the user 1 will give to the 50th movie
best_svd.predict(user_id, movieId)
```

Out[34]:
```
Prediction(uid=1, iid=50, r_ui=None, est=4.908576017286609, details={'was_impos
sible': False})
```

uid=1 → utilisateur 1.

iid=50 → film n°50.

r_ui=None → la note réelle n'est pas connue (puisqu'on prédit une note pour un film non encore noté).

est=4.88 → le modèle prévoit que l'utilisateur donnerait une note de 4.88 / 5 à ce film.

was_impossible=False → la prédiction est valide (il ne manque pas d'informations).

Top-N personalised recommandations based on the SVdD model

In [35]:
```python
def recommended_movies(user_id, n, model, df_movies, data):
    all_movie_ids = df_movies['movieId'].unique()
    trainset = data.build_full_trainset()
```

```
    try:
        user_inner_id = trainset.to_inner_uid(user_id)
        rated_items = [trainset.to_raw_iid(iid) for iid, _ in trainset.ur[user_i
    except ValueError:
        rated_items = []

    unrated_movies = [mid for mid in all_movie_ids if mid not in rated_items]
    predictions = [model.predict(user_id, mid) for mid in unrated_movies]
    predictions.sort(key=lambda x: x.est, reverse=True)
    top_n = predictions[:n]

    top_n_df = pd.DataFrame({
        'movieId': [pred.iid for pred in top_n],
        'predicted_rating': [pred.est for pred in top_n]
    })

    top_n_df = top_n_df.merge(df_movies[['movieId', 'title']], on='movieId', how

    print(f"\nTop {n} recommandations for user {user_id} :\n")
    for i, row in top_n_df.iterrows():
        print(f"Recommendation #{i+1}: {row['title']} (predicted rating : {row['

    return top_n_df
```

In [36]:
```
# Recommandations pour l'utilisateur 1
top5_user1 = recommended_movies(
    user_id=1,
    n=5,
    model=best_svd,
    df_movies=movies_df,
    data=data
)
```

```
Top 5 recommandations for user 1 :

Recommendation #1: Shawshank Redemption, The (1994) (predicted rating : 5.00)
Recommendation #2: Vanya on 42nd Street (1994) (predicted rating : 5.00)
Recommendation #3: Wallace & Gromit: The Best of Aardman Animation (1996) (predic
ted rating : 5.00)
Recommendation #4: Godfather, The (1972) (predicted rating : 5.00)
Recommendation #5: Philadelphia Story, The (1940) (predicted rating : 5.00)
```

In [37]:
```
# Recommandations for user # 1
top5_user2 = recommended_movies(
    user_id=2,
    n=5,
    model=best_svd,
    df_movies=movies_df,
    data=data
)
```

```
Top 5 recommandations for user 2 :

Recommendation #1: Three Billboards Outside Ebbing, Missouri (2017) (predicted ra
ting : 4.62)
Recommendation #2: Day of the Doctor, The (2013) (predicted rating : 4.56)
Recommendation #3: Swept Away (Travolti da un insolito destino nell'azzurro mare
d'Agosto) (1975) (predicted rating : 4.54)
Recommendation #4: Last Tango in Paris (Ultimo tango a Parigi) (1972) (predicted
rating : 4.52)
Recommendation #5: Captain Fantastic (2016) (predicted rating : 4.51)
```

Contact information

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For further inquiries, feedback, or collaboration on this analysis, feel free to reach out. I welcome discussions and any contract to work.