Overall Problem Statement

In the digital era, users are overwhelmed by the vast and ever-growing number of movies available on streaming platforms like Netflix, Amazon Prime, and Disney+. While this abundance of content offers diverse choices, it also creates a significant challenge: finding the right movie that aligns with a user's taste without wasting time.

To address this issue, this project focuses on developing a Movie Recommendation System using supervised machine learning techniques. The system is designed to predict user ratings for movies based on features like movie title, release year, and genres. By analyzing historical rating data and movie metadata, the model learns patterns that help it estimate how much a user would likely enjoy a given movie.

In addition to rating prediction, the project also implements a content-based recommendation engine, which suggests similar movies based on shared attributes like genres and release period. These recommendations can be served through a simple interactive web interface using Streamlit, allowing users to explore personalized suggestions in real time.

The system combines data preprocessing, feature engineering, model training, evaluation, and deployment, and it aims to enhance user experience, reduce content fatigue, and provide a scalable solution for personalized movie recommendations.

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
#loading the dataset
movies=pd.read_csv("movies.csv")
```

```
movies.head()
```

	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

```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62423 entries, 0 to 62422
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
```

```
---  ------   --------------  -----
 0   movieId  62423 non-null  int64
 1   title    62423 non-null  object
 2   genres   62423 non-null  object
dtypes: int64(1), object(2)
memory usage: 1.4+ MB
```

Handling Missing Values

```
movies.isnull().sum()
```

	0
movieId	0
title	0
genres	0

dtype: int64

```
movies.describe()
```

	movieId
count	62423.000000
mean	122220.387646
std	63264.744844
min	1.000000
25%	82146.500000
50%	138022.000000
75%	173222.000000
max	209171.000000

```
ratings=pd.read_csv("ratings.csv")
```

```
ratings.head()
```

	userId	movieId	rating	timestamp
0	1	296	5.0	1.147880e+09
1	1	306	3.5	1.147869e+09
2	1	307	5.0	1.147869e+09
3	1	665	5.0	1.147879e+09
4	1	899	3.5	1.147869e+09

```
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14099221 entries, 0 to 14099220
Data columns (total 4 columns):
 #   Column     Dtype  
---  ------     -----  
 0   userId     int64  
 1   movieId    int64  
 2   rating     float64
 3   timestamp  float64
dtypes: float64(2), int64(2)
memory usage: 430.3 MB
```

```
ratings.isnull().sum()
```

	0
userId	0
movieId	0
rating	0
timestamp	1

dtype: int64

```
ratings.describe()
```

	userId	movieId	rating	timestamp
count	1.409922e+07	1.409922e+07	1.409922e+07	1.409922e+07
mean	4.584414e+04	2.153113e+04	3.532242e+00	1.215547e+09
std	2.626387e+04	3.944369e+04	1.061481e+00	2.269211e+08
min	1.000000e+00	1.000000e+00	5.000000e-01	7.896520e+08
25%	2.325900e+04	1.197000e+03	3.000000e+00	1.012279e+09
50%	4.570200e+04	2.949000e+03	3.500000e+00	1.197211e+09
75%	6.863300e+04	8.636000e+03	4.000000e+00	1.447325e+09
max	9.141100e+04	2.091630e+05	5.000000e+00	1.574328e+09

Removing Duplicate Records

```
#checking duplicates
print(movies.duplicated().sum())
print(ratings.duplicated().sum())
```

```
0
0
```

Detecting and Treating Outliers

```
# Rating distribution
print(ratings['rating'].describe())
```

```
count    1.409922e+07
mean     3.532242e+00
std      1.061481e+00
min      5.000000e-01
25%      3.000000e+00
50%      3.500000e+00
75%      4.000000e+00
max      5.000000e+00
Name: rating, dtype: float64
```

Convert Data Types and Ensure Consistency

```
movies['year'] = movies['title'].str.extract(r'\((\d{4})\)', expand=False)

# Convert 'year' to integer
movies['year'] = movies['year'].dropna().astype(int)
```

```
# Merge movies and ratings on movieId
data = pd.merge(movies, ratings, on='movieId')
```

```
data
```

	movieId	title	genres	year	userId	rating	timestamp
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	1995.0	2	3.5	1.141416e+09
1	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	1995.0	3	4.0	1.439472e+09
2	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	1995.0	4	3.0	1.573944e+09
3	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	1995.0	5	4.0	8.586259e+08
4	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy	1995.0	8	4.0	8.904925e+08
...	...	...	...	...	...	...	...
2604157	209049	No Safe Spaces (2019)	Documentary	2019.0	14059	4.5	1.573965e+09
2604158	209053	Bowling (2012)	Comedy	2012.0	15152	3.5	1.574008e+09
2604159	209055	Very Well, Thank You...	Comedy|Drama	2007.0	15152	3.5	1.574008e+09

Encoding Categorical Variables

```
from sklearn.preprocessing import LabelEncoder

# Encoding movie titles
le = LabelEncoder()
data['title'] = le.fit_transform(data['title'])


# genres were separated by '|', first split them
movies['genres'] = movies['genres'].str.split('|')
movies_exploded = movies.explode('genres')

# Merge exploded genres with ratings
data = pd.merge(movies_exploded, ratings, on='movieId')

# One-Hot Encoding
data = pd.get_dummies(data, columns=['genres'])


# Fit and transform the 'title' column
data['title'] = le.fit_transform(data['title'])
```

```
data
```

	movieId	title	year	userId	rating	timestamp	genres_(no genres listed)	genres_Action	genres_Advent
0	1	27241	1995.0	2	3.5	1.141416e+09	False	False	
1	1	27241	1995.0	3	4.0	1.439472e+09	False	False	
2	1	27241	1995.0	4	3.0	1.573944e+09	False	False	
3	1	27241	1995.0	5	4.0	8.586259e+08	False	False	
4	1	27241	1995.0	8	4.0	8.904925e+08	False	False	
...	...	...	...	...	...	...	...	...	
7080919	209055	28169	2007.0	15152	3.5	1.574008e+09	False	False	F
7080920	209055	28169	2007.0	15152	3.5	1.574008e+09	False	False	F
7080921	209103	27514	1991.0	13737	4.0	1.574112e+09	True	False	F
7080922	209163	2357	2018.0	6964	4.5	1.574285e+09	False	False	F
7080923	209163	2357	2018.0	6964	4.5	1.574285e+09	False	False	F

7080924 rows × 26 columns

Normalizing or Standardizing Features

```
from sklearn.preprocessing import StandardScaler

# Initialize scaler
scaler = StandardScaler()

# Scaling
data[['rating', 'year']] = scaler.fit_transform(data[['rating', 'year']])
```

```
data
```

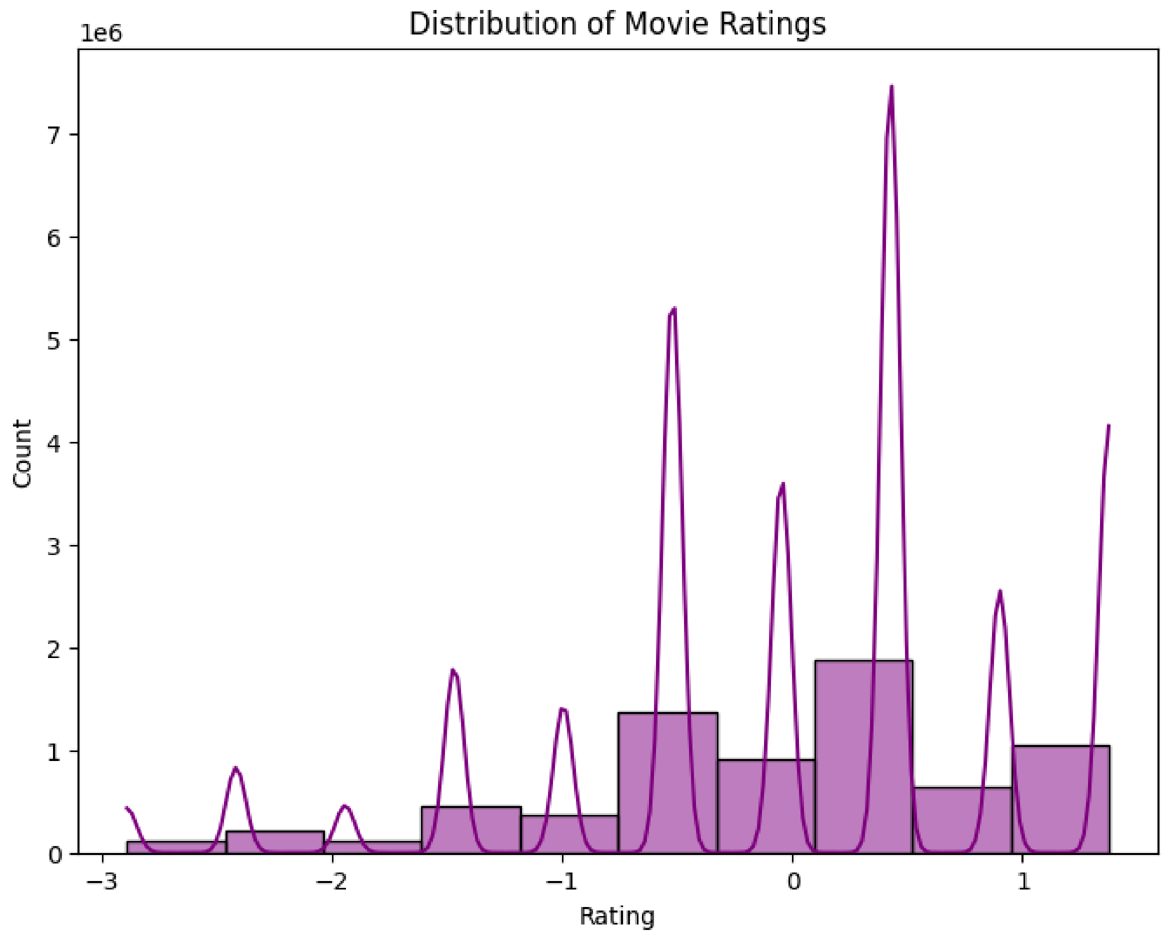
	movieId	title	year	userId	rating	timestamp	genres_(no genres listed)	genres_Action	genres_A
0	1	27241	0.005982	2	-0.046341	1.141416e+09	False	False	
1	1	27241	0.005982	3	0.427300	1.439472e+09	False	False	
2	1	27241	0.005982	4	-0.519982	1.573944e+09	False	False	
3	1	27241	0.005982	5	0.427300	8.586259e+08	False	False	
4	1	27241	0.005982	8	0.427300	8.904925e+08	False	False	
...	...	...	...	...	...	...	...	...	
7080919	209055	28169	0.818271	15152	-0.046341	1.574008e+09	False	False	
7080920	209055	28169	0.818271	15152	-0.046341	1.574008e+09	False	False	
7080921	209103	27514	-0.264781	13737	0.427300	1.574112e+09	True	False	
7080922	209163	2357	1.562870	6964	0.900941	1.574285e+09	False	False	
7080923	209163	2357	1.562870	6964	0.900941	1.574285e+09	False	False	

7080924 rows × 26 columns

Exploratory Data Analysis (EDA)

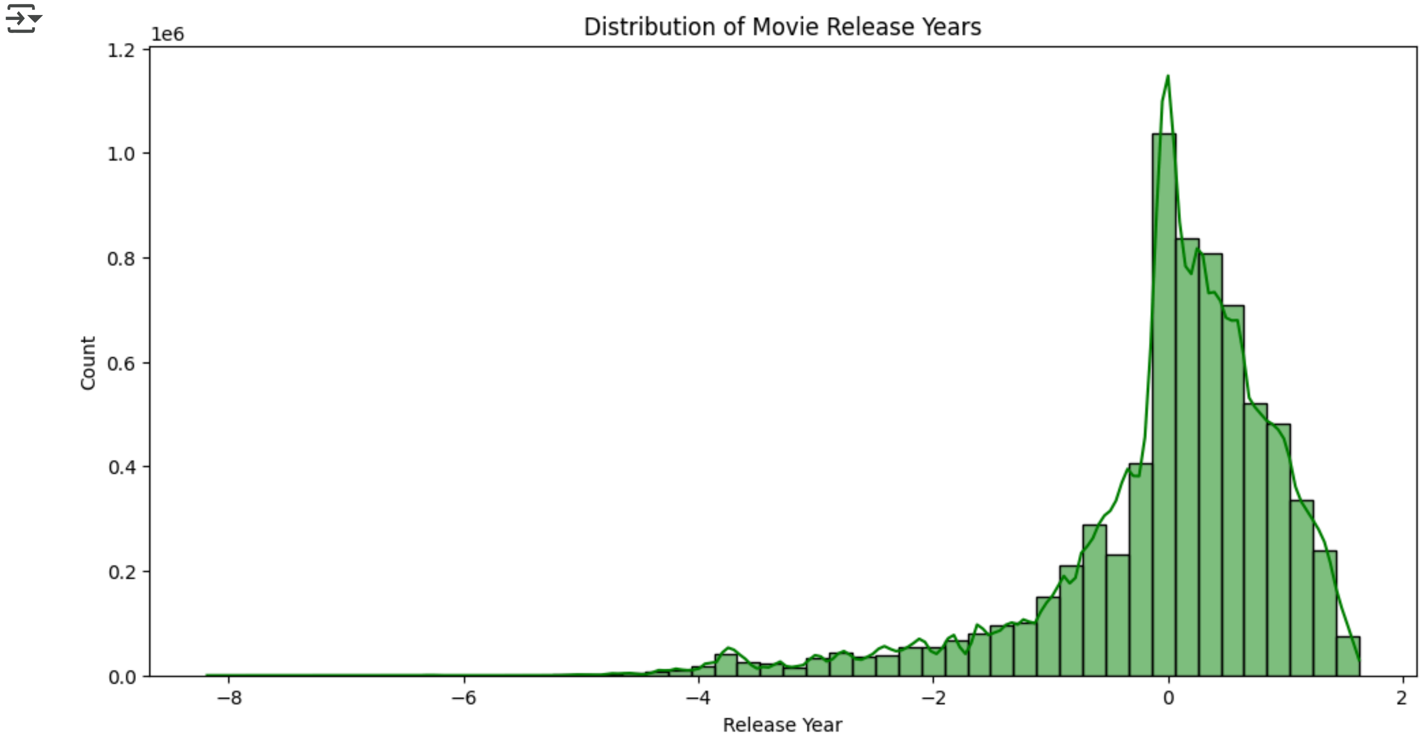
Univariate Analysis

```
#Rating Distribution

import matplotlib.pyplot as plt
import seaborn as sns

# Plot Rating distribution
plt.figure(figsize=(8,6))
sns.histplot(data['rating'], bins=10, kde=True, color='purple')
plt.title('Distribution of Movie Ratings')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.show()
```

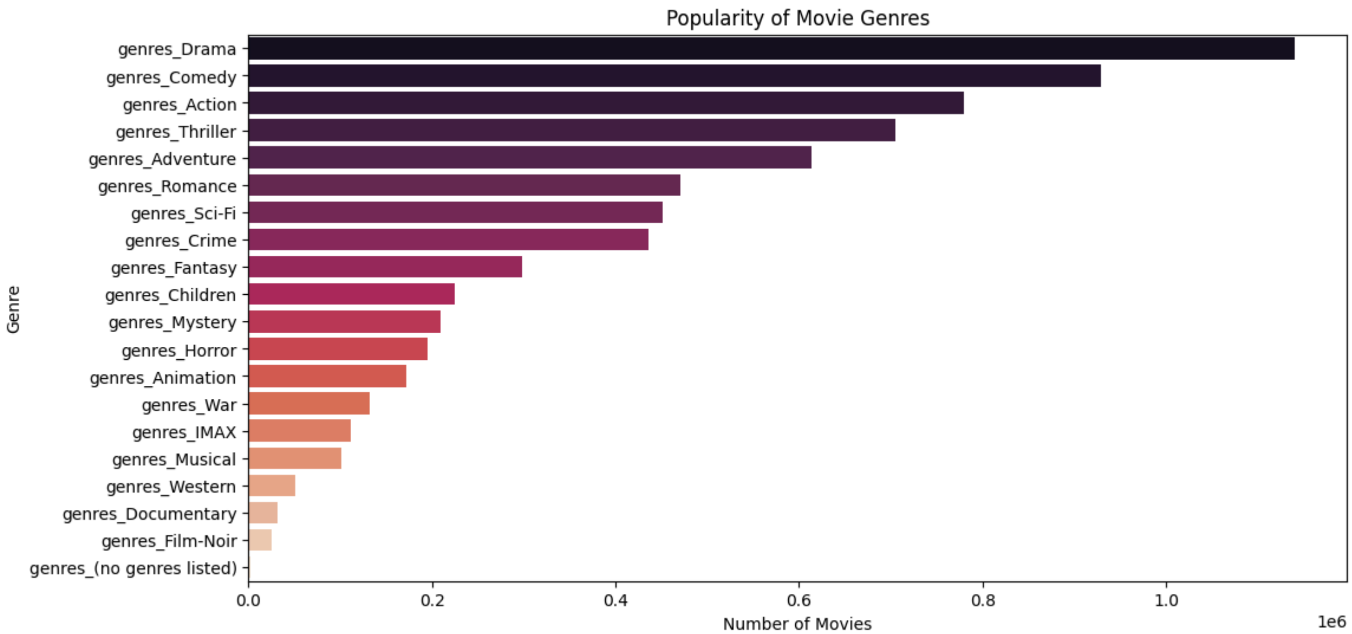


#Year Distribution (Movies Release Year)

```
#Plot year distribution
plt.figure(figsize=(12,6))
sns.histplot(data['year'], bins=50, kde=True, color='green')
plt.title('Distribution of Movie Release Years')
plt.xlabel('Release Year')
plt.ylabel('Count')
plt.show()
```

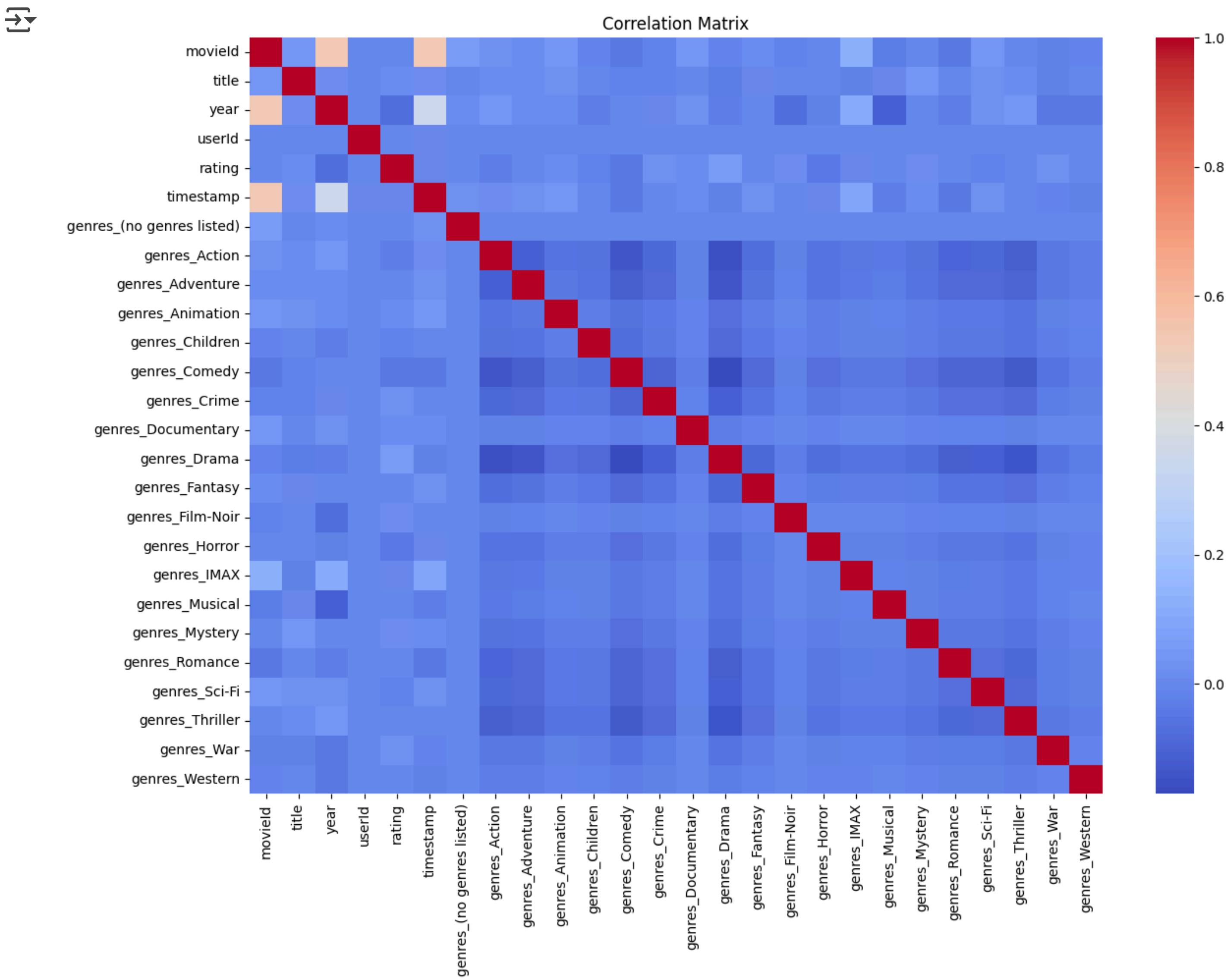



```
#Genre Popularity

# Plot top genres count
genre_columns = [col for col in data.columns if 'genres_' in col]
genre_counts = data[genre_columns].sum().sort_values(ascending=False)

plt.figure(figsize=(12,6))
sns.barplot(x=genre_counts.values, y=genre_counts.index, palette='rocket')
plt.title('Popularity of Movie Genres')
plt.xlabel('Number of Movies')
plt.ylabel('Genre')
plt.show()
```

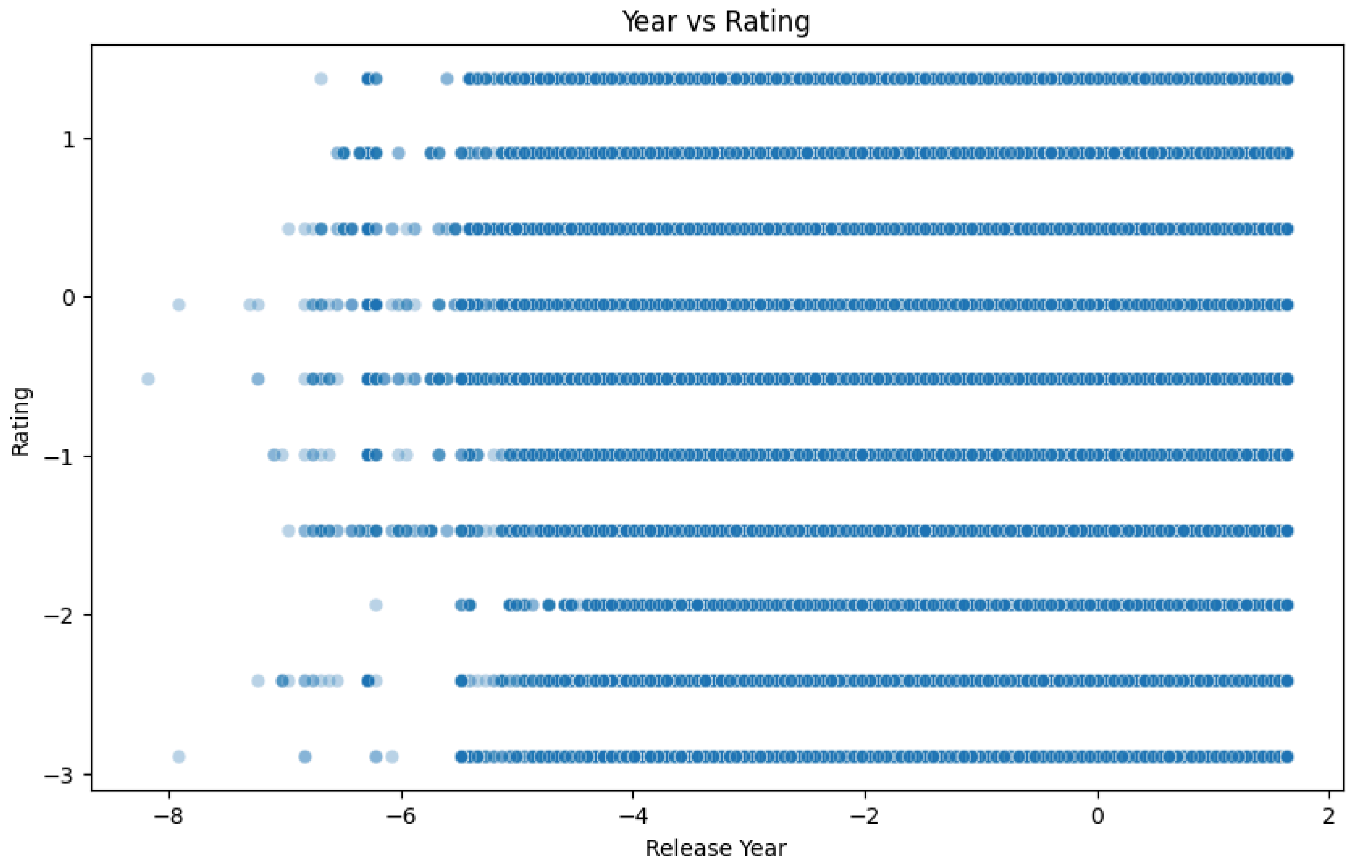


Bivariate / Multivariate Analysis

```
#Correlation Matrix

# Correlation heatmap
plt.figure(figsize=(14,10))
corr_matrix = data.corr()
sns.heatmap(corr_matrix, cmap='coolwarm', annot=False)
plt.title('Correlation Matrix')
plt.show()
```




```
# Scatter plot
plt.figure(figsize=(10,6))
sns.scatterplot(x=data['year'], y=data['rating'], alpha=0.3)
plt.title('Year vs Rating')
plt.xlabel('Release Year')
plt.ylabel('Rating')
plt.show()
```



Feature Engineering and Data Transformation

```
#Binning Release Year into Eras (Optional)
# Create 'era' bins
bins = [1900, 1950, 1970, 1990, 2010, 2025]
labels = ['1900s-50s', '50s-70s', '70s-90s', '90s-2010', '2010s+']
data['year_bin'] = pd.cut(data['year'], bins=bins, labels=labels)

# One-hot encode era
data = pd.get_dummies(data, columns=['year_bin'])
```

```
data
```

	movieId	title	year	userId	rating	timestamp	genres_(no genres listed)	genres_Action	genres_A
0	1	27241	0.005982	2	-0.046341	1.141416e+09	False	False	
1	1	27241	0.005982	3	0.427300	1.439472e+09	False	False	
2	1	27241	0.005982	4	-0.519982	1.573944e+09	False	False	
3	1	27241	0.005982	5	0.427300	8.586259e+08	False	False	
4	1	27241	0.005982	8	0.427300	8.904925e+08	False	False	
...	...	...	...	...	...	...	...	...	
7080919	209055	28169	0.818271	15152	-0.046341	1.574008e+09	False	False	
7080920	209055	28169	0.818271	15152	-0.046341	1.574008e+09	False	False	
7080921	209103	27514	-0.264781	13737	0.427300	1.574112e+09	True	False	
7080922	209163	2357	1.562870	6964	0.900941	1.574285e+09	False	False	
7080923	209163	2357	1.562870	6964	0.900941	1.574285e+09	False	False	

7080924 rows × 31 columns

```
data.isnull().sum()
```

	0
movieId	0
title	0
year	1976
userId	0
rating	0
timestamp	0
genres_(no genres listed)	0
genres_Action	0
genres_Adventure	0
genres_Animation	0
genres_Children	0
genres_Comedy	0
genres_Crime	0
genres_Documentary	0
genres_Drama	0
genres_Fantasy	0
genres_Film-Noir	0
genres_Horror	0
genres_IMAX	0
genres_Musical	0
genres_Mystery	0
genres_Romance	0
genres_Sci-Fi	0
genres_Thriller	0
genres_War	0
genres_Western	0
year_bin_1900s-50s	0
year_bin_50s-70s	0
year_bin_70s-90s	0
year_bin_90s-2010	0
year_bin_2010s+	0

dtype: int64

```
data['year'] = data['year'].fillna(data['year'].mode()[0])
```

```
data.isnull().sum()
```

	0
movieId	0
title	0
year	0
userId	0
rating	0
timestamp	0
genres_(no genres listed)	0
genres_Action	0
genres_Adventure	0
genres_Animation	0
genres_Children	0
genres_Comedy	0
genres_Crime	0
genres_Documentary	0
genres_Drama	0
genres_Fantasy	0
genres_Film-Noir	0
genres_Horror	0
genres_IMAX	0
genres_Musical	0
genres_Mystery	0
genres_Romance	0
genres_Sci-Fi	0
genres_Thriller	0
genres_War	0
genres_Western	0
year_bin_1900s-50s	0
year_bin_50s-70s	0
year_bin_70s-90s	0
year_bin_90s-2010	0
year_bin_2010s+	0

dtype: int64

Polynomial Features (Optional for Linear Regression)

```
from sklearn.preprocessing import PolynomialFeatures

# Example with 2 features
poly = PolynomialFeatures(degree=2, include_bias=False)
poly_features = poly.fit_transform(data[['year', 'rating']])
```

Dimensionality Reduction (Optional)

Apply PCA (Principal Component Analysis)

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Select numeric columns for PCA
X = data.select_dtypes(include=[np.number]).drop(columns=['userId', 'movieId'])

# Standardize
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply PCA
pca = PCA(n_components=0.95)  # Keep 95% variance
X_pca = pca.fit_transform(X_scaled)

print(f"PCA reduced to {X_pca.shape[1]} features.")
```

```
PCA reduced to 4 features.
```

Model Building and Comparison

Data Splitting

```
#Split the data into Training and Testing sets:
from sklearn.model_selection import train_test_split

# Features and Target
X = data.drop(columns=['userId', 'movieId', 'timestamp', 'rating'])  # Drop irrelevant
y = data['rating']  # Target variable

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Model Training

Train Linear Regression

```
from sklearn.linear_model import LinearRegression

# Initialize and train
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

# Predict
y_pred_lr = lr_model.predict(X_test)
print("y_pred_lr",y_pred_lr)
```

```
y_pred_lr [-0.10078242 -0.05494595 -0.11380468 ... -0.06560938 -0.11914513
 -0.12864702]
```

```
# Evaluate Linear Regression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

# Evaluation for Linear Regression
mae_lr = mean_absolute_error(y_test, y_pred_lr)
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
r2_lr = r2_score(y_test, y_pred_lr)
```