DS 7331 - Lab 1 (Video Game Sales with Ratings Dataset Analysis)

Eric Graham

Dataset Information

This project uses the Video Games Sales with Ratings dataset from Kaggle. It includes 16719 observations and 18 features.

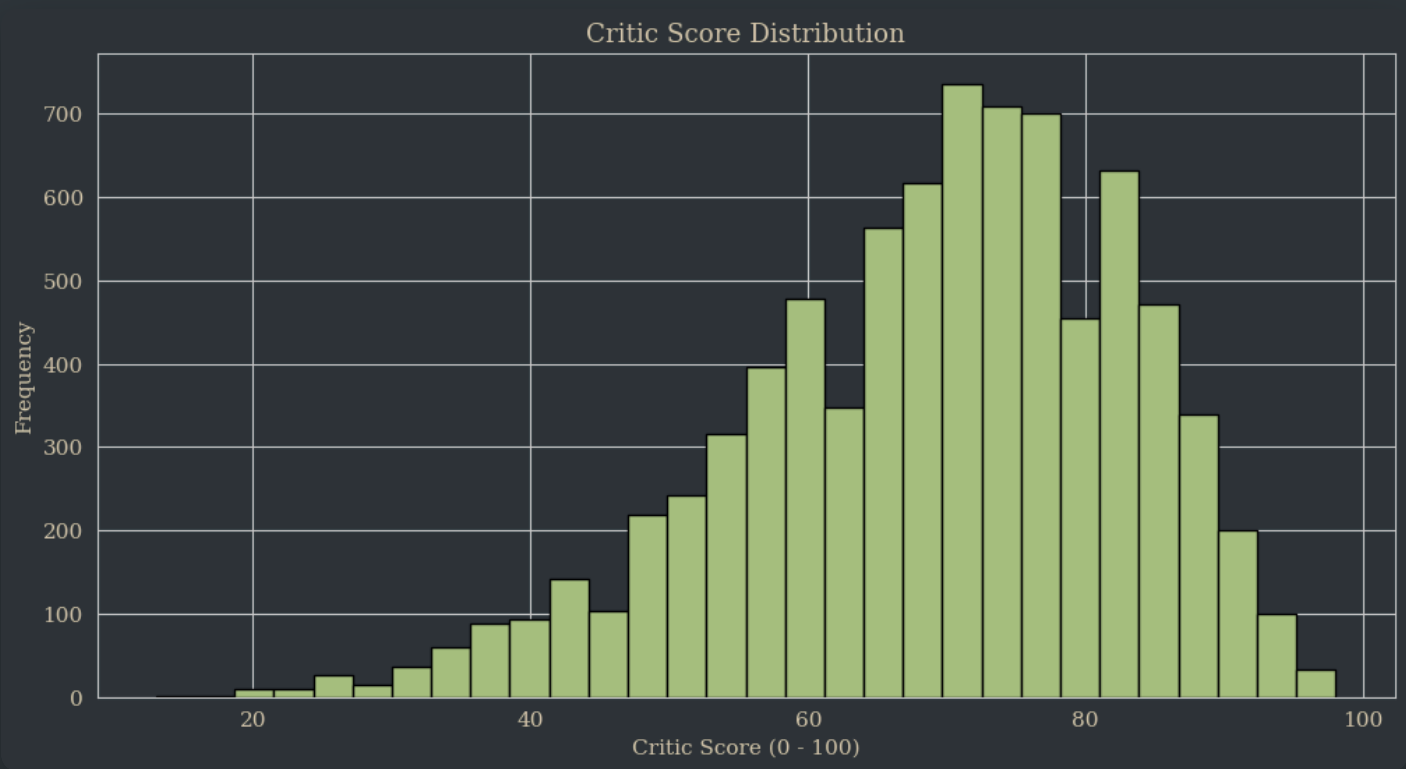
Variable Glossary

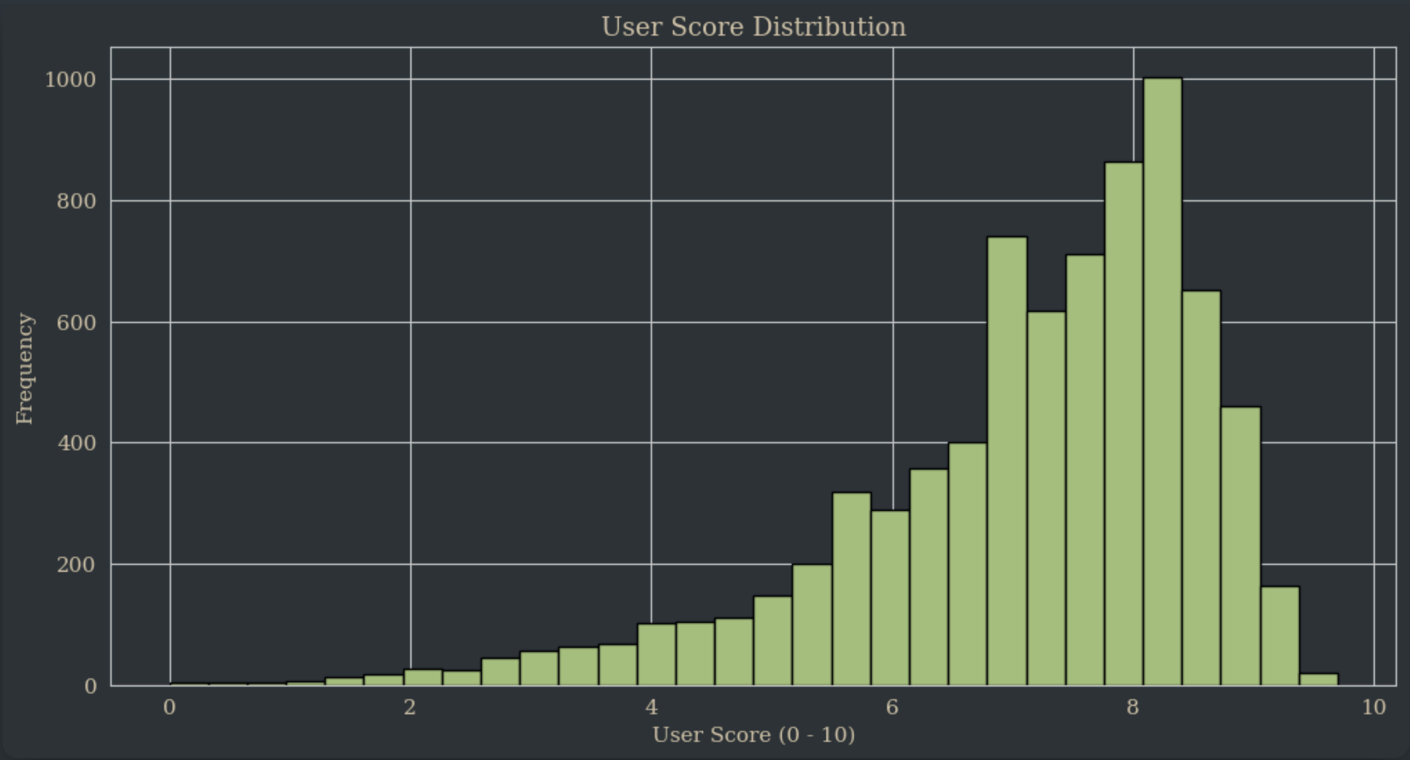
Variable	Type	Description
Name	object	Name of the game
Platform	object	Console on which the game is running
Year_of_Release	float64	Year of the game released
Genre	object	Game's category
Publisher	object	Publisher
NA_Sales	float64	Game sales in North America (in millions of units)
EU_Sales	float64	Game sales in the European Union (in millions of units)
JP_Sales	float64	Game sales in Japan (in millions of units)
Other_Sales	float64	Game sales in the rest of the world, i.e. Africa, Asia excluding Japan, Australia, Europe excluding the E.U. and South America (in millions of units)
Global_Sales	float64	Total sales in the world (in millions of units)
Critic_Score	float64	Aggregate score compiled by Metacritic staff

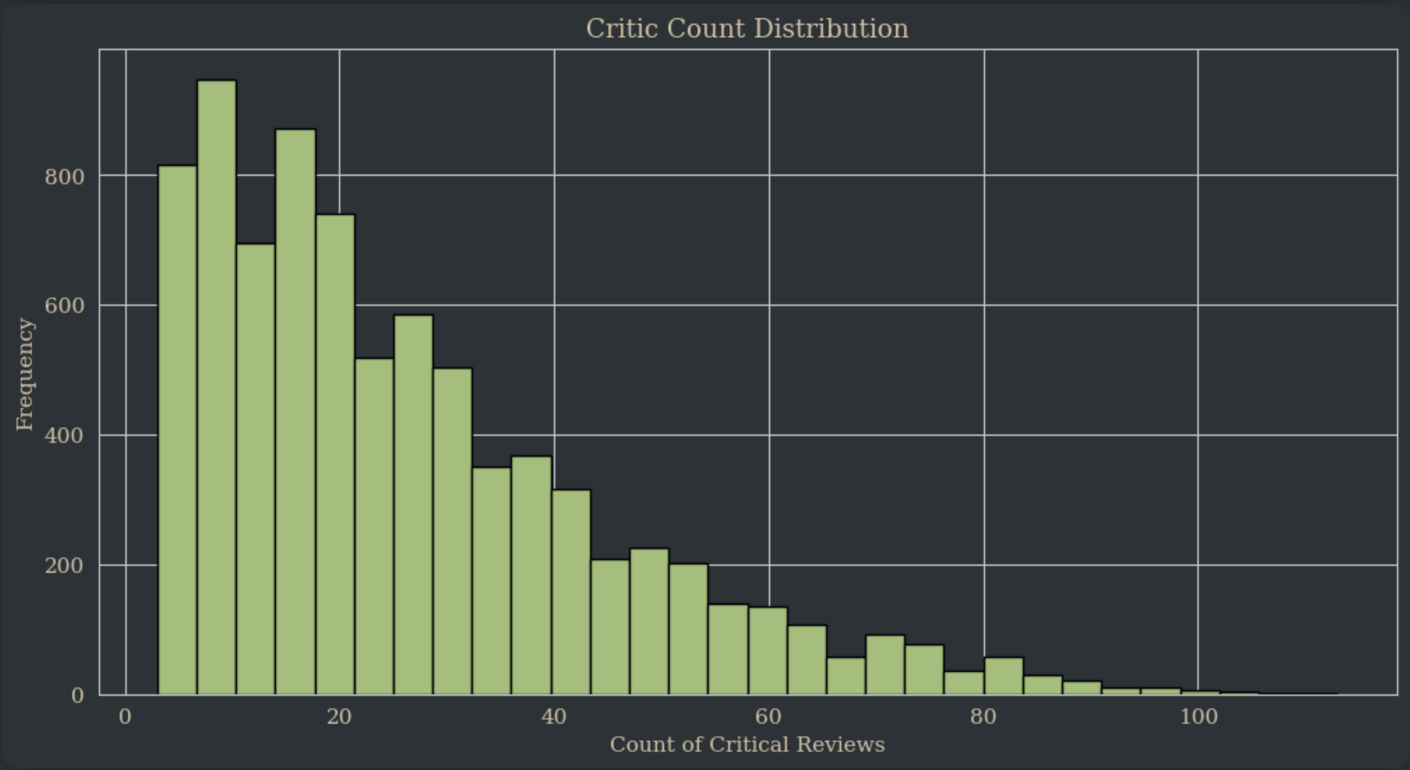
Variable	Type	Description
Critic_Count	float64	The number of critics used in coming up with the Critic_score
User_Score	object	Score by Metacritic's subscribers
User_Count	float64	Number of users who gave the user_score
Developer	object	Party responsible for creating the game
Rating	object	The ESRB ratings (E.g. Everyone, Teen, Adults Only..etc)

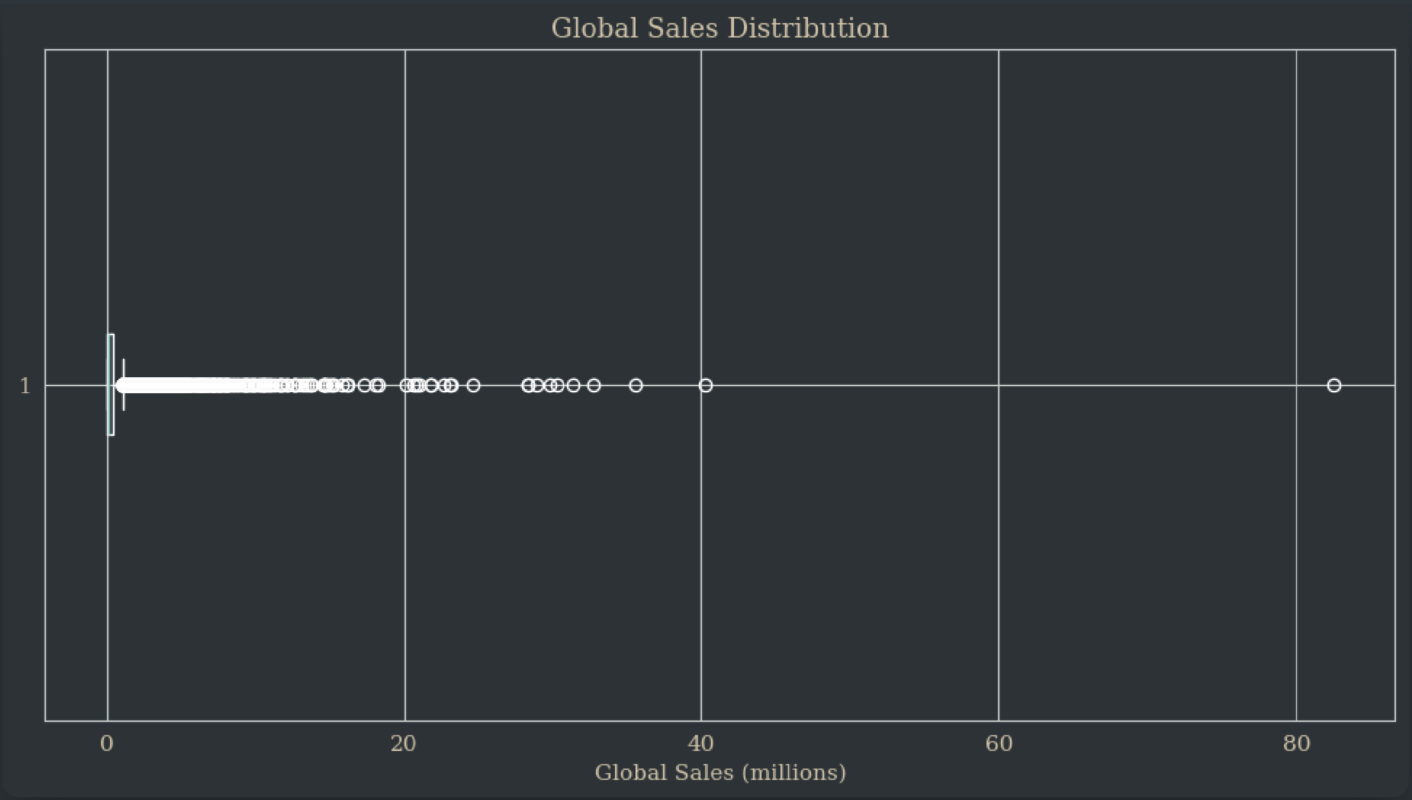
Exploratory Data Analysis Highlights

Numeric Variable Plots

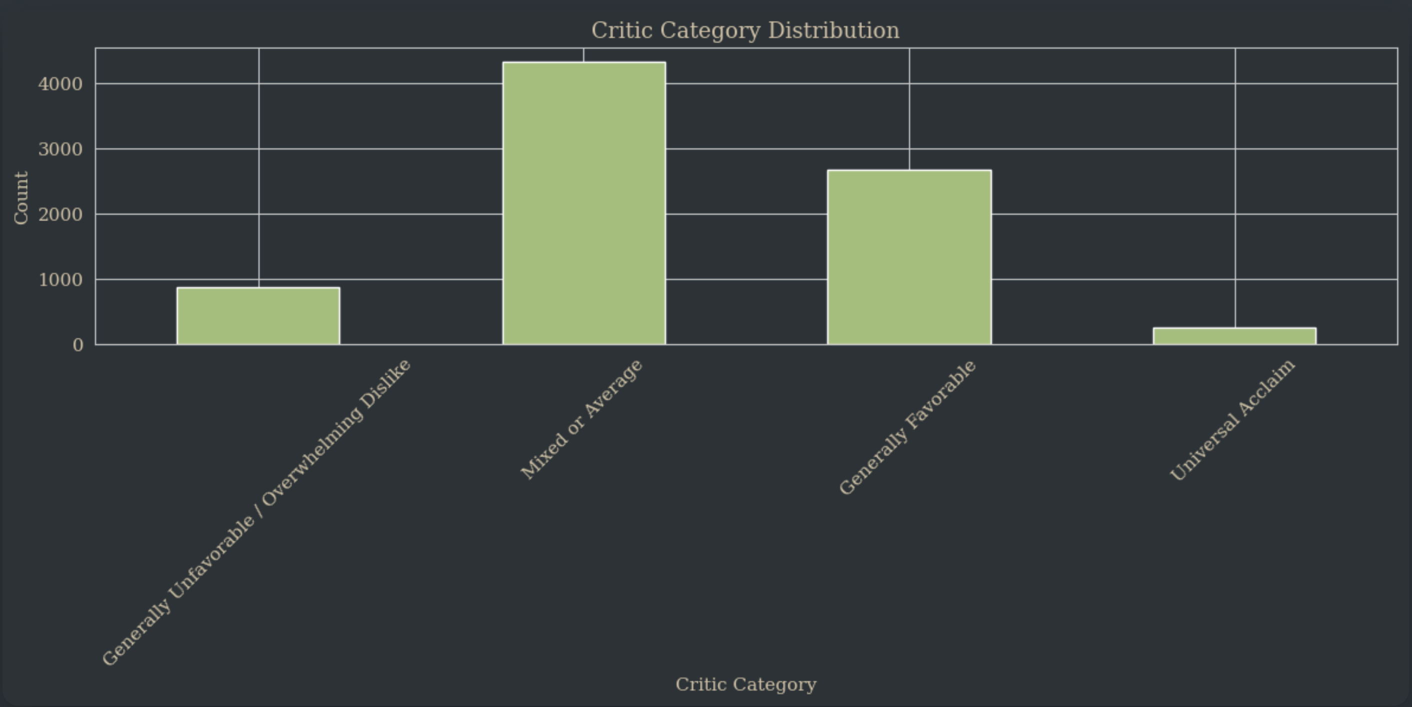


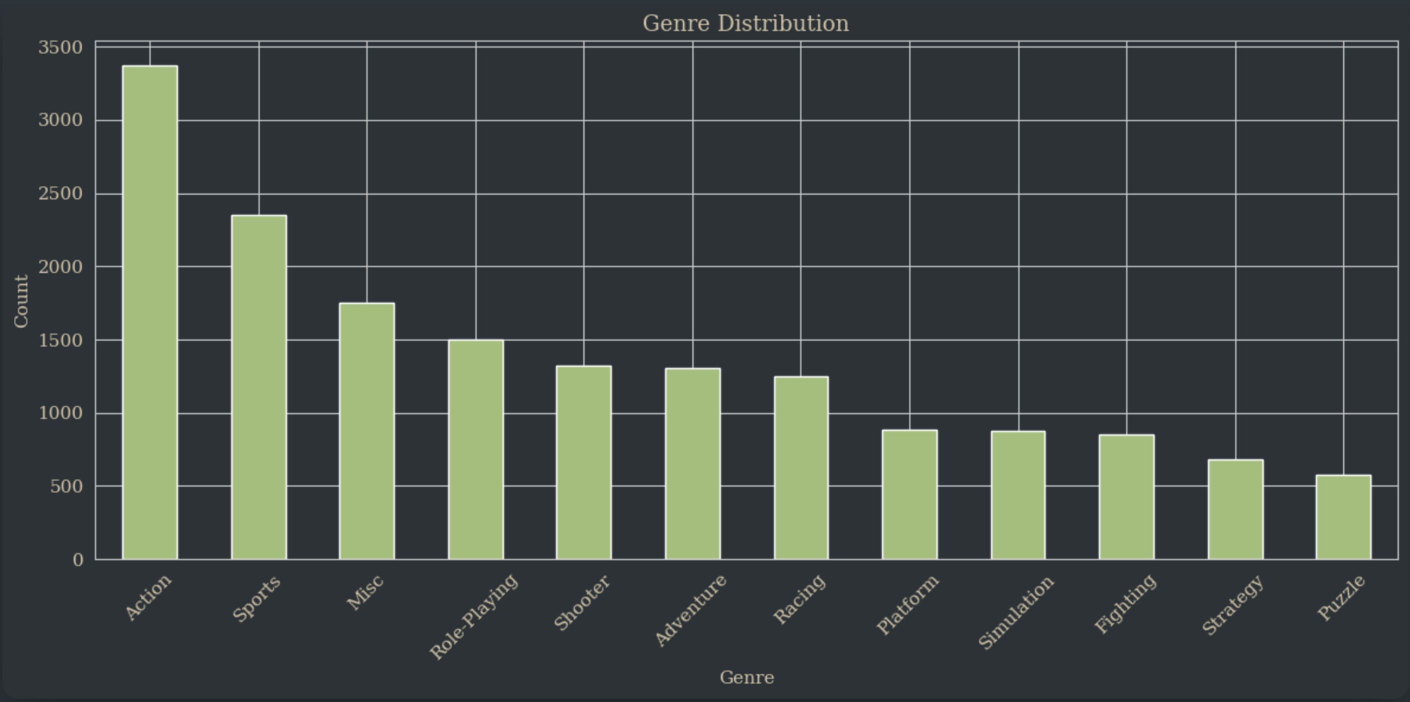

User Score Distribution
Frequency
0
200
400
600
800
1000
0
2
4
6
8
10
User Score (0 - 10)


Critic Count Distribution
Frequency
0
200
400
600
800
0
20
40
60
80
100
Count of Critical Reviews

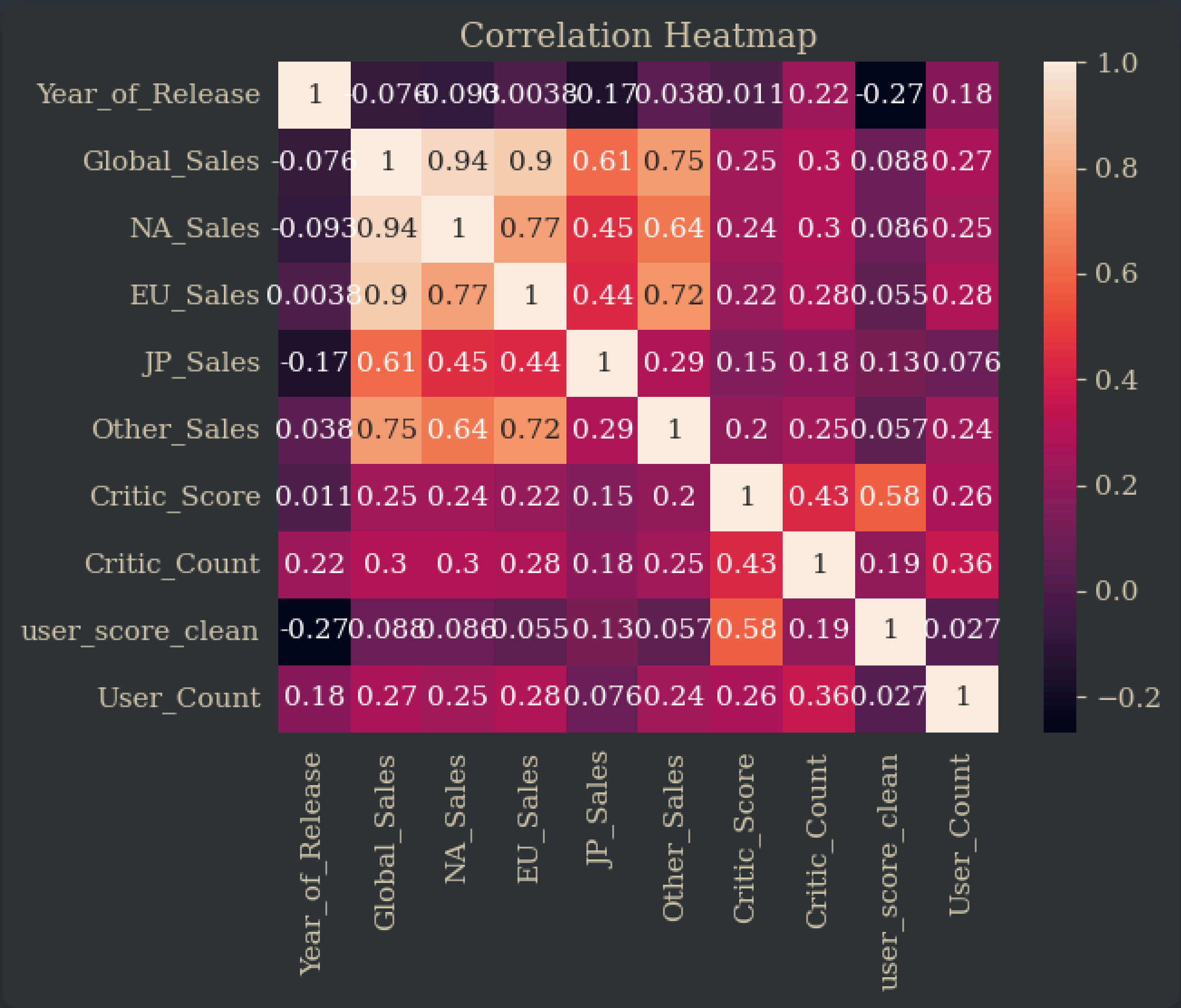


Categorical Variable Plots



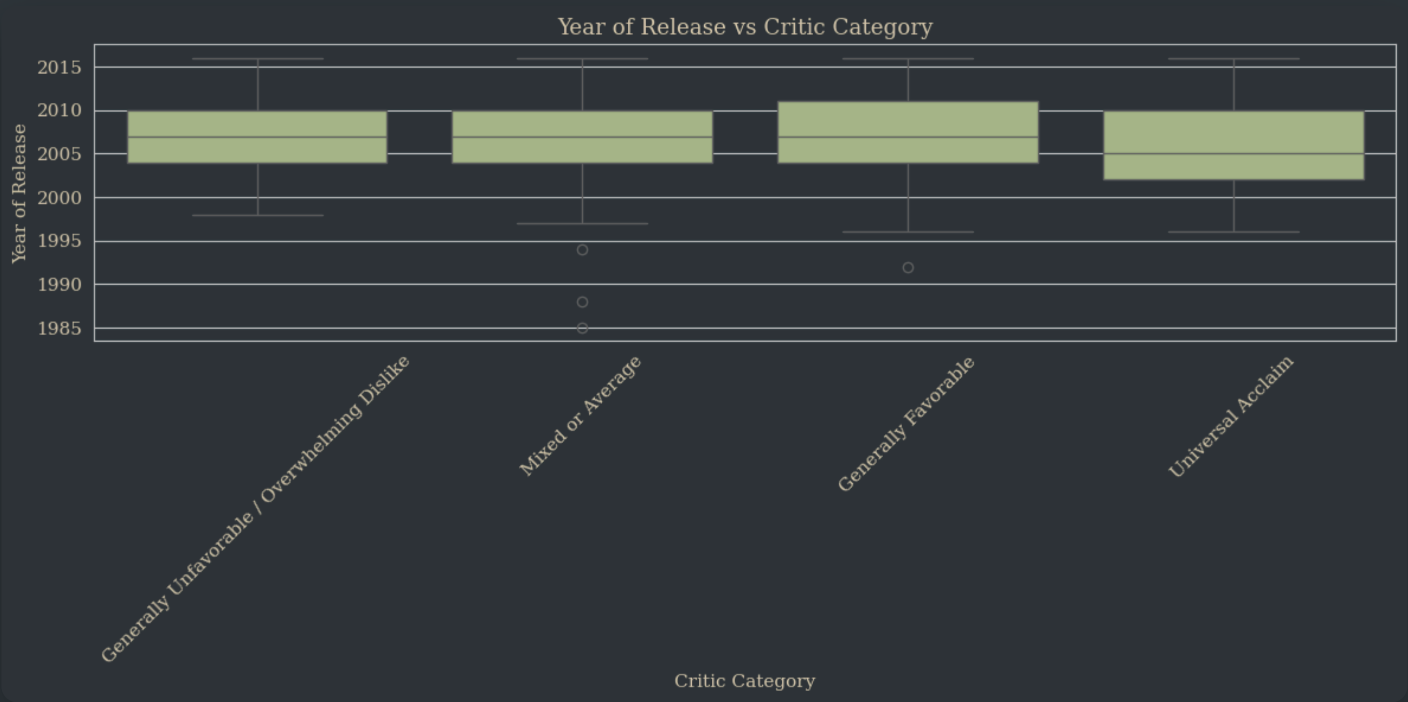


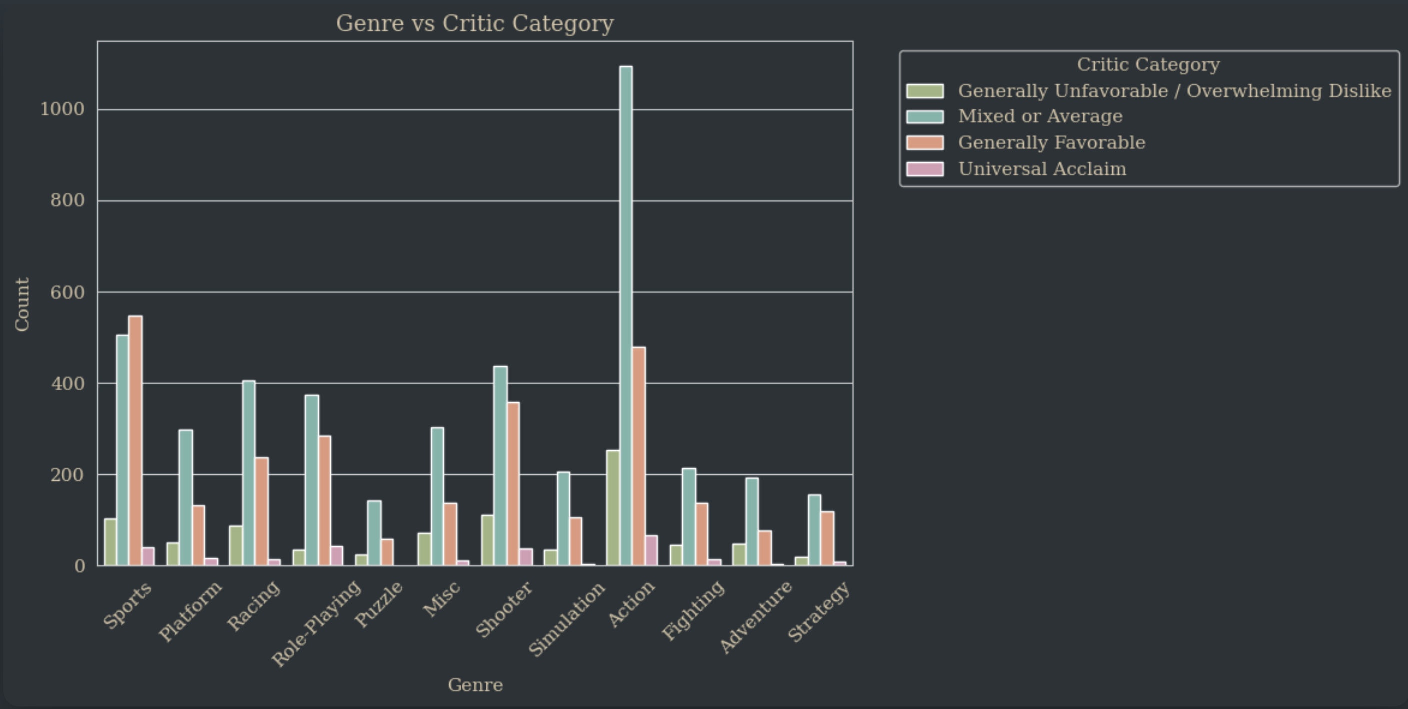
Correlation Heatmap and Matrix

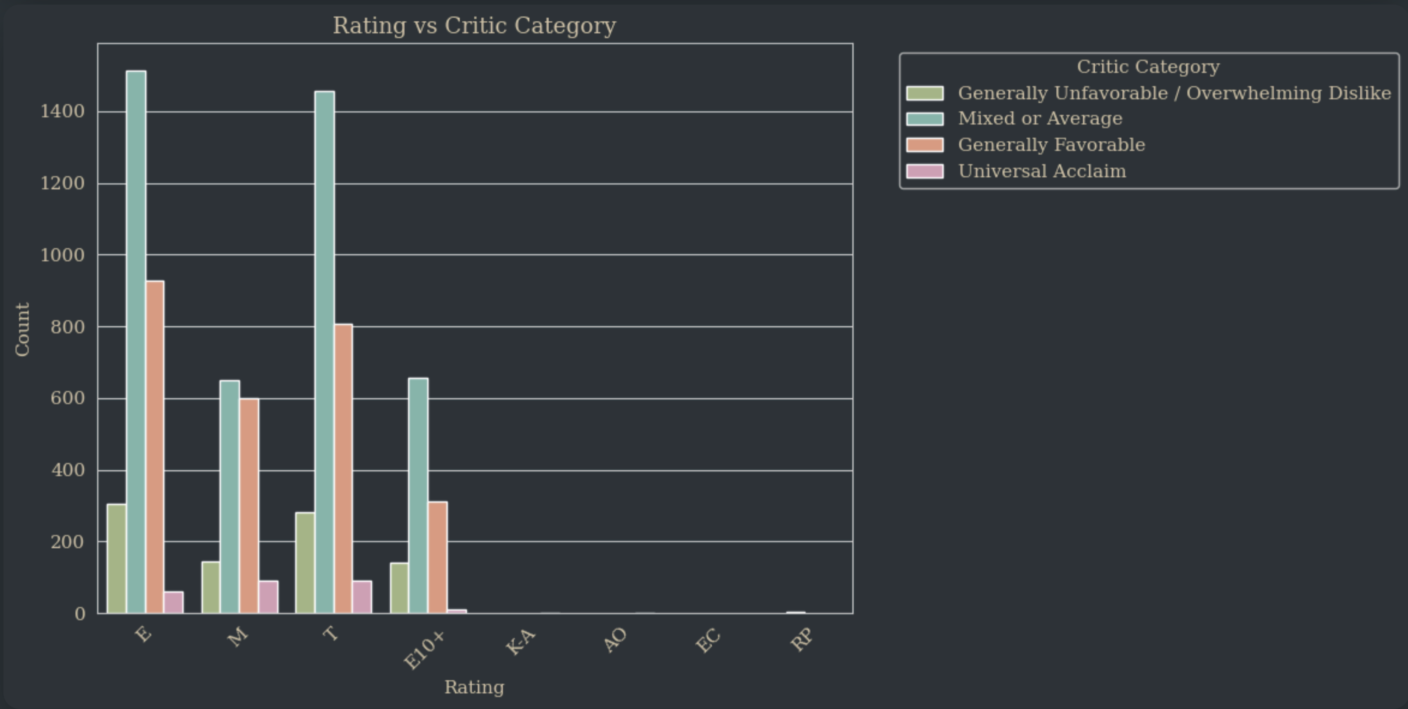


```
Critic_Score          1.000000
user_score_clean      0.580878
Critic_Count          0.425504
User_Count            0.264376
Global_Sales          0.245471
NA_Sales              0.240755
EU_Sales              0.220752
Other_Sales           0.198554
JP_Sales              0.152593
Year_of_Release       0.011411
Name: Critic_Score, dtype: float64
```

Target-Feature Plots







EDA Summary

As noted in greater detail in the notebook and longform report:

- Most games receive "Mixed or Average" or "Generally Favorable" critic scores
- Sales data is heavily right-skewed, indicating that most games don't sell many copies
- Critic_Count is right-skewed, showing that most games don't receive many reviews
- Critic_Count is likely a leaky variable

- User and critic scores moderately correlated (0.58)
- Older games more likely to receive "Universal Acclaim" score
- Genre and Rating are potentially useful categorical predictors

Data Cleaning

Missing Values to Drop

1. **critic_score_category** is our target variable, so we can't properly conduct analysis without it. I will drop all records for which this value is null. This will also drops null values for the **Critic_Score** feature (from which our binned target was derived) and **critic_count**, which I also regard as being redundant with the target variable.
2. Because of overlap and redudancy among these features, I will drop the original Critic_Score and Critic_Count columns from the model entirely.
3. **User_Score** and **user_score_clean** are potentially-valuable indicators of game quality, but null or TBD values in these features make up more than 50% of our dataset, which would be too much synthetic data to impute, so these features will be dropped as well.
4. There are a small number of missing records for **Name** and **Genre** so little is lost by dropping the null observations for these features.
5. There are a moderate number of missing records for **Year_of_Release**. I can't put my finger on it but something feels wrong about imputing year values, so I'm dropping these.

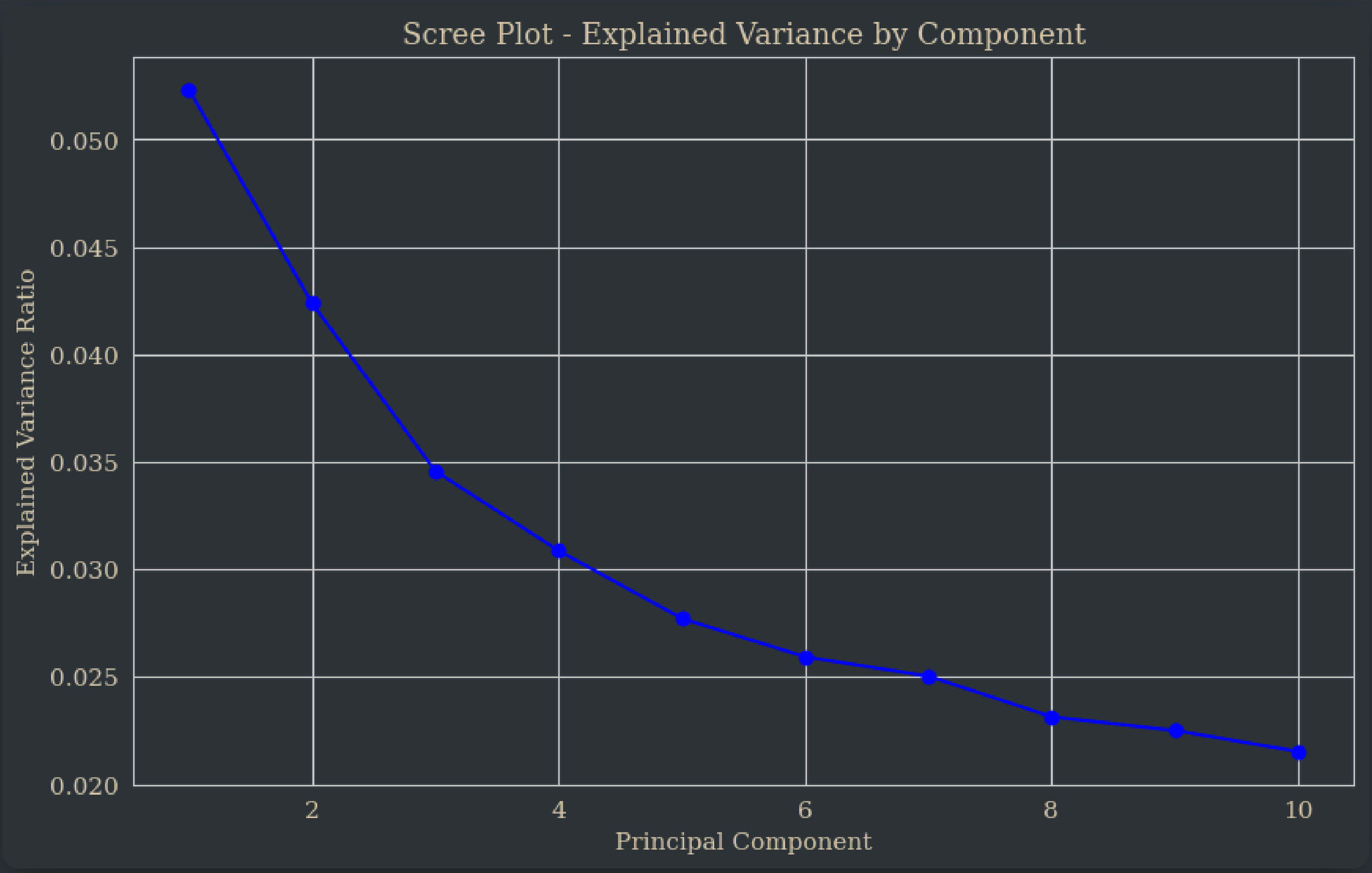
Missing Values to Impute

1. **Rating** is an interesting case because ESRB ratings weren't implemented until 1994, so there is likely a time-based component to this missingness.
2. **Publisher** and **Developer** are strictly categorical features with a multitude of possible labels.

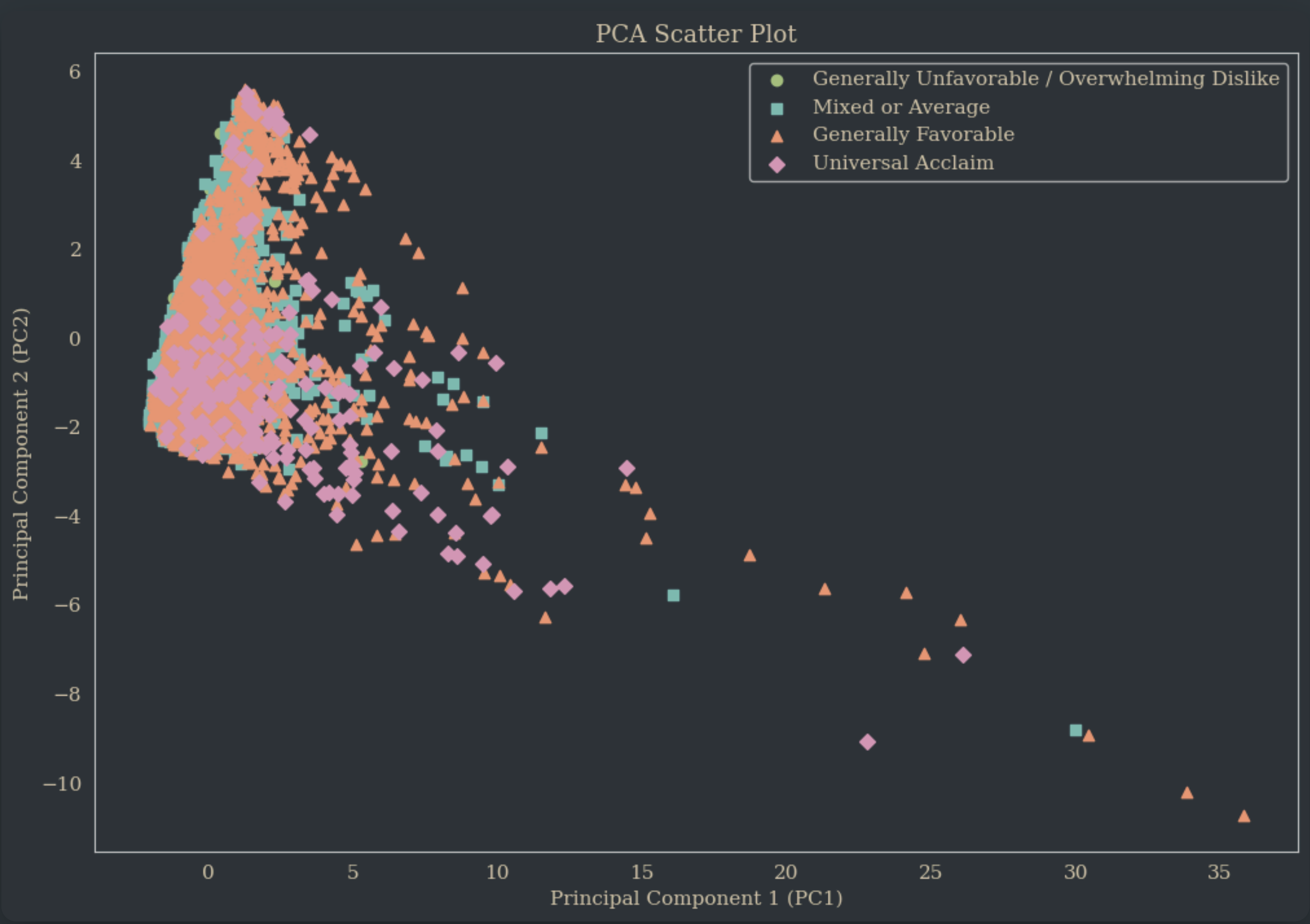
For these three features, I chose to implement an "Unknown" category to preserve potential meaningfulness within

Principal Component Analysis

Scree Plot



PCA Scatter Plot



Feature Contributions

PC1

```
Global_Sales          0.404746
JP_Sales              0.365230
NA_Sales              0.364443
EU_Sales              0.359019
Other_Sales           0.337074
Developer_Nintendo    0.307009
Publisher_Nintendo    0.246304
Developer_Other       0.204038
Publisher_Other       0.165987
Rating_E              0.136028
dtype: float64
```

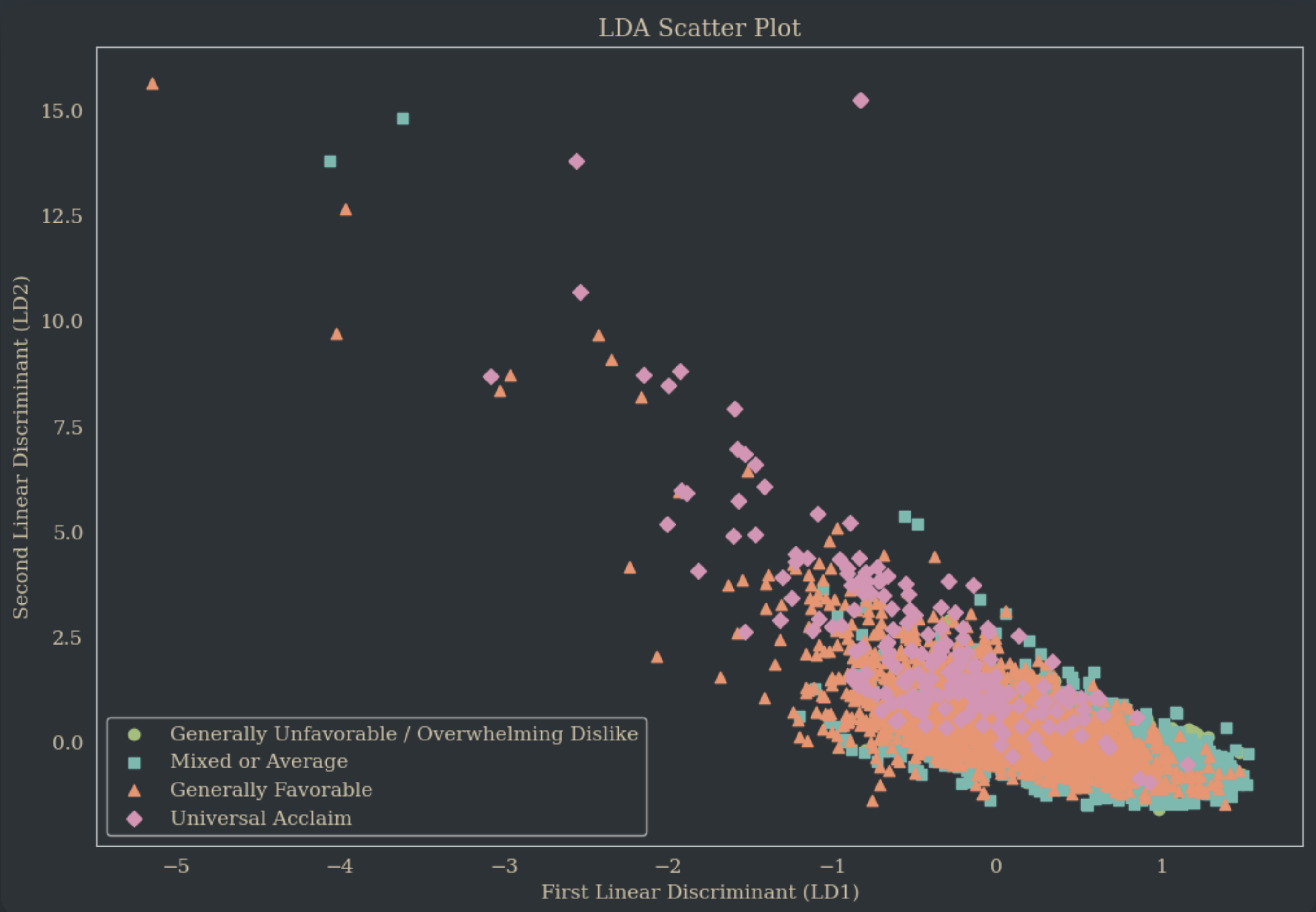
PC2

Rating_E	0.386190
Genre_Sports	0.366101
Developer_Other	0.289871
Publisher_Electronic Arts	0.281128
Year_of_Release	0.235201
Rating_M	0.221180
Developer_EA Sports	0.210954
Developer_EA Canada	0.201888
Developer_EA Tiburon	0.152468
Rating_T	0.151824

dtype: float64

Linear Discriminant Analysis

LDA Scatter Plot



Confusion Matrix and Classification Report

```
[[ 23   1 468  33]
 [  1   1 170   0]
 [  9   4 831   6]
 [  3   0  28  19]]
                                              precision    recall  f1-score   
support

                          Generally Favorable       0.64      0.04      0.08       
525
Generally Unfavorable / Overwhelming Dislike       0.17      0.01      0.01       
172
                             Mixed or Average       0.56      0.98      0.71       
850
                            Universal Acclaim       0.33      0.38      0.35        
50

                                     accuracy                           0.55      
1597
                                    macro avg       0.42      0.35      0.29      
1597
                                 weighted avg       0.53      0.55      0.42      
1597
```

Conclusions and Limitations

The ability of LDA to distinguish feature combinations that predict critical score category is a function of it being a supervised learning model. However, while LDA identified some patterns it struggled to translate them into reliable predictions (especially for the minority classes).

In contrast, PCA didn't distinguish between the critical score categories because that's not what it was designed to do: it was able to show us the the combination of features that explain the most variance in the dataset as a whole. It revealed the general patterns in our data, not patterns that predict a target.

A notable limitation of LDA is that it requires the assumptions of linearity be met. This wasn't confirmed prior to modeling, and may explain some of the issues with model performance. Another possible issue is class imbalance: I took a light approach in feature engineering, but may have left too much imbalance in the dataset.

Ultimately, the LDA model's bias limits its usefulness. Different binning or sampling approaches may be more fruitful than the ones used here, but it seems likely that a different approach might be needed to predict critical scores from this data.