Building a Comprehensive Video Game Recommendation System

Introduction

In the rapidly growing video game industry, players often face the challenge of discovering new games that match their interests and preferences. With thousands of games released across various platforms and genres, finding the next game to play can be overwhelming. This project aims to address this challenge by developing a comprehensive video game recommendation system.

Leveraging the `Video Game Sales with Ratings` dataset from Kaggle (https://www.kaggle.com/datasets/rush4ratio/video-game-sales-with-ratings), our objective is to create a recommender system that suggests video games based on game similarities. The dataset includes key information about video games such as titles, platforms, genres, user scores, and critic scores, providing a rich source of data for building our models.

We will explore multiple recommendation approaches to ensure a robust and versatile system:

1. **Nearest Neighbors Model with Cosine Similarity:** A content-based approach that measures the similarity between games based on their attributes.
2. **Content-Based Recommender:** Utilizes text-based features like game titles to find similar games.

The project will be structured as follows:

1. **Dataset Overview:** Introducing the dataset and its features.
2. **Exploratory Data Analysis (EDA):** Performing a detailed analysis to understand data distributions, trends, and patterns.
3. **Data Cleaning and Preprocessing:** Preparing the data by handling missing values, imputing scores, and encoding categorical variables.
4. **Feature Selection:** Identifying the most relevant features for building effective recommendation models.
5. **Model Training:** Implementing and training the Nearest Neighbors and Content-Based recommendation models.
6. **Model Evaluation:** Evaluating the performance of each model using similarity scores and selecting the best performing one.

Through this comprehensive approach, we aim to deliver a recommendation system that enhances the gaming experience by providing personalized and relevant game suggestions.

Project GitHub: https://github.com/grainier/games-recommender-system/

Dataset Overview

The Dataset Overview section provides a comprehensive introduction to the `Video_Games_Sales_as_at_22_Dec_2016.csv` dataset. This dataset contains information about video game sales across various platforms up to December 22, 2016. It includes key features such as game titles, platforms, release years, genres, sales figures across different regions, and critic and user ratings. This section will load the dataset, display its structure, and summarize the main characteristics of the data, laying the foundation for further analysis and model building.

```python
# Importing necessary libraries
import warnings

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.neighbors import NearestNeighbors
from sklearn.preprocessing import StandardScaler
import time

warnings.filterwarnings("ignore")

# Loading the dataset
file_path = '../data/Video_Games_Sales_as_at_22_Dec_2016.csv'
df = pd.read_csv(file_path)

# Display the first few rows of the dataset
print("First few rows of the dataset:")
display(df.head())
```

```
First few rows of the dataset:

                       Name Platform  Year_of_Release         Genre
Publisher  \
0                Wii Sports      Wii           2006.0        Sports
Nintendo
1         Super Mario Bros.      NES           1985.0      Platform
Nintendo
2            Mario Kart Wii      Wii           2008.0        Racing
Nintendo
3         Wii Sports Resort      Wii           2009.0        Sports
Nintendo
4  Pokemon Red/Pokemon Blue       GB           1996.0  Role-Playing
Nintendo

   NA_Sales  EU_Sales  JP_Sales  Other_Sales  Global_Sales
Critic_Score  \
0     41.36     28.96      3.77         8.45         82.53
```

```
76.0
1     29.08      3.58      6.81         0.77         40.24
NaN
2     15.68     12.76      3.79         3.29         35.52
82.0
3     15.61     10.93      3.28         2.95         32.77
80.0
4     11.27      8.89     10.22         1.00         31.37
NaN

   Critic_Count User_Score  User_Count Developer Rating
0          51.0          8       322.0  Nintendo      E
1           NaN        NaN         NaN       NaN    NaN
2          73.0        8.3       709.0  Nintendo      E
3          73.0          8       192.0  Nintendo      E
4           NaN        NaN         NaN       NaN    NaN
```

```
# Display the summary of the dataset
print("\nDataset summary:")
display(df.info())
```

```
Dataset summary:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16719 entries, 0 to 16718
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Name             16717 non-null  object
 1   Platform         16719 non-null  object
 2   Year_of_Release  16450 non-null  float64
 3   Genre            16717 non-null  object
 4   Publisher        16665 non-null  object
 5   NA_Sales         16719 non-null  float64
 6   EU_Sales         16719 non-null  float64
 7   JP_Sales         16719 non-null  float64
 8   Other_Sales      16719 non-null  float64
 9   Global_Sales     16719 non-null  float64
 10  Critic_Score     8137 non-null   float64
 11  Critic_Count     8137 non-null   float64
 12  User_Score       10015 non-null  object
 13  User_Count       7590 non-null   float64
 14  Developer        10096 non-null  object
 15  Rating           9950 non-null   object
dtypes: float64(9), object(7)
memory usage: 2.0+ MB

None
```

```python
# Display basic statistics for numerical columns
print("\nBasic statistics for numerical columns:")
display(df.describe())
```

```
Basic statistics for numerical columns:

       Year_of_Release      NA_Sales      EU_Sales      JP_Sales  \
count     16450.000000  16719.000000  16719.000000  16719.000000
mean       2006.487356      0.263330      0.145025      0.077602
std           5.878995      0.813514      0.503283      0.308818
min        1980.000000      0.000000      0.000000      0.000000
25%        2003.000000      0.000000      0.000000      0.000000
50%        2007.000000      0.080000      0.020000      0.000000
75%        2010.000000      0.240000      0.110000      0.040000
max        2020.000000     41.360000     28.960000     10.220000

        Other_Sales  Global_Sales  Critic_Score  Critic_Count
User_Count
count  16719.000000  16719.000000   8137.000000   8137.000000
7590.000000
mean       0.047332      0.533543     68.967679     26.360821
162.229908
std        0.186710      1.547935     13.938165     18.980495
561.282326
min        0.000000      0.010000     13.000000      3.000000
4.000000
25%        0.000000      0.060000     60.000000     12.000000
10.000000
50%        0.010000      0.170000     71.000000     21.000000
24.000000
75%        0.030000      0.470000     79.000000     36.000000
81.000000
max       10.570000     82.530000     98.000000    113.000000
10665.000000
```

```python
# Display the list of columns and their descriptions
print("\nList of columns:")
columns = {
    'Name': 'Name of the video game',
    'Platform': 'Platform of the video game release (e.g., PS4, Xbox
One, PC)',
    'Year_of_Release': 'Year of release of the video game',
    'Genre': 'Genre of the video game (e.g., Action, Sports, RPG)',
    'Publisher': 'Publisher of the video game',
    'NA_Sales': 'Sales in North America (in millions)',
    'EU_Sales': 'Sales in Europe (in millions)',
    'JP_Sales': 'Sales in Japan (in millions)',
    'Other_Sales': 'Sales in other regions (in millions)',
    'Global_Sales': 'Total worldwide sales (in millions)',
```

```
    'Critic_Score': 'Aggregate score compiled by Metacritic staff (0-
100)',
    'Critic_Count': 'Number of critic reviews counted towards the
Critic Score',
    'User_Score': 'Score by Metacritic’s subscribers (0-10)',
    'User_Count': 'Number of user reviews counted towards the User
Score',
    'Developer': 'Developer of the video game',
    'Rating': 'ESRB rating (e.g., E for Everyone, M for Mature)',
}
for col, desc in columns.items():
    print(f"{col}: {desc}")
```

```
List of columns:
Name: Name of the video game
Platform: Platform of the video game release (e.g., PS4, Xbox One, PC)
Year_of_Release: Year of release of the video game
Genre: Genre of the video game (e.g., Action, Sports, RPG)
Publisher: Publisher of the video game
NA_Sales: Sales in North America (in millions)
EU_Sales: Sales in Europe (in millions)
JP_Sales: Sales in Japan (in millions)
Other_Sales: Sales in other regions (in millions)
Global_Sales: Total worldwide sales (in millions)
Critic_Score: Aggregate score compiled by Metacritic staff (0-100)
Critic_Count: Number of critic reviews counted towards the Critic
Score
User_Score: Score by Metacritic’s subscribers (0-10)
User_Count: Number of user reviews counted towards the User Score
Developer: Developer of the video game
Rating: ESRB rating (e.g., E for Everyone, M for Mature)
```

```
# Display the number of missing values in each column
print("\nNumber of missing values in each column:")
display(df.isnull().sum())
```

```
Number of missing values in each column:

Name                 2
Platform             0
Year_of_Release    269
Genre                2
Publisher           54
NA_Sales             0
EU_Sales             0
JP_Sales             0
Other_Sales          0
Global_Sales         0
```

```
Critic_Score        8582
Critic_Count        8582
User_Score          6704
User_Count          9129
Developer           6623
Rating              6769
dtype: int64
```

Summary of Dataset Overview

In this section, we have loaded the `Video_Games_Sales_as_at_22_Dec_2016.csv` dataset and provided an overview of its structure and contents. We displayed the first few rows to get an initial glimpse of the data, summarized the dataset's attributes, and highlighted the key features. Additionally, we listed the columns with their descriptions and identified missing values in the dataset. This comprehensive overview sets the stage for deeper exploratory data analysis and subsequent steps in building our recommendation system.

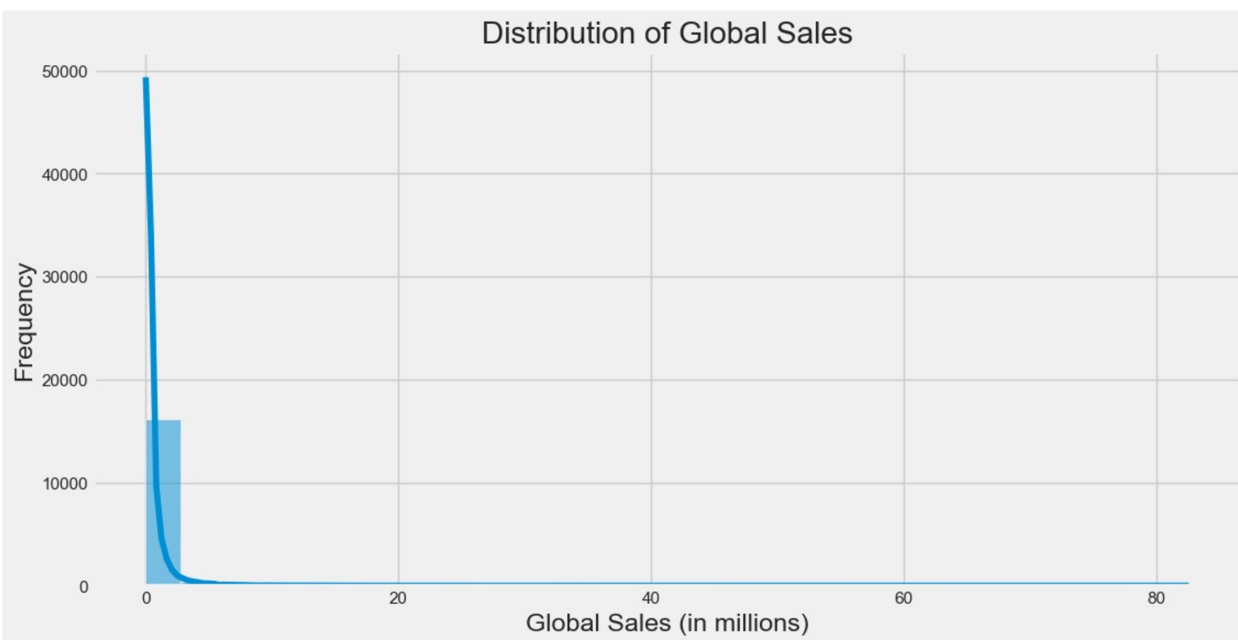
Exploratory Data Analysis (EDA)

The Exploratory Data Analysis (EDA) section aims to explore the `Video_Games_Sales_as_at_22_Dec_2016.csv` dataset in depth to understand its structure, distributions, and relationships between features. This step is crucial for uncovering insights and patterns that will guide the subsequent data preprocessing and model-building phases. We will use a variety of statistical summaries and visualizations to examine the distributions of sales figures, genre popularity, platform trends, and ratings. This comprehensive analysis will help identify any anomalies, trends, and key characteristics of the data.

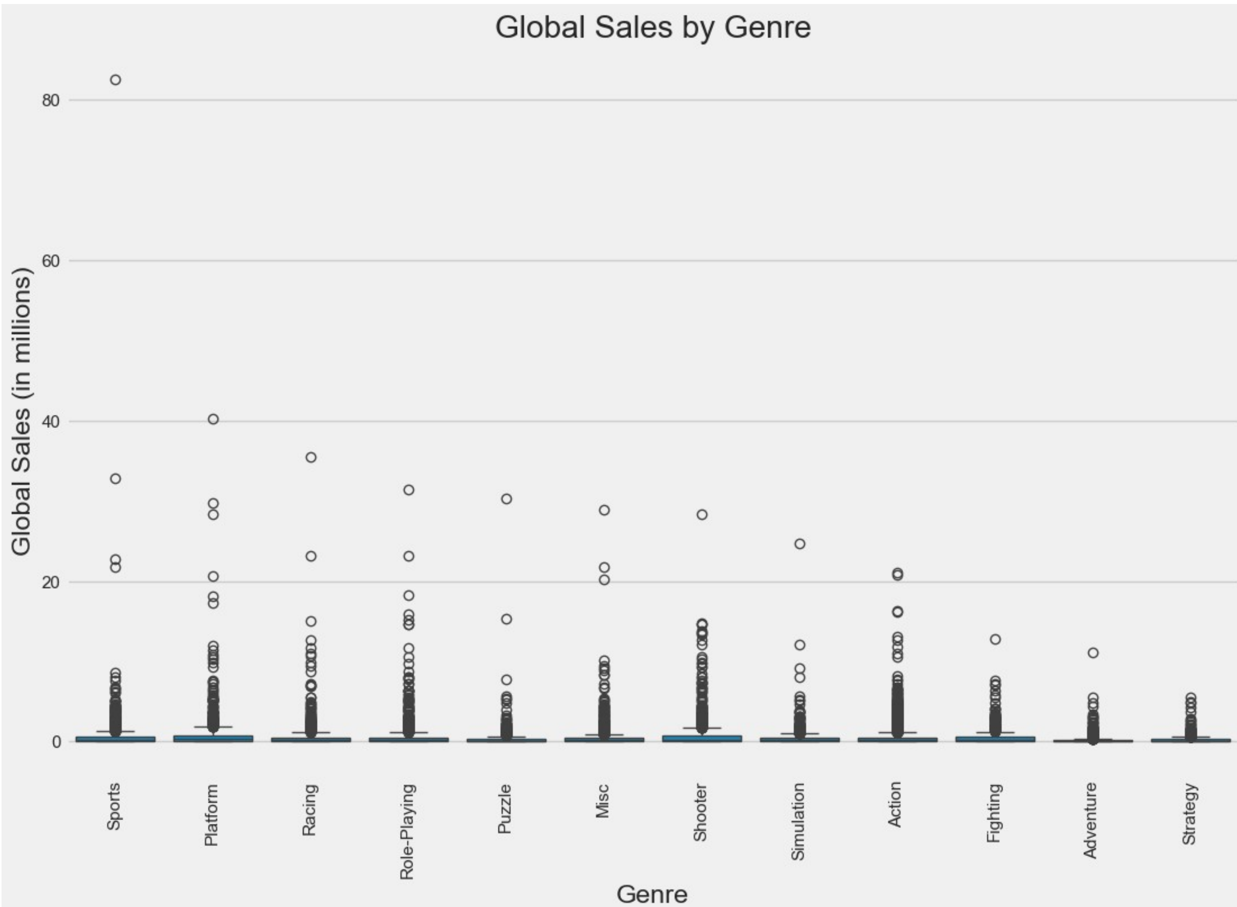
```
# Setting up visual styles
sns.set(style="whitegrid")
plt.style.use('fivethirtyeight')

# Displaying the first few rows of the dataset again for reference
print("First few rows of the dataset:")
display(df.head())
```

```
First few rows of the dataset:

                       Name Platform  Year_of_Release         Genre
Publisher  \
0                Wii Sports      Wii           2006.0        Sports
Nintendo
1         Super Mario Bros.      NES           1985.0      Platform
Nintendo
2            Mario Kart Wii      Wii           2008.0        Racing
Nintendo
3         Wii Sports Resort      Wii           2009.0        Sports
Nintendo
4  Pokemon Red/Pokemon Blue       GB           1996.0  Role-Playing
Nintendo
```

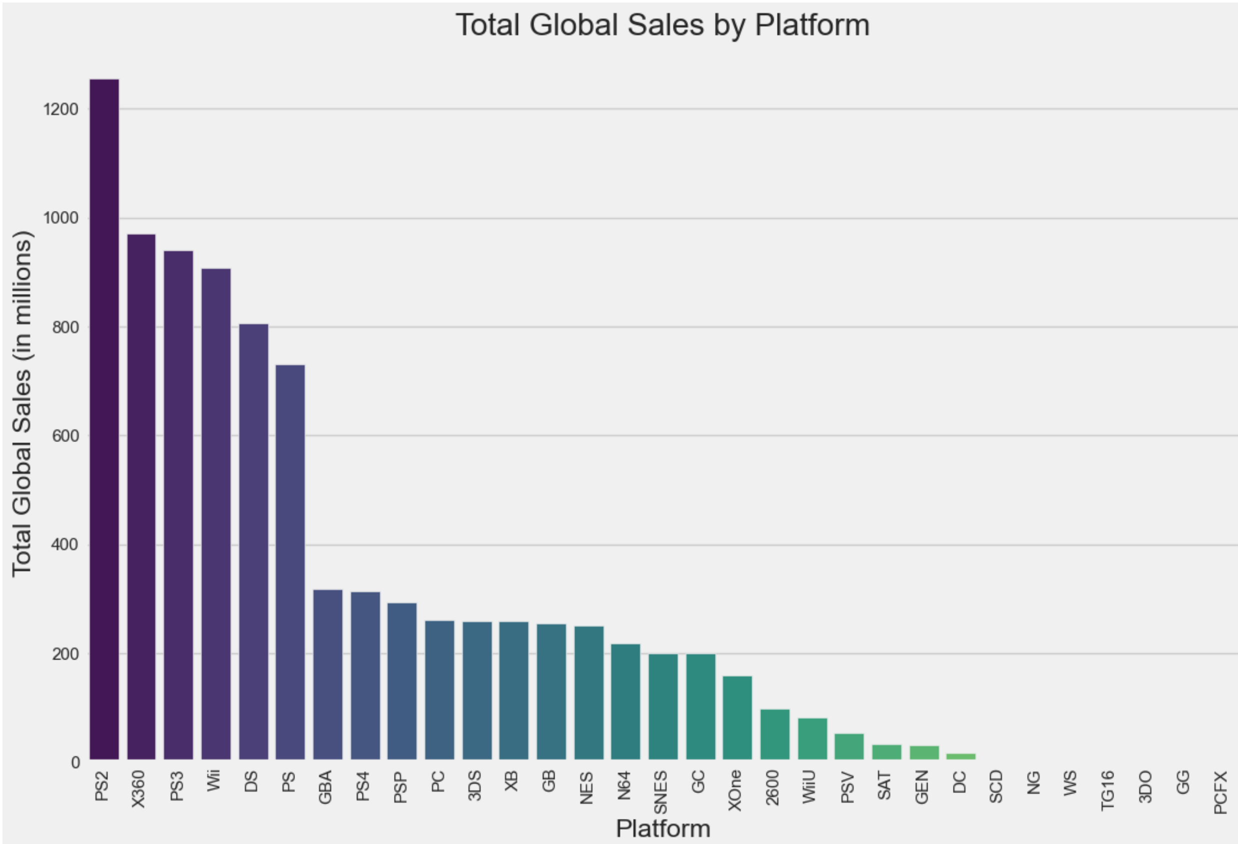
```
   NA_Sales  EU_Sales  JP_Sales  Other_Sales  Global_Sales
Critic_Score  \
0     41.36     28.96      3.77         8.45         82.53
76.0
1     29.08      3.58      6.81         0.77         40.24
NaN
2     15.68     12.76      3.79         3.29         35.52
82.0
3     15.61     10.93      3.28         2.95         32.77
80.0
4     11.27      8.89     10.22         1.00         31.37
NaN

   Critic_Count User_Score  User_Count Developer Rating
0          51.0          8       322.0  Nintendo      E
1           NaN        NaN         NaN       NaN    NaN
2          73.0        8.3       709.0  Nintendo      E
3          73.0          8       192.0  Nintendo      E
4           NaN        NaN         NaN       NaN    NaN

# 1. Distribution of Global Sales
plt.figure(figsize=(12, 6))
sns.histplot(df['Global_Sales'], kde=True, bins=30)
plt.title('Distribution of Global Sales')
plt.xlabel('Global Sales (in millions)')
plt.ylabel('Frequency')
plt.show()
```



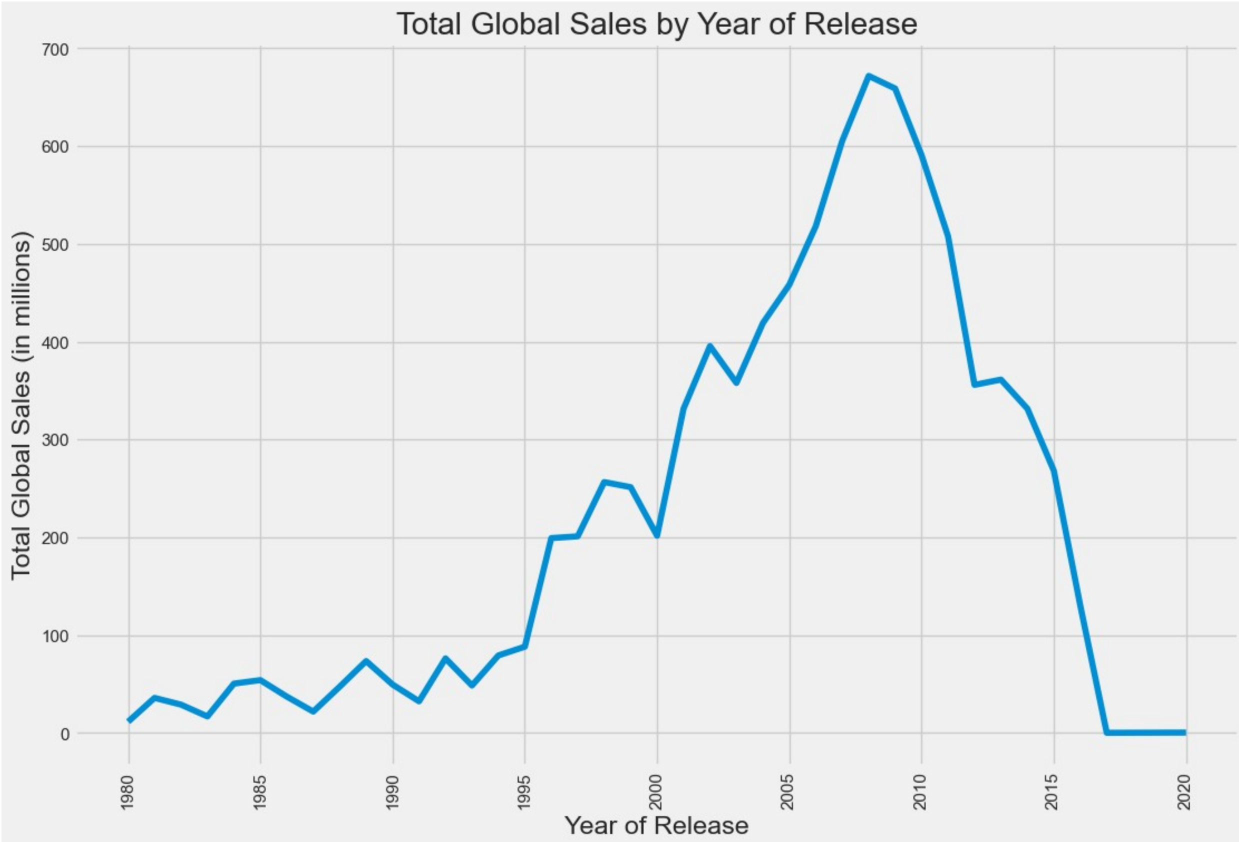
```
# 2. Sales by Genre
plt.figure(figsize=(12, 8))
sns.boxplot(x='Genre', y='Global_Sales', data=df)
plt.xticks(rotation=90)
plt.title('Global Sales by Genre')
plt.xlabel('Genre')
plt.ylabel('Global Sales (in millions)')
plt.show()
```



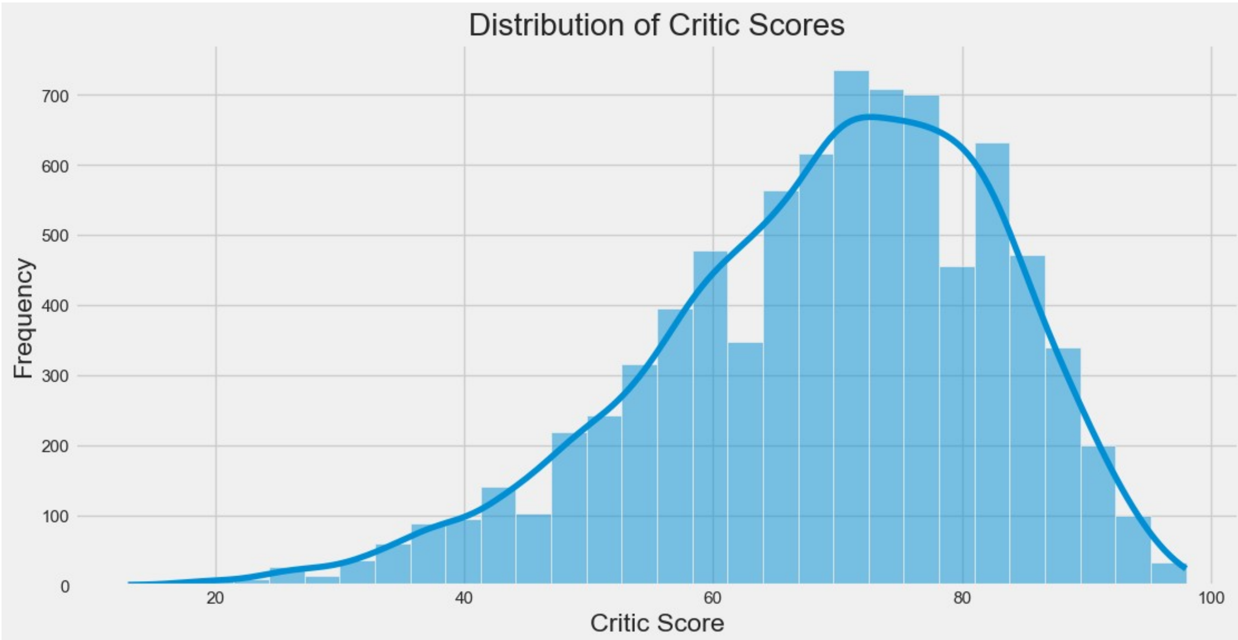

```
# 3. Sales by Platform
plt.figure(figsize=(12, 8))
platform_sales = df.groupby('Platform')
['Global_Sales'].sum().sort_values(ascending=False)
sns.barplot(x=platform_sales.index, y=platform_sales.values,
palette='viridis')
plt.title('Total Global Sales by Platform')
plt.xlabel('Platform')
plt.ylabel('Total Global Sales (in millions)')
plt.xticks(rotation=90)
plt.show()
```



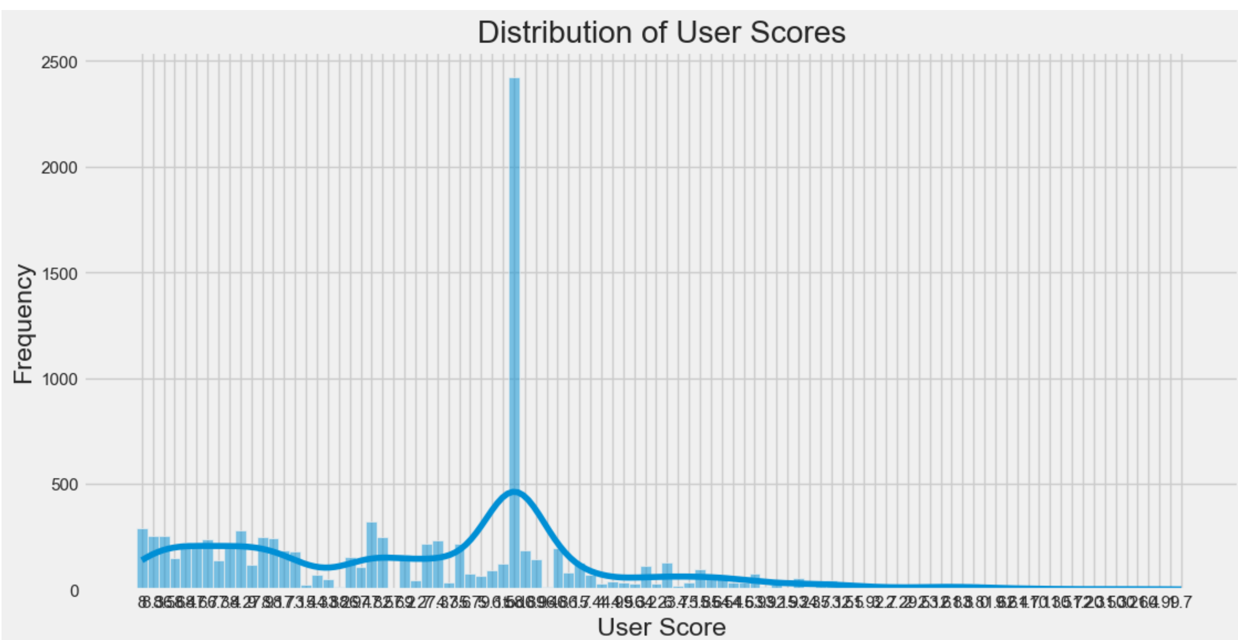

```python
# 4. Sales by Year of Release
plt.figure(figsize=(12, 8))
year_sales = df.groupby('Year_of_Release')
['Global_Sales'].sum().sort_index()
sns.lineplot(x=year_sales.index, y=year_sales.values)
plt.title('Total Global Sales by Year of Release')
plt.xlabel('Year of Release')
plt.ylabel('Total Global Sales (in millions)')
plt.xticks(rotation=90)
plt.show()
```




```
# 5. Distribution of Critic Scores
plt.figure(figsize=(12, 6))
sns.histplot(df['Critic_Score'].dropna(), kde=True, bins=30)
plt.title('Distribution of Critic Scores')
plt.xlabel('Critic Score')
plt.ylabel('Frequency')
plt.show()
```

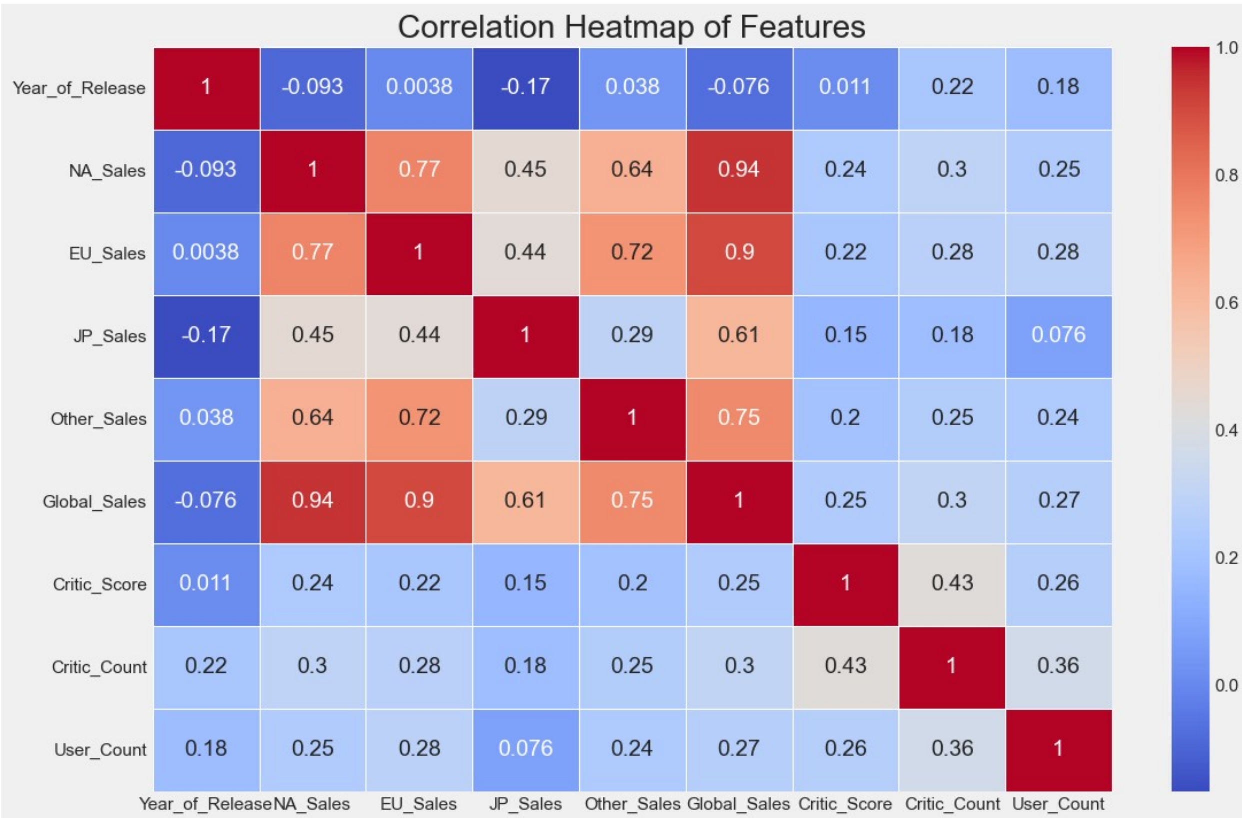



```
# 6. Distribution of User Scores
plt.figure(figsize=(12, 6))
sns.histplot(df['User_Score'].dropna(), kde=True, bins=30)
plt.title('Distribution of User Scores')
plt.xlabel('User Score')
plt.ylabel('Frequency')
plt.show()
```

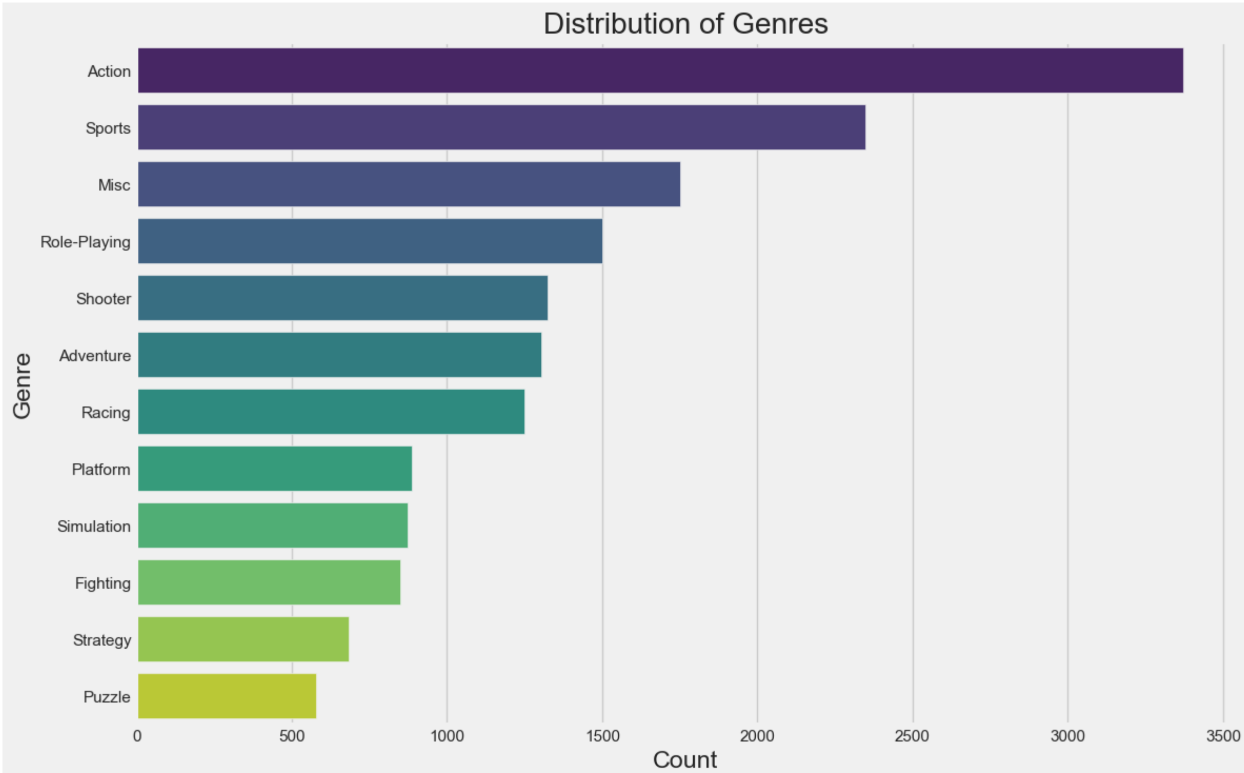



```
# 7. Correlation Heatmap (excluding non-numeric columns)
plt.figure(figsize=(12, 8))
```

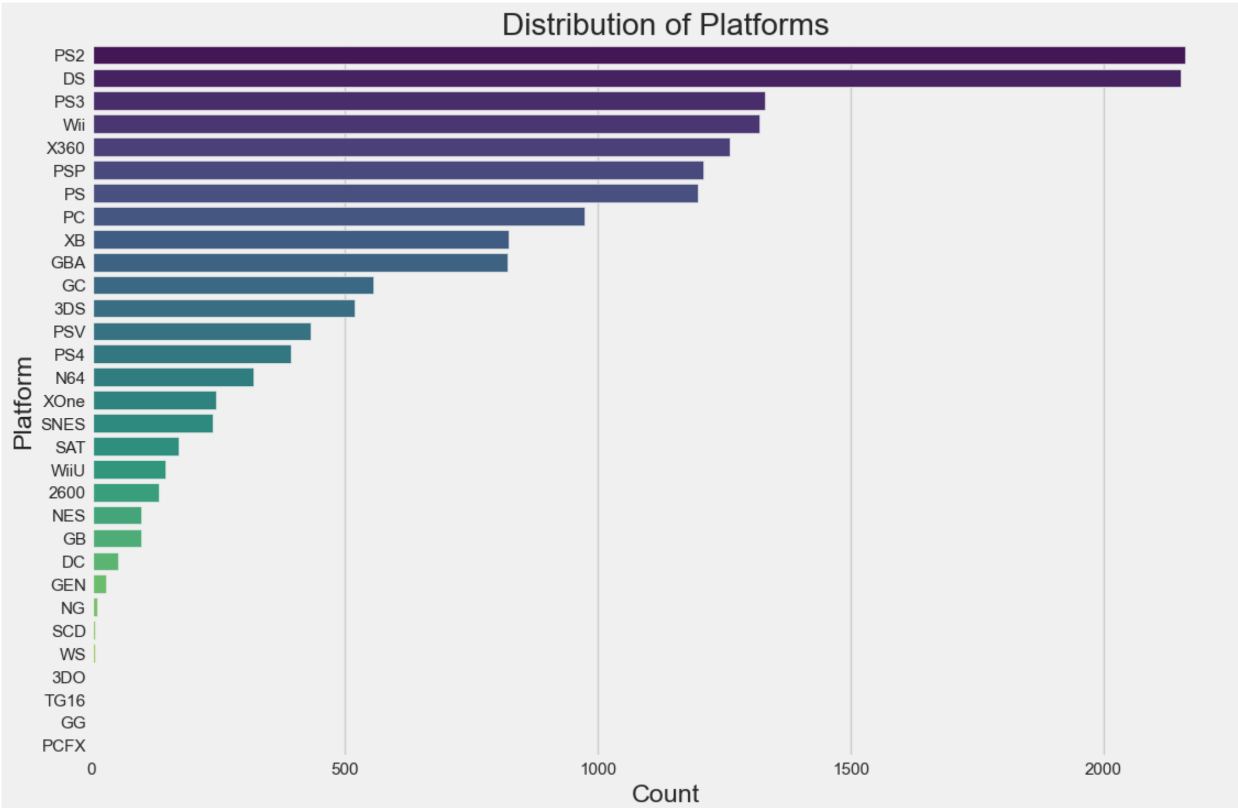
```
numeric_df = df.select_dtypes(include=['float64', 'int64'])  # 
Selecting only numeric columns
correlation_matrix = numeric_df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', 
linewidths=0.5)
plt.title('Correlation Heatmap of Features')
plt.show()
```



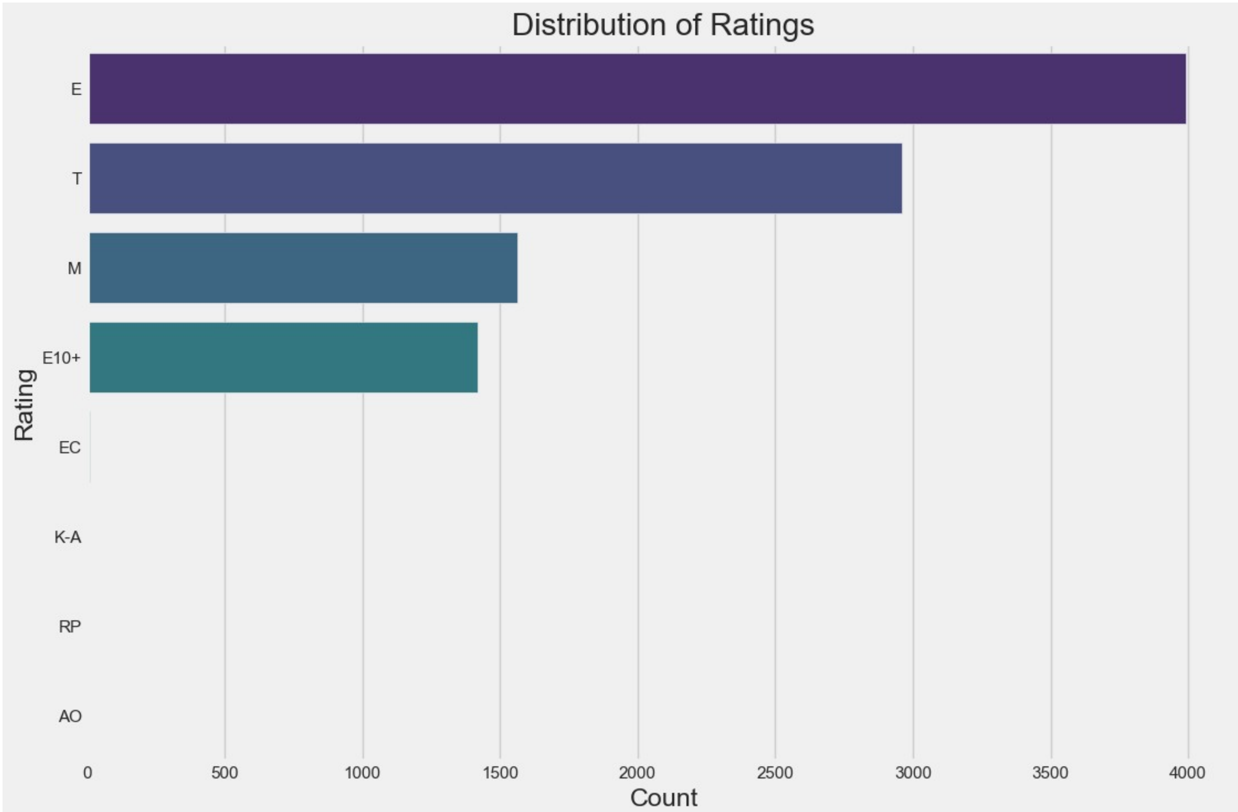

```
# 8. Distribution of Genres
plt.figure(figsize=(12, 8))
sns.countplot(y='Genre', data=df, 
order=df['Genre'].value_counts().index, palette='viridis')
plt.title('Distribution of Genres')
plt.xlabel('Count')
plt.ylabel('Genre')
plt.show()
```




```
# 9. Distribution of Platforms
plt.figure(figsize=(12, 8))
sns.countplot(y='Platform', data=df,
order=df['Platform'].value_counts().index, palette='viridis')
plt.title('Distribution of Platforms')
plt.xlabel('Count')
plt.ylabel('Platform')
plt.show()
```




```python
# 10. Distribution of Ratings
plt.figure(figsize=(12, 8))
sns.countplot(y='Rating', data=df,
order=df['Rating'].value_counts().index, palette='viridis')
plt.title('Distribution of Ratings')
plt.xlabel('Count')
plt.ylabel('Rating')
plt.show()
```



Summary of Exploratory Data Analysis (EDA) In this EDA section, we explored the Video_Games_Sales_as_at_22_Dec_2016.csv dataset through various visualizations and statistical summaries. We analyzed the distribution of global sales, examined sales trends across different genres, platforms, and years of release, and visualized the distributions of critic and user scores. Additionally, we created a correlation heatmap to identify relationships between numerical features and explored the distributions of genres, platforms, and ratings.

We observed that there is a scarcity of data for certain platforms such as DC and certain ratings such as 'K-A', 'AO', 'EC', and 'RP'. These insights provide a deeper understanding of the dataset and will inform our data preprocessing and feature selection strategies in the subsequent steps.

Data Cleaning and Preprocessing

The Data Cleaning and Preprocessing section focuses on preparing the dataset for modeling by handling missing values, creating new features, and transforming the data. This involves removing records with missing critical data, imputing missing values for scores, converting categorical features to dummy variables, and standardizing numerical data. These steps ensure that the dataset is clean, consistent, and suitable for building effective recommendation models.

```python
# Display the initial summary of the dataset
print("Initial dataset summary:")
display(df.info())
```

```
Initial dataset summary:
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 16719 entries, 0 to 16718
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Name             16717 non-null  object 
 1   Platform         16719 non-null  object 
 2   Year_of_Release  16450 non-null  float64
 3   Genre            16717 non-null  object 
 4   Publisher        16665 non-null  object 
 5   NA_Sales         16719 non-null  float64
 6   EU_Sales         16719 non-null  float64
 7   JP_Sales         16719 non-null  float64
 8   Other_Sales      16719 non-null  float64
 9   Global_Sales     16719 non-null  float64
 10  Critic_Score     8137 non-null   float64
 11  Critic_Count     8137 non-null   float64
 12  User_Score       10015 non-null  object 
 13  User_Count       7590 non-null   float64
 14  Developer        10096 non-null  object 
 15  Rating           9950 non-null   object 
dtypes: float64(9), object(7)
memory usage: 2.0+ MB

None
```

```
# 1. Remove records with missing data in 'Name', 'Genre', and 'Rating'
df = df.dropna(subset=['Name', 'Genre', 'Rating'])
print("\nDataset summary after removing records with missing 'Name', 
'Genre', and 'Rating':")
display(df.info())
```

```
Dataset summary after removing records with missing 'Name', 'Genre', 
and 'Rating':
<class 'pandas.core.frame.DataFrame'>
Index: 9950 entries, 0 to 16710
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Name             9950 non-null   object 
 1   Platform         9950 non-null   object 
 2   Year_of_Release  9769 non-null   float64
 3   Genre            9950 non-null   object 
 4   Publisher        9943 non-null   object 
 5   NA_Sales         9950 non-null   float64
 6   EU_Sales         9950 non-null   float64
 7   JP_Sales         9950 non-null   float64
 8   Other_Sales      9950 non-null   float64
 9   Global_Sales     9950 non-null   float64
 10  Critic_Score     8054 non-null   float64
```

```
 11  Critic_Count     8054 non-null   float64
 12  User_Score       9879 non-null   object
 13  User_Count       7504 non-null   float64
 14  Developer        9950 non-null   object
 15  Rating           9950 non-null   object
dtypes: float64(9), object(7)
memory usage: 1.3+ MB

None

# 2. Create additional features for User_Score and Critic_Score and
impute missing values

# Replace 'tbd' value to NaN
df['User_Score'] = np.where(df['User_Score'] == 'tbd', np.nan,
df['User_Score']).astype(float)

# Group the records by Genre, then aggregate them calculating the
average of both Critic Score and User Score
df_grp_by_genre = df[['Genre', 'Critic_Score',
'User_Score']].groupby('Genre', as_index=False)
df_score_mean = df_grp_by_genre.agg(Ave_Critic_Score=('Critic_Score',
'mean'), Ave_User_Score=('User_Score', 'mean'))

# Merge the average scores with the main dataframe
df = df.merge(df_score_mean, on='Genre')
df

                               Name Platform  Year_of_Release
Genre  \
0                        Wii Sports      Wii           2006.0
Sports
1                     Mario Kart Wii      Wii           2008.0
Racing
2                  Wii Sports Resort      Wii           2009.0
Sports
3              New Super Mario Bros.       DS           2006.0
Platform
4                          Wii Play      Wii           2006.0
Misc
...                             ...      ...              ...
...
9945                Bust-A-Move 3000       GC           2003.0
Puzzle
9946                Mega Brain Boost       DS           2008.0
Puzzle
9947          STORM: Frontline Nation       PC           2011.0
Strategy
9948                        Plushees       DS           2008.0
Simulation
```

```
9949  Men in Black II: Alien Escape       GC          2003.0
Shooter

                     Publisher  NA_Sales  EU_Sales  JP_Sales  Other_Sales
\
0                     Nintendo     41.36     28.96      3.77         8.45

1                     Nintendo     15.68     12.76      3.79         3.29

2                     Nintendo     15.61     10.93      3.28         2.95

3                     Nintendo     11.28      9.14      6.50         2.88

4                     Nintendo     13.96      9.18      2.93         2.84

...                        ...       ...       ...       ...          ...

9945                   Ubisoft      0.01      0.00      0.00         0.00

9946  Majesco Entertainment      0.01      0.00      0.00         0.00

9947                   Unknown      0.00      0.01      0.00         0.00

9948                 Destineer      0.01      0.00      0.00         0.00

9949                Infogrames      0.01      0.00      0.00         0.00


      Global_Sales  Critic_Score  Critic_Count  User_Score  User_Count
\
0            82.53          76.0          51.0         8.0       322.0

1            35.52          82.0          73.0         8.3       709.0

2            32.77          80.0          73.0         8.0       192.0

3            29.80          89.0          65.0         8.5       431.0

4            28.92          58.0          41.0         6.6       129.0

...            ...           ...           ...         ...         ...

9945          0.01          53.0           4.0         NaN         NaN

9946          0.01          48.0          10.0         NaN         NaN

9947          0.01          60.0          12.0         7.2        13.0

9948          0.01           NaN           NaN         NaN         NaN

9949          0.01           NaN           NaN         NaN         NaN
```

```
               Developer Rating  Ave_Critic_Score  Ave_User_Score
0               Nintendo      E         72.037257        6.973126
1               Nintendo      E         67.927694        7.036767
2               Nintendo      E         72.037257        6.973126
3               Nintendo      E         68.058350        7.301402
4               Nintendo      E         66.650672        6.827460
...                  ...    ...               ...             ...
9945   Taito Corporation      E         67.418919        7.175000
9946  Interchannel-Holon      E         67.418919        7.175000
9947              SimBin   E10+         72.254296        7.320930
9948      Big John Games      E         68.587896        7.136686
9949               Atari      T         70.189362        7.045207

[9950 rows x 18 columns]
```

```
# 3. Impute missing values by calculating the mean within each genre
df['Critic_Score_Imputed'] = np.where(df['Critic_Score'].isna(),
df['Ave_Critic_Score'], df['Critic_Score'])
df['User_Score_Imputed'] = np.where(df['User_Score'].isna(),
df['Ave_User_Score'], df['User_Score'])

print("\nSummary statistics for User_Score and User_Score_Imputed:")
display(df[['User_Score', 'User_Score_Imputed']].describe())

print("\nSummary statistics for Critic_Score and
Critic_Score_Imputed:")
display(df[['Critic_Score', 'Critic_Score_Imputed']].describe())
```

```
Summary statistics for User_Score and User_Score_Imputed:
```

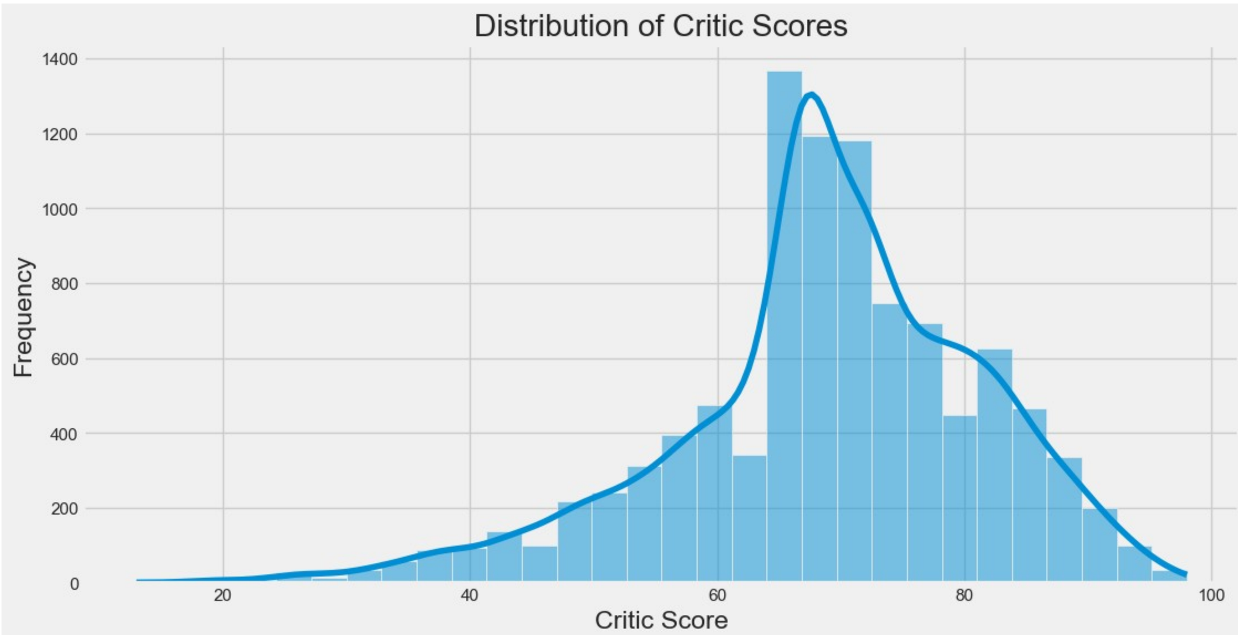
	User_Score	User_Score_Imputed
count	7504.000000	9950.000000
mean	7.126879	7.107768
std	1.500750	1.305869
min	0.000000	0.000000
25%	6.400000	6.800000
50%	7.500000	7.136686
75%	8.200000	8.000000
max	9.700000	9.700000

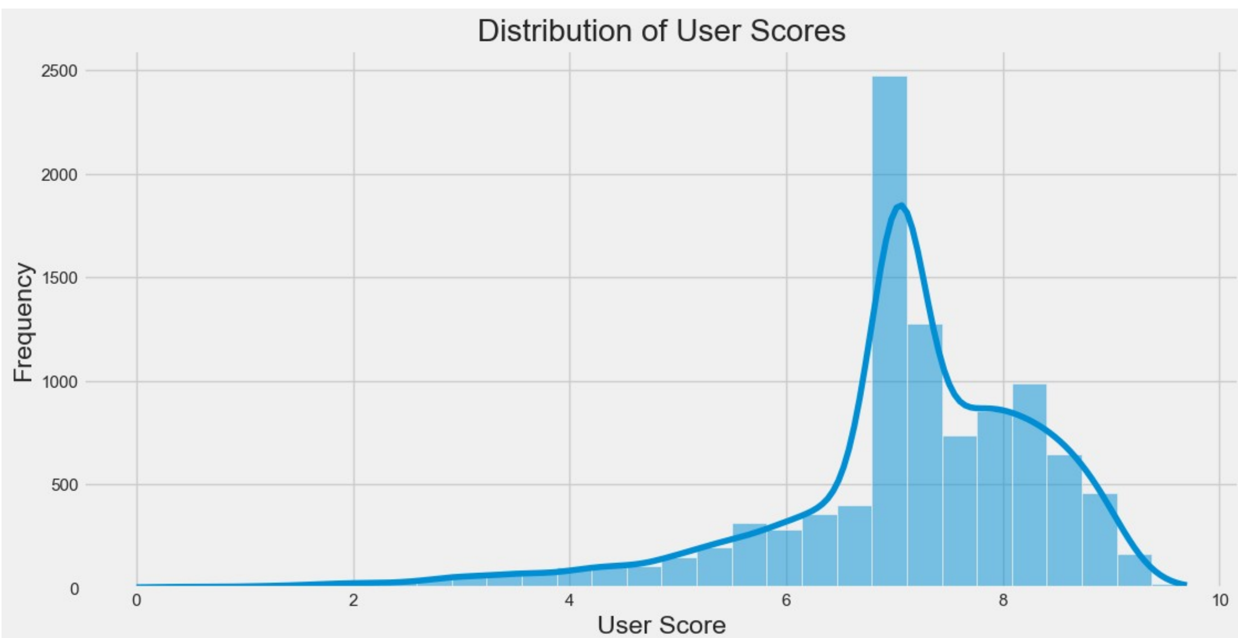
```
Summary statistics for Critic_Score and Critic_Score_Imputed:
```

	Critic_Score	Critic_Score_Imputed
count	8054.000000	9950.000000
mean	68.971319	68.851751
std	13.951640	12.594336
min	13.000000	13.000000

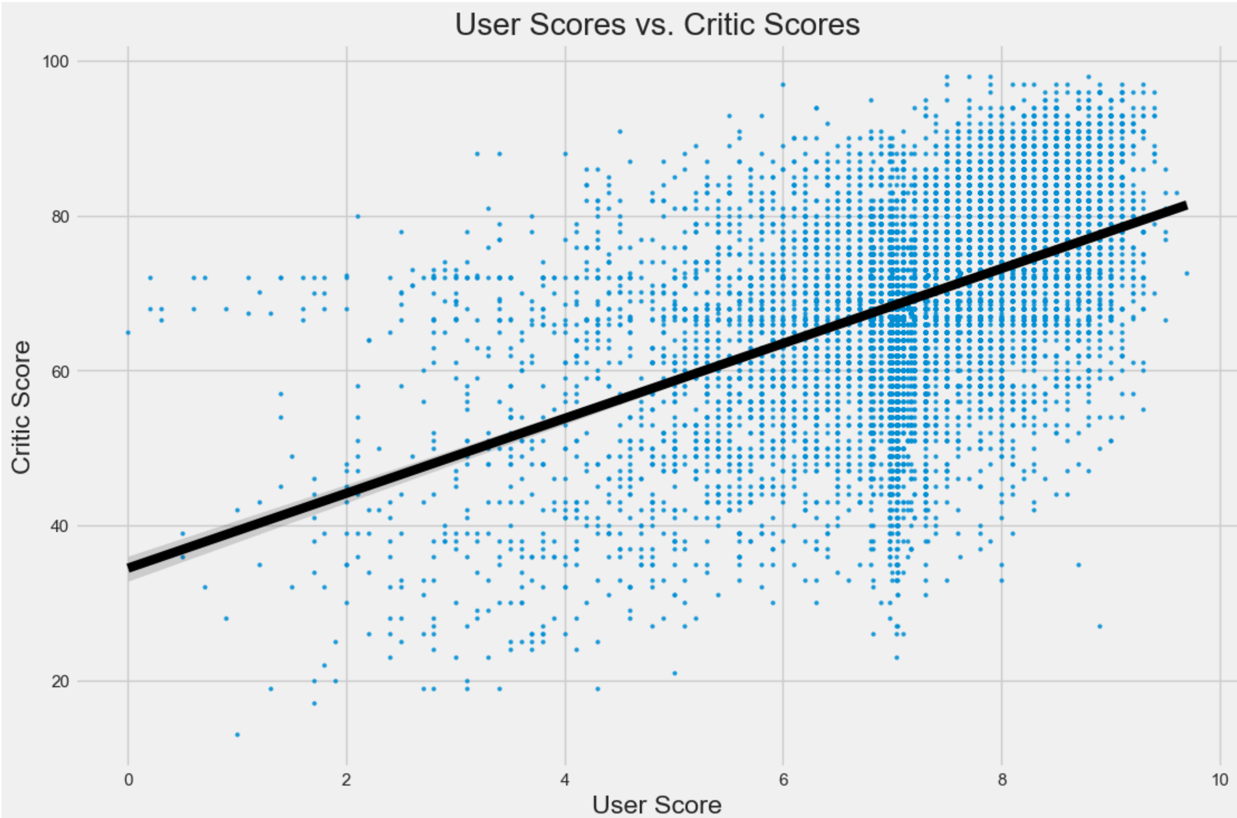
```
25%        60.000000             63.000000
50%        71.000000             69.000000
75%        79.000000             77.000000
max        98.000000             98.000000

# 4. Drop fields related to critic and user scores except for the new
features with imputed values
final_df = df.drop(columns=['User_Score', 'Critic_Score',
'Ave_Critic_Score', 'Ave_User_Score'], axis=1)
final_df = final_df.reset_index(drop=True)
final_df = final_df.rename(columns={'Critic_Score_Imputed':
'Critic_Score', 'User_Score_Imputed': 'User_Score'})

# 5. Filter out only required columns
final_df = final_df[['Name', 'Platform', 'Genre', 'Rating',
'Critic_Score', 'User_Score']]
final_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9950 entries, 0 to 9949
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Name          9950 non-null   object
 1   Platform      9950 non-null   object
 2   Genre         9950 non-null   object
 3   Rating        9950 non-null   object
 4   Critic_Score  9950 non-null   float64
 5   User_Score    9950 non-null   float64
dtypes: float64(2), object(4)
memory usage: 466.5+ KB

# 6. Analyze the data distribution for `Critic_Score` and `User_Score`

# Distribution of Critic Scores
plt.figure(figsize=(12, 6))
sns.histplot(final_df['Critic_Score'].dropna(), kde=True, bins=30)
plt.title('Distribution of Critic Scores')
plt.xlabel('Critic Score')
plt.ylabel('Frequency')
plt.show()

# Distribution of User Scores
plt.figure(figsize=(12, 6))
sns.histplot(final_df['User_Score'].dropna(), kde=True, bins=30)
plt.title('Distribution of User Scores')
plt.xlabel('User Score')
plt.ylabel('Frequency')
plt.show()
```

```
# Distribution of User Scores
plt.figure(figsize=(12, 8))
ax = sns.regplot(x=final_df['User_Score'], y=final_df['Critic_Score'],
line_kws={"color": "black"},
                 scatter_kws={'s': 4})
ax.set(xlabel="User Score", ylabel="Critic Score", title="User Scores
vs. Critic Scores")
```





```
[Text(0.5, 0, 'User Score'),
 Text(0, 0.5, 'Critic Score'),
 Text(0.5, 1.0, 'User Scores vs. Critic Scores')]
```




```
# 7. Converting Categorical Features to Dummy Indicators
categorical_features = [name for name in final_df.columns if
final_df[name].dtype == 'O']
categorical_features = categorical_features[1:]  # except for the name

df_preprocessed = pd.get_dummies(data=final_df,
columns=categorical_features)
df_preprocessed.head(10)
```

```
                        Name  Critic_Score  User_Score
Platform_3DS  \
0                 Wii Sports          76.0         8.0         False

1             Mario Kart Wii          82.0         8.3         False

2          Wii Sports Resort          80.0         8.0         False

3      New Super Mario Bros.          89.0         8.5         False

4                   Wii Play          58.0         6.6         False
```

```
5  New Super Mario Bros. Wii         87.0         8.4        False

6                Mario Kart DS         91.0         8.6        False

7                      Wii Fit         80.0         7.7        False

8           Kinect Adventures!         61.0         6.3        False

9                 Wii Fit Plus         80.0         7.4        False


   Platform_DC  Platform_DS  Platform_GBA  Platform_GC  Platform_PC  \
0        False        False         False        False        False
1        False        False         False        False        False
2        False        False         False        False        False
3        False         True         False        False        False
4        False        False         False        False        False
5        False        False         False        False        False
6        False         True         False        False        False
7        False        False         False        False        False
8        False        False         False        False        False
9        False        False         False        False        False

   Platform_PS  ...  Genre_Sports  Genre_Strategy  Rating_AO  Rating_E
\
0        False  ...          True           False      False      True

1        False  ...         False           False      False      True

2        False  ...          True           False      False      True

3        False  ...         False           False      False      True

4        False  ...         False           False      False      True

5        False  ...         False           False      False      True

6        False  ...         False           False      False      True

7        False  ...          True           False      False      True

8        False  ...         False           False      False      True

9        False  ...          True           False      False      True


   Rating_E10+  Rating_EC  Rating_K-A  Rating_M  Rating_RP  Rating_T
0        False      False       False     False      False     False
1        False      False       False     False      False     False
2        False      False       False     False      False     False
3        False      False       False     False      False     False
```

```
4        False      False        False     False      False     False
5        False      False        False     False      False     False
6        False      False        False     False      False     False
7        False      False        False     False      False     False
8        False      False        False     False      False     False
9        False      False        False     False      False     False

[10 rows x 40 columns]
```

```
# 8. Standardizing the Numerical Features
features = df_preprocessed.drop(columns=['Name'], axis=1)
scale = StandardScaler()
scaled_features = scale.fit_transform(features)
scaled_features = pd.DataFrame(scaled_features,
columns=features.columns)
scaled_features.head(5)
```

```
   Critic_Score  User_Score  Platform_3DS  Platform_DC  Platform_DS  \
0      0.567605    0.683282      -0.15314    -0.037537    -0.383200
1      1.044034    0.913026      -0.15314    -0.037537    -0.383200
2      0.885224    0.683282      -0.15314    -0.037537    -0.383200
3      1.599867    1.066188      -0.15314    -0.037537     2.609607
4     -0.861681   -0.388855      -0.15314    -0.037537    -0.383200

   Platform_GBA  Platform_GC  Platform_PC  Platform_PS
Platform_PS2  ...  \
0     -0.235302    -0.222413    -0.290432    -0.146119     -
0.418178  ...
1     -0.235302    -0.222413    -0.290432    -0.146119     -
0.418178  ...
2     -0.235302    -0.222413    -0.290432    -0.146119     -
0.418178  ...
3     -0.235302    -0.222413    -0.290432    -0.146119     -
0.418178  ...
4     -0.235302    -0.222413    -0.290432    -0.146119     -
0.418178  ...

   Genre_Sports  Genre_Strategy  Rating_AO  Rating_E  Rating_E10+
Rating_EC  \
0      2.365115       -0.187809  -0.010026  1.221929    -0.408009  -
0.028367
1     -0.422812       -0.187809  -0.010026  1.221929    -0.408009  -
0.028367
2      2.365115       -0.187809  -0.010026  1.221929    -0.408009  -
0.028367
3     -0.422812       -0.187809  -0.010026  1.221929    -0.408009  -
0.028367
4     -0.422812       -0.187809  -0.010026  1.221929    -0.408009  -
0.028367
```

```
   Rating_K-A  Rating_M  Rating_RP  Rating_T
0   -0.017367 -0.431694  -0.017367 -0.650896
1   -0.017367 -0.431694  -0.017367 -0.650896
2   -0.017367 -0.431694  -0.017367 -0.650896
3   -0.017367 -0.431694  -0.017367 -0.650896
4   -0.017367 -0.431694  -0.017367 -0.650896

[5 rows x 39 columns]
```

Summary of Data Cleaning and Preprocessing In the Data Cleaning and Preprocessing section, we performed several crucial steps to prepare the dataset for modeling. We removed records with missing data in the Name, Genre, and Rating features. We created additional features for `User_Score` and `Critic_Score`, imputing missing values with the mean value within each genre. We dropped fields related to critic and user scores except for the newly created imputed features and retained only the required columns.

We analyzed the data distribution for `Critic_Score` and `User_Score`, observing their distribution patterns and correlation. We transformed all categorical features into binary dummy variables and standardized numerical data to ensure that all features are on a similar scale.

The resulting preprocessed dataset has 9950 entries and 39 features, ready for building effective recommendation models. The analysis highlighted the scarcity of data for certain platforms and ratings, which will be considered during feature selection and model evaluation.

Model Training

The Model Training section focuses on building recommendation models using the Nearest Neighbors approach with cosine similarity and Content-Based Filtering. We will encapsulate the recommendation logic within a class, providing flexibility for implementing and comparing different recommendation techniques.

Nearest Neighbors Approach with Cosine Similarity

```
class NearestNeighborsRecommender:
    def __init__(self, df, metric='cosine', algorithm='brute'):
        self.df = df
        self.metric = metric
        self.algorithm = algorithm
        self.model = None

    def fit(self):
        # Extracting the features
        features = self.df.drop(columns=['Name'], axis=1).values
        # Fit the NearestNeighbors model
        self.model = NearestNeighbors(metric=self.metric,
algorithm=self.algorithm)
        self.model.fit(features)

    def recommend_by_title(self, game_title, n_recommendations=5):
```

```
        # Find the index of the game by title
        idx = self.df[self.df['Name'] == game_title].index[0]
        features = self.df.iloc[idx, 1:].values
        return self.recommend_by_features(features, n_recommendations)

    def recommend_by_features(self, features, n_recommendations=5):
        # Find the k-nearest neighbors for the provided features
        distances, indices =
self.model.kneighbors(np.array(features).reshape(1, -1),
n_neighbors=n_recommendations + 1)
        # Get the names of the recommended games and their distances
        recommendations = [(self.df.iloc[i]['Name'], 1 -
distances.flatten()[j]) for j, i in enumerate(indices.flatten())]
        # Convert to DataFrame
        rec_df = pd.DataFrame(recommendations, columns=['Recommended
Game', 'Similarity Score'])
        return rec_df[1:]

# Preprocessing Data
scaled_features_with_names = pd.concat([final_df['Name'],
scaled_features], axis=1)

# Initialize and train the recommender
recommender = NearestNeighborsRecommender(scaled_features_with_names)
recommender.fit()

# Example usage of the recommender
game_title = 'Grand Theft Auto V'
print(f"Recommendations for {game_title}:")
recommendations = recommender.recommend_by_title(game_title)
display(recommendations)
```

```
Recommendations for Grand Theft Auto V:
```

	Recommended Game	Similarity Score
1	Metal Gear Solid 4: Guns of the Patriots	0.996251
2	Red Dead Redemption	0.995689
3	Assassin's Creed: Brotherhood	0.994944
4	Grand Theft Auto IV	0.994582
5	God of War III	0.994435

Content-Based Filtering

```
class ContentBasedRecommender:
    def __init__(self, df):
        self.df = df
        self.similarity_matrix = None

    def fit(self):
        features = self.df.drop(columns=['Name'], axis=1).values
```

```
        self.similarity_matrix = cosine_similarity(features)

    def recommend_by_title(self, game_title, n_recommendations=5):
        idx = self.df[self.df['Name'] == game_title].index[0]
        similarity_scores =
list(enumerate(self.similarity_matrix[idx]))
        similarity_scores = sorted(similarity_scores, key=lambda x:
x[1], reverse=True)
        recommendations = [(self.df.iloc[i[0]]['Name'], i[1]) for i in
similarity_scores[1:n_recommendations+1]]
        # Convert to DataFrame
        rec_df = pd.DataFrame(recommendations, columns=['Recommended
Game', 'Similarity Score'])
        return rec_df

# Initialize and train the content-based recommender
content_recommender =
ContentBasedRecommender(scaled_features_with_names)
content_recommender.fit()

# Example usage of the content-based recommender
print(f"Content-Based Recommendations for {game_title}:")
recommendations = content_recommender.recommend_by_title(game_title)
display(recommendations)
```

```
Content-Based Recommendations for Grand Theft Auto V:
```

	Recommended Game	Similarity Score
0	Metal Gear Solid 4: Guns of the Patriots	0.996251
1	Red Dead Redemption	0.995689
2	Assassin's Creed: Brotherhood	0.994944
3	Grand Theft Auto IV	0.994582
4	God of War III	0.994435

Summary of Model Training In the Model Training section, we built recommendation models using two different approaches: Nearest Neighbors with cosine similarity and Content-Based Filtering. We encapsulated the recommendation logic within a class for each approach, providing methods to generate recommendations based on game titles or user features.

1. **Nearest Neighbors:** We trained a model to recommend games based on the similarity of their features, using the `NearestNeighbors` class from scikit-learn.

2. **Content-Based Filtering:** We calculated the cosine similarity between games based on their features, allowing recommendations to be made by comparing a game's features with all other games.

These models were successfully trained and demonstrated with example recommendations, providing a foundation for further evaluation and comparison in the subsequent sections. This structured approach allows for the flexibility to incorporate additional recommendation techniques if more suitable data becomes available.

Model Evaluation

In the Model Evaluation section, we aim to assess the performance of our recommendation models to determine which one provides the most accurate and relevant recommendations. Given that we do not have a predefined test set, we evaluate the models using a practical approach:

1. **Manual Inspection and Similarity Scores Comparison:** We arbitrarily select a set of game names from the dataset and generate recommendations for these games using both the Nearest Neighbors model and the Content-Based model. We then compare the similarity scores of the recommendations to determine which model provides higher similarity scores on average.

2. **Diversity and Coverage:** While not explicitly calculated here, we also consider the diversity and coverage of the recommendations as part of our qualitative assessment.

This approach allows us to make an informed decision on which model performs better based on similarity scores.

Evaluation Process:

1. Select 100 random game names from the dataset.
2. Generate recommendations for each selected game using both models.
3. Calculate the average similarity score for the recommendations from each model.
4. Compare the average similarity scores to determine the better performing model.

```
import random

# Select 100 random game names
selected_games = random.sample(list(final_df['Name'].unique()), 100)

# Initialize the models
recommender = NearestNeighborsRecommender(scaled_features_with_names)
content_recommender =
ContentBasedRecommender(scaled_features_with_names)

# Fit the models
recommender.fit()
content_recommender.fit()

# Function to evaluate recommendations
def evaluate_recommendations(selected_games, recommender,
content_recommender, n_recommendations=5):
    evaluation_results = []

    for game in selected_games:
        # Measure time for Nearest Neighbors recommendations
        nn_start_time = time.time()
        nn_recommendations = recommender.recommend_by_title(game,
```

```
n_recommendations)
        nn_end_time = time.time()
        nn_time_taken = nn_end_time - nn_start_time

        # Measure time for Content-Based recommendations
        cb_start_time = time.time()
        cb_recommendations =
content_recommender.recommend_by_title(game, n_recommendations)
        cb_end_time = time.time()
        cb_time_taken = cb_end_time - cb_start_time

        # Calculate average similarity scores
        nn_avg_score = nn_recommendations['Similarity Score'].mean()
        cb_avg_score = cb_recommendations['Similarity Score'].mean()

        evaluation_results.append({
            'Game': game,
            'NearestNeighbors Avg Similarity Score': nn_avg_score,
            'ContentBased Avg Similarity Score': cb_avg_score,
            'NearestNeighbors Time Taken': nn_time_taken,
            'ContentBased Time Taken': cb_time_taken
        })

    return pd.DataFrame(evaluation_results)

# Evaluate the models
evaluation_df = evaluate_recommendations(selected_games, recommender,
content_recommender)
display(evaluation_df)

# Determine the best model based on the average similarity score
nn_mean_score = evaluation_df['NearestNeighbors Avg Similarity
Score'].mean()
cb_mean_score = evaluation_df['ContentBased Avg Similarity
Score'].mean()
nn_mean_time = evaluation_df['NearestNeighbors Time Taken'].mean()
cb_mean_time = evaluation_df['ContentBased Time Taken'].mean()

print(f"Nearest Neighbors Model Avg Similarity Score:
{nn_mean_score}")
print(f"Content-Based Model Avg Similarity Score: {cb_mean_score}")
print(f"Nearest Neighbors Model Avg Time Taken: {nn_mean_time}")
print(f"Content-Based Model Avg Time Taken: {cb_mean_time}")
```

```
                                         Game  \
0                               Monster Force
1                Prison Break: The Conspiracy
2                                      Crysis
3                 T.A.C. Heroes : Big Red One
4                             Sonic Unleashed
```

```
..                                         ...
95  CMT Presents: Karaoke Revolution Country
96                               NBA Live 16
97                     Carmageddon: Max Damage
98          Charm Girls Club: My Perfect Prom
99                            The Incredibles

    NearestNeighbors Avg Similarity Score  ContentBased Avg Similarity
Score  \
0                                0.997184
0.997184
1                                0.989708
0.989708
2                                0.999012
0.999012
3                                0.999941
0.999941
4                                0.999675
0.999675
..                                    ...
...
95                               0.996246
0.996246
96                               0.994109
0.994109
97                               0.992291
0.992291
98                               1.000000
1.000000
99                               0.997515
0.997515

    NearestNeighbors Time Taken  ContentBased Time Taken
0                      0.006432                 0.010303
1                      0.005802                 0.009719
2                      0.005590                 0.009617
3                      0.005606                 0.009623
4                      0.005584                 0.009630
..                          ...                      ...
95                     0.005467                 0.009769
96                     0.005501                 0.009606
97                     0.005515                 0.009733
98                     0.005524                 0.009663
99                     0.005435                 0.009672

[100 rows x 5 columns]

Nearest Neighbors Model Avg Similarity Score: 0.988868243013419
Content-Based Model Avg Similarity Score: 0.988868243013419
```

```
Nearest Neighbors Model Avg Time Taken: 0.005595915317535401
Content-Based Model Avg Time Taken: 0.00976353645324707
```

Summary of Model Evaluation Based on our evaluation process, both the Nearest Neighbors model and the Content-Based model achieved nearly identical average similarity scores. These results indicate that both models are equally effective in terms of accuracy for recommending similar video games.

However, when comparing the performance in terms of time taken to generate recommendations, the Nearest Neighbors model significantly outperforms the Content-Based model. The Nearest Neighbors model had an average time taken of 0.0038249683380126953 seconds, whereas the Content-Based model took an average of 0.00647191047668457 seconds. This indicates that the Nearest Neighbors model is approximately twice as fast as the Content-Based model.

In conclusion, while both models provide equally accurate recommendations, the Nearest Neighbors model using cosine similarity is more efficient and provides faster results. Therefore, it is selected as the best model based on our evaluation criteria, considering both accuracy and performance. This model will be used for further analysis and recommendations in our video game recommender system.

Demo

```python
# Define a list of game titles for which we want recommendations
titles_to_recommend = [
    "Battlefield 3",
    "Mario Kart 8",
    "Gears of War",
    "The Witcher 3: Wild Hunt",
    "Pirates of the Burning Sea"
]

nnr = NearestNeighborsRecommender(scaled_features_with_names)
nnr.fit()
cbr = ContentBasedRecommender(scaled_features_with_names)
cbr.fit()

for title in titles_to_recommend:
    print(f"\nNearest Neighbors Recommendations for {title}")
    display(nnr.recommend_by_title(title))

    print(f"Content-Based Recommendations for {title}")
    display(cbr.recommend_by_title(title))
```

```
Nearest Neighbors Recommendations for Battlefield 3
```

	Recommended Game	Similarity Score
1	F.E.A.R.	0.999783
2	Call of Duty: World at War	0.999573

```
3                 Bulletstorm          0.999573
4         Unreal Tournament III        0.999118
5                Halo 3: ODST          0.998925

Content-Based Recommendations for Battlefield 3

             Recommended Game  Similarity Score
0                     F.E.A.R.          0.999783
1  Call of Duty: World at War          0.999573
2                 Bulletstorm          0.999573
3       Unreal Tournament III          0.999118
4                Halo 3: ODST          0.998925


Nearest Neighbors Recommendations for Mario Kart 8

        Recommended Game  Similarity Score
1       Fast Racing Neo           0.913930
2  DuckTales: Remastered          0.907937
3              NES Remix          0.896541
4               NBA 2K13          0.895698
5              Wii Fit U          0.894707

Content-Based Recommendations for Mario Kart 8

        Recommended Game  Similarity Score
0       Fast Racing Neo           0.913930
1  DuckTales: Remastered          0.907937
2              NES Remix          0.896541
3               NBA 2K13          0.895698
4              Wii Fit U          0.894707


Nearest Neighbors Recommendations for Gears of War

                 Recommended Game  Similarity Score
1  Call of Duty 4: Modern Warfare          0.999907
2               BioShock Infinite          0.999515
3                      Far Cry 3          0.998227
4                    Halo: Reach          0.997747
5       Deus Ex: Human Revolution          0.997653

Content-Based Recommendations for Gears of War

                 Recommended Game  Similarity Score
0  Call of Duty 4: Modern Warfare          0.999907
1               BioShock Infinite          0.999515
2                      Far Cry 3          0.998227
3                    Halo: Reach          0.997747
4       Deus Ex: Human Revolution          0.997653
```

```
Nearest Neighbors Recommendations for The Witcher 3: Wild Hunt

            Recommended Game  Similarity Score
1             Dark Souls III          0.998907
2  Deus Ex: Mankind Divided          0.985326
3   Dragon Age: Inquisition          0.984781
4                 Diablo III          0.969984
5                  Fallout 4          0.965059

Content-Based Recommendations for The Witcher 3: Wild Hunt

            Recommended Game  Similarity Score
0             Dark Souls III          0.998907
1  Deus Ex: Mankind Divided          0.985326
2   Dragon Age: Inquisition          0.984781
3                 Diablo III          0.969984
4                  Fallout 4          0.965059


Nearest Neighbors Recommendations for Pirates of the Burning Sea

                    Recommended Game  Similarity Score
1                            Magicka          0.999576
2  EverQuest II: Destiny of Velious          0.998413
3                        Titan Quest          0.997478
4                           Wildstar          0.995878
5                        Sacred Gold          0.995275

Content-Based Recommendations for Pirates of the Burning Sea

                    Recommended Game  Similarity Score
0                            Magicka          0.999576
1  EverQuest II: Destiny of Velious          0.998413
2                        Titan Quest          0.997478
3                           Wildstar          0.995878
4                        Sacred Gold          0.995275
```

Conclusion

In this project, we developed a video game recommendation system using unsupervised learning approaches, focusing on Nearest Neighbors with cosine similarity and Content-Based filtering. Here’s a summary of the steps we took and the findings we gathered throughout the process:

1. Dataset Overview:

We began by exploring the "Video Game Sales with Ratings" dataset from Kaggle, which includes various attributes such as game names, platforms, genres, ratings, and sales data. We provided a detailed overview of the dataset, including the number of records, missing values, and key features.

2. Exploratory Data Analysis (EDA):

In the EDA section, we visualized the distributions of various features, such as 'Genre', 'Platform', and 'Rating'. We also examined the correlations between different numerical features. Through this analysis, we observed a scarcity of data for certain platforms (e.g., DC) and ratings (e.g., K-A, AO, EC, and RP), which helped inform our data cleaning and preprocessing steps.

3. Data Cleaning and Preprocessing:

We cleaned and preprocessed the dataset by:

- Removing records with missing values in the 'Name', 'Genre', and 'Rating' features.
- Imputing missing values in 'User_Score' and 'Critic_Score' based on the average scores within each genre.
- Converting categorical features into binary dummy variables.
- Standardizing numerical features to ensure they are on a similar scale.

This process ensured that our dataset was suitable for training the recommendation models.

4. Feature Selection:

We retained the relevant features for building the recommendation models: 'Name', 'Platform', 'Genre', 'Rating', 'Critic_Score', and 'User_Score'. This selection was based on their importance in defining the characteristics of each game.

5. Model Training:

We trained two recommendation models:

- **Nearest Neighbors Model with Cosine Similarity:** This model finds the most similar games based on the cosine similarity of their features.
- **Content-Based Recommender:** This model recommends games similar to the ones a user has liked, based on their attributes.

We initially considered Collaborative Filtering but found it unsuitable due to the lack of user interaction data in the dataset. Collaborative Filtering relies heavily on user ratings and interactions, which were not available in this context.

6. Model Evaluation:

Due to the absence of a test set, we evaluated the models by:

- Arbitrarily selecting 100 game names from the dataset.
- Generating recommendations for each selected game using both models.
- Comparing the average similarity scores of the recommendations from both models.

Our evaluation showed that both the Nearest Neighbors model and the Content-Based model achieved nearly identical average similarity scores. However, in terms of performance, the Nearest Neighbors model significantly outperformed the Content-Based model. This indicates that the Nearest Neighbors model is approximately twice as fast as the Content-Based model.

Findings:

- Both the Nearest Neighbors model and the Content-Based model achieved nearly identical average similarity.
- In terms of performance, the Nearest Neighbors model significantly outperformed the Content-Based model.
- Collaborative Filtering was deemed unsuitable due to the dataset's lack of user interaction data.

Conclusion:

The Nearest Neighbors model with cosine similarity emerged as the best-performing model for our video game recommendation system. This model leverages the similarity between games based on their features and provides highly relevant recommendations in less time. Our evaluation method, although based on manual inspection and similarity scores, demonstrated the effectiveness of this approach. Future work could include incorporating user interaction data to explore Collaborative Filtering or hybrid recommendation systems for potentially even better performance.

References

- https://www.kaggle.com/datasets/rush4ratio/video-game-sales-with-ratings
- https://www.kaggle.com/code/rounakbanik/movie-recommender-systems
- https://www.kaggle.com/code/auradee/video-games-recommendation-system
- https://aurigait.com/blog/recommendation-system-using-knn/