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- Scheduled project review date/time: February 12, 2025
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- Github link :https://github.com/charlesot/phase-4.git (https://github.com/charlesot/phase-4.git)

1 Novelle Movies Recommendation system Project Summary

1.1 Project overview

Unlike established streaming services, small businesses in Kenya that sell movies have high customer churn and dissatisfaction rates because they cannot recommend movies to their customers. The business owners have to watch all the movies to give recommendations, this not only wastes time but also increases missed opportunities to sell movies that the vendor has never watched. The Novelle Movies recommendation system project will develop a personalized movie recommendation system that will enable small business owners to improve sales and retention of their customers through improved customer experience

1.2 Business understanding

- Small businesses in Kenya that sell movies have high customer churn and dissatisfaction rates.
- They spend a lot of time watching all the movies to give recommendations.
- They miss opportunities to sell movies that vendors have never watched.
- They have limited resources to develop a personalized movie recommendation system.

1.2.1 Project objectives

- Increase customer engagement by recommending movies based on user preference
- Increase sales by supporting customers to find movies of their taste
- Be able to make recommendations to new customers

1.2.2 Key features of Novelle Movie recommendation system

- Collaborative filtering (SVD) for personalized recommendations for existing active users
- Content-based filtering using movie genre and tags to handle new users
- Hybrid system that combines both methods for the best recommendation

1.3 Data understanding

The project will use the MovieLens small dataset from the GroupLens research lab at the University of Minnesota. It contains 100,863 ratings and 3683 tag applications on 9742 movies. It was created by 610 users between March 29, 1996, and september 24, 2018. The dataset was generated on September 26, 2018, and is available for download at http://grouplens.org/datasets/ (http://grouplens.org/datasets/).

1.3.0.1 Dataset citation

F. Maxwell Harper and Joseph A. Konstan. 2015. The MovieLens Datasets: History and Context. ACM Transactions on Interactive Intelligent Systems (TiiS) 5, 4: 19:1–19:19. https://doi.org/10.1145/2827872 (https://doi.org/10.1145/2827872)

1.3.1 Variables

The MovieLens small dataset has the following

- Movies.csv which contains the movie details (movieId, title, genres)
- ratings.CSV which contains user ratings (userId, movieId, rating, timestamp)
- tags.CSV contains user-generated movie tags (userId, movieId, tag, timestamp)

1.4 Data preparation

1.4.1 Import the Python libraries to use

import pandas as pd import seaborn as sns import numpy as np import matplotlib.pyplot as plt from surprise import SVD, Dataset, Reader, SVDpp from surprise.model_selection import train_test_split, cross_validate from surprise import accuracy from collections import defaultdict from sklearn.feature_extraction.text import TfidfVectorizer from sklearn.metrics.pairwise import linear_kernel from sklearn.pipeline import Pipeline

1.4.2 Load the dataset

Dataset if downloaded from http://grouplens.org/datasets/ (http://grouplens.org/datasets/) and loaded into pandas data frames movies_df = pd.read_csv(r'./Data\movies.csv') tags_df = pd.read_csv(r'./Data\tags.csv') ratings_df = pd.read_csv(r'./Data\ratings.csv')

1.4.3 Exploration

- The ratings_df, tags_df, and movies_df data frames were explored to see the first five rows, the information, shape, missing entries, and the number of unique users and movies.
- The column timestamp dropped because it was not being used
- All tags converted to lowercase
- All the tags per movie aggregate
- The movies_df and the tag_df merged on movieID column
- All Nan features filled with an empty string

- "genre" and "tags" combined to form one feature a "combined_feature"
- The modified movies_df is merged with the ratings_df to form merged_df dataframe which will be used in development of the model
- merged_df data frame is further explored to identify the top ten rated movies, the distribution of the movie rating, the 10 most rated movies, and the distribution number of ratings per user

1.5 Modelling

1.5.1 Collabotarive filtering (SVD) modeling

- Used Surprise SVD to predict user preferences: data split into training and testing with test_size of 0.2 and random _state of 42 . training of the model used n_factor of 50
- Model evaluates using root mean square error (RMSE) and mean absolute error (MAE)
- function developed to get movie recommendations using SVD MAE: 0.5781 RMSE: 0.7500

1.5.2 Content-based filtering

- The TF_IDF and cosine similarity to recommend movies based on combined features

1.5.3 Hybrid recommendation

- Hybrid recommendation system combines collaborative filtering (SVD) and content-based filtering. If the user has rated at least 5 movies, use collaborative filtering (SVD). If the user has rated less than 5 movies, use content-based filtering and recommend the top-rated movie. If the user has not rated any movies, recommend the top-rated movies to address the cold start problem

1.6 Model improvement: Hyperparameter Tuning

- GridSearchCV was used to improve performance but it shoed no change in performance . Best RMSE parameters: {'n_factors': 150, 'n_epochs': 30, 'lr_all': 0.005, 'reg_all': 0.1} Best MAE parameters: {'n_factors': 150, 'n_epochs': 30, 'lr_all': 0.005, 'reg_all': 0.1} MAE: 0.5781 RMSE: 0.7500

Importing Important python libraries

In [2]:
```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from surprise import SVD, Dataset, Reader, SVDpp
from surprise.model_selection import train_test_split, cross_validate
from surprise import accuracy
from collections import defaultdict
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel
from sklearn.pipeline import Pipeline
```

loading dataset

In [3]:
```
movies_df = pd.read_csv(r'./Data\movies.csv')
tags_df = pd.read_csv(r'./Data\tags.csv')
ratings_df = pd.read_csv(r'./Data\ratings.csv')
```

Data Exploration

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

Out[4]:

	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 [5]:
```
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 [6]:
```
movies_df.shape
```

Out[6]:
```
(9742, 3)
```

- Movies_df has 9742 columns and 3 rows . It alsk has no null values. The Columns include MovieId, title and genres.

In [7]:
```
tags_df.head()
```

Out[7]:

	userId	movieId	tag	timestamp
0	2	60756	funny	1445714994
1	2	60756	Highly quotable	1445714996
2	2	60756	will ferrell	1445714992
3	2	89774	Boxing story	1445715207
4	2	89774	MMA	1445715200

In [8]:
```
tags_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3683 entries, 0 to 3682
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   userId     3683 non-null   int64 
 1   movieId    3683 non-null   int64 
 2   tag        3683 non-null   object
 3   timestamp  3683 non-null   int64 
dtypes: int64(3), object(1)
memory usage: 115.2+ KB
```

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

Out[9]:
```
(3683, 4)
```

- tags_df has 3683 rows and 4 columns . It also has no null values. Columns include UserId, MovieId, tag and timestamp

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

Out[10]:

	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 [11]:
```python
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 [12]:
```python
ratings_df.shape
```

Out[12]:
```
(100836, 4)
```

In [13]:
```python
# Movie ID to movie name mapping
movie_names = movies_df.set_index('movieId')['title'].to_dict()
n_users = len(ratings_df.userId.unique())
n_items = len(ratings_df.movieId.unique())
print('----------------------------------------------------------------')
print("Number of unique users:", n_users)
print('----------------------------------------------------------------')
print("Number of unique movies:", n_items)
print('----------------------------------------------------------------')
print("The full rating matrix will have:", n_users*n_items, 'elements.')
print('----------- ----------------------------------------------------')
print("Number of ratings:", len(ratings_df))
print('----------- ----------------------------------------------------')
```

```
----------------------------------------------------------------
Number of unique users: 610
----------------------------------------------------------------
Number of unique movies: 9724
----------------------------------------------------------------
The full rating matrix will have: 5931640 elements.
----------- ----------------------------------------------------
Number of ratings: 100836
----------- ----------------------------------------------------
```

In [14]:
```
ratings_df.describe().T
```

Out[14]:

	count	mean	std	min	25%	50%	75%	max
userId	100836.0	3.261276e+02	1.826185e+02	1.0	1.770000e+02	3.250000e+02	4.770000e+02	6.100000e+02
movieId	100836.0	1.943530e+04	3.553099e+04	1.0	1.199000e+03	2.991000e+03	8.122000e+03	1.936090e+05
rating	100836.0	3.501557e+00	1.042529e+00	0.5	3.000000e+00	3.500000e+00	4.000000e+00	5.000000e+00
timestamp	100836.0	1.205946e+09	2.162610e+08	828124615.0	1.019124e+09	1.186087e+09	1.435994e+09	1.537799e+09

- rating_df has 100836 rows and 4 columns. The columns include movieId, ratings and timestamp . The number of unique users is 610, number of unique movies 9724, and number of rating 100836

1.7 Data preparation

1.7.1 Merging the tag data set with the movies data set

In [15]:
```
# dropping the timestamp which is not going to be used
tags_df.drop(columns= ['timestamp'], inplace= True)
```

In [16]:
```
# convert tags to lowercase
tags_df['tag'] = tags_df['tag'].str.lower()
```

In [17]:
```python
# Aggregate all tags per movie
movie_tags = tags_df.groupby('movieId')['tag'].apply(lambda x: " ".join (x)).reset_index()
movie_tags
```

Out[17]:

	movieId	tag
0	1	pixar pixar fun
1	2	fantasy magic board game robin williams game
2	3	moldy old
3	5	pregnancy remake
4	7	remake
...	...	...
1567	183611	comedy funny rachel mcadams
1568	184471	adventure alicia vikander video game adaptation
1569	187593	josh brolin ryan reynolds sarcasm
1570	187595	emilia clarke star wars
1571	193565	anime comedy gintama remaster

1572 rows × 2 columns

In [18]:
```python
# merge all tags with movies dataset
movies_df = movies_df.merge(movie_tags, on='movieId',how='left')
movies_df.head()
```

Out[18]:

	movieId	title	genres	tag
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	pixar pixar fun
1	2	Jumanji (1995)	Adventure|Children|Fantasy	fantasy magic board game robin williams game
2	3	Grumpier Old Men (1995)	Comedy|Romance	moldy old
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance	NaN
4	5	Father of the Bride Part II (1995)	Comedy	pregnancy remake

In [19]:
```python
# fill NaN feature with empty string
movies_df['tag'].fillna(' ', inplace = True)
```

In [20]:
```
#combining genre and tags into one feature
movies_df['combined_feature'] = movies_df['genres'] +' '+ movies_df['tag']
movies_df.head()
```

Out[20]:

	movieId	title	genres	tag	combined_feature
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	pixar pixar fun	Adventure|Animation|Children|Comedy|Fantasy pi...
1	2	Jumanji (1995)	Adventure|Children|Fantasy	fantasy magic board game robin williams game	Adventure|Children|Fantasy fantasy magic board...
2	3	Grumpier Old Men (1995)	Comedy|Romance	moldy old	Comedy|Romance moldy old
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance		Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy	pregnancy remake	Comedy pregnancy remake

In [21]:
```
#merge rating and movies
merged_df = ratings_df.merge(movies_df,on ='movieId', how='left')
merged_df.head()
```

Out[21]:

	userId	movieId	rating	timestamp	title	genres	tag	combined_feature
0	1	1	4.0	964982703	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	pixar pixar fun	Adventure|Animation|Children|Comedy|Fantasy pi...
1	1	3	4.0	964981247	Grumpier Old Men (1995)	Comedy|Romance	moldy old	Comedy|Romance moldy old
2	1	6	4.0	964982224	Heat (1995)	Action|Crime|Thriller		Action|Crime|Thriller
3	1	47	5.0	964983815	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller	mystery twist ending serial killer	Mystery|Thriller mystery twist ending serial k...
4	1	50	5.0	964982931	Usual Suspects, The (1995)	Crime|Mystery|Thriller	mindfuck suspense thriller tricky twist ending...	Crime|Mystery|Thriller mindfuck suspense thril...

In [22]:
```
merged_df.shape
```
Out[22]:
```
(100836, 8)
```

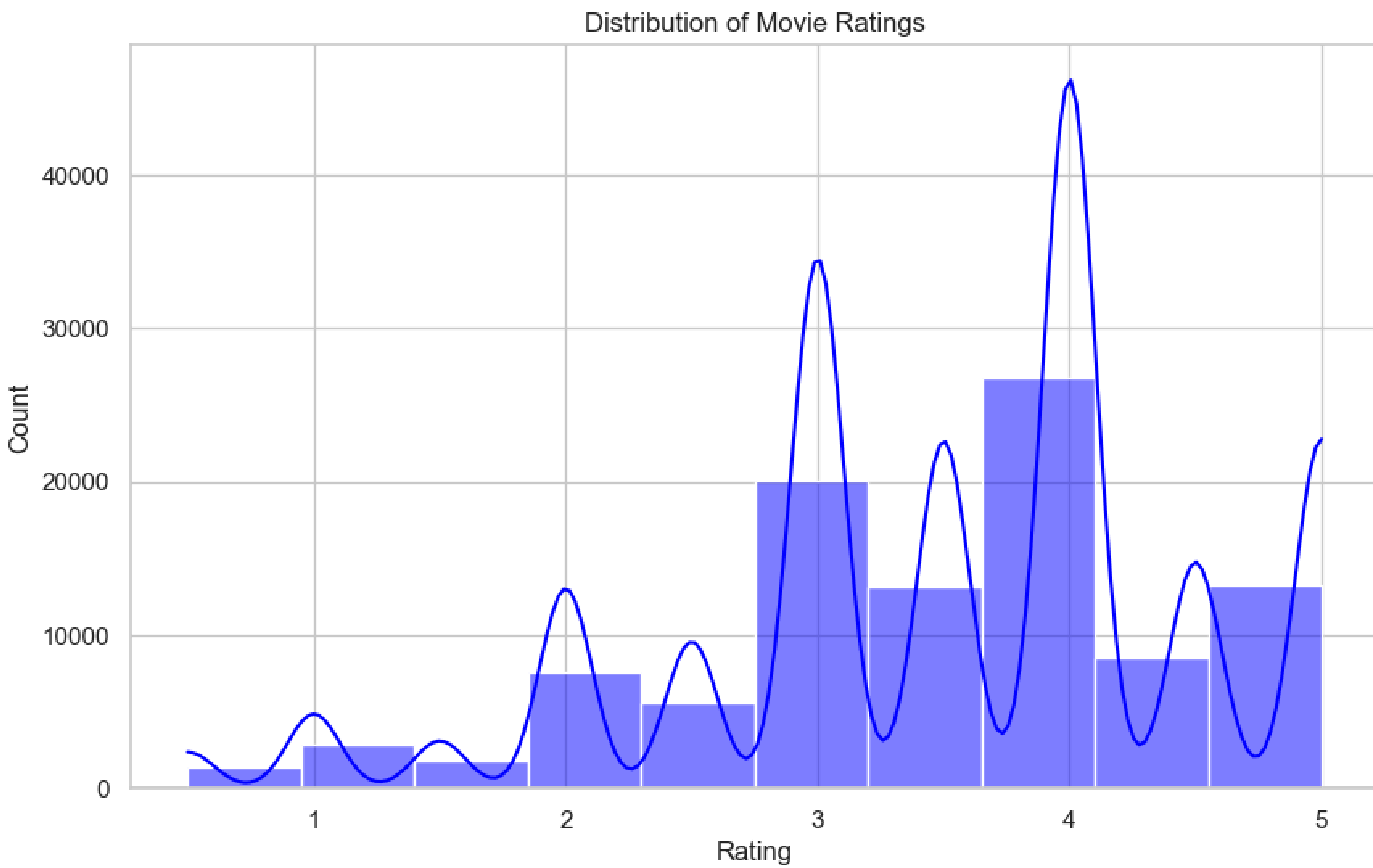
In [23]:

```
#Top ten most rated movies
top_movies = merged_df['movieId'].value_counts().head(10)
print(movies_df[movies_df['movieId'].isin(top_movies.index)])
```

```
      movieId                                       title  \
97        110                            Braveheart (1995)
224       260  Star Wars: Episode IV - A New Hope (1977)
257       296                          Pulp Fiction (1994)
277       318            Shawshank Redemption, The (1994)
314       356                          Forrest Gump (1994)
418       480                         Jurassic Park (1993)
461       527                      Schindler's List (1993)
507       589           Terminator 2: Judgment Day (1991)
510       593            Silence of the Lambs, The (1991)
1939     2571                           Matrix, The (1999)

                                 genres  \
97                    Action|Drama|War
224            Action|Adventure|Sci-Fi
257        Comedy|Crime|Drama|Thriller
277                        Crime|Drama
314           Comedy|Drama|Romance|War
418   Action|Adventure|Sci-Fi|Thriller
461                          Drama|War
507                      Action|Sci-Fi
510             Crime|Horror|Thriller
1939            Action|Sci-Fi|Thriller

                                                    tag  \
97    beautiful scenery epic historical inspirationa...
224   classic space action action sci-fi epic great ...
257   good dialogue great soundtrack non-linear cult...
277   prison stephen king wrongful imprisonment morg...
314   shrimp vietnam bubba gump shrimp lieutenant da...
418                                            dinosaur
461   moving thought-provoking holocaust based on a ...
507   apocalypse arnold schwarzenegger nuclear war s...
510   hannibal lector disturbing drama gothic psycho...
1939  martial arts sci-fi alternate universe philoso...

                                       combined_feature
97    Action|Drama|War beautiful scenery epic histor...
224   Action|Adventure|Sci-Fi classic space action a...
257   Comedy|Crime|Drama|Thriller good dialogue grea...
277   Crime|Drama prison stephen king wrongful impri...
314   Comedy|Drama|Romance|War shrimp vietnam bubba ...
418           Action|Adventure|Sci-Fi|Thriller dinosaur
461   Drama|War moving thought-provoking holocaust b...
507   Action|Sci-Fi apocalypse arnold schwarzenegger...
510   Crime|Horror|Thriller hannibal lector disturbi...
1939  Action|Sci-Fi|Thriller martial arts sci-fi alt...
```

Distribution of ratings

In [24]:
```
# Set plot style
sns.set(style="whitegrid")

# Plot distribution of movie ratings
plt.figure(figsize=(10, 6))
sns.histplot(ratings_df["rating"], bins=10, kde=True, color="blue")
plt.xlabel("Rating")
plt.ylabel("Count")
plt.title("Distribution of Movie Ratings")
plt.show()
```

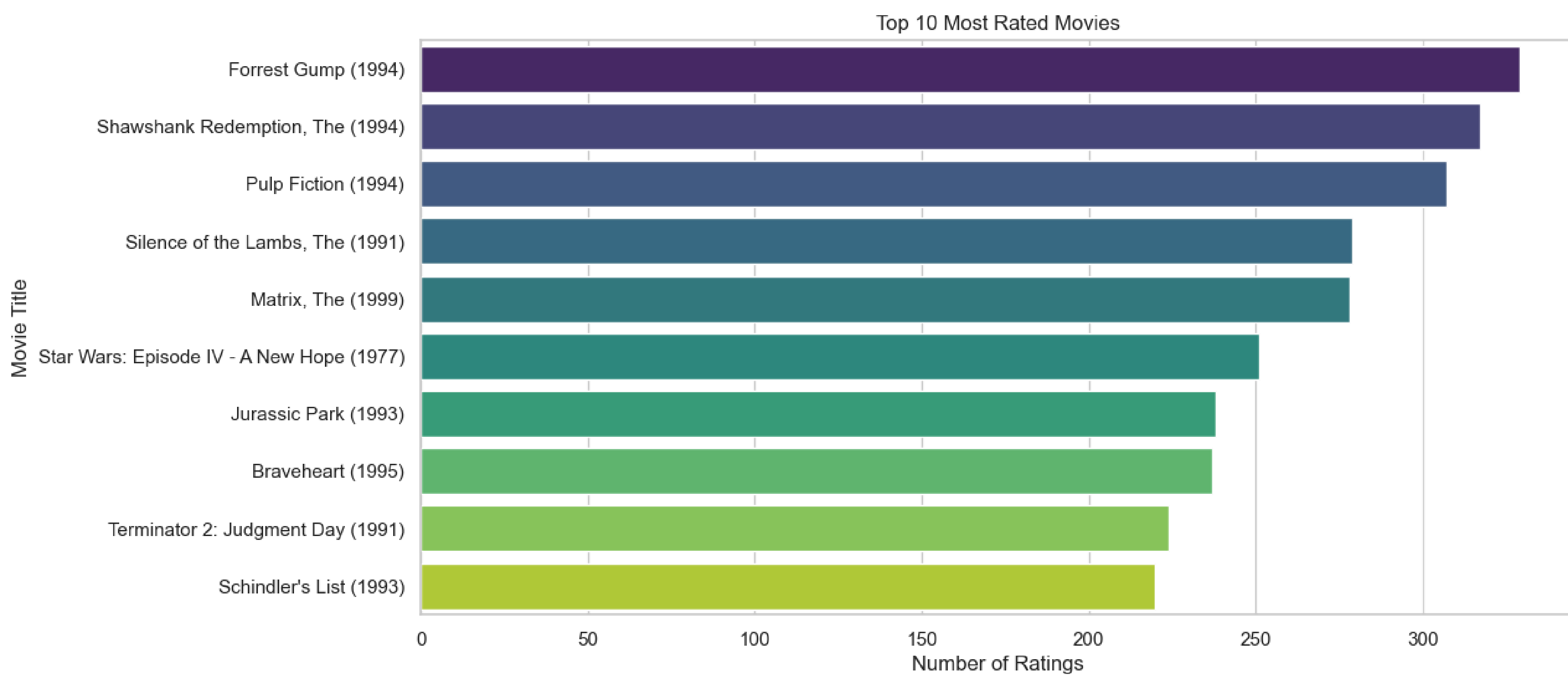


- The rating distribution is not normally distributed , most of the movies are rated 3 and 4.

In [25]:

```
#Top 10 most rated movies (Bar Chart)
top_movies_df = merged_df['movieId'].value_counts().head(10).reset_index()
top_movies_df.columns = ['movieId', 'count']
top_movies_df = top_movies_df.merge(movies_df[['movieId', 'title']], on='movieId')

plt.figure(figsize=(12, 6))
sns.barplot(y=top_movies_df['title'], x=top_movies_df['count'], palette='viridis')
plt.xlabel('Number of Ratings')
plt.ylabel('Movie Title')
plt.title('Top 10 Most Rated Movies')
plt.show()
```

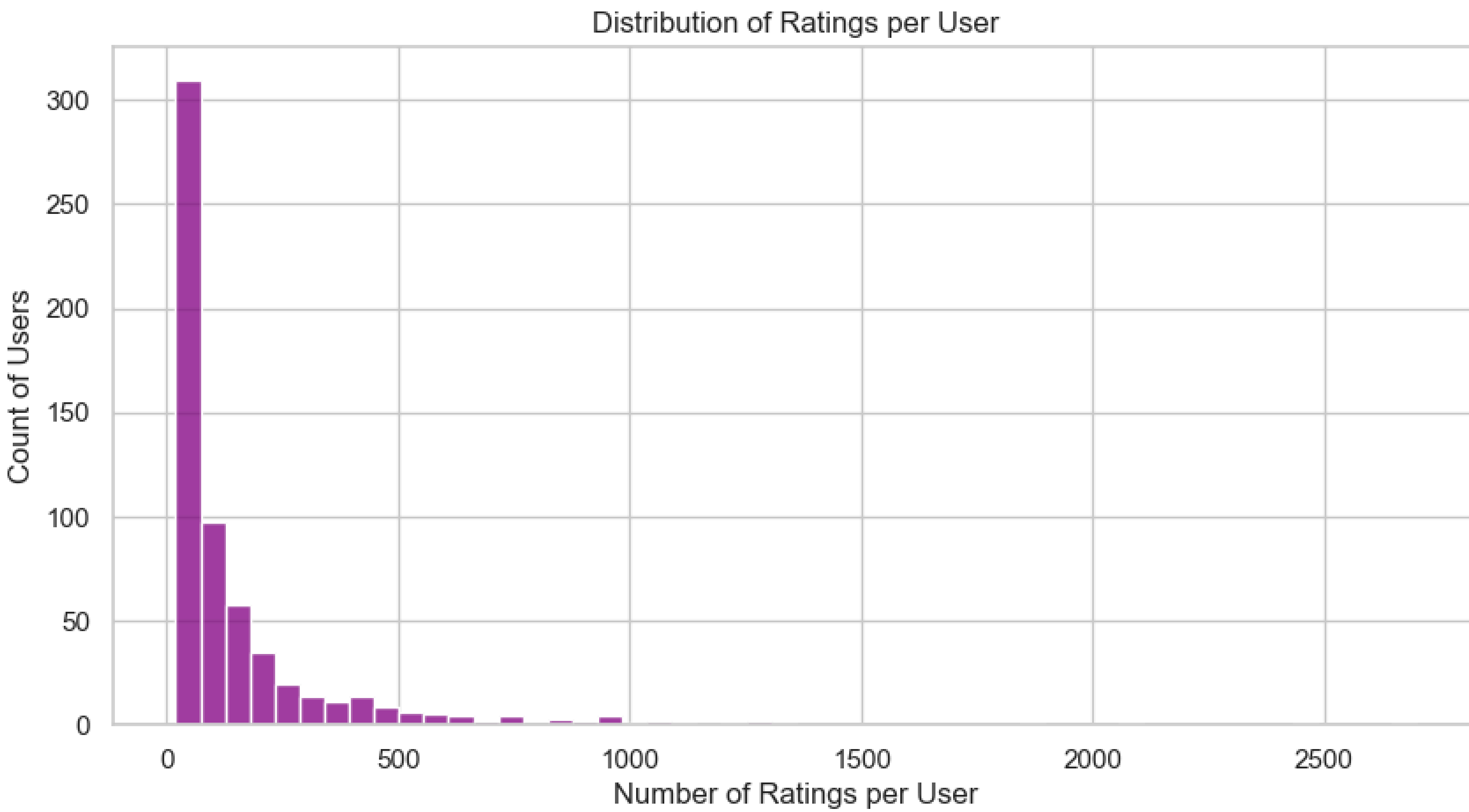
```
C:\Users\ondie\AppData\Local\Temp\ipykernel_28960\2097743499.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hu
e` and set `legend=False` for the same effect.

  sns.barplot(y=top_movies_df['title'], x=top_movies_df['count'], palette='viridis')
```



- The above chart shows the top 10 most rated movies in the dataset , the top three being forest gump, Shawshank Redemption and Pulp Fiction

In [26]:

```
# Number of Ratings per User
plt.figure(figsize=(10, 5))
sns.histplot(ratings_df['userId'].value_counts(), bins=50, color='purple')
plt.xlabel('Number of Ratings per User')
plt.ylabel('Count of Users')
plt.title('Distribution of Ratings per User')
plt.show()
```



- The chart shows that some users made a lot of rating over 500 which is an outlier hence could have skewed the data

1.8 Modelling

1.8.1 Collaborative filtering (SVD) Modelling

Using Surprise SVD to predict user preference

In [27]:
```
#Define rating scale
reader = Reader(rating_scale= (0.5, 5.0))
```

In [28]:
```
# load dataset into surprise
data = Dataset.load_from_df(merged_df[['userId', 'movieId', 'rating']],reader)
```

In [29]:
```
# splitting data into training and testing
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)
```

In [30]:
```
# Training the model
svd_model = SVD(n_factors =50,biased=True,random_state=42)
svd_model.fit(trainset)
```

Out[30]:
```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x2834c1f0f10>
```

In [31]:
```
#evaluate model
cross_validate(svd_model, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
```

```
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std     
RMSE (testset)    0.8734  0.8735  0.8725  0.8695  0.8701  0.8718  0.0017  
MAE (testset)     0.6706  0.6697  0.6722  0.6671  0.6687  0.6696  0.0017  
Fit time          4.09    3.81    4.20    4.28    3.72    4.02    0.22    
Test time         0.14    0.21    0.25    0.19    0.26    0.21    0.04    
```

Out[31]:
```
{'test_rmse': array([0.87341519, 0.87351045, 0.87253639, 0.8695487 , 0.87014758]),
 'test_mae': array([0.6705536 , 0.66966496, 0.67217526, 0.66711141, 0.66868581]),
 'fit_time': (4.094316005706787,
  3.8148553371429443,
  4.204718351364136,
  4.278996467590332,
  3.7208986282348633),
 'test_time': (0.14482641220092773,
  0.21235418319702148,
  0.2457277774810791,
  0.18819522857666016,
  0.2647862434387207)}
```

In [32]:
```
# model accuracy
predictions = svd_model.test(testset)
print('-----------------------------------------------------------------')
mae = accuracy.mae(predictions)
rmse = accuracy.rmse(predictions)
print('-----------------------------------------------------------------')
```

```
-----------------------------------------------------------------
MAE:  0.5808
RMSE: 0.7552
-----------------------------------------------------------------
```

Interpretation of model accuracy

- The mean absolute error of 0.5781 indicate dthat on overage the predicted ratings deviates from the actual rating by 0.58 which is significant
- The root mean squared error of 0.75 indicates that some oredictions devialte significantly
- lower value so both RMSE and MAE indicate btter model performance

Predict movie ratings

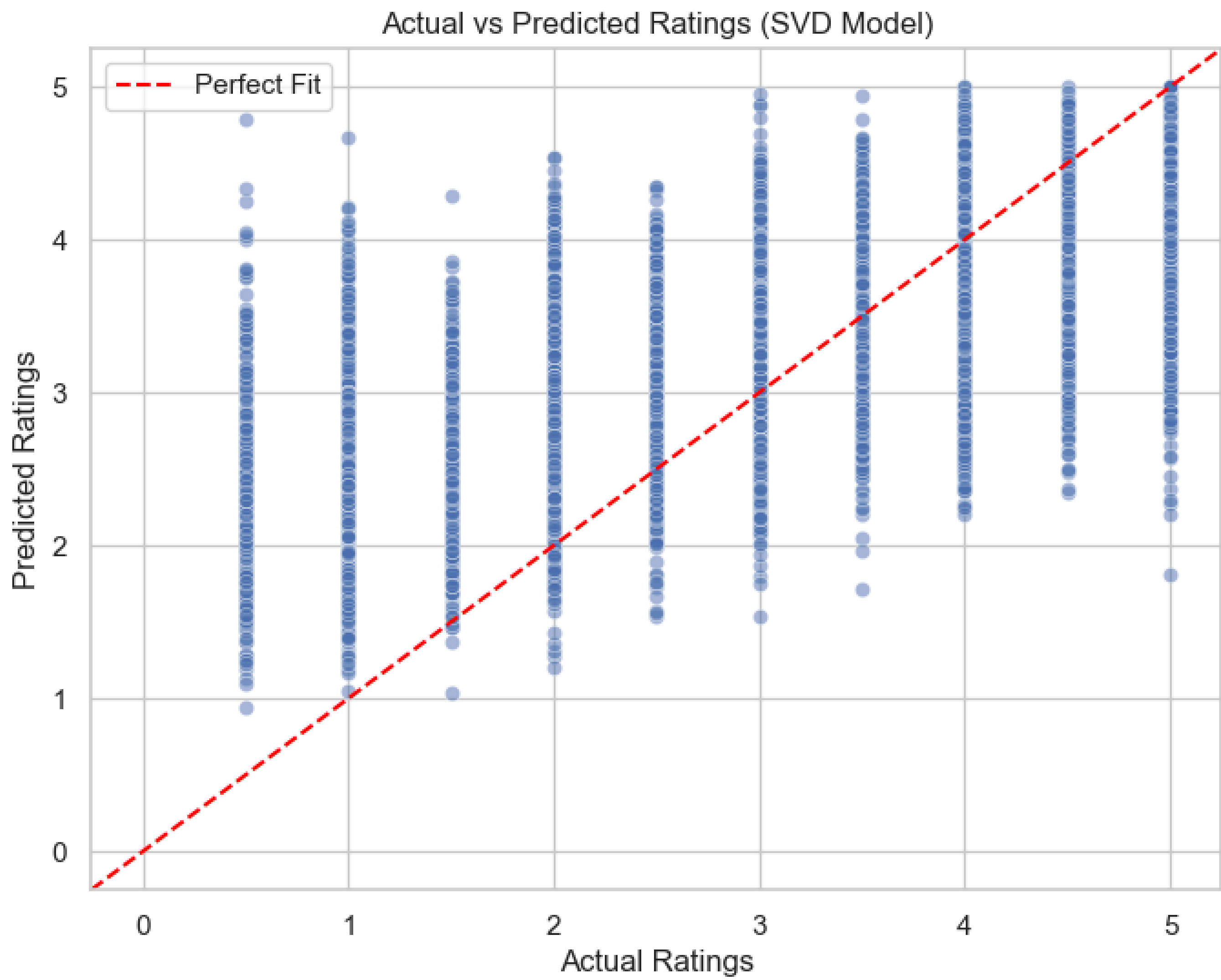
In [33]:

```python
# Function to get movie recommendations using SVD
def get_svd_recommendations(user_id, svd_model, movies_df, ratings_df, top_n=5):
    rated_movies = ratings_df[ratings_df["userId"] == user_id]["movieId"].tolist()

    predictions = []
    for movie_id in movies_df["movieId"].unique():
        if movie_id not in rated_movies:
            pred = svd_model.predict(user_id, movie_id)
            predictions.append((movie_id, pred.est))

    # Sort by predicted rating
    predictions.sort(key=lambda x: x[1], reverse=True)
    recommended_movies = movies_df[movies_df["movieId"].isin([m[0] for m in predictions[:top_n]])]

    return recommended_movies
```

VIsualization of model Accuracy

In [34]:

```
#Extract actual vs. predicted ratings for visualization
actual_ratings = [pred.r_ui for pred in predictions]
predicted_ratings = [pred.est for pred in predictions]

# Create a scatter plot of actual vs predicted ratings
plt.figure(figsize=(8, 6))
sns.scatterplot(x=actual_ratings, y=predicted_ratings, alpha=0.5)
plt.xlabel("Actual Ratings")
plt.ylabel("Predicted Ratings")
plt.title("Actual vs Predicted Ratings (SVD Model)")
plt.axline((0, 0), slope=1, color='red', linestyle='--', label="Perfect Fit")
plt.legend()
plt.show()
```



- The graph shows that the model has high predicted ratings for low rated movies and high rated movies have low predictied ratings.

1.8.2 content based filtering

Using TF-IDF and cosine similarity to recommend movies based on combined features

In [35]:
```
# using TF-IDF to combined features
content_pipeline= Pipeline([
    ('tdidf',  TfidfVectorizer(stop_words= 'english'))])
tfidf_matrix = content_pipeline.fit_transform(movies_df["combined_feature"])
cosine_sim = linear_kernel(tfidf_matrix,tfidf_matrix)
```

In [36]:
```
# Function to get content-based recommendations
def get_content_based_recommendations(movie_id, movies_df, tfidf_matrix, top_n=5):
    movie_index = movies_df.index[movies_df["movieId"] == movie_id].tolist()[0]
    cosine_similarities = linear_kernel(tfidf_matrix[movie_index], tfidf_matrix).flatten()

    # Get top N similar movies
    similar_indices = cosine_similarities.argsort()[-(top_n+1):-1][::-1]
    recommended_movies = movies_df.iloc[similar_indices]

    return recommended_movies
```

In [37]:
```python
#Get recommendations for a specific user using SVD
specific_user_id = 1  # Change this value as needed
svd_recommendations = get_svd_recommendations(specific_user_id, svd_model, movies_df, ratings_df)

print(f"SVD-based recommendations for User {specific_user_id}:")
print(svd_recommendations[['title']])

# Get a content-based recommendation for a specific user
user_top_movie_id = ratings_df[ratings_df['userId'] == specific_user_id].sort_values(by='rating', ascending=False).ilc
content_recommendations = get_content_based_recommendations(user_top_movie_id, movies_df, tfidf_matrix)

print(f"Content-based recommendations for User {specific_user_id} based on their top-rated movie:")
print(content_recommendations[['title']])
```

```
SVD-based recommendations for User 1:
                                                 title
98                                  Taxi Driver (1976)
277                   Shawshank Redemption, The (1994)
596          Ghost in the Shell (Kôkaku kidôtai) (1995)
602   Dr. Strangelove or: How I Learned to Stop Worr...
613                                Trainspotting (1996)
Content-based recommendations for User 1 based on their top-rated movie:
                                           title
7344                               Baarìa (2009)
554                           Underground (1995)
5453  Carabineers, The (Carabiniers, Les) (1963)
726                      To Be or Not to Be (1942)
9553                          War Machine (2017)
```

1.8.3 Hybrid recommendation

In [38]:

```python
"""
    Hybrid recommendation system combines collaborative filtering (SVD) and content-based filtering.
    If user has rated at least 5 movies, use collaborative filtering (SVD).
    If user has rated less than 5 movies, use content-based filtering and recommend the top-rated movie.
    If user has not rated any movies, recommend the top-rated movies to address cold start problem
"""
def hybrid_recommendation(user_id, svd_model, movies_df, ratings_df, tfidf_matrix, top_n=5):
    user_rated_movies = ratings_df[ratings_df["userId"] == user_id]

    if len(user_rated_movies) >= 5:
        recommended_movies = get_svd_recommendations(user_id, svd_model, movies_df, ratings_df, top_n)
        recommendation_type = "Collaborative Filtering (SVD)"
    elif 0 < len(user_rated_movies) < 5:
        top_movie = user_rated_movies.sort_values(by="rating", ascending=False).iloc[0]["movieId"]
        recommended_movies = get_content_based_recommendations(top_movie, movies_df, tfidf_matrix, top_n)
        recommendation_type = "Tags-Enhanced Content-Based Filtering"
    else:
        top_movies = ratings_df.groupby("movieId")["rating"].mean().sort_values(ascending=False).head(top_n).index
        recommended_movies = movies_df[movies_df["movieId"].isin(top_movies)]
        recommendation_type = "Popular Movies for Cold-Start Users"

    return recommended_movies, recommendation_type
```

1.8.4 Model improvement with hyperparameter Tuning

In [39]:
```
from surprise.model_selection import GridSearchCV

def tune_svd_hyperparameters(data):
    param_grid = {
        'n_factors': [50, 100, 150],
        'n_epochs': [20, 30],
        'lr_all': [0.002, 0.005],
        'reg_all': [0.02, 0.1]
    }

    gs = GridSearchCV(SVD, param_grid, measures=['rmse', 'mae'], cv=5)
    gs.fit(data)

    print('----------------------------------------------------------------')
    print("Best RMSE parameters:", gs.best_params['rmse'])
    print("Best MAE parameters:", gs.best_params['mae'])
    print('----------------------------------------------------------------')
    return gs.best_estimator['rmse']

# Run hyperparameter tuning
tuned_model = tune_svd_hyperparameters(data)
tuned_model.fit(trainset)
# Evaluate tuned model
predictions_tuned = tuned_model.test(testset)
print('----------------------------------------------------------------')
mae = accuracy.mae(predictions_tuned)
rmse = accuracy.rmse(predictions_tuned)
print('----------------------------------------------------------------')
```

```
----------------------------------------------------------------
Best RMSE parameters: {'n_factors': 100, 'n_epochs': 30, 'lr_all': 0.005, 'reg_all': 0.1}
Best MAE parameters: {'n_factors': 100, 'n_epochs': 30, 'lr_all': 0.005, 'reg_all': 0.1}
----------------------------------------------------------------
----------------------------------------------------------------
MAE:  0.6703
RMSE: 0.8722
----------------------------------------------------------------
```

In [40]:
```python
# Evaluate tuned model
predictions_tuned = tuned_model.test(testset)
print('----------------------------------------------------------------')
mae = accuracy.mae(predictions_tuned)
rmse = accuracy.rmse(predictions_tuned)
print('----------------------------------------------------------------')
```

```
----------------------------------------------------------------
MAE:  0.6703
RMSE: 0.8722
----------------------------------------------------------------
```

1.8.5 SVDPP used to improve performance

In [ ]:
```python
# Train-Test Split
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)

# Train the SVD++ model
svdpp_model = SVDpp()
svdpp_model.fit(trainset)

# Evaluate SVD++ model
print('----------------------------------------------------------------')
cross_validate(svdpp_model, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
print('----------------------------------------------------------------')

# Calculate RMSE and MAE on test set for SVD++
predictions_svdpp = svdpp_model.test(testset)
print('----------------------------------------------------------------')
rmse= accuracy.rmse(predictions_svdpp)
mae= accuracy.mae(predictions_svdpp)
print('----------------------------------------------------------------')
```

1.8.6 Recommendations and Next steps

- Consider a Hybrid recommendation system that combines collaborative filtering (SVD) and content-based filtering.
- If the user has rated at least 5 movies, use collaborative filtering (SVD).
- If the user has rated less than 5 movies, use content-based filtering and recommend the top-rated movie.
- If the user has not rated any movies, recommend the top-rated movies to address cold start problem
- SVDpp had slightly better performance and needs to be explored further used to improve performance RMSE: 0.7194 MAE: 0.5506
- Use the large MovieLens dataset for modeling
- Deploy the updated model for ease of use

- Connect the updated model to customer accounts

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