Data Loading and Pre-Processing

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Load the datasets with the specified encoding
movies = pd.read_csv('/kaggle/input/movies-dataset/ml-1m/movies.dat',
sep='::', header=None, names=['movieid', 'title', 'genres'],
engine='python', encoding='ISO-8859-1')
ratings =
pd.read_csv('/kaggle/input/movies-dataset/ml-1m/ratings.dat',
sep='::', header=None, names=['userid', 'movieid', 'rating',
'timestamp'], engine='python', encoding='ISO-8859-1')
users = pd.read_csv('/kaggle/input/movies-dataset/ml-1m/users.dat',
sep='::', header=None, names=['userid', 'gender', 'age', 'occupation',
'zipcode'], engine='python', encoding='ISO-8859-1')

# Convert timestamp to datetime for aggregation
ratings['timestamp'] = pd.to_datetime(ratings['timestamp'], unit='s')

# Merge datasets
movies['year'] = movies['title'].str.extract(r'(\d{4})').astype(float)
rating_movies = pd.merge(ratings, movies, on='movieid', how='left')
final_data = pd.merge(rating_movies, users, on='userid', how='left')
current_year = pd.Timestamp.now().year
valid_year_range = (1900, current_year)

# Filter rows with valid years
final_data = final_data[(final_data['year'] >= valid_year_range[0]) &
(final_data['year'] <= valid_year_range[1])]

# Handle missing values
movies.dropna(inplace=True)
ratings.dropna(inplace=True)
users.dropna(inplace=True)
final_data.dropna(inplace=True)

# 1. Discretization
# Discretize 'rating' into Low, Medium, and High categories
bins = [0, 2, 3, 5]
labels = ['Low', 'Medium', 'High']
final_data['rating_category'] = pd.cut(final_data['rating'],
bins=bins, labels=labels, right=True)

# Check the distribution of the discretized ratings
rating_distribution = final_data['rating_category'].value_counts()
print("Discretized Rating Distribution:")
print(rating_distribution)
```

```
Discretized Rating Distribution:
rating_category
High      574893
Medium    260958
Low       163592
Name: count, dtype: int64
```

```python
# 2. Sampling
sampled_data = final_data.groupby('rating_category',
group_keys=False).apply(lambda x: x.sample(frac=0.1))
print("Sampled Data Distribution:")
sampled_data['rating_category'].value_counts()
```

```
Sampled Data Distribution:
```

```
/tmp/ipykernel_30/4085315540.py:3: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
  sampled_data = final_data.groupby('rating_category',
group_keys=False).apply(lambda x: x.sample(frac=0.1))
/tmp/ipykernel_30/4085315540.py:3: DeprecationWarning:
DataFrameGroupBy.apply operated on the grouping columns. This behavior
is deprecated, and in a future version of pandas the grouping columns
will be excluded from the operation. Either pass
`include_groups=False` to exclude the groupings or explicitly select
the grouping columns after groupby to silence this warning.
  sampled_data = final_data.groupby('rating_category',
group_keys=False).apply(lambda x: x.sample(frac=0.1))
```

```
rating_category
High      57489
Medium    26096
Low       16359
Name: count, dtype: int64
```

```python
# 3. Aggregation
# Aggregate average ratings by year
ratings_by_year = final_data.groupby('year')
['rating'].mean().reset_index()
print("Average Ratings by Year:")
ratings_by_year
```

```
Average Ratings by Year:
```

	year	rating
0	1900.0	2.950000
1	1919.0	3.466667
2	1920.0	3.666667
3	1921.0	3.790323
4	1922.0	3.991597

```
..      ...       ...
79  1998.0  3.461354
80  1999.0  3.496168
81  2000.0  3.370538
82  2001.0  4.068765
83  2010.0  3.417021

[84 rows x 2 columns]
```

```
# 4. Dimensionality Reduction / Feature Selection
# Drop non-essential features
features_to_drop = ['zipcode', 'timestamp']
final_data_reduced = final_data.drop(columns=features_to_drop)
# Final dataset summary
print("Final Data Info:")
final_data_reduced.info()
```

```
Final Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 10 columns):
 #   Column           Non-Null Count    Dtype
---  ------           --------------    -----
 0   userid           1000209 non-null  int64
 1   movieid          1000209 non-null  int64
 2   rating           1000209 non-null  int64
 3   title            1000209 non-null  object
 4   genres           1000209 non-null  object
 5   year             1000209 non-null  float64
 6   gender           1000209 non-null  object
 7   age              1000209 non-null  int64
 8   occupation       1000209 non-null  int64
 9   rating_category  1000209 non-null  category
dtypes: category(1), float64(1), int64(5), object(3)
memory usage: 69.6+ MB
```

```
final_data.head()
```

```
   userid  movieid  rating           timestamp  \
0       1     1193       5 2000-12-31 22:12:40
1       1      661       3 2000-12-31 22:35:09
2       1      914       3 2000-12-31 22:32:48
3       1     3408       4 2000-12-31 22:04:35
4       1     2355       5 2001-01-06 23:38:11

                                    title
genres  year  \
0  One Flew Over the Cuckoo's Nest (1975)
Drama  1975
1        James and the Giant Peach (1996)  Animation|Children's|
```

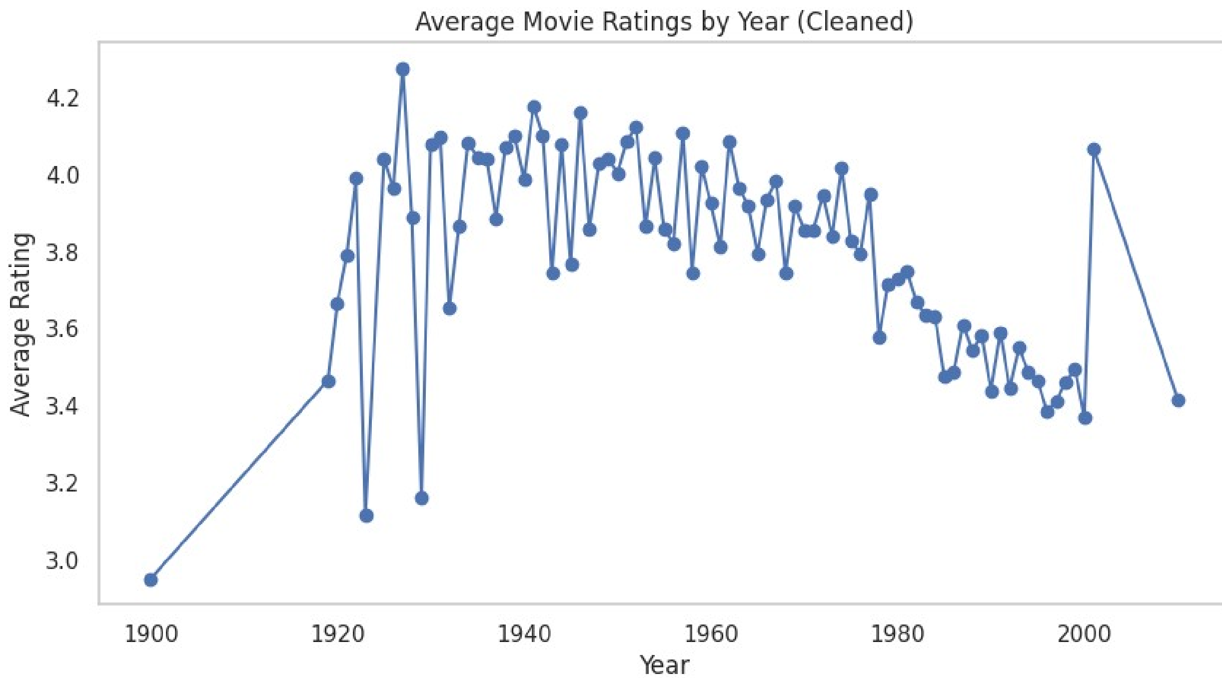
```
Musical  1996
2                      My Fair Lady (1964)               Musical|
Romance  1964
3                   Erin Brockovich (2000)
Drama  2000
4                     Bug's Life, A (1998)   Animation|Children's|
Comedy  1998

  gender  age  occupation zipcode
0      F    1          10   48067
1      F    1          10   48067
2      F    1          10   48067
3      F    1          10   48067
4      F    1          10   48067
```

```
final_data.describe()
```

```
             userid       movieid        rating  \
count  1.000209e+06  1.000209e+06  1.000209e+06
mean   3.024512e+03  1.865540e+03  3.581564e+00
min    1.000000e+00  1.000000e+00  1.000000e+00
25%    1.506000e+03  1.030000e+03  3.000000e+00
50%    3.070000e+03  1.835000e+03  4.000000e+00
75%    4.476000e+03  2.770000e+03  4.000000e+00
max    6.040000e+03  3.952000e+03  5.000000e+00
std    1.728413e+03  1.096041e+03  1.117102e+00

                           timestamp          year           age
occupation
count                        1000209  1.000209e+06  1.000209e+06
1.000209e+06
mean   2000-10-22 19:41:35.404665856  1.987296e+03  2.973831e+01
8.036138e+00
min              2000-04-25 23:05:32  1.600000e+03  1.000000e+00
0.000000e+00
25%              2000-08-03 11:37:17  1.982000e+03  2.500000e+01
2.000000e+00
50%              2000-10-31 18:46:46  1.992000e+03  2.500000e+01
7.000000e+00
75%              2000-11-26 06:42:19  1.997000e+03  3.500000e+01
1.400000e+01
max              2003-02-28 17:49:50  9.000000e+03  5.600000e+01
2.000000e+01
std                              NaN  4.308257e+01  1.175198e+01
6.531336e+00
```

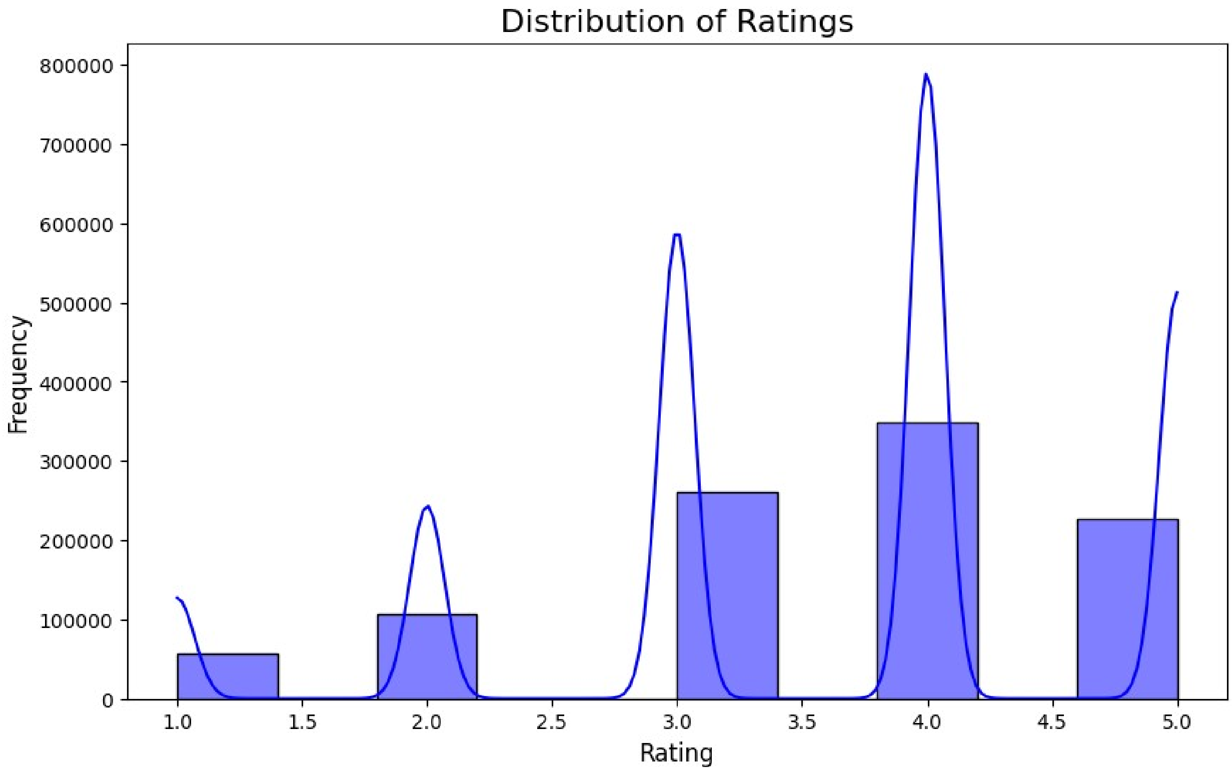
```
# Visualization of ratings over cleaned years
plt.figure(figsize=(10, 5))
plt.plot(ratings_by_year['year'], ratings_by_year['rating'],
marker='o', linestyle='-', color='b')
```

```
plt.title('Average Movie Ratings by Year (Cleaned)')
plt.xlabel('Year')
plt.ylabel('Average Rating')
plt.grid()
plt.show()
```

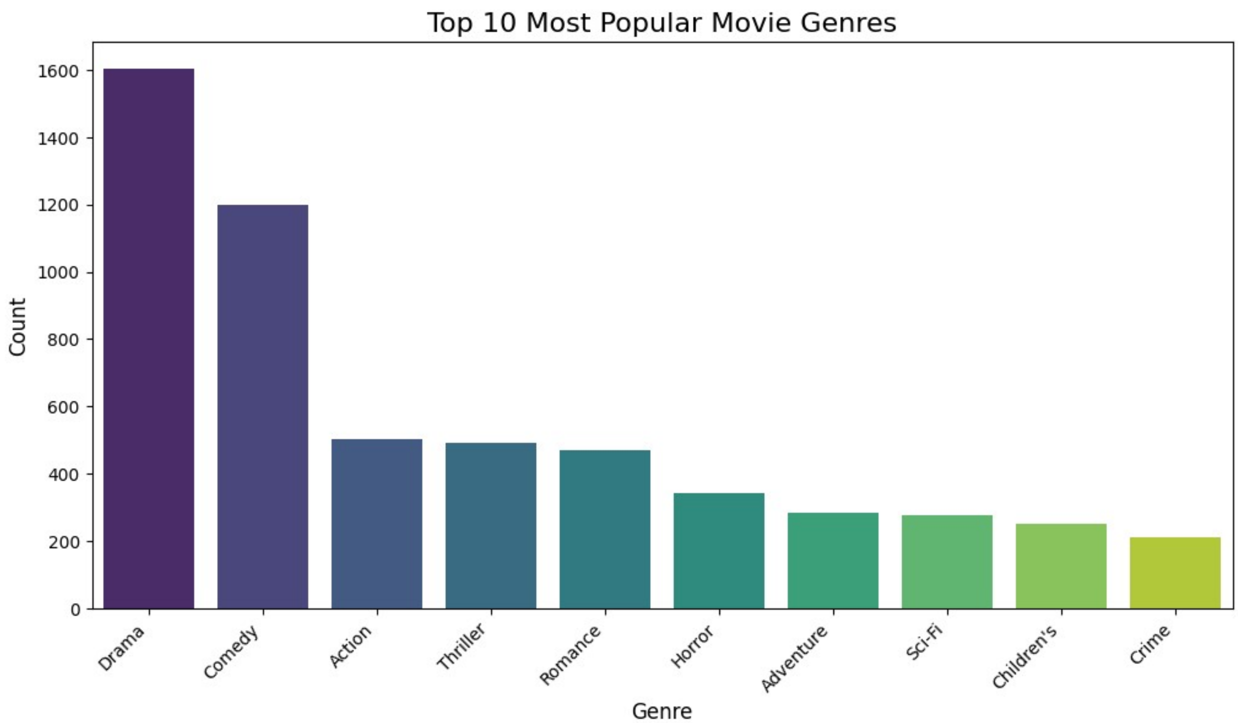


Exploratory Data Analysis

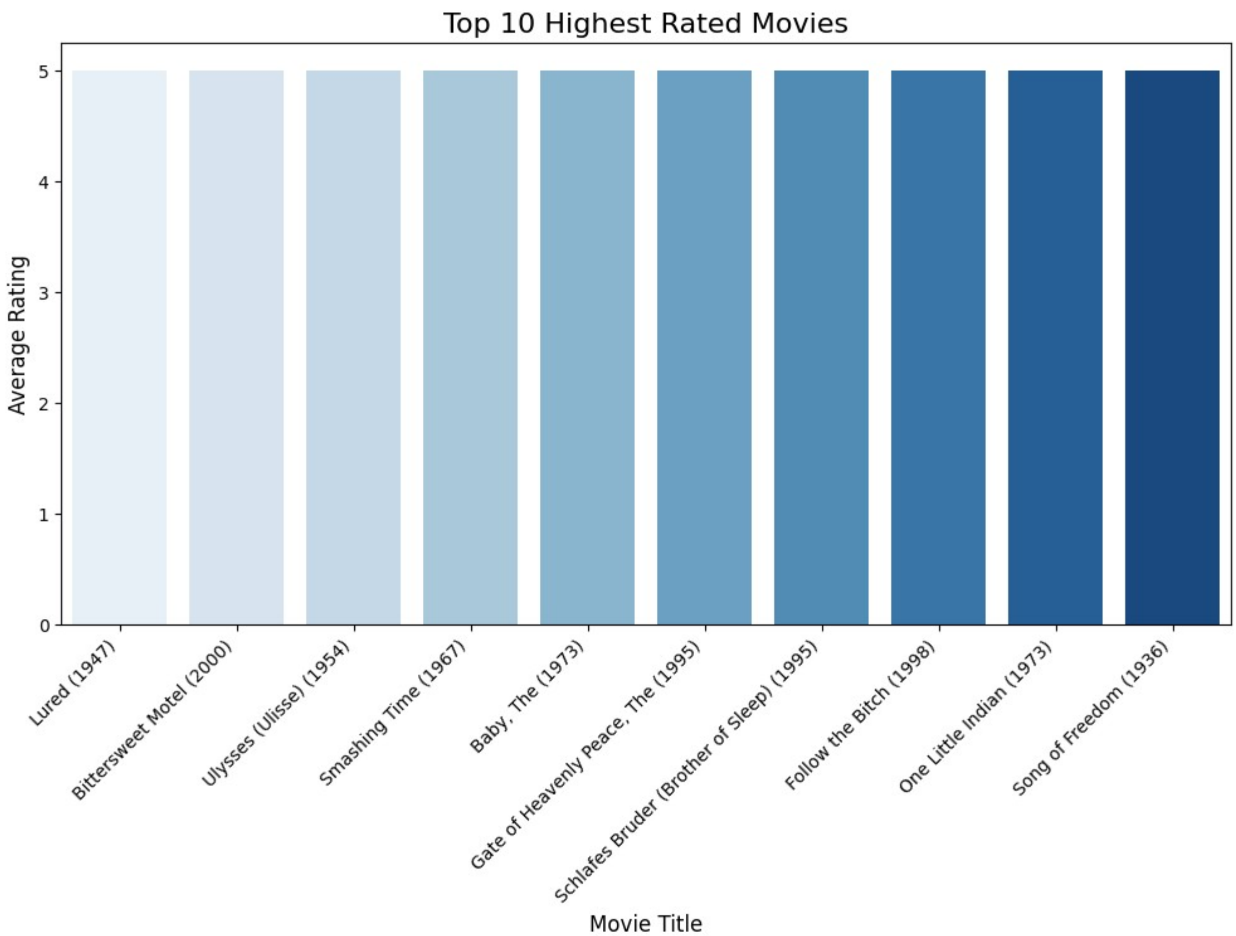
```
# Plot the distribution of ratings
plt.figure(figsize=(10, 6))
sns.histplot(rating['rating'], bins=10, kde=True, color='blue')
plt.title('Distribution of Ratings', fontsize=16)
plt.xlabel('Rating', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.show()

/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



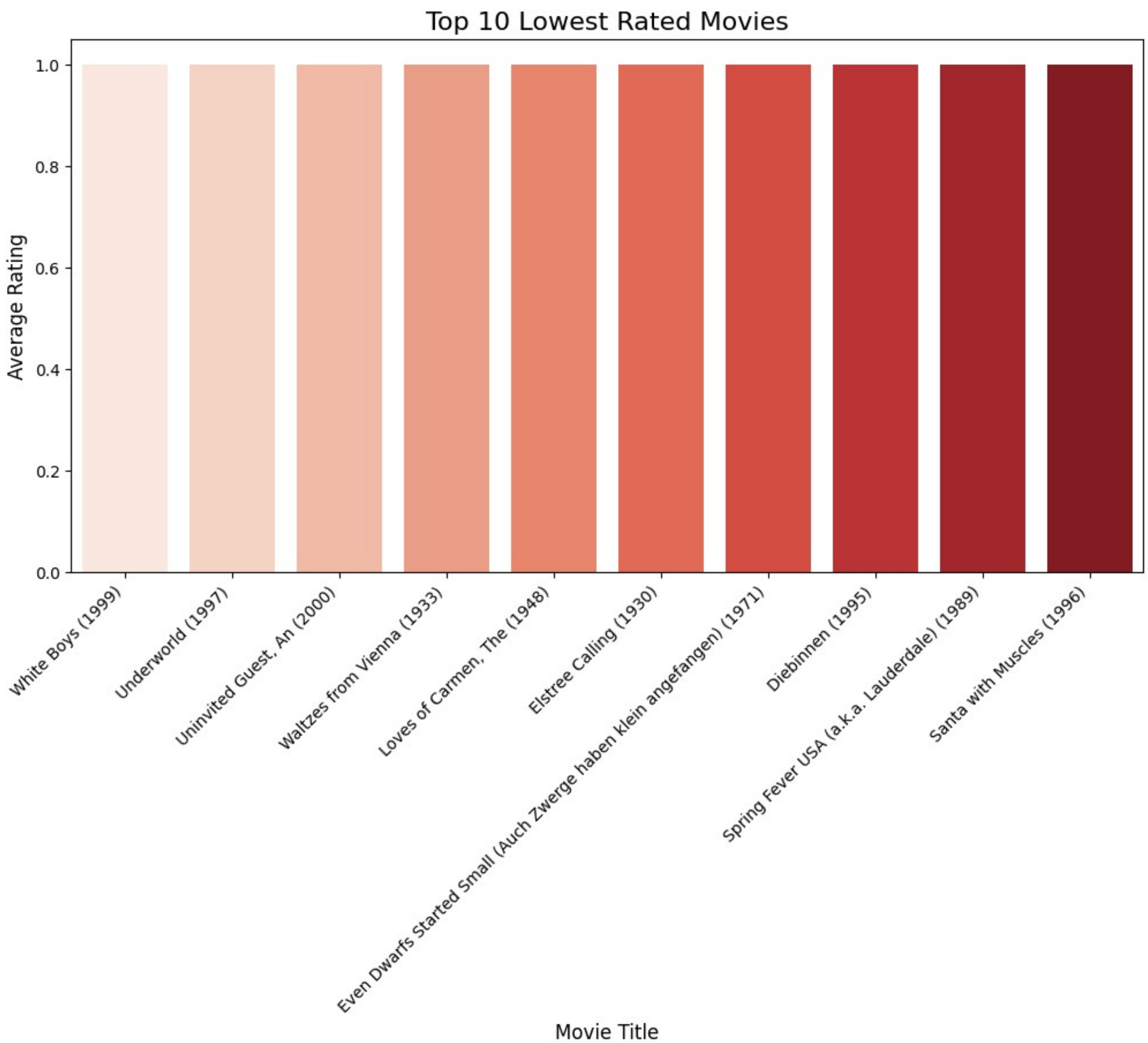

```python
# Frequency of genres from movies
genres_series = movies['genres'].str.split('|', expand=True).stack()
genre_counts = genres_series.value_counts()

# Plot the top 10 most common genres
plt.figure(figsize=(12, 6))
sns.barplot(x=genre_counts.head(10).index,
y=genre_counts.head(10).values, palette='viridis')
plt.title('Top 10 Most Popular Movie Genres', fontsize=16)
plt.xlabel('Genre', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.show()
```




```
# Calculate average rating for each movie
avg_movie_ratings = rating_movies.groupby('title')['rating'].mean()

# Top 10 highest-rated movies
top_movies = avg_movie_ratings.sort_values(ascending=False).head(10)

# Bottom 10 lowest-rated movies
bottom_movies = avg_movie_ratings.sort_values().head(10)

# Plot the top 10 highest-rated movies
plt.figure(figsize=(12, 6))
sns.barplot(x=top_movies.index, y=top_movies.values, palette='Blues')
plt.title('Top 10 Highest Rated Movies', fontsize=16)
plt.xlabel('Movie Title', fontsize=12)
plt.ylabel('Average Rating', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.show()

# Plot the bottom 10 lowest-rated movies
plt.figure(figsize=(12, 6))
sns.barplot(x=bottom_movies.index, y=bottom_movies.values,
palette='Reds')
plt.title('Top 10 Lowest Rated Movies', fontsize=16)
plt.xlabel('Movie Title', fontsize=12)
plt.ylabel('Average Rating', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.show()
```



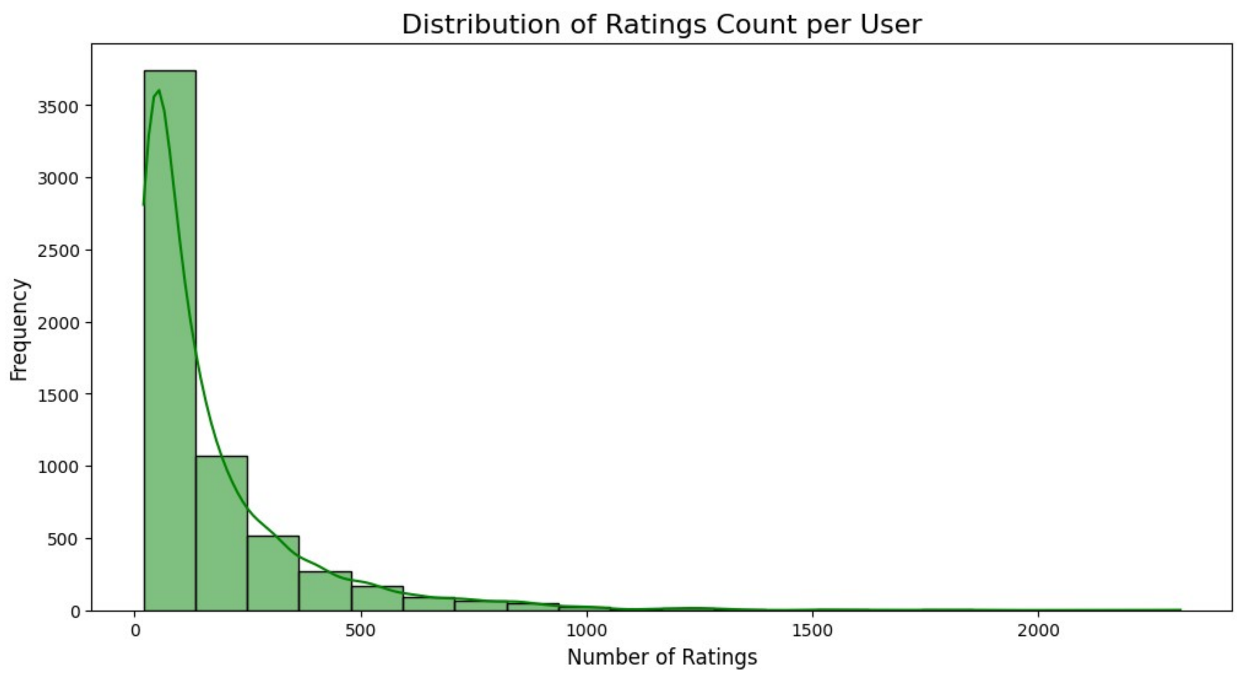
Top 10 Highest Rated Movies
Average Rating
0
1
2
3
4
5
Lured (1947)
Bittersweet Motel (2000)
Ulysses (Ulisse) (1954)
Smashing Time (1967)
Baby, The (1973)
Gate of Heavenly Peace, The (1995)
Schlafes Bruder (Brother of Sleep) (1995)
Follow the Bitch (1998)
One Little Indian (1973)
Song of Freedom (1936)
Movie Title

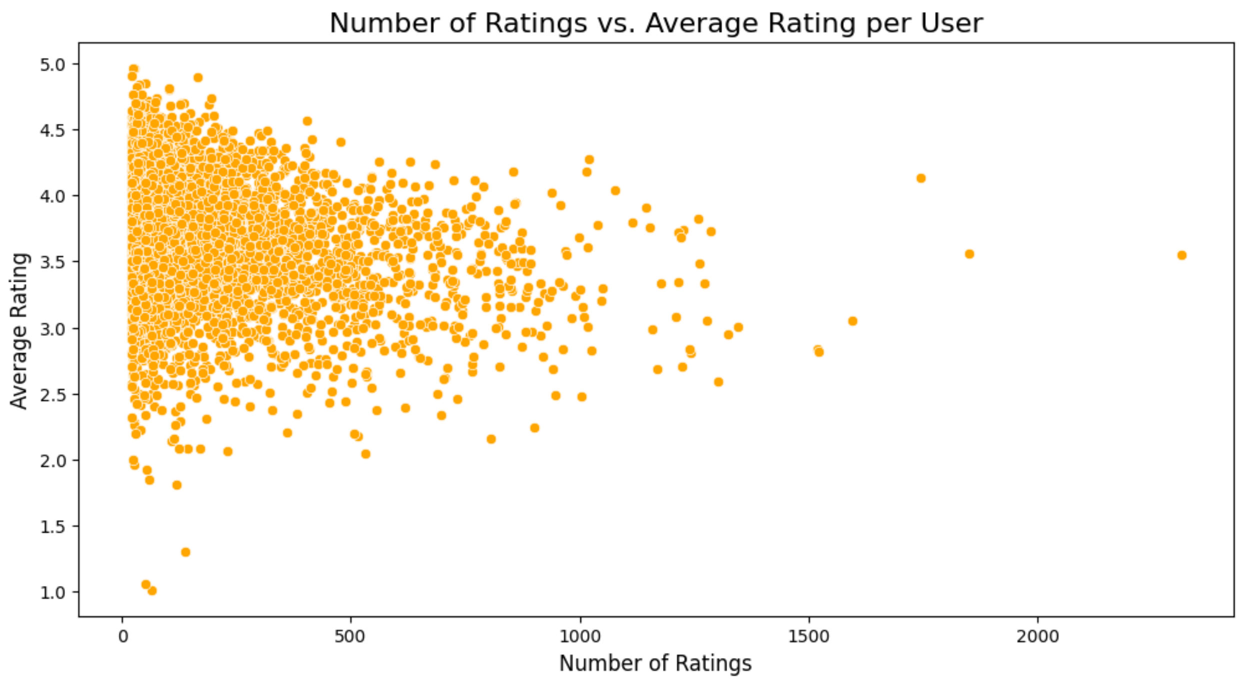



```
# Calculate the number of ratings per user
user_ratings_count = rating.groupby('userid').size()

# Plot the number of ratings per user
plt.figure(figsize=(12, 6))
sns.histplot(user_ratings_count, bins=20, kde=True, color='green')
plt.title('Distribution of Ratings Count per User', fontsize=16)
plt.xlabel('Number of Ratings', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.show()

# Scatter plot of number of ratings vs. average rating
avg_user_rating = rating.groupby('userid')['rating'].mean()

plt.figure(figsize=(12, 6))
sns.scatterplot(x=user_ratings_count, y=avg_user_rating,
```

```
color='orange')
plt.title('Number of Ratings vs. Average Rating per User',
fontsize=16)
plt.xlabel('Number of Ratings', fontsize=12)
plt.ylabel('Average Rating', fontsize=12)
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```





Model Imlementation

Collavorative Filtering

```
def collaborative_filtering(movie_title, top_n=10):
    # Create a pivot table with users as rows and movies as columns
    user_movie_matrix = rating_movies.pivot_table(index='userid',
columns='title', values='rating').fillna(0)

    # Convert the matrix to a sparse format
    user_movie_sparse = csr_matrix(user_movie_matrix.values)

    # Build the model using Nearest Neighbors
    model = NearestNeighbors(metric='cosine', algorithm='brute')
    model.fit(user_movie_sparse.T)  # Transpose to make movies as rows
and users as features

    # Find the index of the given movie
    if movie_title not in user_movie_matrix.columns:
        raise ValueError(f"The movie '{movie_title}' is not found in
the dataset.")
    movie_index = user_movie_matrix.columns.get_loc(movie_title)

    # Calculate distances and indices of nearest neighbors
    distances, indices =
model.kneighbors(user_movie_sparse.T[movie_index], n_neighbors=top_n +
1)

    # Return similar movies
```

```
    similar_movies = [user_movie_matrix.columns[i] for i in
indices.flatten()][1:]  # Exclude the input movie itself
    return similar_movies
```

Content based Filtering

```
# Content-Based Filtering Model
def content_based_filtering(movie_title, top_n=10):
    # Use genres for similarity calculation
    count_vectorizer = CountVectorizer(tokenizer=lambda x:
x.split('|'))
    genre_matrix = count_vectorizer.fit_transform(movies['genres'])

    # Compute cosine similarity
    cosine_sim = cosine_similarity(genre_matrix, genre_matrix)

    # Find the index of the given movie
    movie_index = movies[movies['title'] == movie_title].index[0]

    # Get similarity scores for the movie
    similarity_scores = list(enumerate(cosine_sim[movie_index]))
    similarity_scores = sorted(similarity_scores, key=lambda x: x[1],
reverse=True)

    # Extract the top similar movies
    similar_movies_indices = [i[0] for i in similarity_scores[1:top_n
+ 1]]  # Exclude the input movie itself
    similar_movies = movies.iloc[similar_movies_indices]
['title'].tolist()
    return similar_movies
```

Recommendation System

```
# Unified Recommendation System
def recommend_movies(movie_title, model, top_n=10):
    if model == 'collaborative':
        return collaborative_filtering(movie_title, top_n)
    elif model == 'content':
        return content_based_filtering(movie_title, top_n)
    else:
        raise ValueError("Invalid model type. Choose either
'collaborative' or 'content'.")

# Example Usage
movie_name = "Toy Story (1995)"
print(f"Collaborative Filtering Recommendations for '{movie_name}':")
collab_recommendations = recommend_movies(movie_name,
model='collaborative')
print(pd.DataFrame(collab_recommendations))
```

```
content_recommendations = recommend_movies(movie_name,
model='content')
print(f"\nContent-Based Filtering Recommendations for
'{movie_name}':")
print(pd.DataFrame(content_recommendations))
```

```
Collaborative Filtering Recommendations for 'Toy Story (1995)':
                                                    0
0                                  Toy Story 2 (1999)
1                                Groundhog Day (1993)
2                                      Aladdin (1992)
3                                Bug's Life, A (1998)
4                           Back to the Future (1985)
5                                         Babe (1995)
6  Star Wars: Episode V - The Empire Strikes Back...
7                                 Men in Black (1997)
8                                 Forrest Gump (1994)
9                                  Matrix, The (1999)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/feature_extraction/
text.py:528: UserWarning: The parameter 'token_pattern' will not be
used since 'tokenizer' is not None'
  warnings.warn(
```

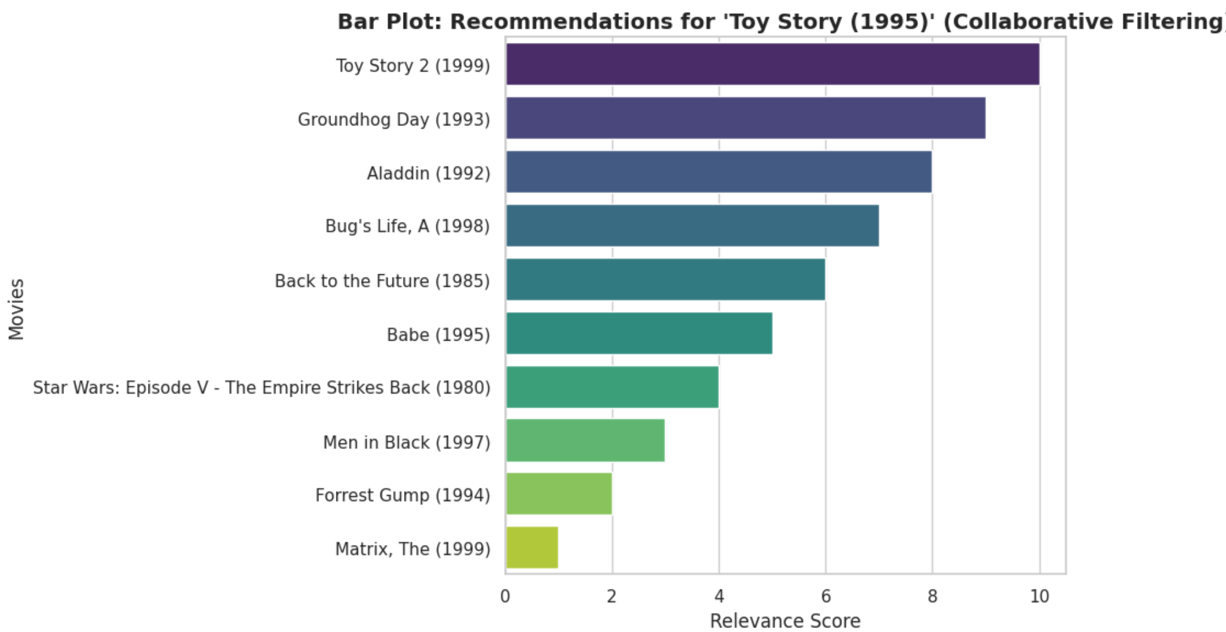
```
Content-Based Filtering Recommendations for 'Toy Story (1995)':
                                                 0
0           Aladdin and the King of Thieves (1996)
1                            American Tail, An (1986)
2       American Tail: Fievel Goes West, An (1991)
3                           Rugrats Movie, The (1998)
4                                Bug's Life, A (1998)
5                                  Toy Story 2 (1999)
6                               Saludos Amigos (1943)
7                                  Chicken Run (2000)
8  Adventures of Rocky and Bullwinkle, The (2000)
9                               Goofy Movie, A (1995)
```

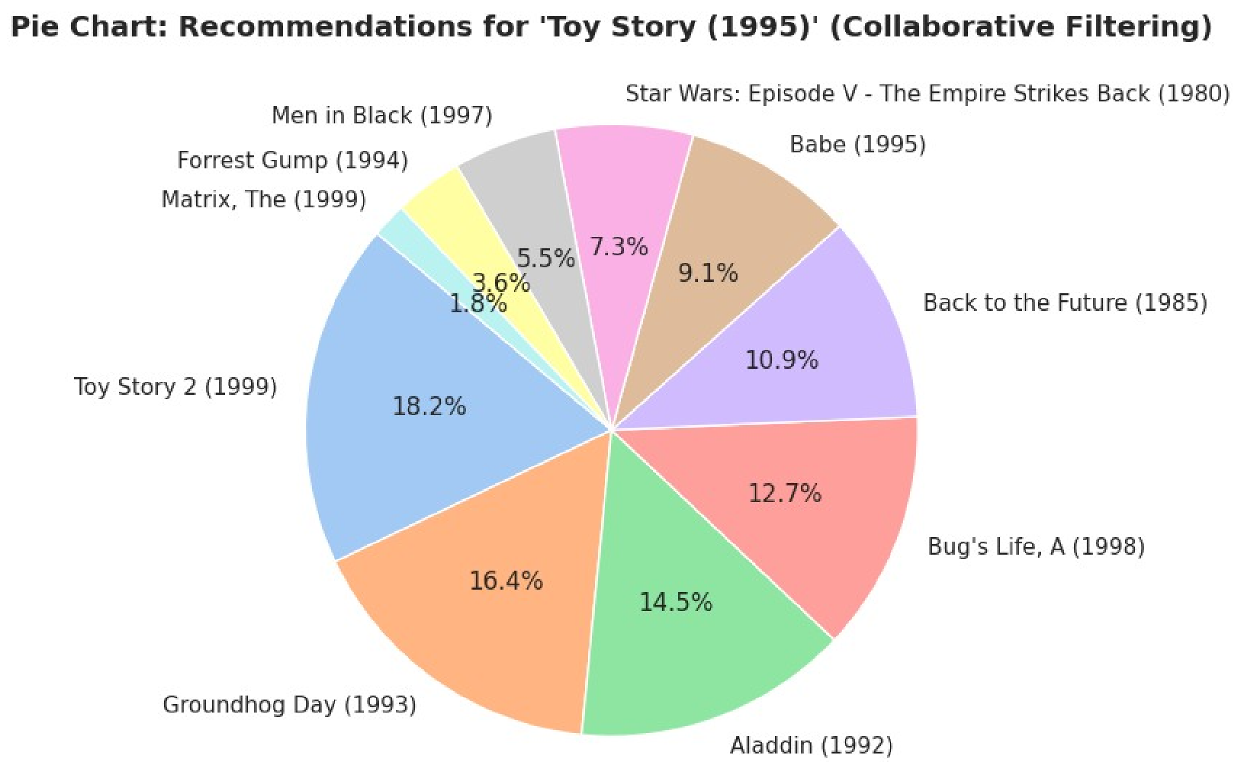
Recommendation Visualization

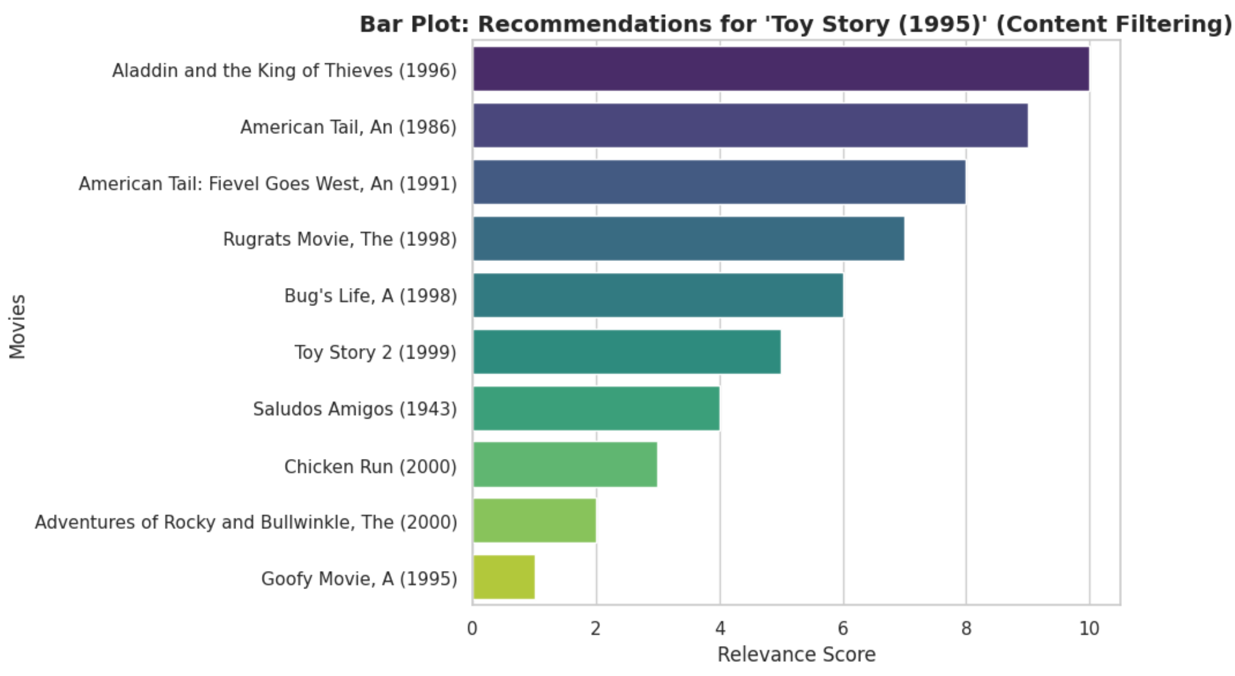
```
import seaborn as sns
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import pandas as pd

def visualize_recommendations(movie_title, recommendations,
model_type):
    if isinstance(recommendations, pd.DataFrame):
        data = recommendations[['title', 'Similarity Score']]  #
Extract the necessary columns for visualization
```

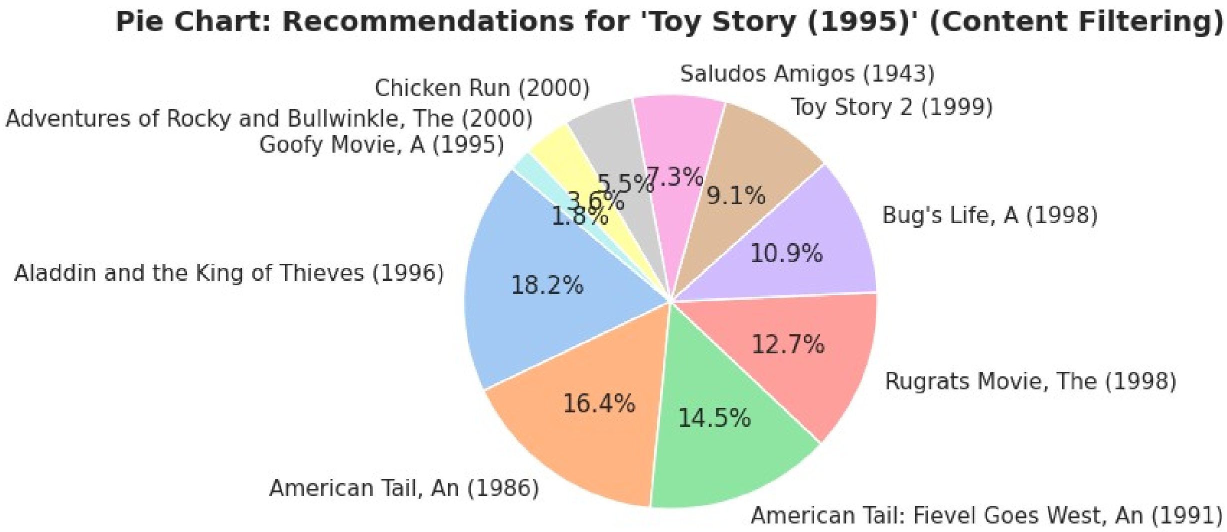
```
        data['Score'] = data['Similarity Score']  # Use the similarity
score for visualization
        recommendations_list = data['title'].tolist()
        scores = data['Score'].tolist()
    else:
        data = pd.DataFrame({'Movie': recommendations, 'Score':
range(len(recommendations), 0, -1)})
        recommendations_list = data['Movie'].tolist()
        scores = data['Score'].tolist()

    sns.set_theme(style="whitegrid")

    # 1. Horizontal Bar Plot
    plt.figure(figsize=(10, 6))
    sns.barplot(
        data=data,
        y='Movie',
        x='Score',
        palette="viridis"
    )
    plt.title(f"Bar Plot: Recommendations for '{movie_title}'
({model_type.title()} Filtering)", fontsize=14, weight='bold')
    plt.xlabel('Relevance Score', fontsize=12)
    plt.ylabel('Movies', fontsize=12)
    plt.tight_layout()
    plt.show()

    # 2. Word Cloud for Movie Titles
    wordcloud = WordCloud(
        background_color='white',
        width=800,
        height=400,
        colormap='plasma'
    ).generate(" ".join(recommendations_list))

    plt.figure(figsize=(10, 6))
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.title(f"Word Cloud: Recommendations for '{movie_title}'
({model_type.title()} Filtering)", fontsize=14, weight='bold')
    plt.tight_layout()
    plt.show()

    # 3. Pie Chart of Recommendations
    plt.figure(figsize=(8, 8))
    colors = sns.color_palette('pastel')[0:len(recommendations_list)]
    plt.pie(scores, labels=recommendations_list, autopct='%1.1f%%',
startangle=140, colors=colors)
    plt.title(f"Pie Chart: Recommendations for '{movie_title}'
({model_type.title()} Filtering)", fontsize=14, weight='bold')
```

```
    plt.tight_layout()
    plt.show()

movie_name = "Toy Story (1995)"
visualize_recommendations(movie_name,collab_recommendations,
model_type='collaborative')

movie_name = "Toy Story (1995)"
visualize_recommendations(movie_name,content_recommendations,
model_type='content')
```




Pie Chart: Recommendations for 'Toy Story (1995)' (Collaborative Filtering)
Star Wars: Episode V - The Empire Strikes Back (1980)
Men in Black (1997)
Forrest Gump (1994)
Matrix, The (1999)
Babe (1995)
Back to the Future (1985)
Toy Story 2 (1999)
Bug's Life, A (1998)
Groundhog Day (1993)
Aladdin (1992)
5.5%
7.3%
9.1%
3.6%
1.8%
10.9%
18.2%
12.7%
16.4%
14.5%


Bar Plot: Recommendations for 'Toy Story (1995)' (Content Filtering)
Aladdin and the King of Thieves (1996)
American Tail, An (1986)
American Tail: Fievel Goes West, An (1991)
Rugrats Movie, The (1998)
Bug's Life, A (1998)
Toy Story 2 (1999)
Saludos Amigos (1943)
Chicken Run (2000)
Adventures of Rocky and Bullwinkle, The (2000)
Goofy Movie, A (1995)
Movies
0
2
4
6
8
10
Relevance Score



SVD Model

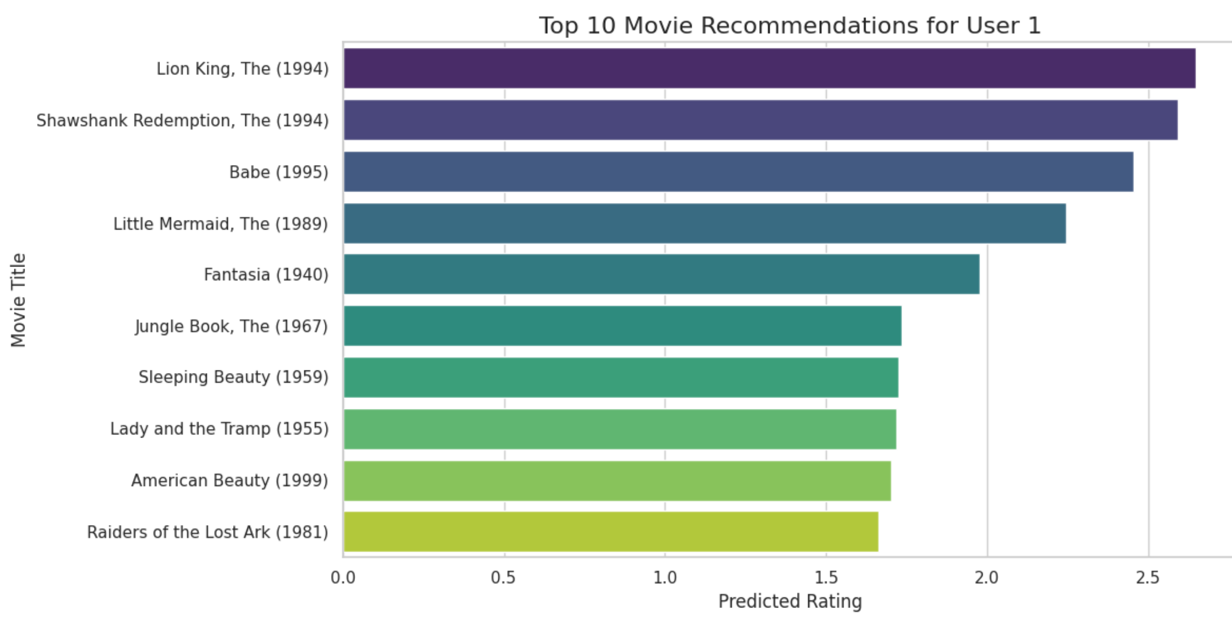
```
from sklearn.decomposition import TruncatedSVD
from sklearn.metrics import mean_squared_error
from scipy.sparse import csr_matrix

# Create a pivot table where rows are user_ids, columns are movie_ids,
and values are ratings
user_movie_matrix = rating.pivot(index='userid', columns='movieid',
values='rating').fillna(0)

# Convert the dataframe to a sparse matrix format
```

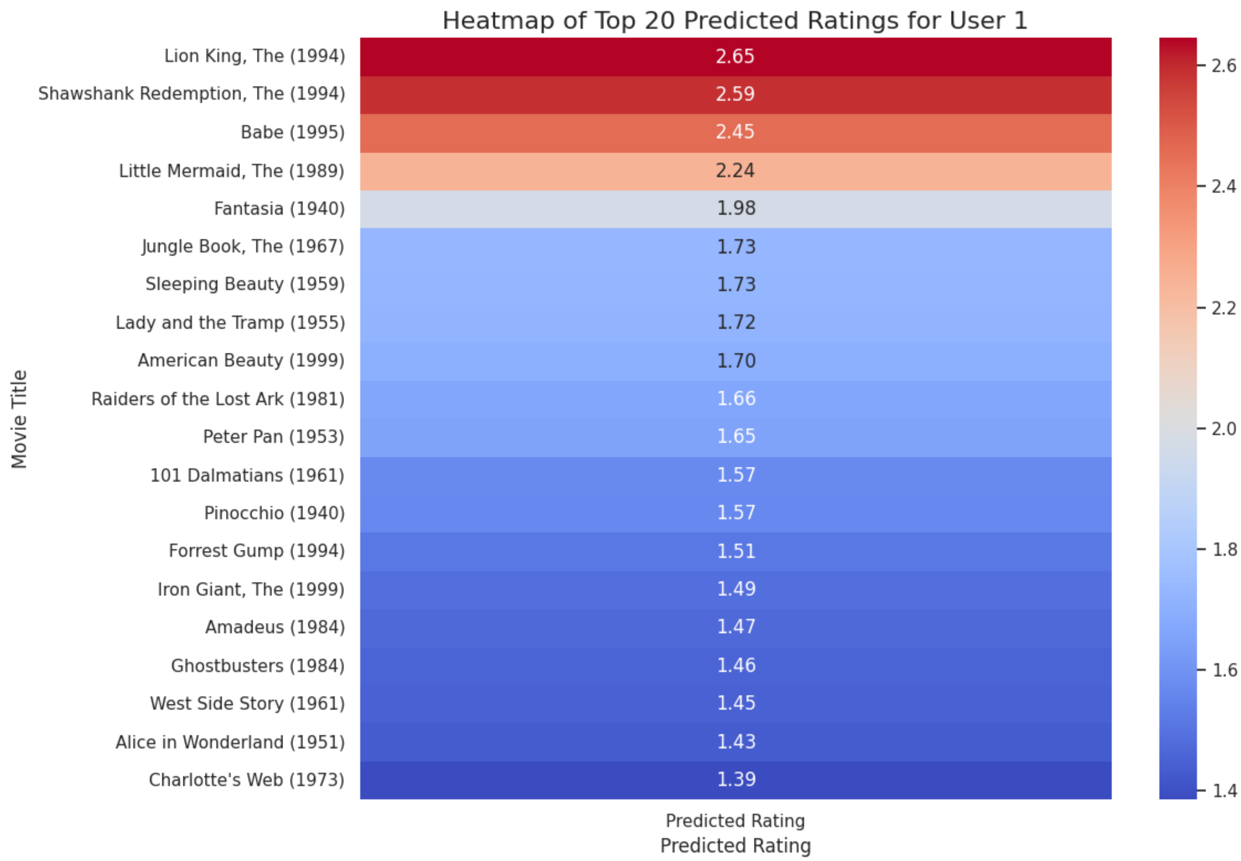
```
matrix = csr_matrix(user_movie_matrix.values)

# Apply SVD (Singular Value Decomposition)
svd = TruncatedSVD(n_components=50, random_state=42)
matrix_svd = svd.fit_transform(matrix)

# Reconstruct the rating matrix
reconstructed_matrix = svd.inverse_transform(matrix_svd)
reconstructed_matrix = pd.DataFrame(reconstructed_matrix,
columns=user_movie_matrix.columns, index=user_movie_matrix.index)

# Calculate Mean Squared Error
mse = mean_squared_error(user_movie_matrix.values,
reconstructed_matrix.values)

# Recommend movies for a specific user (e.g., User 1)
def recommend_movies_for_user(user_id, top_n=10):
    # Get the user's original ratings
    user_ratings = user_movie_matrix.loc[user_id]

    # Get predicted ratings for the user
    user_predictions = reconstructed_matrix.loc[user_id]

    # Filter out movies the user has already rated
    movies_not_watched = user_ratings[user_ratings == 0].index
    recommendations =
user_predictions[movies_not_watched].sort_values(ascending=False).head
(top_n)

    # Map movie IDs to titles
    recommendations = pd.DataFrame({
        'Movie ID': recommendations.index,
        'Predicted Rating': recommendations.values
    })
    recommendations = recommendations.merge(movies[['movieid',
'title']], left_on='Movie ID', right_on='movieid')
    return recommendations[['title', 'Predicted Rating']]

# Visualize top 10 recommended movies for User 1
user_id = 1
recommendations = recommend_movies_for_user(user_id, top_n=10)

print("Top 10 Recommendations:")
print(recommendations)
```

```
Top 10 Recommendations:
                              title  Predicted Rating
0              Lion King, The (1994)          2.645647
1  Shawshank Redemption, The (1994)          2.591461
2                       Babe (1995)          2.454103
```

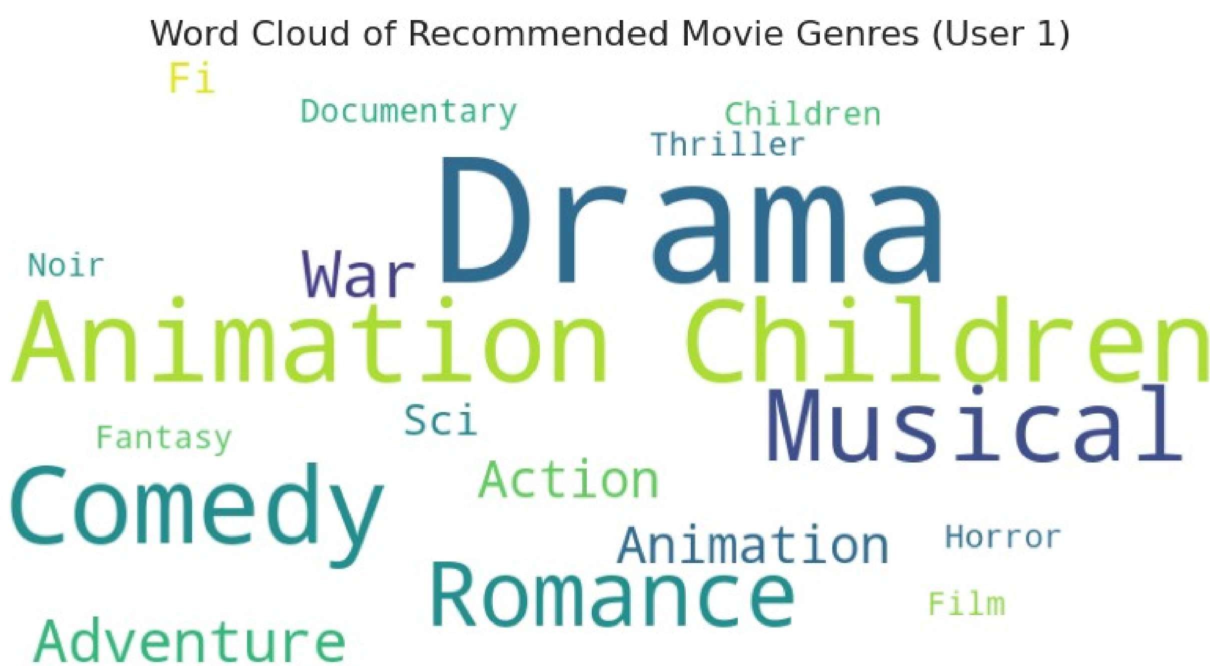
```
3       Little Mermaid, The (1989)          2.244342
4                  Fantasia (1940)          1.975137
5          Jungle Book, The (1967)          1.733368
6           Sleeping Beauty (1959)          1.725543
7        Lady and the Tramp (1955)          1.719660
8           American Beauty (1999)          1.702523
9    Raiders of the Lost Ark (1981)          1.663852

from wordcloud import WordCloud

# Heatmap of predicted ratings for a specific user
def plot_heatmap_for_user(user_id):
    user_predictions = reconstructed_matrix.loc[user_id]
    user_ratings = user_movie_matrix.loc[user_id]

    # Get movies not watched by the user
    unwatched_movies = user_ratings[user_ratings == 0].index
    unwatched_predictions = user_predictions[unwatched_movies]

    # Create a dataframe for heatmap
    heatmap_data = 
unwatched_predictions.sort_values(ascending=False).head(20)
    heatmap_data = heatmap_data.to_frame(name='Predicted 
Rating').reset_index()
    heatmap_data = heatmap_data.merge(movies[['movieid', 'title']], 
left_on='movieid', right_on='movieid')
    heatmap_data.set_index('title', inplace=True)

    plt.figure(figsize=(12, 8))
    sns.heatmap(heatmap_data[['Predicted Rating']], annot=True, 
cmap='coolwarm', fmt=".2f", cbar=True)
    plt.title(f'Heatmap of Top 20 Predicted Ratings for User 
{user_id}', fontsize=16)
    plt.xlabel('Predicted Rating', fontsize=12)
    plt.ylabel('Movie Title', fontsize=12)
    plt.tight_layout()
    plt.show()

# Word Cloud of recommended genres
def plot_genre_wordcloud(user_id, top_n=50):
    recommendations = recommend_movies_for_user(user_id, top_n)
    genres = movies[movies['title'].isin(recommendations['title'])]
['genres'].str.split('|').sum()
    genre_text = ' '.join(genres)

    wordcloud = WordCloud(width=800, height=400, 
background_color='white', colormap='viridis').generate(genre_text)
    plt.figure(figsize=(10, 6))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
```

```
    plt.title(f'Word Cloud of Recommended Movie Genres (User
{user_id})', fontsize=16)
    plt.show()

# Visualize recommendations
user_id = 1
recommendations = recommend_movies_for_user(user_id, top_n=10)

# Bar plot of top recommendations
plt.figure(figsize=(12, 6))
sns.barplot(
    data=recommendations,
    x='Predicted Rating',
    y='title',
    palette='viridis'
)
plt.title(f'Top 10 Movie Recommendations for User {user_id}',
fontsize=16)
plt.xlabel('Predicted Rating', fontsize=12)
plt.ylabel('Movie Title', fontsize=12)
plt.tight_layout()
plt.show()

# Heatmap visualization
plot_heatmap_for_user(user_id)

# Word cloud visualization
plot_genre_wordcloud(user_id, top_n=50)
```





Heatmap of Top 20 Predicted Ratings for User 1
Lion King, The (1994)
Shawshank Redemption, The (1994)
Babe (1995)
Little Mermaid, The (1989)
Fantasia (1940)
Jungle Book, The (1967)
Sleeping Beauty (1959)
Lady and the Tramp (1955)
American Beauty (1999)
Raiders of the Lost Ark (1981)
Peter Pan (1953)
101 Dalmatians (1961)
Pinocchio (1940)
Forrest Gump (1994)
Iron Giant, The (1999)
Amadeus (1984)
Ghostbusters (1984)
West Side Story (1961)
Alice in Wonderland (1951)
Charlotte's Web (1973)
2.65
2.59
2.45
2.24
1.98
1.73
1.73
1.72
1.70
1.66
1.65
1.57
1.57
1.51
1.49
1.47
1.46
1.45
1.43
1.39
Movie Title
Predicted Rating
Predicted Rating
2.6
2.4
2.2
2.0
1.8
1.6
1.4

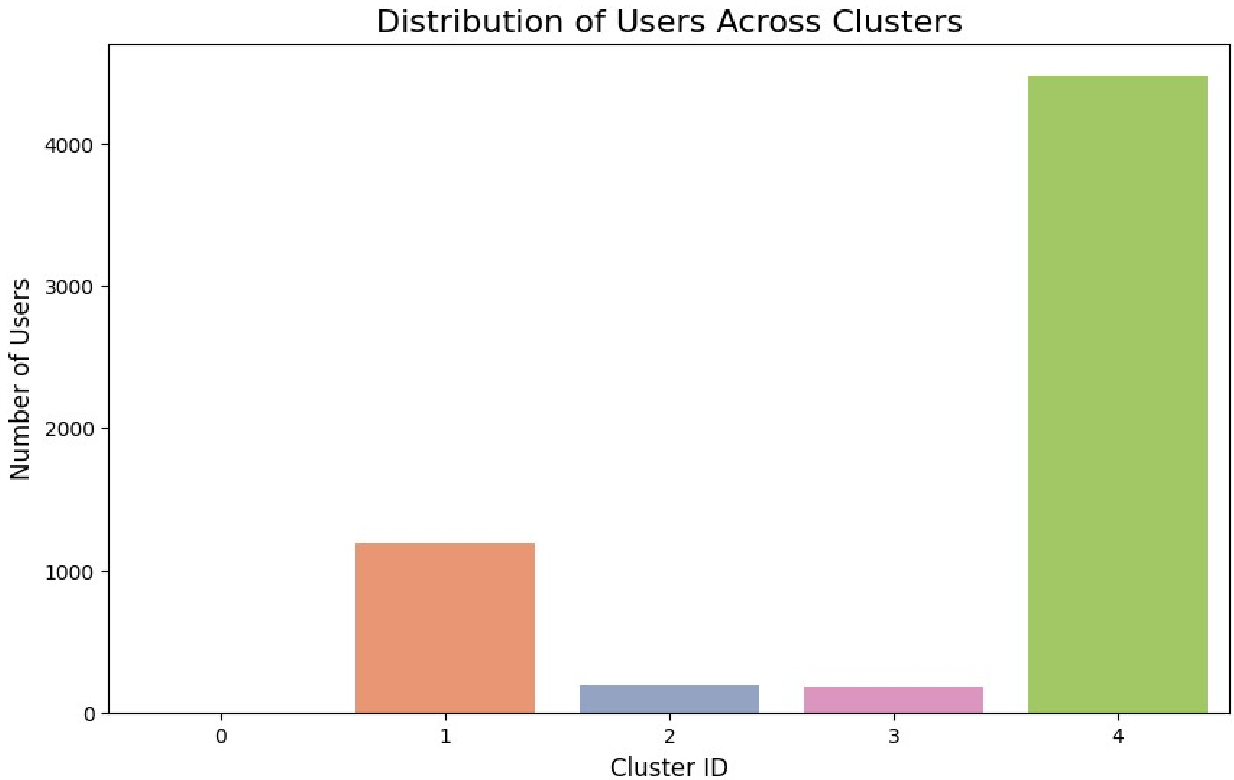


Word Cloud of Recommended Movie Genres (User 1)
Fi
Documentary
Children
Thriller
Drama
Noir
War
Animation Children
Musical
Sci
Fantasy
Action
Comedy
Animation
Horror
Romance
Film
Adventure

K-Mean Clustering

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Standardize the data for clustering
scaler = StandardScaler()
scaled_matrix = scaler.fit_transform(user_movie_matrix)

# Apply KMeans clustering
kmeans = KMeans(n_clusters=5, random_state=42)
clusters = kmeans.fit_predict(scaled_matrix)

# Map clusters to users
user_clusters = pd.DataFrame({'userid': user_movie_matrix.index,
'cluster': clusters})

# Compute average ratings for each cluster
cluster_means = user_movie_matrix.copy()
cluster_means['cluster'] = clusters  # Add cluster information
cluster_avg_ratings =
cluster_means.groupby('cluster').mean().mean(axis=1)

# Assign predicted labels based on cluster averages
cluster_labels = cluster_means['cluster'].map(cluster_avg_ratings >=
threshold).astype(int)


# Apply KMeans clustering with 5 clusters (you can tune this
parameter)
kmeans = KMeans(n_clusters=5, random_state=42)
user_movie_matrix['cluster'] = kmeans.fit_predict(scaled_matrix)

# Visualizing the cluster distribution
plt.figure(figsize=(10, 6))
sns.countplot(x='cluster', data=user_movie_matrix, palette='Set2')
plt.title('Distribution of Users Across Clusters', fontsize=16)
plt.xlabel('Cluster ID', fontsize=12)
plt.ylabel('Number of Users', fontsize=12)
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/
_kmeans.py:870: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly
to suppress the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:870
: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
warning
  warnings.warn(
```



Distribution of Users Across Clusters
Number of Users
4000
3000
2000
1000
0
0
1
2
3
4
Cluster ID