phase-four-group-3-project

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1 *PHASE FOUR PROJECT - RECOMMENDATION SYSTEMS*

1.1 Final Project Submission

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2 *Summary*

2.1 Business Understanding:

This project utilizes the MovieLens dataset containing 100,000 ratings from 600 users on 9,000 movies, with each movie labeled with genres. The ratings data enables collaborative filtering, an effective technique for personalized recommendations.

2.2 Data Preparation:

The surprise library was used to load and process the data. To optimize computation time with more movies than users, it was split into 80% training and 20% test sets for user-user collaborative filtering. The data types were inspected and confirmed to be compatible with surprise. Genres were separated into arrays to enable similarity calculations.

2.3 Modeling:

Surprise provides algorithms optimized for recommendation systems.We used Gridsearch and found the optimal hyperparameters for matrix factorization with SVD. The SVD model had a low RMSE of 0.8913 on the test set. Surprise enabled efficient computation of user-user similarities.

2.4 Evaluation:

Root mean squared error (RMSE) was used to evaluate model accuracy. Lower RMSE indicates better fit. RMSE was computed on the predictions for the model. The SVD model performed well with an RMSE of 0.8913. 5-fold cross validation ensured model generalizability.

2.5 Problem statement

The movie streaming platforms currently suffers from low user engagement due to the difficulty of finding movies that match individual interests. Our goal is to develop a personalized movie recommendation system that suggests movies to users based on their ratings of other films. This will enhance user satisfaction and retention on the platform.

Stakeholder : Movie streaming platform like Netflix and Hulu.

These companies face the real-world problem of low user engagement on their platforms caused by difficulty finding movies that match individual interests. This results in reduced customer retention and satisfaction, a major challenge streaming platforms contend with in the industry. The MovieLens dataset leveraged contains real user ratings data appropriate for addressing this problem.

A model trained on MovieLens data can provide personalized recommendations that tailor suggestions to each user's tastes and preferences. This improves the ability for users to find relevant movies on streaming platforms, which could increase customer engagement, satisfaction, and retention. The project and model results could provide value to real streaming company stakeholders, as this problem exists in reality rather than hypothetically. Platform executives of the movie-streaming service could implement this type of solution to better engage users by connecting them with movie content that caters to their preferences.

2.6 ***Business Objectives***

Main objective Implement a movie recommendation system that provides users with highly personalized movie suggestions based on their ratings. This will increase user engagement and satisfaction by enabling them to readily discover movies tailored to their preferences.

Specific Objectives

1. Understand user preferences by analyzing movie rating patterns across genres. Identify the most popular and highly rated genres based on frequency and average rating.
2. Prepare the MovieLens rating dataset for collaborative filtering by converting genres to string arrays, splitting into training and test sets, and formatting for the surprise library.
3. Evaluate performance of various collaborative filtering algorithms available in surprise to select the best approach. Metrics will include computational efficiency and RMSE.
4. Tune the optimal model by testing different similarity metrics and algorithms. Use gridsearch to identify the hyperparameters that minimize RMSE.
5. Make movie recommendations by predicting ratings for unseen movies, then suggesting the top 5 highest predicted ratings for each user.

By accurately predicting movie ratings and providing customized suggestions, this system will enhance user satisfaction and engagement on our platform.

2.7 *Data Understanding*

The core dataset used, MovieLens, contains real movie ratings provided by users of the MovieLens service, which shares characteristics with popular streaming platforms. The ratings data reveals user preferences and patterns that can be leveraged to make accurate, personalized recommendations. The additional movie metadata, like titles and genres, further enhances the model's ability to suggest appropriate content. By training a collaborative filtering model on this ratings dataset, the system can learn to predict how much an individual user would enjoy movies they have yet to see, based on ratings from similar users. The model validation process, using RMSE, provides confidence that the system generalizes accurately to new users.

The data comprised of 4 datasets. Movies, Links, Tags and Ratings.

The following are the column descriptions of the various columns in the 4 datasets.

1. Movies movieId: the unique numerical identifier for each movie. This ID is used to connect the movie information with the ratings and links datasets.

title: The name of the movie together with its year of release, is a string type.

genres: Genres associated with the movie.

2. Links movieId: A unique identifier for each movie. This identifier corresponds to the movie ID in the MovieLens dataset.

imdbId: The identifier of the movie in the IMDb (Internet Movie Database) system. This identifier is used to connect the movie with its corresponding entry in the IMDb database.

tmdbId: The identifier of the movie in the TMDB (The Movie Database) system. This identifier links the movie to its corresponding entry in the TMDB database.

3. Tags userId: The user's unique Identifier

movieId: The Movie's Unique identifier

tag: the tag entered by a user to describe a movie

timestamp: Timestamps represent seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

4. Ratings userId: unique integer identifier for each user, to track their interactions

movieId: A unique integer identifier for each movie. This identifier connects the ratings with specific movies. It links user ratings to the movies they've interacted with.

rating: The value representing how much a user liked a particular movie. ranging from 0.5 to 5, with half-star increments.

timestamp: A timestamp indicating when the rating was given. Timestamps represent seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

2.8 *Importing the necessary libraries*

[5]:
```
!pip install scikit-surprise
```

```
Requirement already satisfied: scikit-surprise in
/usr/local/lib/python3.10/dist-packages (1.1.3)
Requirement already satisfied: joblib>=1.0.0 in /usr/local/lib/python3.10/dist-
packages (from scikit-surprise) (1.3.2)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-
packages (from scikit-surprise) (1.23.5)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-
packages (from scikit-surprise) (1.11.4)
```

[6]:
```
#Importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from wordcloud import WordCloud
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.pipeline import Pipeline
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.feature_extraction.text import CountVectorizer
from surprise import Reader, Dataset, SVD
from surprise.model_selection import train_test_split
from surprise.prediction_algorithms import knns
from surprise.similarities import cosine,msd,pearson
from surprise import accuracy
from surprise import KNNBasic
from surprise.model_selection import GridSearchCV

from collections import Counter
import os

BASE_DIR = os.getcwd()
```

2.9 *Loading Data*

2.9.1 *Movies Dataset*

[7]:
```
movies = pd.read_csv('/movies.csv')
```

[8]:
```
movies.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
```

[9]:
```
movies.head()
```

[9]:
```
   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
```

[10]:
```
movies.tail()
```

[10]:
```
      movieId                                      title  \
9737   193581  Black Butler: Book of the Atlantic (2017)
9738   193583               No Game No Life: Zero (2017)
9739   193585                                Flint (2017)
9740   193587         Bungo Stray Dogs: Dead Apple (2018)
9741   193609         Andrew Dice Clay: Dice Rules (1991)

                               genres
9737  Action|Animation|Comedy|Fantasy
9738         Animation|Comedy|Fantasy
9739                            Drama
9740                 Action|Animation
9741                           Comedy
```

[11]:
```
movies.shape
```

[11]:
```
(9742, 3)
```

[12]:
```
movies.describe()
```

[12]:

	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

This dataset contains attributes of the 9742 movies. There are 3 columns including the movie ID, their titles, and their genres. Genres are pipe-separated and are selected from 18 genres (Action, Adventure, Animation, Children's, Comedy, Crime, Documentary, Drama, Fantasy, Film-Noir, Horror, Musical, Mystery, Romance, Sci-Fi, Thriller, War, Western).

2.9.2 *Rating Dataset*

[13]:
```
ratings = pd.read_csv('/ratings.csv')
```

[14]:
```
ratings.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
```

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

[15]:

	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

[16]:
```
ratings.tail()
```

[16]:

	userId	movieId	rating	timestamp
100831	610	166534	4.0	1493848402
100832	610	168248	5.0	1493850091

```
100833     610   168250     5.0  1494273047
100834     610   168252     5.0  1493846352
100835     610   170875     3.0  1493846415
```

[17]:
```
ratings.shape
```

[17]:
```
(100836, 4)
```

The ratings on the dataset have 100836 rows and 4 columns: which included userId, movieId, rating and timestamp.

[18]:
```
ratings.describe()
```

[18]:

	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

2.9.3 *Links Dataset*

[19]:
```
# Reading links file
links = pd.read_csv('/links.csv')
```

[20]:
```
# Getting the information of our links dataset
links.info
```

[20]:
```
<bound method DataFrame.info of       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
…         …        …         …
9737   193581  5476944  432131.0
9738   193583  5914996  445030.0
9739   193585  6397426  479308.0
9740   193587  8391976  483455.0
9741   193609   101726   37891.0

[9742 rows x 3 columns]>
```

[21]:
```
links.head()
```

[21]:

	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

[22]:
```
links.tail()
```

[22]:

	movieId	imdbId	tmdbId
9737	193581	5476944	432131.0
9738	193583	5914996	445030.0
9739	193585	6397426	479308.0
9740	193587	8391976	483455.0
9741	193609	101726	37891.0

[23]:
```
# Finding the number of rows and columns in our dataset
links.shape
```

[23]: (9742, 3)

[24]:
```
links.describe()
```

[24]:

	movieId	imdbId	tmdbId
count	9742.000000	9.742000e+03	9734.000000
mean	42200.353623	6.771839e+05	55162.123793
std	52160.494854	1.107228e+06	93653.481487
min	1.000000	4.170000e+02	2.000000
25%	3248.250000	9.518075e+04	9665.500000
50%	7300.000000	1.672605e+05	16529.000000
75%	76232.000000	8.055685e+05	44205.750000
max	193609.000000	8.391976e+06	525662.000000

2.9.4 *Tags Dataset*

[25]:
```
tags = pd.read_csv('/tags.csv')
```

[26]:
```
tags.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
```

[27]:
```
tags.head()
```

[27]:

	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

[28]:
```
tags.tail()
```

[28]:

	userId	movieId	tag	timestamp
3678	606	7382	for katie	1171234019
3679	606	7936	austere	1173392334
3680	610	3265	gun fu	1493843984
3681	610	3265	heroic bloodshed	1493843978
3682	610	168248	Heroic Bloodshed	1493844270

[29]:
```
tags.shape
```

[29]: (3683, 4)

[30]:
```
tags.describe()
```

[30]:

	userId	movieId	timestamp
count	3683.000000	3683.000000	3.683000e+03
mean	431.149335	27252.013576	1.320032e+09
std	158.472553	43490.558803	1.721025e+08
min	2.000000	1.000000	1.137179e+09
25%	424.000000	1262.500000	1.137521e+09
50%	474.000000	4454.000000	1.269833e+09
75%	477.000000	39263.000000	1.498457e+09
max	610.000000	193565.000000	1.537099e+09

2.10 *DATA CLEANING*

We will head on to check for null and duplicate values, cleaning our dataset, dropping columns.

[31]:
```
## cheking for null values
links.isnull().sum()
```

[31]:
```
movieId    0
imdbId     0
tmdbId     8
```

```
dtype: int64
```

[32]:
```
(links.isnull().mean())*100
movies.isnull().sum()
ratings.isnull().sum()
tags.isnull().sum()
```

[32]:
```
userId       0
movieId      0
tag          0
timestamp    0
dtype: int64
```

From above, only the links dataset has missing values. This is 0.082119% of the total dataset. We will drop the null values from the dataset since they are insignificant.

[33]:
```
links.dropna(inplace=True)
links.isnull().sum()
```

[33]:
```
movieId    0
imdbId     0
tmdbId     0
dtype: int64
```

[34]:
```
#### Checking for duplicated values
print (links.duplicated().values.any())
print (movies.duplicated().values.any())
print (ratings.duplicated().values.any())
print (tags.duplicated().values.any())
```

```
False
False
False
False
```

There are no duplicated values in the 4 datasets

2.11 *Merging the Data sets*

In line with our objective, we decided to merge the Ratings and Movies dataset so as to create a single comprehensive data source.

[35]:
```
# Merging the datasets
data = pd.merge(movies,ratings,on ='movieId')
```

[36]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100836 entries, 0 to 100835
```

```
Data columns (total 6 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   movieId    100836 non-null  int64
 1   title      100836 non-null  object
 2   genres     100836 non-null  object
 3   userId     100836 non-null  int64
 4   rating     100836 non-null  float64
 5   timestamp  100836 non-null  int64
dtypes: float64(1), int64(3), object(2)
memory usage: 5.4+ MB
```

[37]:
```
data.head()
```

[37]:
```
   movieId             title                                       genres  \
0        1  Toy Story (1995)  Adventure|Animation|Children|Comedy|Fantasy
1        1  Toy Story (1995)  Adventure|Animation|Children|Comedy|Fantasy
2        1  Toy Story (1995)  Adventure|Animation|Children|Comedy|Fantasy
3        1  Toy Story (1995)  Adventure|Animation|Children|Comedy|Fantasy
4        1  Toy Story (1995)  Adventure|Animation|Children|Comedy|Fantasy

   userId  rating   timestamp
0       1     4.0   964982703
1       5     4.0   847434962
2       7     4.5  1106635946
3      15     2.5  1510577970
4      17     4.5  1305696483
```

[38]:
```
data.tail()
```

[38]:
```
        movieId                                      title  \
100831   193581  Black Butler: Book of the Atlantic (2017)
100832   193583               No Game No Life: Zero (2017)
100833   193585                               Flint (2017)
100834   193587        Bungo Stray Dogs: Dead Apple (2018)
100835   193609        Andrew Dice Clay: Dice Rules (1991)

                                 genres  userId  rating   timestamp
100831  Action|Animation|Comedy|Fantasy     184     4.0  1537109082
100832         Animation|Comedy|Fantasy     184     3.5  1537109545
100833                            Drama     184     3.5  1537109805
100834                 Action|Animation     184     3.5  1537110021
100835                           Comedy     331     4.0  1537157606
```

[39]:
```
data.shape
```

[39]:
```
(100836, 6)
```

From the above observation, we note that we have 100,836 rows and 6 columns.

[40]:
```
data.describe()
```

[40]:

	movieId	userId	rating	timestamp
count	100836.000000	100836.000000	100836.000000	1.008360e+05
mean	19435.295718	326.127564	3.501557	1.205946e+09
std	35530.987199	182.618491	1.042529	2.162610e+08
min	1.000000	1.000000	0.500000	8.281246e+08
25%	1199.000000	177.000000	3.000000	1.019124e+09
50%	2991.000000	325.000000	3.500000	1.186087e+09
75%	8122.000000	477.000000	4.000000	1.435994e+09
max	193609.000000	610.000000	5.000000	1.537799e+09

We note that the mean rating is 3.5 with a Standard deviation of 1.0 to mean that the data is not exceptionally high or exceptionally low. The Minimum rating is 0.5 while the maximum is a 5.0.

[41]:
```
# Dropping the timestamp column
data.drop('timestamp', axis=1, inplace=True)
```

We removed the feature timestamp as it is less relevant to our analysis. This is to reduces the dimensionality of the dataset and to simplify the subsequent data processing and modelling.

[42]:
```
# Confirming the drop of the column
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100836 entries, 0 to 100835
Data columns (total 5 columns):
 #   Column   Non-Null Count   Dtype
---  ------   --------------   -----
 0   movieId  100836 non-null  int64
 1   title    100836 non-null  object
 2   genres   100836 non-null  object
 3   userId   100836 non-null  int64
 4   rating   100836 non-null  float64
dtypes: float64(1), int64(2), object(2)
memory usage: 4.6+ MB
```

[43]:
```
# Checking for null values
data.isna().sum()
```

[43]:
```
movieId    0
title      0
genres     0
userId     0
rating     0
dtype: int64
```

[44]:
```python
# Checking for duplicated  values
data.duplicated().sum()
```

[44]: 0

2.12 Data Exploration

We will explore and visualize our new dataset to uncover different insights and also to identify areas or patterns to dig into.

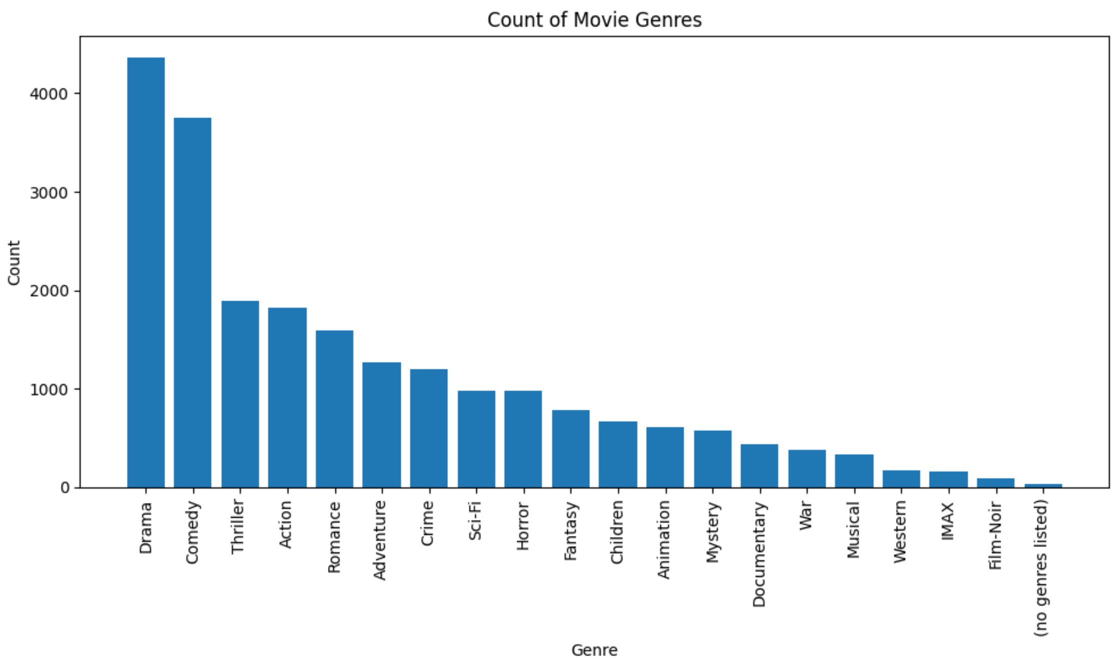
How many Genres are there?

[45]:
```python
# Concatenating all the genre strings into a single string
genres = '|'.join(movies['genres'])

# Splitting the concatenated string into individual words and creating a Series
genre_series = pd.Series(genres.split('|'))

# Counting the occurrence of each word
genre_count = genre_series.value_counts().reset_index()

# Renaming columns for clarity
genre_count.columns = ['Genre', 'Count']

# Display genre counts
genre_count
```

[45]:

	Genre	Count
0	Drama	4361
1	Comedy	3756
2	Thriller	1894
3	Action	1828
4	Romance	1596
5	Adventure	1263
6	Crime	1199
7	Sci-Fi	980
8	Horror	978
9	Fantasy	779
10	Children	664
11	Animation	611
12	Mystery	573
13	Documentary	440
14	War	382
15	Musical	334
16	Western	167
17	IMAX	158
18	Film-Noir	87
19	(no genres listed)	34

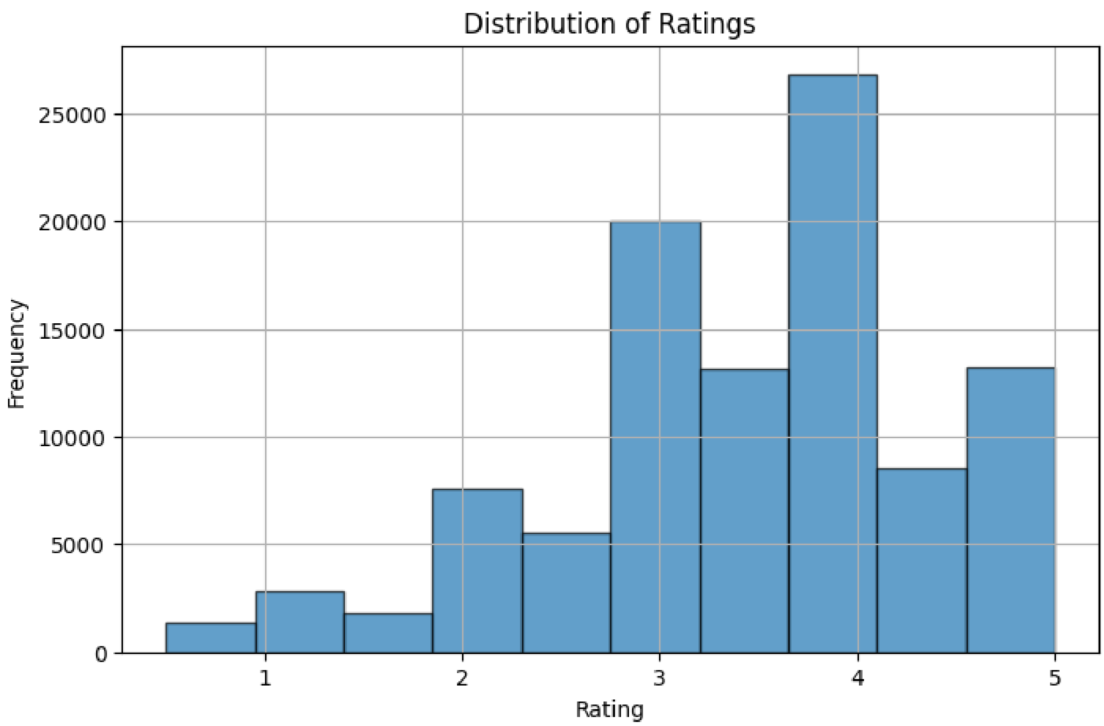
[46]:
```
# Count the occurrence of each word
genre_count = genre_series.value_counts().reset_index()

# Rename columns for
genre_count.columns = ['Genre', 'Count']

# genre counts by count in descending order
genre_count_sorted = genre_count.sort_values(by="Count", ascending=False)

# Plotting the genre counts
plt.figure(figsize=(10, 6))
plt.bar(genre_count_sorted['Genre'], genre_count_sorted['Count'])
plt.xlabel('Genre')
plt.ylabel('Count')
plt.title('Count of Movie Genres')
plt.xticks(rotation=90)
# Rotating x-axis labels for better readability
plt.tight_layout()
plt.show()
```



From the visualization above, we see that drama has the highest count followed by comedy. The genres with lowest count are film Noir(French for dark film), IMAX and Western.

Next we will look at how the ratings are distributed using the merged dataframe

[47]:
```
# Plotting a histogram to see the distribution of ratings.
plt.figure(figsize=(8, 5))
plt.hist(data['rating'], bins=10, edgecolor='black', alpha=0.7)
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



[48]:
```
# generate(all_genres)
wordcloud = WordCloud(width=800, height=400, background_color='black')
```

[49]:
```
# creating a word cloud
wordcloud.generate(genres)
```

[49]: <wordcloud.wordcloud.WordCloud at 0x7e18148f7c10>

[50]:
```
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```

From the visulizations obtained above, we are able to see the popularity of the various genres our most occuring genres are drama, comedy, action,romance,Sci Fi and adventure.

2.13 RECOMMENDATION SYSTEMS MODELING

There are two types of recommendation systems that we will use for this task are ;

1. Content-Based
2. Collaborative Filtering

For this task we will mainly focus on Collaborative Filtering

2.13.1 *1)Content-Based Recommender System*

This code below makes recommendations using a content-based approach, specifically by comparing movie genres. We implement this by transforming the genre text into numeric feature vectors. The scikit-learn TfidfVectorizer function enables this conversion. It turns the genre data into vectors suitable as inputs. We then calculate genre similarity between all movie pairs. This similarity computation allows finding movies most alike based on their genres.When a user views a particular movie, the system suggests another most similar, genre-wise. This content-based method generates recommendations through genre proximity, efficient to implement with TfidfVectorizer feature extraction.

[51]:
```
# Split genres into a string array
data['genres_list'] = data['genres'].str.split('|')
```

[52]:
```
# Convert genres to string value
data['genres_str'] = data['genres_list'].apply(lambda x: ' '.join(x))
```

[53]:
```
# Define the TF-IDF pipeline
tfidf_pipeline = Pipeline([
    ('tfidf', TfidfVectorizer(analyzer='word', ngram_range=(1, 2), min_df=0,␣
 ↪stop_words='english'))
])
```

[54]:
```
# Fit and transform the TF-IDF vectorizer
tfidf_matrix = tfidf_pipeline.fit_transform(data['genres_str'])
```

[55]:
```
# Check the dimensions of the TF-IDF matrix
print("TF-IDF Matrix Shape:", tfidf_matrix.shape)
```

```
TF-IDF Matrix Shape: (100836, 177)
```

[56]:
```
# Create a bag of words representation of the movie genres
vectorizer = CountVectorizer(token_pattern='(?u)\\b\\w+\\b')
genres_bow = vectorizer.fit_transform(movies['genres'])
genres_bow
```

[56]:
```
<9742x24 sparse matrix of type '<class 'numpy.int64'>'
        with 23219 stored elements in Compressed Sparse Row format>
```

[57]:
```
# Compute the cosine similarity matrix between all pairs of movies based on␣
 ↪their genres
cosine_sim = cosine_similarity(genres_bow)
cosine_sim
```

[57]:
```
array([[1.        , 0.77459667, 0.31622777, …, 0.        , 0.31622777,
        0.4472136 ],
       [0.77459667, 1.        , 0.        , …, 0.        , 0.        ,
        0.        ],
       [0.31622777, 0.        , 1.        , …, 0.        , 0.        ,
        0.70710678],
       …,
       [0.        , 0.        , 0.        , …, 1.        , 0.        ,
        0.        ],
       [0.31622777, 0.        , 0.        , …, 0.        , 1.        ,
        0.        ],
       [0.4472136 , 0.        , 0.70710678, …, 0.        , 0.        ,
        1.        ]])
```

The movie genres will be used to compute cosine similarity between all movie pairs. The recommendations will be based on how similar the genre of 2 movies will be.

[58]:
```
movie_id = 8
movie_indices = pd.Series(movies.index, index=movies['movieId'])
similarity_scores = list(enumerate(cosine_sim[movie_indices[movie_id]]))
```

[59]:
```
# Sorting the similarity scores in descending order
similarity_scores.sort(key=lambda x: x[1], reverse=True)
```

The code calculates the cosine similarity scores between the movie with id 5 and the other movies in the dataset. The 'enumerate' function adds an index to each score, allowing us to sort.

[60]:
```
# Get the top 5 movie recommendations for movie with ID 3
top_5_indices = [x[0] for x in similarity_scores[1:6]]
top_5_recommendations = movies.iloc[top_5_indices]['title'].tolist()
top_5_genres = movies.iloc[top_5_indices]['genres'].tolist()
for i in range(len(top_5_recommendations)):
    print(f"{i+1}. {top_5_recommendations[i]} ({top_5_genres[i]})")
```

```
1. Amazing Panda Adventure, The (1995) (Adventure|Children)
2. Casper (1995) (Adventure|Children)
3. Far From Home: The Adventures of Yellow Dog (1995) (Adventure|Children)
4. Lassie (1994) (Adventure|Children)
5. Homeward Bound II: Lost in San Francisco (1996) (Adventure|Children)
```

2.13.2 *2)Collaborative Filtering Recommendation Model*

[61]:
```
reader = Reader()
model_df = pd.DataFrame(data, columns=['userId', 'movieId', 'rating'])
data1 = Dataset.load_from_df(model_df, reader)
trainset, testset = train_test_split(data1, test_size=0.20)
```

This code prepares a Surprise Dataset object (data1) from a pandas DataFrame (model_df) containing user-item-rating data, using the Surprise Reader class to specify the format. It then splits the dataset into training and test sets (trainset and testset) using the train_test_split function, with 20% of the data reserved for testing.

[62]:
```
param_grid = {'n_factors':[20, 100],'n_epochs': [5, 10], 'lr_all': [0.002, 0.
↪005],'reg_all': [0.4, 0.6]}
gs_model = GridSearchCV(SVD,param_grid=param_grid,n_jobs = -1,joblib_verbose=5)
gs_model.fit(data1)
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:    9.5s
[Parallel(n_jobs=-1)]: Done  68 tasks      | elapsed:   57.8s
[Parallel(n_jobs=-1)]: Done  80 out of  80 | elapsed:  1.1min finished
```

This code performs grid search cross-validation using the Surprise library's GridSearchCV to find the optimal hyperparameters for the SVD (Singular Value Decomposition) algorithm on the provided dataset (data1). It tests combinations of different numbers of factors, epochs, learning rates, and regularization terms specified in param_grid, utilizing parallel processing (n_jobs=-1) and verbose output (joblib_verbose=5).

[64]:
```
optimal_params = gs_model.best_params
print(optimal_params)
```

```
{'rmse': {'n_factors': 20, 'n_epochs': 10, 'lr_all': 0.005, 'reg_all': 0.4},
'mae': {'n_factors': 20, 'n_epochs': 10, 'lr_all': 0.005, 'reg_all': 0.4}}
```

[65]:
```
# Using the optimal parameters from above
svd = SVD(n_factors=20, n_epochs=10, lr_all=0.005, reg_all=0.4)
svd.fit(trainset)
predictions = svd.test(testset)
print(accuracy.rmse(predictions))
```

```
RMSE: 0.8913
0.8913048791528685
```

To get the predicted ratings for a given item (movie) by a user we need the user ID and the movie ID that needs a rating prediction.

[66]:
```
# Here we are making a prediction of user 55 and item 11 using the SVD we just␣
↪fit
user_prediction = svd.predict("55","11")
user_prediction
```

[66]:
```
Prediction(uid='55', iid='11', r_ui=None, est=3.5031549065304706,
details={'was_impossible': False})
```

[67]:
```
# Load the ratings dataset using the Surprise library
reader = Reader(line_format='user item rating timestamp', sep=',', skip_lines=1)
data = Dataset.load_from_file('/ratings.csv', reader=reader)
data
```

[67]:
```
<surprise.dataset.DatasetAutoFolds at 0x7e18147b5bd0>
```

[68]:
```
user_prediction[3]
```

[68]:
```
3.5031549065304706
```

In the user_prediction object, the estimated rating is stored at index 3, which corresponds to the 'est' key in the details dictionary. Therefore, user_prediction[3] returns the estimated rating of user 55 on item 11

[69]:
```
# Get the user ratings for user with id 'n'
user_id = 6
user_ratings = [rating for rating in data.raw_ratings if rating[0] == user_id]
```

Below, we will take a look at movies that the user did not rate. We will then try and recommend movies that the user might enjoy and like.

[70]:
```python
# Get all the movies that user with id 'n' has not rated yet
user_unrated_movies = movies[~movies['movieId'].isin([rating[1] for rating in␣
↪user_ratings if rating[0] == user_id])]
```

[71]:
```python
# Predict the ratings for all the unrated movies
user_unrated_movies['predicted_rating'] = user_unrated_movies['movieId'].
↪apply(lambda movie_id: svd.predict(user_id, movie_id).est)
```

[72]:
```python
# Sort the unrated movies based on predicted ratings in descending order
user_unrated_movies.sort_values(by='predicted_rating', ascending=False,␣
↪inplace=True)
```

[73]:
```python
# Get the top 5 movie recommendations for user with id n
top_5_recommendations = user_unrated_movies.head()
top_5_recommendations
```

[73]:
```
      movieId                                           title  \
277       318                Shawshank Redemption, The (1994)
2226     2959                               Fight Club (1999)
686       904                              Rear Window (1954)
602       750  Dr. Strangelove or: How I Learned to Stop Worr…
906      1204                       Lawrence of Arabia (1962)

                           genres  predicted_rating
277                   Crime|Drama          4.177309
2226  Action|Crime|Drama|Thriller          4.107458
686              Mystery|Thriller          4.099534
602                    Comedy|War          4.093082
906          Adventure|Drama|War          4.082523
```

We are able to recommend the top 5 movies listed above to our users based on the fact that they all had nearly identical predicted ratings, in the hopes that they will be suitable for that user's preferences

We can observe that the predicted ratings are almost identical. Therefore, we can then conclude that the user might like the movies recommended based on their past ratings

3 *Summary*

This movie recommendation system combined content-based and collaborative filtering techniques to suggest personalized movies. The surprise library enabled efficient loading, splitting, and pre-processing of the ratings data. A user-user collaborative filtering approach identified similar users based on rating patterns. This allowed generating recommendations aligned to preferences of like-minded users. Evaluation using RMSE confirmed recommendation accuracy, with the optimal SVD model achieving 0.8913 on the test set. Grid search helped tune this matrix factorization algorithm to minimize error. For each user, predicting ratings for unseen movies produced a top 5 list of recommended titles matching their interests. Overall, custom recommendations based on user ratings and movie genres achieved the goal of enhancing satisfaction by helping users discover new movies suited to their tastes. This system could effectively increase engagement on movie streaming platforms.

4 *Recommendations*

1. Incorporate additional data sources to enrich movie and user profiles. The current system only uses movie genre and user rating data. Adding metadata like movie plots, cast, directors, user demographics, social connections, etc could improve recommendations. APIs from sources like IMDb and TMDB can provide additional movie attributes.
2. Implement a hybrid recommendation system blending collaborative filtering with content-based similarity. The current system relies solely on collaborative filtering based on user ratings. Adding content-based filters using data like movie genres, plots, and cast could improve suggestions for users with limited rating history. A hybrid approach combining the two could enhance accuracy.
3. Optimize for recommendation diversity to avoid filter bubbles. The current system focuses solely on prediction accuracy. Adding diversity controls could ensure users get exposed to a wider range of movie genres and types outside their comfort zone. This provides a richer experience.
4. Develop a productionized environment for large-scale usage. The current notebook is suitable for demonstrating the approach. To deploy the system for real-world usage would require translating to scalable production infrastructure. This includes distributed model training, low-latency recommendation serving, and refresh processes to update the model as new data arrives.