MOVIE RECOMMENDER SYSTEM

Introduction

This project focuses on building a movie recommender system based on the Movielens dataset. I consists of 100,000 ratings by 610 unique users for 9724 unique movies. The objective is to build that can recomend top 5 movies to the users based on their ratings using collaborative filtering. project addresses the business problem of personalized movie recommendations using the Movi dataset. The dataset contains user ratings, movie metadata (title, genres, IDs), and tags, making i suited for collaborative filtering approaches since it captures both user behavior and movie attrib The final dataset retained userId, movieId, title, genres, rating, and rating year, which represent th important features for capturing user preferences over time.

For data preparation, we dropped duplicate identifiers, merged multiple files (ratings, movies, lin and imputed missing values with zeroes to ensure all users and movies were represented in the interaction matrix. We also applied scaling for model stability. Data preparation was handled with (merging/cleaning), scikit-learn (SimpleImputer, StandardScaler, Pipeline), and numpy (matrix ope

Modeling was performed using collaborative filtering via matrix factorization. Specifically, we bui Pipeline with TruncatedSVD for dimensionality reduction and Ridge Regression as the estimator. Hyperparameters were tuned with GridSearchCV, enabling cross-validated selection of latent fact regularization strength.Evaluation was conducted with train-test split and 5-fold cross-validation. model achieved strong predictive performance, with RMSE of 3.29.

Import libraries

In [ ]:
```
# Import  libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_sc
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.pipeline import Pipeline
from sklearn.decomposition import TruncatedSVD
from sklearn.linear_model import Ridge
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error, make_scorer
import warnings
warnings.filterwarnings('ignore')
```

Load and merge datasets

In [2]:
```
# Load and display the first few rows of the dataset
df_links=pd.read_csv('ml-latest-small\links.csv')
df_links.head()
```

Out[2]:

	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0

In [3]:

```
#Load and display the first few rows of the movies dataset
df_movies=pd.read_csv('ml-latest-small\movies.csv')
df_movies.head()
```

Out[3]:

	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 [4]:

```
#Load and display the first few rows of the ratings dataset
df_ratings=pd.read_csv(r'ml-latest-small\\ratings.csv')
df_ratings.head()
```

Out[4]:

	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 [5]:

```
#Load and display the first few rows of the tags dataset
df_tags=pd.read_csv(r'ml-latest-small\\tags.csv')
df_tags.head()
```

Out[5]:

	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]:

```
#Merge all datasets into a single dataframe
ratings_tags = pd.merge(df_ratings, df_tags, on=["userId", "movieId"], how="left
ratings_tags_movies = pd.merge(ratings_tags, df_movies, on="movieId", how="left"
df_merged = pd.merge(ratings_tags_movies, df_links, on="movieId", how="left")
df_merged.head()
```

Out[8]:

	userId	movieId	rating	timestamp_x	tag	timestamp_y	title	genres	imdbId
0	1	1	4.0	964982703	NaN	NaN	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	114709
1	1	3	4.0	964981247	NaN	NaN	Grumpier Old Men (1995)	Comedy|Romance	113228
2	1	6	4.0	964982224	NaN	NaN	Heat (1995)	Action|Crime|Thriller	113277
3	1	47	5.0	964983815	NaN	NaN	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller	114369
4	1	50	5.0	964982931	NaN	NaN	Usual Suspects, The (1995)	Crime|Mystery|Thriller	114814

In [7]:

```
# Display information about the final dataframe
df_merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 102677 entries, 0 to 102676
Data columns (total 10 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   userId       102677 non-null  int64  
 1   movieId      102677 non-null  int64  
 2   rating       102677 non-null  float64
 3   timestamp_x  102677 non-null  int64  
 4   tag          3476 non-null    object 
 5   timestamp_y  3476 non-null    float64
 6   title        102677 non-null  object 
 7   genres       102677 non-null  object 
 8   imdbId       102677 non-null  int64  
 9   tmdbId       102664 non-null  float64
dtypes: float64(3), int64(4), object(3)
memory usage: 7.8+ MB
```

Data Cleaning

In [9]:

```
# Cleaninng and renaming columns for clarity
df_merged = df_merged.rename(columns={
    "timestamp_x": "rating_timestamp",
    "timestamp_y": "tag_timestamp"
})
```

In [10]:

```
# Checking for duplicates
df_merged.duplicated().sum()
```

Out[10]: 0

Exploratory Data Analysis

In [11]:

```
# Checking for missing values
df_merged.isnull().sum()
```

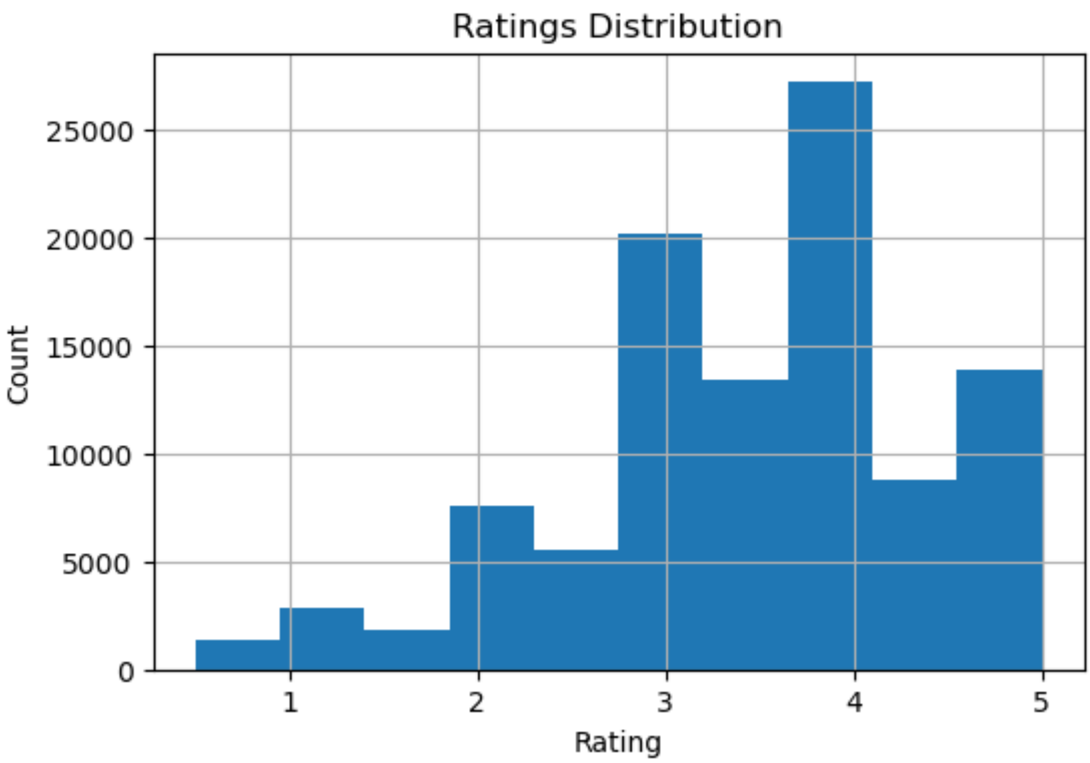
```
Out[11]: userId                   0
         movieId                  0
         rating                   0
         rating_timestamp         0
         tag                  99201
         tag_timestamp        99201
         title                    0
         genres                   0
         imdbId                   0
         tmdbId                  13
         dtype: int64
```

```
In [12]: # Unique users and movies
n_users = df_merged['userId'].nunique()
n_movies = df_merged['movieId'].nunique()
print(f"\nUnique users: {n_users}, Unique movies: {n_movies}")
```

```
Unique users: 610, Unique movies: 9724
```

```
In [13]: # Checking rating usefulness; if ratings are varied and not all the same, they c
df_merged['rating'].describe()

plt.figure(figsize=(6,4))
df_merged['rating'].hist(bins=10)
plt.title("Ratings Distribution")
plt.xlabel("Rating")
plt.ylabel("Count")
plt.show()
```

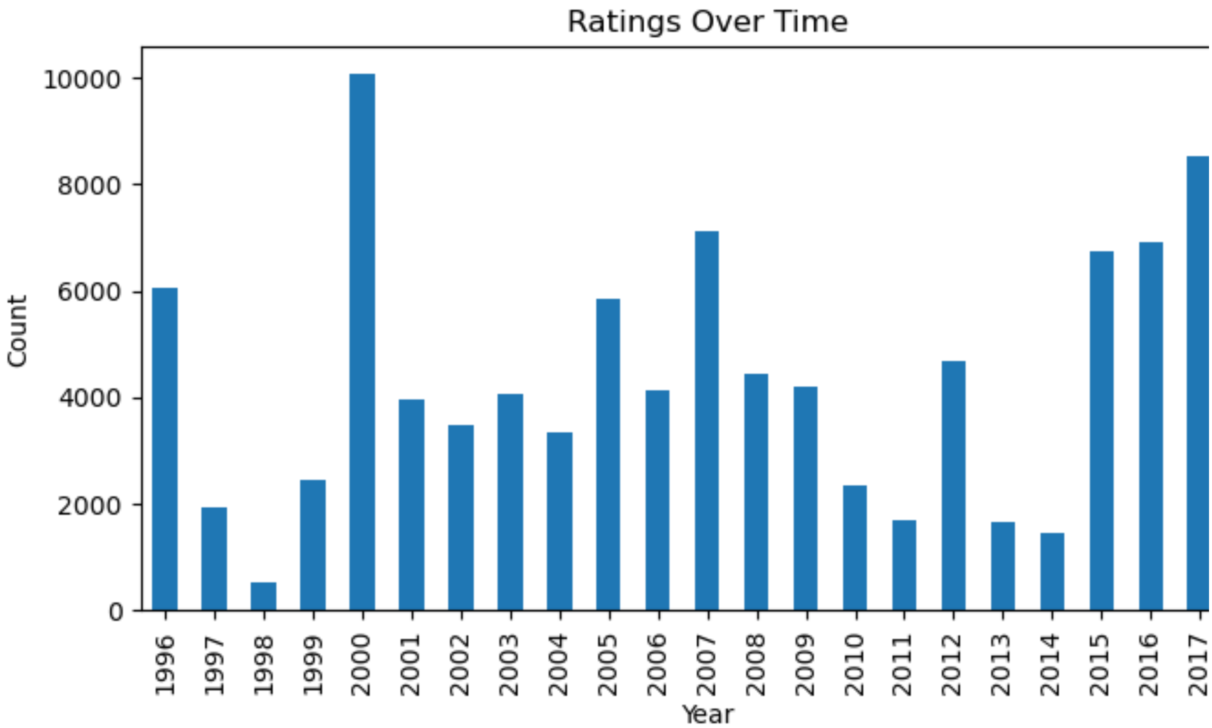



```
In [14]: # rating timestamp analysis;if ratings show clear temporal trends, keep transfor
if 'rating_timestamp' in df_merged.columns:
    df_merged['rating_timestamp'] = pd.to_datetime(df_merged['rating_timestamp']
    df_merged['rating_year'] = df_merged['rating_timestamp'].dt.year

    print("\n=== Ratings per Year ===")
    print(df_merged['rating_year'].value_counts().sort_index().head())
```

```
    df_merged['rating_year'].value_counts().sort_index().plot(kind="bar", figsiz
    plt.title("Ratings Over Time")
    plt.xlabel("Year")
    plt.ylabel("Count")
    plt.show()
```

```
=== Ratings per Year ===
rating_year
1996     6040
1997     1916
1998      507
1999     2439
2000    10074
Name: count, dtype: int64
```



In [15]:
```
# Tag analysis; if too sparse, may not be useful
if 'tag' in df_merged.columns:
    print("\n=== Most Common Tags ===")
    print(df_merged['tag'].value_counts().head(10))

    tag_missing_ratio = df_merged['tag'].isnull().mean()
    print(f"Tag missing ratio: {tag_missing_ratio:.2f}")
```

```
=== Most Common Tags ===
tag
In Netflix queue     55
atmospheric          36
Disney               23
superhero            23
funny                23
surreal              23
religion             22
thought-provoking    22
quirky               21
psychology           20
Name: count, dtype: int64
Tag missing ratio: 0.97
```

In [16]:
```python
# Genre analysis
if 'genres' in df_merged.columns:
    print("\n=== Most Common Genres ===")
    print(df_merged['genres'].value_counts().head(10))
```

```
=== Most Common Genres ===
genres
Comedy                                 7250
Drama                                  6403
Comedy|Romance                         4001
Comedy|Drama|Romance                   3039
Drama|Romance                          2880
Comedy|Drama                           2863
Action|Adventure|Sci-Fi                2430
Crime|Drama                            2347
Action|Crime|Thriller                  1574
Action|Adventure|Sci-Fi|Thriller       1463
Name: count, dtype: int64
```

In [17]:
```python
#  External IDs analysis
if 'imdbId' in df_merged.columns and 'tmdbId' in df_merged.columns:
    print("\n=== External IDs Info ===")
    print("Unique imdbIds:", df_merged['imdbId'].nunique())
    print("Unique tmdbIds:", df_merged['tmdbId'].nunique())
```

```
=== External IDs Info ===
Unique imdbIds: 9724
Unique tmdbIds: 9715
```

In [18]:
```python
# Final dataframe selection
Df_columns_keep = ['userId', 'movieId', 'rating', 'rating_year', 'genres','title
df_final = df_merged[Df_columns_keep]
df_final.head()
```

Out[18]:

	userId	movieId	rating	rating_year	genres	
0	1	1	4.0	2000	Adventure|Animation|Children|Comedy|Fantasy	Toy Stor
1	1	3	4.0	2000	Comedy|Romance	Grumpier (
2	1	6	4.0	2000	Action|Crime|Thriller	Hea
3	1	47	5.0	2000	Mystery|Thriller	Seven (a.k.a
4	1	50	5.0	2000	Crime|Mystery|Thriller	Usual Suspe

Data Preprocessing

In [19]:
```python
# Encode categorical features
user_enc = LabelEncoder()
movie_enc = LabelEncoder()
genre_enc = LabelEncoder()
title_enc = LabelEncoder()

df_final['userId_enc'] = user_enc.fit_transform(df_final['userId'])
df_final['movieId_enc'] = movie_enc.fit_transform(df_final['movieId'])
df_final['genres_enc'] = genre_enc.fit_transform(df_final['genres'].astype(str))
df_final['title_enc'] = title_enc.fit_transform(df_final['title'])
```

In [20]:
```
# Features (X) and Target (y)
X = df_final[['userId_enc', 'movieId_enc', 'rating_year', 'genres_enc','title_er
y = df_final['rating']
```

In [21]:
```
# Split ratings data into train and test sets
train_ratings, test_ratings = train_test_split(df_final, test_size=0.2, random_s

# Create user-movie matrix
user_movie_matrix_train = train_ratings.pivot_table(index='userId', columns='mov
user_movie_matrix_test = test_ratings.pivot_table(index='userId', columns='movie

# Align dimensions;if test has unseen users/movies
user_movie_matrix_test = user_movie_matrix_test.reindex(index=range(n_users), cc
user_movie_matrix_train= user_movie_matrix_train.reindex(index=range(n_users), c

X_train = user_movie_matrix_train.values
y_train = user_movie_matrix_train.values
```

In [33]:
```
# Display shape and a sample
print("Matrix shape:", user_movie_matrix_train.shape)
user_movie_matrix_train.head()
```

Matrix shape: (610, 9724)

Out[33]:

movieId	0	1	2	3	4	5	6	7	8	9	...	9714	9715	9716	9717	9718	9
userId																	
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	
1	0.0	4.0	0.0	4.0	0.0	0.0	4.0	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	
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	
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	

5 rows × 9724 columns

In [35]:
```
# Compute user-user similarity matrix
user_similarity = cosine_similarity(user_movie_matrix_train)
user_similarity_df = pd.DataFrame(
    user_similarity,
    index=user_movie_matrix_train.index,
    columns=user_movie_matrix_train.index
)
# Display a sample
user_similarity_df.head()
```

Out[35]:

userId	0	1	2	3	4	5	6	7	8
userId									
0	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.0	1.000000	0.034755	0.039183	0.165461	0.137692	0.124770	0.143811	0.135497
2	0.0	0.034755	1.000000	0.000000	0.000000	0.041284	0.064996	0.068174	0.000000
3	0.0	0.039183	0.000000	1.000000	0.002961	0.006385	0.003619	0.000000	0.006890
4	0.0	0.165461	0.000000	0.002961	1.000000	0.130157	0.085226	0.125647	0.048075

5 rows × 610 columns

Define pipeline and Gridsearchcv

In [23]:

```
# Define pipeline
pipe = Pipeline([
    ("imputer", SimpleImputer(strategy="constant", fill_value=0)),
    ('scaler', StandardScaler()),
    ("svd", TruncatedSVD()),
    ("ridge", Ridge()),
])
# Hyperparameter grid
param_grid = {
    "svd__n_components": [20, 50, 100],
    "ridge__alpha": [0.01, 0.1, 1, 10]
}

# Cross-validation
cv = KFold(n_splits=5, shuffle=True, random_state=42)

grid = GridSearchCV(pipe, param_grid, cv=cv, scoring="neg_mean_squared_error", v
 # Fit on training matrix (users × movies)
grid.fit(X_train, y_train)


print("Best Params:", grid.best_params_)
print("Best CV Score (MSE):", -grid.best_score_)
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
Best Params: {'ridge__alpha': 1, 'svd__n_components': 100}
Best CV Score (MSE): 0.10228348384991699
```

Make predicton and Model evaluation

In [25]:

```
   # Predictions for test users
preds = grid.best_estimator_.predict(user_movie_matrix_test.values)

# Compute RMSE
y_true, y_pred = [], []
for row in range(user_movie_matrix_test.shape[0]):
    for col in range(user_movie_matrix_test.shape[1]):
        if user_movie_matrix_test.iloc[row, col] > 0:  # only evaluate on actual
            y_true.append(user_movie_matrix_test.iloc[row, col])
            y_pred.append(preds[row, col])

rmse = np.sqrt(mean_squared_error(y_true, y_pred))
print("Test RMSE:", rmse)
```

```
Test RMSE: 3.2944222855896497
```

Recommend top 5 movies for a user

In [31]:

```python
def recommend_movies(user_id, preds, df, top_n=5):
    user_idx = user_enc.transform([user_id])[0]
    user_preds = preds[user_idx]

    # Movies already rated by the user
    rated_movies = df[df['userId'] == user_id]['movieId'].values
    rated_items = movie_enc.transform(rated_movies)

    # Exclude rated movies
    user_preds = user_preds.copy()
    user_preds[rated_items] = -np.inf

    # Top-N recommendations
    top_items = np.argsort(user_preds)[-top_n:][::-1]
    movie_ids = movie_enc.inverse_transform(top_items)
    return df[df['movieId'].isin(movie_ids)][['title', 'genres']].drop_duplicate

# Example: recommend for user 1
print(recommend_movies(1, preds, df_final, top_n=5))
```

```
                                            title                   genres
735                            I Love Trouble (1994)            Action|Comedy
753                       Age of Innocence, The (1993)                  Drama
2347                               Virtuosity (1995)  Action|Sci-Fi|Thriller
14411  Cemetery Man (Dellamorte Dellamore) (1994)                  Horror
86979                          Band of the Hand (1986)      Action|Crime|Drama
```

Conclusion and Recommendation

Our recommender system shows that collaborative filtering with matrix factorization can generat and personalized movie suggestions. By using user ratings and key metadata, the model achieve accuracy with an RMSE of 3.29 meaning most recommendations matched user interests. Howeve improve the model, future work should explore hybrid approaches that combine collaborative ar content-based filtering, add time-awareness to capture changing preferences, and focus on incre diversity in recommendations. Overall, this project provides a strong baseline for a movie recommendation engine and a foundation for building more advanced systems.