movie_recommendation

December 8, 2024

[5]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from ast import literal_eval
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.metrics.pairwise import linear_kernel, cosine_similarity
from nltk.stem.snowball import SnowballStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.corpus import wordnet
from surprise import Reader, Dataset, SVD
from surprise.model_selection import cross_validate

import warnings; warnings.simplefilter('ignore')
```

[6]:
```
f_path=r'/Users/91950/Documents/293C-Add/movies_metadata.csv'
md = pd. read_csv(f_path)
md.head()
```

[6]:
```
   adult                              belongs_to_collection    budget  \
0  False  {'id': 10194, 'name': 'Toy Story Collection', …  30000000
1  False                                                NaN  65000000
2  False  {'id': 119050, 'name': 'Grumpy Old Men Collect…         0
3  False                                                NaN  16000000
4  False  {'id': 96871, 'name': 'Father of the Bride Col…         0

                                              genres  \
0  [{'id': 16, 'name': 'Animation'}, {'id': 35, '…
1  [{'id': 12, 'name': 'Adventure'}, {'id': 14, '…
2  [{'id': 10749, 'name': 'Romance'}, {'id': 35, …
3  [{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam…
4                     [{'id': 35, 'name': 'Comedy'}]

                               homepage     id    imdb_id original_language  \
0  http://toystory.disney.com/toy-story    862  tt0114709                en
1                                   NaN   8844  tt0113497                en
```

```
2                                  NaN  15602  tt0113228                en
3                                  NaN  31357  tt0114885                en
4                                  NaN  11862  tt0113041                en

                original_title  \
0                    Toy Story
1                      Jumanji
2             Grumpier Old Men
3            Waiting to Exhale
4  Father of the Bride Part II

                                            overview  … release_date  \
0  Led by Woody, Andy's toys live happily in his …  …   1995-10-30
1  When siblings Judy and Peter discover an encha…  …   1995-12-15
2  A family wedding reignites the ancient feud be…  …   1995-12-22
3  Cheated on, mistreated and stepped on, the wom…  …   1995-12-22
4  Just when George Banks has recovered from his …  …   1995-02-10

       revenue runtime                                   spoken_languages  \
0  373554033.0    81.0           [{'iso_639_1': 'en', 'name': 'English'}]
1  262797249.0   104.0  [{'iso_639_1': 'en', 'name': 'English'}, {'iso…
2          0.0   101.0           [{'iso_639_1': 'en', 'name': 'English'}]
3   81452156.0   127.0           [{'iso_639_1': 'en', 'name': 'English'}]
4   76578911.0   106.0           [{'iso_639_1': 'en', 'name': 'English'}]

     status                                          tagline  \
0  Released                                              NaN
1  Released           Roll the dice and unleash the excitement!
2  Released  Still Yelling. Still Fighting. Still Ready for…
3  Released  Friends are the people who let you be yourself…
4  Released  Just When His World Is Back To Normal… He's …

                         title  video vote_average vote_count
0                    Toy Story  False          7.7     5415.0
1                      Jumanji  False          6.9     2413.0
2             Grumpier Old Men  False          6.5       92.0
3            Waiting to Exhale  False          6.1       34.0
4  Father of the Bride Part II  False          5.7      173.0

[5 rows x 24 columns]
```

[7]:
```python
md['genres'] = md['genres'].fillna('[]').apply(literal_eval).apply(lambda x: [i['name'] for i in x] if isinstance(x, list) else [])
```

[8]:
```python
vote_counts = md[md['vote_count'].notnull()]['vote_count'].astype('int')
vote_averages = md[md['vote_average'].notnull()]['vote_average'].astype('int')
C = vote_averages.mean()
```

```
C
```

[8]: 5.244896612406511

[9]:
```
m = vote_counts.quantile(0.95)
m
```

[9]: 434.0

[10]:
```
md['year'] = pd.to_datetime(md['release_date'], errors='coerce').apply(lambda x:
 ↪ str(x).split('-')[0] if x != np.nan else np.nan)
```

[11]:
```
qualified = md[(md['vote_count'] >= m) & (md['vote_count'].notnull()) &␣
 ↪(md['vote_average'].notnull())][['title', 'year', 'vote_count',␣
 ↪'vote_average', 'popularity', 'genres']]
qualified['vote_count'] = qualified['vote_count'].astype('int')
qualified['vote_average'] = qualified['vote_average'].astype('int')
qualified.shape
```

[11]: (2274, 6)

[12]:
```
def weighted_rating(x):
    v = x['vote_count']
    R = x['vote_average']
    return (v/(v+m) * R) + (m/(m+v) * C)
```

[13]:
```
qualified['wr'] = qualified.apply(weighted_rating, axis=1)
```

[14]:
```
qualified = qualified.sort_values('wr', ascending=False).head(250)
```

[15]:
```
qualified.head(15)
```

[15]:

	title	year	vote_count	\
15480	Inception	2010	14075	
12481	The Dark Knight	2008	12269	
22879	Interstellar	2014	11187	
2843	Fight Club	1999	9678	
4863	The Lord of the Rings: The Fellowship of the Ring	2001	8892	
292	Pulp Fiction	1994	8670	
314	The Shawshank Redemption	1994	8358	
7000	The Lord of the Rings: The Return of the King	2003	8226	
351	Forrest Gump	1994	8147	
5814	The Lord of the Rings: The Two Towers	2002	7641	
256	Star Wars	1977	6778	
1225	Back to the Future	1985	6239	
834	The Godfather	1972	6024	
1154	The Empire Strikes Back	1980	5998	
46	Se7en	1995	5915	

```
       vote_average  popularity  \
15480             8   29.108149
12481             8  123.167259
22879             8   32.213481
2843              8   63.869599
4863              8   32.070725
292               8  140.950236
314               8   51.645403
7000              8   29.324358
351               8   48.307194
5814              8   29.423537
256               8   42.149697
1225              8   25.778509
834               8   41.109264
1154              8   19.470959
46                8    18.45743

                                                  genres        wr
15480  [Action, Thriller, Science Fiction, Mystery, A…  7.917588
12481                 [Drama, Action, Crime, Thriller]  7.905871
22879              [Adventure, Drama, Science Fiction]  7.897107
2843                                           [Drama]  7.881753
4863                     [Adventure, Fantasy, Action]  7.871787
292                                  [Thriller, Crime]  7.868660
314                                     [Drama, Crime]  7.864000
7000                     [Adventure, Fantasy, Action]  7.861927
351                          [Comedy, Drama, Romance]  7.860656
5814                     [Adventure, Fantasy, Action]  7.851924
256               [Adventure, Action, Science Fiction]  7.834205
1225      [Adventure, Comedy, Science Fiction, Family]  7.820813
834                                     [Drama, Crime]  7.814847
1154              [Adventure, Action, Science Fiction]  7.814099
46                           [Crime, Mystery, Thriller]  7.811669
```

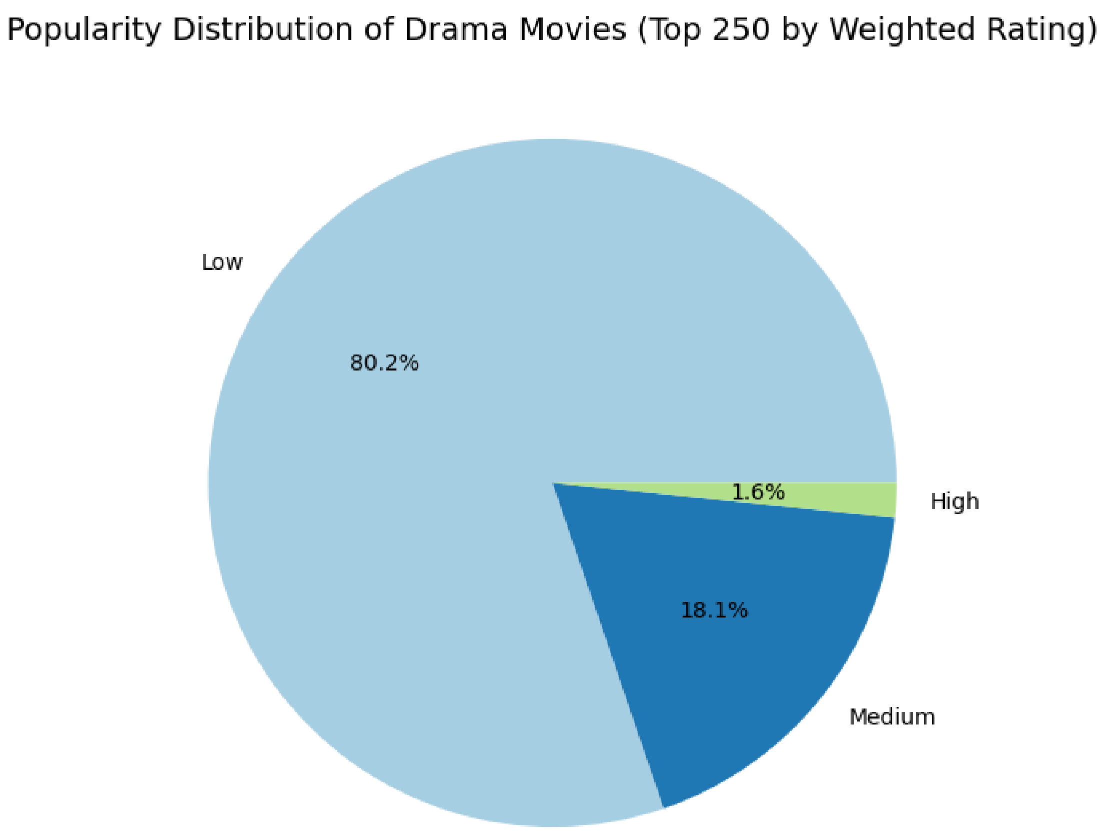
[16]:
```
s = md.apply(lambda x: pd.Series(x['genres']),axis=1).stack().
 ↪reset_index(level=1, drop=True)
s.name = 'genre'
gen_md = md.drop('genres', axis=1).join(s)
```

[19]:
```
import matplotlib.pyplot as plt
import pandas as pd

def build_chart(genre, percentile=0.85):
    # Filter the dataframe for the selected genre
    df = gen_md[gen_md['genre'] == genre]
```

```python
    # Extract necessary columns and clean data
    vote_counts = df[df['vote_count'].notnull()]['vote_count'].astype('int')
    vote_averages = df[df['vote_average'].notnull()]['vote_average'].
↪astype('int')
    C = vote_averages.mean()
    m = vote_counts.quantile(percentile)

    # Select qualified movies based on vote count and vote average thresholds
    qualified = df[(df['vote_count'] >= m) & (df['vote_count'].notnull()) &␣
↪(df['vote_average'].notnull())][['title', 'year', 'vote_count',␣
↪'vote_average', 'popularity']]
    qualified['vote_count'] = qualified['vote_count'].astype('int')
    qualified['vote_average'] = qualified['vote_average'].astype('int')

    # Calculate weighted rating (wr)
    qualified['wr'] = qualified.apply(lambda x: (x['vote_count']/
↪(x['vote_count']+m) * x['vote_average']) + (m/(m+x['vote_count']) * C),␣
↪axis=1)

    # Sort the movies by weighted rating and select top 250
    qualified = qualified.sort_values('wr', ascending=False).head(250)

    # Ensure the 'popularity' column is numeric, and drop rows with NaN values␣
↪in popularity
    qualified['popularity'] = pd.to_numeric(qualified['popularity'],␣
↪errors='coerce')
    qualified = qualified.dropna(subset=['popularity'])

    # Create a pie chart based on 'popularity' (you can choose another feature␣
↪like 'vote_average' or 'wr' if desired)
    popularity_bins = ['Low', 'Medium', 'High']
    # Define thresholds for categorizing popularity
    qualified['popularity_category'] = pd.cut(qualified['popularity'], bins=[0,␣
↪20, 60, 100], labels=popularity_bins)

    # Get the count of each popularity category
    popularity_counts = qualified['popularity_category'].value_counts()

    # Plot the pie chart with multiple colors
    plt.figure(figsize=(7, 7))
    plt.pie(popularity_counts, labels=popularity_counts.index, autopct='%1.
↪1f%%', colors=plt.cm.Paired.colors)
    plt.title(f'Popularity Distribution of {genre} Movies (Top 250 by Weighted␣
↪Rating)', fontsize=14)
    plt.show()
```

```
    # Return the filtered DataFrame
    return qualified
```

[20]:
```
build_chart('Drama').head(25)
```



[20]:
```
                           title  year  vote_count  vote_average  \
10309  Dilwale Dulhania Le Jayenge  1995         661             9
12481              The Dark Knight  2008       12269             8
22879                 Interstellar  2014       11187             8
2843                    Fight Club  1999        9678             8
314       The Shawshank Redemption  1994        8358             8
351                   Forrest Gump  1994        8147             8
834                  The Godfather  1972        6024             8
24860           The Imitation Game  2014        5895             8
359                  The Lion King  1994        5520             8
18465             The Intouchables  2011        5410             8
22841     The Grand Budapest Hotel  2014        4644             8
586       The Silence of the Lambs  1991        4549             8
```

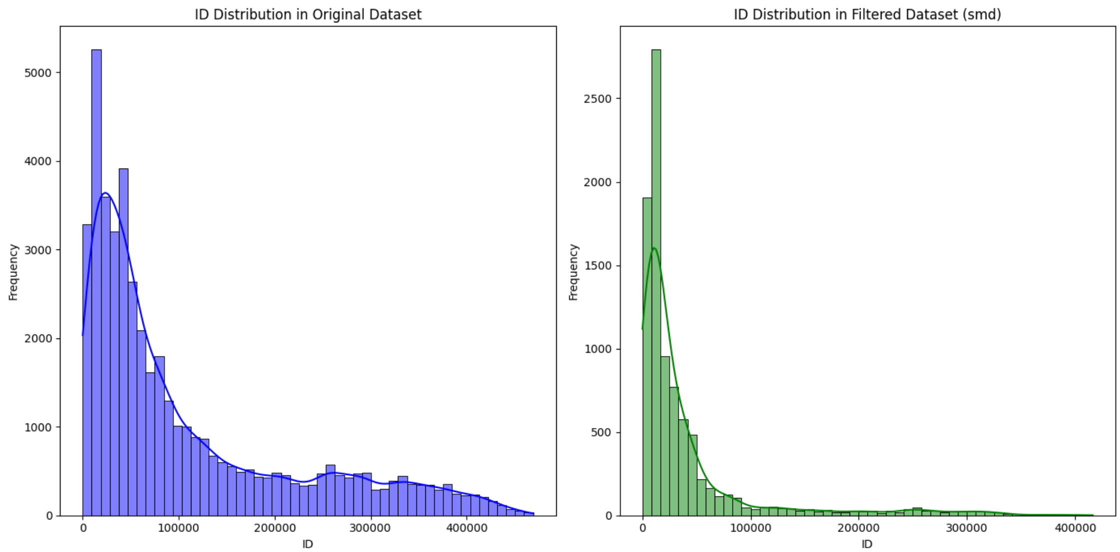
```
11354                    The Prestige  2006        4510            8
522                  Schindler's List  1993        4436            8
23673                        Whiplash  2014        4376            8
289              Leon: The Professional  1994        4293            8
3030                   The Green Mile  1999        4166            8
2211                Life Is Beautiful  1997        3643            8
1163                A Clockwork Orange  1971        3432            8
1178             The Godfather: Part II  1974        3418            8
49                 The Usual Suspects  1995        3334            8
1170                        GoodFellas  1990        3211            8
2216                American History X  1998        3120            8
4135                         Scarface  1983        3017            8
1152   One Flew Over the Cuckoo's Nest  1975        3001            8

       popularity        wr popularity_category
10309   34.457024  8.607205              Medium
12481  123.167259  7.983111                 NaN
22879   32.213481  7.981489              Medium
2843    63.869599  7.978628                High
314     51.645403  7.975286              Medium
351     48.307194  7.974653              Medium
834     41.109264  7.965843              Medium
24860   31.595940  7.965106              Medium
359     21.605761  7.962771              Medium
18465   16.086919  7.962025                 Low
22841   14.442048  7.955873                 Low
586      4.307222  7.954968                 Low
11354   16.945560  7.954586                 Low
522     41.725123  7.953842              Medium
23673   64.299990  7.953222                High
289     20.477329  7.952334              Medium
3030    19.966780  7.950910                 Low
2211    39.394970  7.944021              Medium
1163    17.112594  7.940662                 Low
1178    36.629307  7.940425              Medium
49      16.302466  7.938961                 Low
1170    15.424092  7.936682                 Low
2216    18.157166  7.934884                 Low
4135    11.299673  7.932721                 Low
1152    35.529554  7.932372              Medium
```

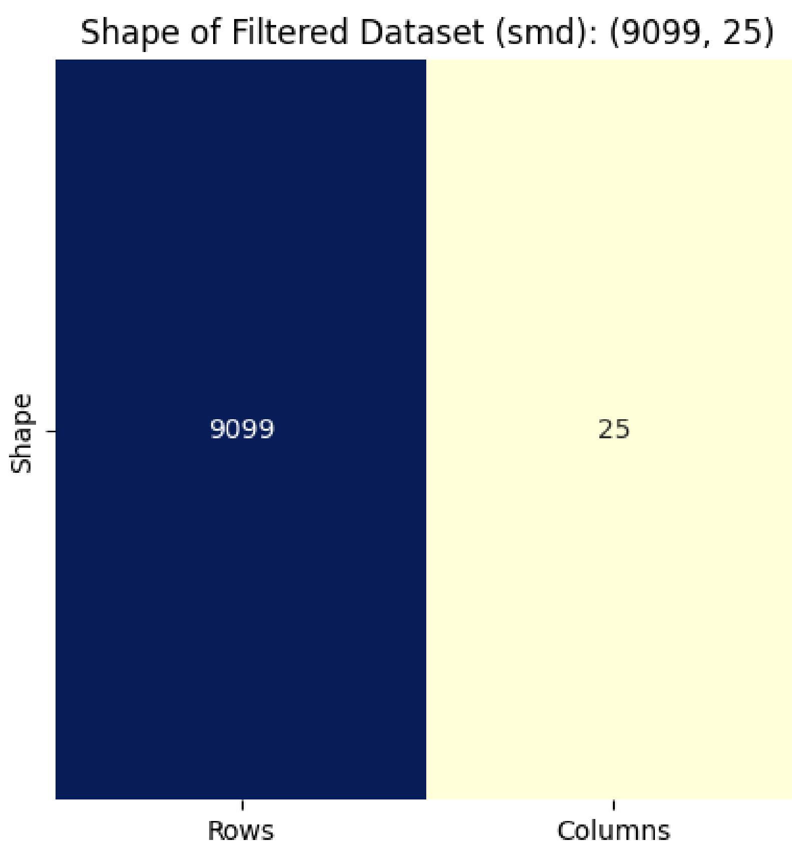
[25]:
```
f_path=r'/Users/91950/Documents/293C-Add/links_small.csv'
links_small = pd.read_csv(f_path)
links_small = links_small[links_small['tmdbId'].notnull()]['tmdbId'].
 ↪astype('int')
```

[26]:
```
md = md.drop([19730, 29503, 35587])
```

[29]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Assuming md is a DataFrame and links_small is a list or array of IDs
md['id'] = md['id'].astype('int')

# Filter the dataset based on 'id' in 'links_small'
smd = md[md['id'].isin(links_small)]

# Plot the distribution of 'id' in the original dataset and the filtered one
plt.figure(figsize=(14, 7))

# Plot the distribution of 'id' in the original dataset
plt.subplot(1, 2, 1)
sns.histplot(md['id'], bins=50, kde=True, color='blue')
plt.title("ID Distribution in Original Dataset")
plt.xlabel("ID")
plt.ylabel("Frequency")

# Plot the distribution of 'id' in the filtered dataset (smd)
plt.subplot(1, 2, 2)
sns.histplot(smd['id'], bins=50, kde=True, color='green')
plt.title("ID Distribution in Filtered Dataset (smd)")
plt.xlabel("ID")
plt.ylabel("Frequency")

plt.tight_layout()
plt.show()

# Now print the shape of the filtered dataset as a graph representation
smd_shape = smd.shape
plt.figure(figsize=(5, 5))
sns.heatmap([[smd_shape[0], smd_shape[1]]], annot=True, fmt='d', cmap="YlGnBu",␣
↪cbar=False,
            xticklabels=["Rows", "Columns"], yticklabels=["Shape"])
plt.title(f"Shape of Filtered Dataset (smd): {smd_shape}")
plt.show()
```


ID Distribution in Original Dataset
ID Distribution in Filtered Dataset (smd)
Frequency
ID
0
100000
200000
300000
400000
1000
2000
3000
4000
5000
500
1500
2500


Shape of Filtered Dataset (smd): (9099, 25)
Shape
9099
25
Rows
Columns

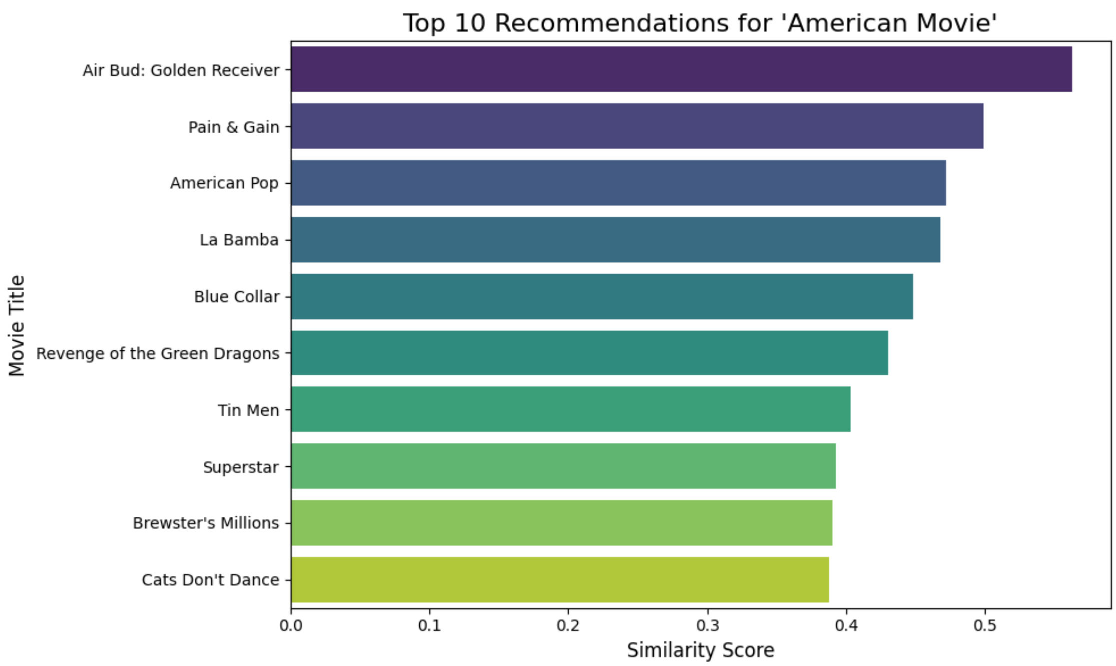
[37]:
```python
smd['tagline'] = smd['tagline'].fillna('')
smd['description'] = smd['overview'] + smd['tagline']
smd['description'] = smd['description'].fillna('')
tf = TfidfVectorizer(analyzer='word', ngram_range=(1, 2), min_df=0.01,␣
↪stop_words='english')
tfidf_matrix = tf.fit_transform(smd['description'])
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
cosine_sim[0]
```

[37]:
```
array([1.        , 0.        , 0.        , …, 0.        , 0.06566461,
       0.        ])
```

[38]:
```python
smd = smd.reset_index()
titles = smd['title']
indices = pd.Series(smd.index, index=smd['title'])
```

[53]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

def get_recommendations_with_graph(title, top_n=10):
    # Get the index of the movie that matches the title
    idx = indices[title]

    # Get the similarity scores for the movie
    sim_scores = list(enumerate(cosine_sim[idx]))

    # Sort the movies based on similarity scores
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)

    # Get the top N similar movie indices (excluding the original movie)
    sim_scores = sim_scores[1:top_n+1]
    movie_indices = [i[0] for i in sim_scores]

    # Get the corresponding movie titles and similarity scores
    recommended_titles = titles.iloc[movie_indices]
    similarity_scores = [x[1] for x in sim_scores]

    # Create a DataFrame for easier manipulation
    recommendations_df = pd.DataFrame({
        'Movie Title': recommended_titles,
        'Similarity Score': similarity_scores
    })

    # Set up the plot
    plt.figure(figsize=(10, 6))
```

```python
    # Create a horizontal bar plot using seaborn
    sns.barplot(x='Similarity Score', y='Movie Title', data=recommendations_df,
 ↪palette='viridis')

    # Title and labels
    plt.title(f"Top {top_n} Recommendations for '{title}'", fontsize=16)
    plt.xlabel('Similarity Score', fontsize=12)
    plt.ylabel('Movie Title', fontsize=12)

    # Show the plot
    plt.tight_layout()
    plt.show()

    return recommendations_df

# Example usage
get_recommendations_with_graph('American Movie')
```



[53]:

	Movie Title	Similarity Score
1707	Air Bud: Golden Receiver	0.562491
8283	Pain & Gain	0.499357
2973	American Pop	0.472206
2773	La Bamba	0.467615
2645	Blue Collar	0.448342
8623	Revenge of the Green Dragons	0.430133

```
1129                        Tin Men          0.403227
2329                      Superstar          0.392529
3208              Brewster's Millions        0.389989
1198                 Cats Don't Dance        0.388185
```

[64]:
```python
from sklearn.model_selection import train_test_split
import pandas as pd

# Load the data
f_path = r'/Users/91950/Documents/293C-Add/ratings_small.csv'
ratings = pd.read_csv(f_path)

# Split the data into train and test sets using sklearn's train_test_split
train_df, test_df = train_test_split(ratings, test_size=0.2, random_state=42)

# Setup Reader and load the dataset
reader = Reader()
train_data = Dataset.load_from_df(train_df[['userId', 'movieId', 'rating']],␣
 ↪reader)
test_data = Dataset.load_from_df(test_df[['userId', 'movieId', 'rating']],␣
 ↪reader)

# Check the first few rows of the ratings data
ratings.head()
```

[64]:

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205

[66]:
```python
svd = SVD()
results = cross_validate(svd, 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)    0.8939  0.8967  0.8951  0.9005  0.8903  0.8953  0.0033
MAE (testset)     0.6869  0.6907  0.6895  0.6930  0.6843  0.6889  0.0030
Fit time          1.28    1.63    1.62    1.34    1.34    1.44    0.15
Test time         0.48    0.25    0.20    0.16    0.13    0.24    0.12
```

[68]:
```python
trainset = data.build_full_trainset()
svd.fit(trainset)
```

[68]: <surprise.prediction_algorithms.matrix_factorization.SVD at 0x1aa91f8c830>

[69]:
```python
ratings[ratings['userId'] == 1]
```

[69]:

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205
5	1	1263	2.0	1260759151
6	1	1287	2.0	1260759187
7	1	1293	2.0	1260759148
8	1	1339	3.5	1260759125
9	1	1343	2.0	1260759131
10	1	1371	2.5	1260759135
11	1	1405	1.0	1260759203
12	1	1953	4.0	1260759191
13	1	2105	4.0	1260759139
14	1	2150	3.0	1260759194
15	1	2193	2.0	1260759198
16	1	2294	2.0	1260759108
17	1	2455	2.5	1260759113
18	1	2968	1.0	1260759200
19	1	3671	3.0	1260759117

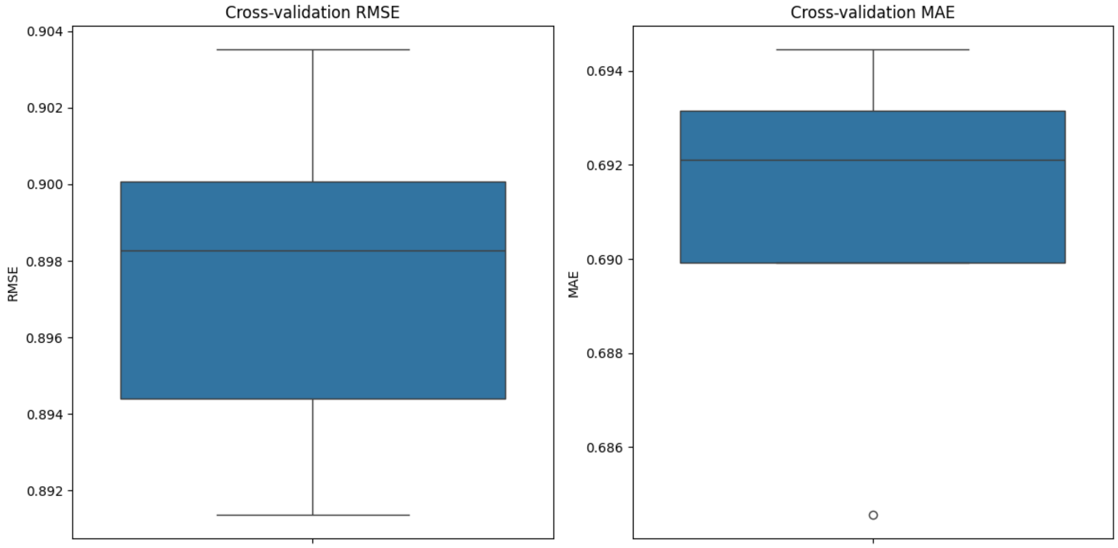
[70]:
```python
svd.predict(1, 302, 3)
```

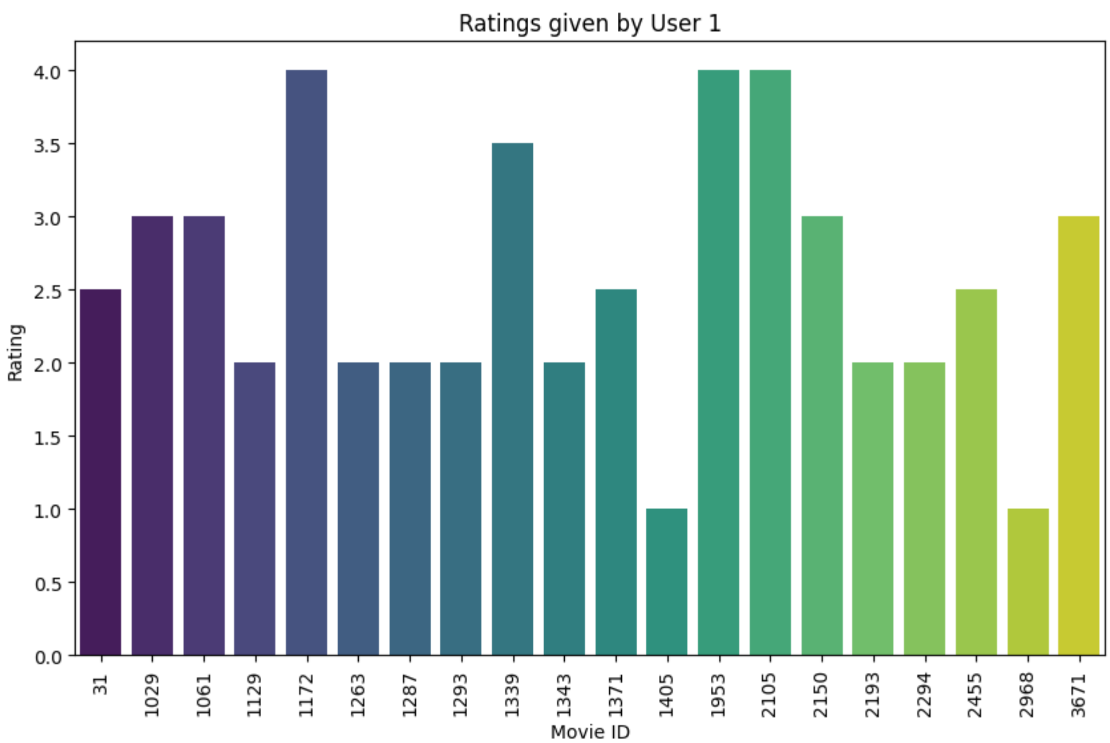
[70]:
```
Prediction(uid=1, iid=302, r_ui=3, est=2.8230487751680573,
details={'was_impossible': False})
```

[71]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
from surprise import SVD, Dataset, Reader
from surprise.model_selection import cross_validate
import pandas as pd

# Load the data
f_path = r'/Users/91950/Documents/293C-Add/ratings_small.csv'
ratings = pd.read_csv(f_path)

# Setup Reader and load the dataset
reader = Reader()
data = Dataset.load_from_df(ratings[['userId', 'movieId', 'rating']], reader)

# Create an SVD model
svd = SVD()

# Evaluate the model using cross-validation
```

```
results = cross_validate(svd, data, measures=['RMSE', 'MAE'], cv=5,␣
 ↪verbose=True)

# Plot RMSE and MAE results from cross-validation
cv_results = pd.DataFrame(results)
plt.figure(figsize=(12, 6))

# Plot RMSE
plt.subplot(1, 2, 1)
sns.boxplot(data=cv_results['test_rmse'])
plt.title('Cross-validation RMSE')
plt.ylabel('RMSE')

# Plot MAE
plt.subplot(1, 2, 2)
sns.boxplot(data=cv_results['test_mae'])
plt.title('Cross-validation MAE')
plt.ylabel('MAE')

plt.tight_layout()
plt.show()

# Train the model on the full training set
trainset = data.build_full_trainset()
svd.fit(trainset)

# Show ratings for userId 1
user_ratings = ratings[ratings['userId'] == 1]

# Plot a bar chart of ratings for userId 1
plt.figure(figsize=(10, 6))
sns.barplot(x='movieId', y='rating', data=user_ratings, palette='viridis')
plt.title('Ratings given by User 1')
plt.xlabel('Movie ID')
plt.ylabel('Rating')
plt.xticks(rotation=90)
plt.show()
```

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8914  0.9035  0.8983  0.8944  0.9001  0.8975  0.0043
MAE (testset)     0.6846  0.6945  0.6921  0.6899  0.6932  0.6908  0.0035
Fit time          1.31    1.26    1.14    1.28    1.24    1.25    0.06
Test time         0.17    0.13    0.16    0.16    0.42    0.21    0.11
```


Cross-validation RMSE
Cross-validation MAE
RMSE
MAE
0.904
0.902
0.900
0.898
0.896
0.894
0.892
0.694
0.692
0.690
0.688
0.686


Ratings given by User 1
Rating
Movie ID
31
1029
1061
1129
1172
1263
1287
1293
1339
1343
1371
1405
1953
2105
2150
2193
2294
2455
2968
3671

[ ]: