Daniel-MM24 / recommendation_system

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recommendation_system / movie_recommendation.ipynb

Daniel-MM24 Updating notebook 19d8cac · 22 minutes ago

797 lines (797 loc) · 76.2 KB

Business and Data Understanding

This project focuses on developing a personalized movie recommendation system using the Movielens small dataset, which consists of 100,000 ratings from 610 users on 9,724 movies. The dataset is ideal for recommendation modeling as it captures user-movie interactions (ratings) and movie metadata (genres, titles), enabling both collaborative filtering (CF) and content-based filtering (CBF). The dataset exhibits a sparsity of approximately 1.5%, necessitating efficient matrix factorization techniques to provide meaningful recommendations. Descriptive statistics indicate an average rating of 3.5 with a standard deviation of 1.06, ensuring a balanced distribution of user preferences.

Objective

The objective of this project is to build a robust and efficient movie recommendation system that provides personalized recommendations to users based on their past ratings and preferences. By leveraging collaborative filtering and content-based filtering techniques, the system can effectively address the cold start problem and provide accurate recommendations.

Data Preparation

The dataset underwent preprocessing to handle missing values and clean genre descriptions. The `pandas` library was used for data manipulation, `matplotlib` for visualization while `nltk` and `langdetect` assisted in multilingual stopword removal for genre-based content filtering. The `TfidfVectorizer` from `sklearn` transformed genre data into numerical representations, enabling similarity computations for CBF. These steps ensured structured and optimized data for recommendation modeling.

Modeling Approach

The core recommendation model is based on `Singular Value Decomposition (SVD)` from the `surprise` library, chosen for its efficiency in handling sparse matrices. Hyperparameter tuning was performed using `GridSearchCV`, optimizing parameters such as `n_factors`, `n_epochs`, `lr_all` and regularization terms. To address the cold start problem, a hybrid approach was developed:

- If a user has rated fewer movies than the dynamic median threshold, content-based filtering (CBF) recommends movies

based on genre similarity.
- Otherwise, collaborative filtering (CF) via SVD generates personalized recommendations based on learned latent factors.

Evaluation and Results

The final hybrid model significantly outperformed the standalone CF approach. The results were:

- Optimized SVD Model: Training RMSE = 0.8055, Validating RMSE = 0.8718
- Baseline SVD Model: Training RMSE = 0.6363, Validating RMSE = 0.8738

The evaluation used cross-validation to ensure robustness.

The hybrid approach demonstrated superior performance by balancing personalization (CF) and generalization (CBF), particularly for new users.

Data Exploration

In [1]:

```
# Import required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

from surprise import SVD
from surprise import Dataset, Reader
from surprise.model_selection import cross_validate
from surprise.model_selection import GridSearchCV
```

In [2]:

```
# Load datasets
ratings_df = pd.read_csv('ratings.csv')
movies_df = pd.read_csv('movies.csv')

# Display first few rows
```

```python
print("Ratings Data: ")
print(ratings_df.head())

print("\n Movies Data:")
print(movies_df.head())
```

```
Ratings Data:
   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

 Movies Data:
   movieId                               title  \
0        1                    Toy Story (1995)
1        2                      Jumanji (1995)
2        3             Grumpier Old Men (1995)
3        4            Waiting to Exhale (1995)
4        5  Father of the Bride Part II (1995)

                                        genres
0  Adventure|Animation|Children|Comedy|Fantasy
1                   Adventure|Children|Fantasy
2                               Comedy|Romance
3                         Comedy|Drama|Romance
4                                       Comedy
```

In [3]:

```python
# Check for misssing values
print("Missing values in ratings\n", ratings_df.isnull().sum())
print("\nMissing values in movies\n", movies_df.isnull().sum())
```

```
Missing values in ratings
 userId       0
movieId      0
rating       0
timestamp    0
dtype: int64

Missing values in movies
 movieId    0
title      0
genres     0
dtype: int64
```

In [4]:
```
# Summary statistics for movies_df and ratings_df
movies_summary = movies_df.describe()
ratings_summary = ratings_df.describe()

print("Movies summary statistics:\n", movies_summary)
print("\nRatings summary statistics:\n", ratings_summary)
```

```
Movies summary statistics:
               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

Ratings summary statistics:
               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
```

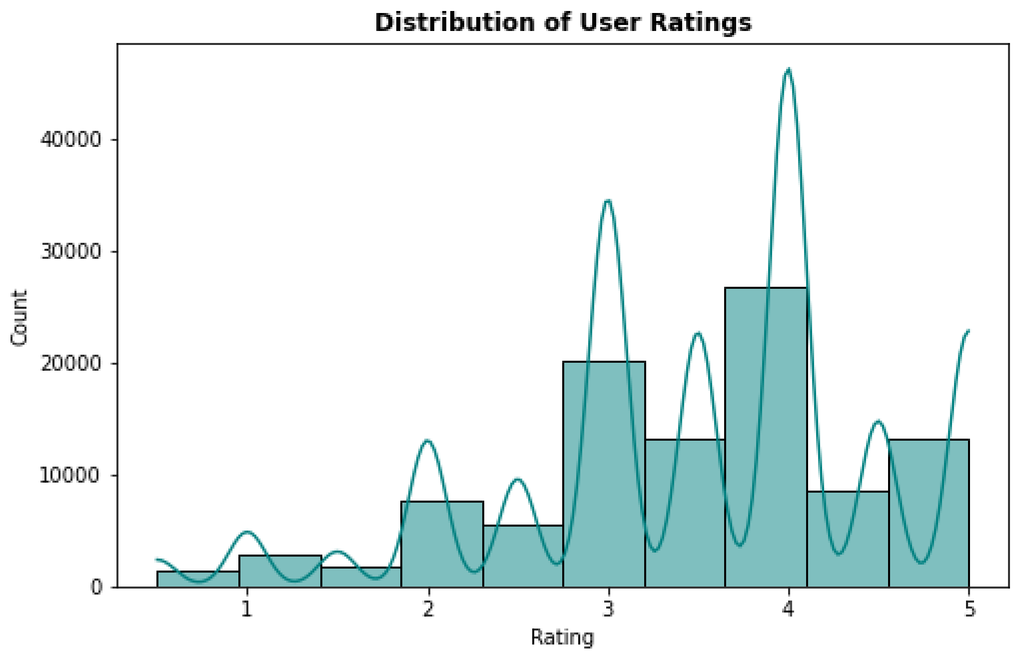
In [5]:
```
# Data exploration
# Unique users and movies
num_users = ratings_df['userId'].nunique()
num_movies = ratings_df['movieId'].nunique()
num_genres = movies_df['genres'].nunique()

print(f"Number of unique users: {num_users}")
print(f"Number of unique movies: {num_movies}")
print(f"Number of unique movie genres: {num_genres}")
```

```
Number of unique users: 610
Number of unique movies: 9724
Number of unique movie genres: 951
```

Visualizations

In [6]:

```
# Rating distribution
plt.figure(figsize=(8, 5))
sns.histplot(ratings_df['rating'], bins=10, kde=True, color='teal')
plt.title("Distribution of User Ratings", fontweight='bold')
plt.xlabel("Rating")
plt.ylabel("Count")
plt.show()
```



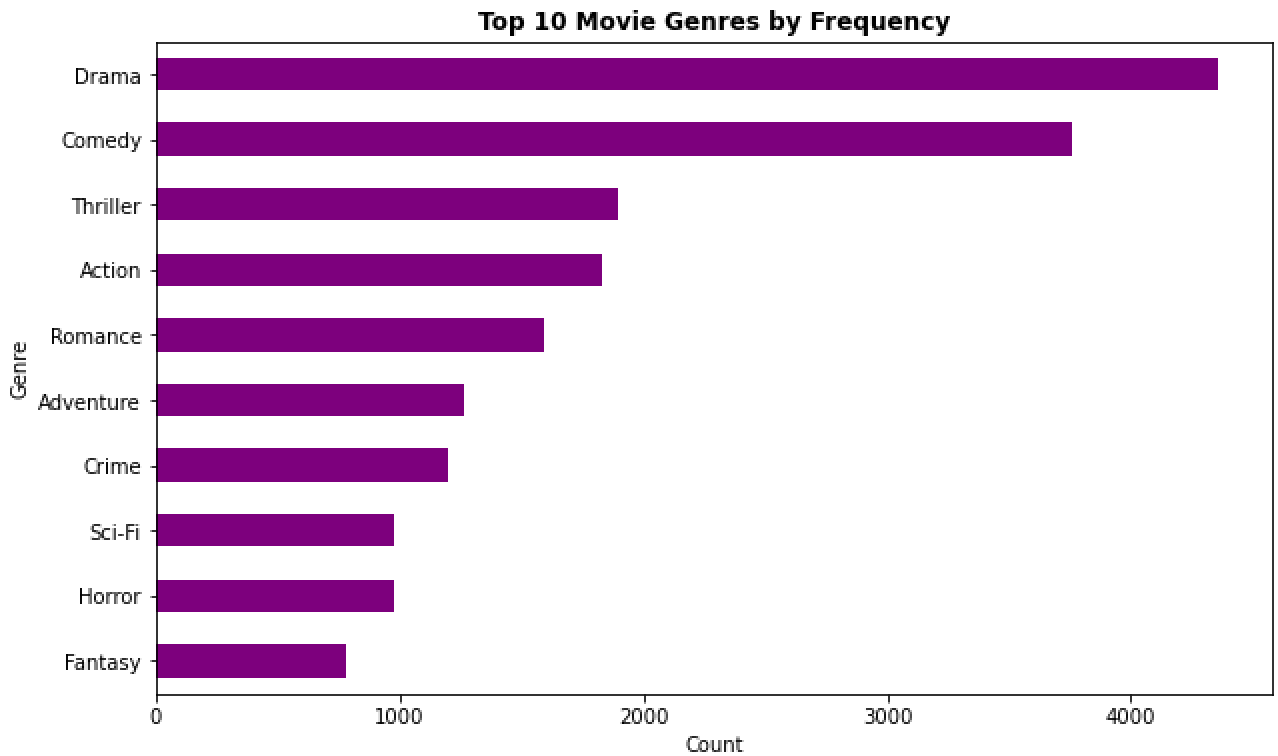
Observations

The graph shows a bimodal distribution of user ratings with peaks around 3 and 4, indicating that these are the most common ratings. The distribution is slightly positively skewed, suggesting a general tendency towards higher ratings. The low frequency of ratings 1 and 2 indicates that very low ratings are less common.

In [7]:

```
# Top 10 genres by frequency
genre_counts = movies_df['genres'].str.split('|', expand=True).stack().value_counts().head(10)
plt.figure(figsize=(10, 6))
```

```
genre_counts.plot(kind='barh', color='purple')
plt.title("Top 10 Movie Genres by Frequency", fontweight='bold')
plt.xlabel("Count")
plt.ylabel("Genre")
plt.gca().invert_yaxis()
plt.show()
```



Obervations

This chart provides an overview of the relative popularity of the top 10 movie genres based on their frequency within a given dataset. It highlights the strong preference for Drama and provides a comparative view of other popular genres.

Building a Recommendation System

Cross Validation

Training and validating perfomance across folds

Using cross validation instead of a single train-test-split provides a more reliable estimate by reducing data variability. K-Fold cross-validation ensures that the model is trained and tested on different subsets of data multiple times, reducing variance and improving generelaization.

In [8]:

```
# Define the read format for the Surprise Library
reader = Reader(rating_scale=(0.5, 5.0))

# Load the data into Surprises dataset format
data = Dataset.load_from_df(ratings_df[['userId', 'movieId', 'rating']], reader)

# Define the SVD model
svd = SVD()

# Perform 5-fold Cross validation
cv_results = cross_validate(svd, data, measures=['RMSE', 'MAE'], cv=5, return_train_measures=True, verbose=True
print(f"Average Test RMSE: {cv_results['test_rmse'].mean()}")


# Print the mean RMSE for training and test sets
print(f"Mean Training RMSE: {cv_results['train_rmse'].mean():.4f}")
print(f"Mean Validation RMSE: {cv_results['test_rmse'].mean():.4f}")
```

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8745  0.8744  0.8657  0.8786  0.8757  0.8738  0.0043
MAE (testset)     0.6708  0.6724  0.6656  0.6761  0.6725  0.6715  0.0034
RMSE (trainset)   0.6345  0.6345  0.6378  0.6384  0.6362  0.6363  0.0016
MAE (trainset)    0.4929  0.4930  0.4951  0.4951  0.4940  0.4940  0.0010
Fit time          7.76    7.61    6.86    6.58    8.46    7.45    0.67
Test time         0.20    0.17    0.27    0.18    0.22    0.21    0.04
Average Test RMSE: 0.873773473838906
Mean Training RMSE: 0.6363
Mean Validation RMSE: 0.8738
```

The model is overfitting. The Training RMSE is much lower than the validation RMSE

Improving Cross-Validation with GridSearchCV

To enhance the perfomance of the Singular Value Decomposition (SVD) model, GridSearchCV is used to systematically tune hypeparameters. Instead of manually selecting values, GridSearchCV tests multiple combinations and finds the optimal parameters that minimize RMSE.

In [9]:

```
# Define the parameter grid for hyperparameter tuning
param_grid = {
    'n_factors': [50], # [50, 100, 150],
    'n_epochs': [10], #[10, 20, 30],
    'lr_all': [0.01], #[0.002, 0.005, 0.01],
    'reg_all': [0.1] #[0.02, 0.05, 0.1]
}

# Perform Grid Search
grid_search = GridSearchCV(SVD, param_grid, measures=['RMSE', 'MAE'],  return_train_measures=True, n_jobs=-1, c

# Fit on the data
grid_search.fit(data)

# Get the best parameters
best_params = grid_search.best_params['rmse']
print(f"Best Parameters: {best_params}")
```

```
Best Parameters: {'n_factors': 50, 'n_epochs': 10, 'lr_all': 0.01, 'reg_all': 0.1}
```

In [10]:

```
# Train the best model
optimized_svd = SVD(n_factors=best_params['n_factors'],
                     n_epochs=best_params['n_epochs'],
                     lr_all=best_params['lr_all'],
                     reg_all=best_params['reg_all'])

cv_results = cross_validate(optimized_svd, data, measures=['RMSE', 'MAE'], return_train_measures=True, cv=5, ve
print(f"Average Test RMSE: {cv_results['test_rmse'].mean()}")


# Print the mean RMSE for training and test sets
print(f"Mean Training RMSE: {cv_results['train_rmse'].mean():.4f}")
print(f"Mean Validation RMSE: {cv_results['test_rmse'].mean():.4f}")
```

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

```
                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8641  0.8663  0.8795  0.8745  0.8750  0.8718  0.0058
MAE (testset)     0.6648  0.6674  0.6766  0.6718  0.6737  0.6709  0.0042
RMSE (trainset)   0.8063  0.8064  0.8040  0.8056  0.8051  0.8055  0.0009
MAE (trainset)    0.6228  0.6221  0.6206  0.6216  0.6224  0.6219  0.0008
Fit time          2.07    2.17    2.21    2.16    2.29    2.18    0.07
Test time         0.25    0.28    0.26    0.30    0.28    0.28    0.02
Average Test RMSE: 0.8718491705035649
Mean Training RMSE: 0.8055
Mean Validation RMSE: 0.8718
```

GridSearchCV helps automate hyperparameter tuning, ensuring that the model achieves the best bias-variance tradeoff. By optimizing regularization, learning rate, and latent factors overfitting is reduced.

Collaborative Filtering

Collaborative filtering (CF) is a popular technique for building recommendation systems. It utilizes the relationship between users and items to make predictions about user preferences. In the context of movie recommendation, CF can be used to recommend movies that users have similar preferences to those they have already watched.

Collaborative filtering using the baseline model (SVD)

In [22]:

```python
def get_top_5_recommendations(user_id, model, movies_df, ratings_df, n=5):
    # Get a list of all movie IDs
    all_movie_ids = movies_df['movieId'].unique()

    # Get movies the user has already rated
    rated_movies = ratings_df[ratings_df['userId'] == user_id]['movieId'].values

    # Get only movies the user has not rated
    unseen_movies = [movie for movie in all_movie_ids if movie not in rated_movies]

    #Predict ratings for unseen movies
    predictions = [model.predict(user_id, movie_id) for movie_id in unseen_movies]

    # Sort predictions by estimated rating
    top_n_predictions = sorted(predictions, key=lambda x: x.est, reverse=True)[:n]

    # Get movie titles for the recommended movie ids
    recommended_movie_ids = [pred.iid for pred in top_n_predictions]
```

```python
    recommended_movies = movies_df[movies_df['movieId'].isin(recommended_movie_ids)]

    return recommended_movies[['movieId', 'title']]

# Get top 5 recommendations
print("Recommendation for user 1")
user_id = 1
recommendations = get_top_5_recommendations(user_id, svd, movies_df, ratings_df, n=5)
print("Top 5 Movie Recommendations:")
print(recommendations)
print("\n")

print("Recommendation for user 168")
user_id = 168
recommendations = get_top_5_recommendations(user_id, svd, movies_df, ratings_df, n=5)
print("Top 5 Movie Recommendations:")
print(recommendations)
```

```
Recommendation for user 1
Top 5 Movie Recommendations:
     movieId                                        title
277      318              Shawshank Redemption, The (1994)
681      899                    Singin' in the Rain (1952)
686      904                            Rear Window (1954)
694      912                             Casablanca (1942)
704      922  Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)


Recommendation for user 168
Top 5 Movie Recommendations:
      movieId                             title
474       541               Blade Runner (1982)
510       593  Silence of the Lambs, The (1991)
680       898    Philadelphia Story, The (1940)
935      1235           Harold and Maude (1971)
1616     2160            Rosemary's Baby (1968)
```

Collaborative Filtering using the optimized (SVD)

In [23]:

```python
def get_top_5_recommendations(user_id, model, movies_df, ratings_df, n=5):
    # Get a list of all movie IDs
    all_movie_ids = movies_df['movieId'].unique()

    # Get movies the user has already rated
```

```
    # Get movies the user has already rated
    rated_movies = ratings_df[ratings_df['userId'] == user_id]['movieId'].values

    # Get only movies the user has not rated
    unseen_movies = [movie for movie in all_movie_ids if movie not in rated_movies]

    #Predict ratings for unseen movies
    predictions = [model.predict(user_id, movie_id) for movie_id in unseen_movies]

    # Sort predictions by estimated rating
    top_n_predictions = sorted(predictions, key=lambda x: x.est, reverse=True)[:n]

    # Get movie titles for the recommended movie ids
    recommended_movie_ids = [pred.iid for pred in top_n_predictions]
    recommended_movies = movies_df[movies_df['movieId'].isin(recommended_movie_ids)]

    return recommended_movies[['movieId', 'title']]

# Get top 5 recommendations
print("Recommendation for user 1")
user_id = 1
recommendations = get_top_5_recommendations(user_id, optimized_svd, movies_df, ratings_df, n=5)
print("Top 5 Movie Recommendations:")
print(recommendations)
print("\n")

print("Recommendation for user 168")
user_id = 168
recommendations = get_top_5_recommendations(user_id, optimized_svd, movies_df, ratings_df, n=5)
print("Top 5 Movie Recommendations:")
print(recommendations)
```

```
Recommendation for user 1
Top 5 Movie Recommendations:
     movieId                                              title
277      318                   Shawshank Redemption, The (1994)
602      750  Dr. Strangelove or: How I Learned to Stop Worr...
686      904                                Rear Window (1954)
878     1172     Cinema Paradiso (Nuovo cinema Paradiso) (1989)
924     1223    Grand Day Out with Wallace and Gromit, A (1989)


Recommendation for user 168
Top 5 Movie Recommendations:
     movieId                                title
46        50       Usual Suspects, The (1995)
```

```
277     318                Shawshank Redemption, The (1994)
686     904                               Rear Window (1954)
901    1199                                    Brazil (1985)
924    1223  Grand Day Out with Wallace and Gromit, A (1989)
```

Hybrid Recommendation System

Hybrid recommendation system with cold start detection

In [17]:

```python
def hybrid_recommendation(user_id, model, movies_df, ratings_df, n=5, alpha=0.5):
    """
    Hybrid recommendation system combining Collaborative Filtering (CF) and Content-Based Filtering (CBF).
    """
    # Calculate dynamic threshold (median number of ratings per user)
    dynamic_threshold = ratings_df.groupby("userId")["movieId"].count().median()

    # Compute TF-IDF matrix for movie genres)
    tfidf = TfidfVectorizer(stop_words="english")
    tfidf_matrix = tfidf.fit_transform(movies_df["genres"].fillna(""))
    cosine_sim = cosine_similarity(tfidf_matrix, tfidf_matrix)

    # Get user ratings
    user_ratings = ratings_df[ratings_df["userId"] == user_id]

    if len(user_ratings) < dynamic_threshold:
        print(f"Cold Start User Detected (User {user_id}) → Using Content-Based Filtering")

        # Get movies the user has rated
        rated_movies = user_ratings.merge(movies_df, on="movieId")[["movieId", "title"]]

        # Find similar movies based on genre similarity
        similar_movies = set()
        for movie_id in rated_movies["movieId"]:
            idx = movies_df[movies_df["movieId"] == movie_id].index[0]
            similar_indices = cosine_sim[idx].argsort()[-(n+5):-1]
            similar_movies.update(movies_df.iloc[similar_indices]["movieId"].values)

        # Remove movies the user has already rated
        similar_movies = list(set(similar_movies) - set(user_ratings["movieId"]))

        # Get movie titles for recommendations
        cbf_movies = movies_df[movies_df["movieId"].isin(similar_movies)].head(n)
```

```python
        return cbf_movies[["movieId", "title"]]

    else:
        print(f"User {user_id} has rated enough movies → Using Hybrid Recommendations")

        # Step 1: Collaborative Filtering Predictions
        all_movie_ids = set(movies_df["movieId"].unique())
        rated_movies = set(user_ratings["movieId"].values)
        unseen_movies = list(all_movie_ids - rated_movies)

        predictions = [model.predict(user_id, movie_id) for movie_id in unseen_movies]
        cf_scores = {pred.iid: pred.est for pred in predictions}

        # Step 2: Content-Based Filtering Scores
        rated_movie_ids = user_ratings["movieId"].values
        similarity_scores = {}

        for movie_id in rated_movie_ids:
            idx = movies_df[movies_df["movieId"] == movie_id].index[0]
            similar_indices = cosine_sim[idx].argsort()[-(n+5):-1]
            for sim_idx in similar_indices:
                sim_movie_id = movies_df.iloc[sim_idx]["movieId"]
                similarity_scores[sim_movie_id] = similarity_scores.get(sim_movie_id, 0) + cosine_sim[idx, sim_

        # Normalize similarity scores
        max_sim_score = max(similarity_scores.values(), default=1)
        cbf_scores = {k: v / max_sim_score * 5 for k, v in similarity_scores.items()}  # Scale to 5

        # Step 3: Merge CF & CBF Scores Using Weighted Hybrid Score
        hybrid_scores = {}
        for movie_id in unseen_movies:
            cf_score = cf_scores.get(movie_id, 0)
            cbf_score = cbf_scores.get(movie_id, 0)
            hybrid_scores[movie_id] = alpha * cf_score + (1 - alpha) * cbf_score

        # Step 4: Get Top N Recommendations
        top_movie_ids = sorted(hybrid_scores, key=hybrid_scores.get, reverse=True)[:n]
        recommended_movies = movies_df[movies_df["movieId"].isin(top_movie_ids)]

        return recommended_movies[["movieId", "title"]]

# Example usage:
user_id = 150
recommendations = hybrid_recommendation(user_id, optimized_svd, movies_df, ratings_df, n=5, alpha=0.5)
print("Top 5 Hybrid Movie Recommendations:")
print(recommendations)
```

```
print("\n")

user_id = 1
recommendations = hybrid_recommendation(user_id, optimized_svd, movies_df, ratings_df, n=5, alpha=0.5)
print("Top 5 Hybrid Movie Recommendations:")
print(recommendations)
```

```
Cold Start User Detected (User 150) → Using Content-Based Filtering
Top 5 Hybrid Movie Recommendations:
     movieId                  title
86        97  Hate (Haine, La) (1995)
88       100         City Hall (1996)
91       103     Unforgettable (1996)
274      315   Specialist, The (1994)
418      480     Jurassic Park (1993)


User 1 has rated enough movies → Using Hybrid Recommendations
Top 5 Hybrid Movie Recommendations:
      movieId                                              title
3398     4623                                Major League (1989)
3418     4649                     Wet Hot American Summer (2001)
3422     4660  Scenes from the Class Struggle in Beverly Hill...
8425   111362                  X-Men: Days of Future Past (2014)
8475   112852                     Guardians of the Galaxy (2014)
```

How This Hybrid Recommendation System Works

`Dynamic Thresholding for Cold Start Detection`

The function dynamically detrmines a threshold for switching between Content-Based Filtering (CBF) and Collaborative Filtering (CF) by calculating the median number of ratings per user in the dataset. The median serves as an adaptive threshold, meaning the system does not rely on a manually set value that might not generelize well across different datasets. If a user has rated fewer movies than this threshold, they are considered a cold start user, and content-based recommendations are provided. Otherwise, collaborative filtering is used.

`Cold Start Handling with Content-Based Filtering`

For users with too few ratings, traditional CF methods cannot generate meaningful recommendations due to a lack of personal preference data. To address this, the function leverages TF-IDF (Term Frequency-Inverse Document Frequency) and

Cosine Similarity to find movies similar to those the user has rated. TF-IDF transforms movie genres into numerical vectors, capturing the importance of each genre, while Cosine Similarity measures how closely related different movies are based on their genres. This ensures that even new users receive recommendations that align with their interests.

`Collaborative Filtering (CF) for Engaged Users`

Once a user has rated more movies than the threshold, Singular Value Decomposition (SVD) is used to generate recommendations. SVD is a powerful matrix factorization technique that learns hidden patterns in user-movie interactions. It predicts how much a user will like unseen movies based on past ratings. This method excels at capturing complex user preferences and identifying similarities between users and movies beyond just genres.

`Scalability and Adaptability`

A key advantage of this approach is its automatic adaptability as new users join. Because the threshold is dynamically calculated from the dataset (instead of being hardcoded), the system remains robust and scalable without requiring manual tuning. As more users provide ratings, the median naturally shifts, ensuring that the recommendation method is always optimized for the current dataset size and distribution. This makes it a flexible solution suitable for real-world applications where user activity varies over time.