Predicting the Success of Video Games Based on Rating Scores

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1 Introduction

There has been an ever increasing standard for video games at this present time. Players are constantly wanting smoother game play, more compelling story line, and more stunning visuals. The video game player base as well as video game critics have become more and more critical of video games. Gaming companies have to appease these standards due to the fact that these reviews become a major source of whether a video game becomes successful or not. The gaming community find that the opinions of critics to be less influential than the opinions of the gamers themselves.

A problem rises where gamers who have not purchased a recent game don't know what or who to believe. User Critics usually consist of a large number of players but the percentage of user critics who do not know what they are saying or are extremely biased whether it's towards the game itself or towards specific publishers. Actual critic reviews, however, are more reliable but the quality of critic reviews from sites like IGN, Kotaku, and so forth have been declining in quality. With the issue raised, I will try to gauge whether or not we should put more emphasis on professional critic review scores or user critic review scores in order to predict whether or not a video game will be successful in the future.

2 Related Work

2.1 Predicting Video Game Sales in the European Market

This study by Walter Steven Beaujon focused on the predicting the game and console sales in the European market. He used a data set with data relevant to game sales from the year 2005 to the year 2011. He created a simple regression model which would predict the sale rates for video games that are recently released for roughly two to six weeks. He used this model to test against all the data that he had acquired.

2.2 Machine Learning for Predicting Success of Video Games

This study by Michal Trněný focused on using machine learning algorithms for predicting the success of video games. In his paper, he focused on studying the known factors that affect the success rate for video games and tried to apply these to factor to algorithms like Random Forest and SVM in order to estimate a game's success and to create a proper database for video game data analysis because Michal Trněný believes that no proper data set exists.

2.3 Predicting player churn in destiny: A Hidden Markov models approach to predicting player departure in a major online game

In this study by Marco Tamassia, William Raffe, Rafet Sifa, they decided to study the recent game Destiny. They decided to intensely study players actions and daily activities in the game in order to predict retention and churn rates in the video game. They discussed the challenges of studying such aspects in a video game, the analysis of the behavioral features that they studied and used the Hidden Markov Models to develop a prediction model for the game.

2.4 Other Related Articles

An article titled *Steam Gauge: Do strong reviews lead to stronger sales on Steam?* by Kyle Orland discuses the impact of reviews on game sales on the popular PC gaming platform Steam. He used a data set using MetaCritic Review scores and correlated it with the sale rates of popular games on Steam.

2.5 Discussion

A lot of studies have agreed that the data sets that have to use are not as good as they could be. There are just too many factors to properly create perfect models that accurately predict which games are going to be successful and which games are not going to be successful. What is commonly predicted in these studies is that video games do die out. Specifically in the *Predicting Video Game Sales in the European Market*, a lot of the games studied suffered drastic decrease in sales after the first week of release. This is also commonly mentioned in the *Machine Learning for Predicting Success of Video Games* study where it is shown that games suffer in sales after the 4-6 week period after their initial release. This goes hand in hand with the study done by Tamassia on Destiny who was trying to create a retention model for the video game Destiny. From these studies, it can be said, even despite the vast range of influences video games do have on sales, that the so called "hype" for a said video game title does die out pretty quick.

Regarding the prediction models produced by both the Beaujon paper as well as the Trněný paper, both papers seem to find correlations with before release information and time period which games are being sold. Beaujon's paper emphasizes that the holidays are the best time to sell new games because of the frequent spending and the large number of deals that go on. Trněný's paper emphasizes that knowledge of the game's core features before release to the potential player base drastically increases sales. Both studies agree upon the fact that good and well known developers are key to a game's success. While Indie-games can be successful, triple A video game titles most likely come from big video game publishing companies.

3 Methodology

The data set I used comes from Kaggle, which was influenced by the data sets analyzed by past papers originating from VGChartz. The data set is an improvement because it takes in MetaCritic rating scores as well as having the general sale information.

The column variables in the data are as follows:
Name, Platform, Year of Release, Genre, Publisher, NA Sales, EU Sales, JP Sales, Other Sales, Global Sales,Critic Score, Critic Count, User Score, User Count, Developer, and ESRB Rating.

The key points in the data are the Critic Score, which are the values compiled from MetaCritic and User Score retrieved from MetaCritic subscribers.

	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales	Critic_Score	Critic_Count	User_Sco
0	Wii Sports	Wii	2006.0	Sports	Nintendo	41.36	28.96	3.77	8.45	82.53	76.0	51.0	8
1	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	0.77	40.24	NaN	NaN	Na
2	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.68	12.76	3.79	3.29	35.52	82.0	73.0	8
3	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.61	10.93	3.28	2.95	32.77	80.0	73.0	8
4	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.22	1.00	31.37	NaN	NaN	Na

Figure 1: First five rows of the data set

From this data, using Python and Python's libraries, will do preliminary data preprocessing to eliminate outliers and null variables. From there I did some simple data visualization to get a better idea of what the data entails and to look for significant correlations between variables. From there I clustered significant relations between variables in hope of finding something interesting. Lastly, I implemented predictive models that used critic scores and compared it to predictive models that used user scores in order to determine the solution to my problem of which critics are the most influential and most correct in predicting a game's success.

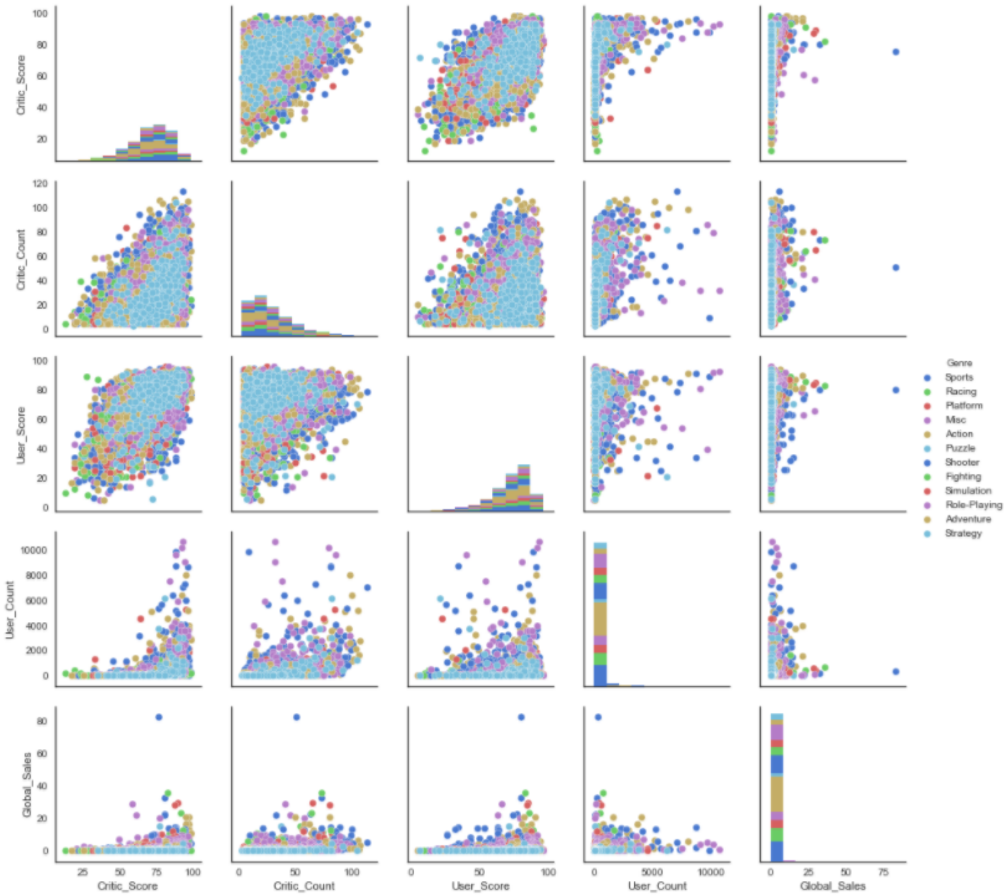

Figure 2: Visualizations of Scatter Plots Comparing Critic Score, Critic Count, User Score, User Count and Global Sales

4 Experiment

4.1 Data Preprocessing

Given the data set, I cleared most of the NaN and null variables that provided little to no input to my comparisons between Critic Scores and User Scores. Besides that, I altered the data types of certain column variables in order to make it easier to compare values.

4.2 Data Visualization

I sought to see if there was any important correlations between variables. Notably, I wanted to see the correlations between the five significant variables: Critic Score, Critic Count, User Score, User Count and Global Sales. As shown in Fig. 2, I graphed scatter plots comparing all these values. A few of the notable relations I saw are comparisons between User Score and Critic Score, Critic Score and Critic Count and Critic Score and Global Sales.

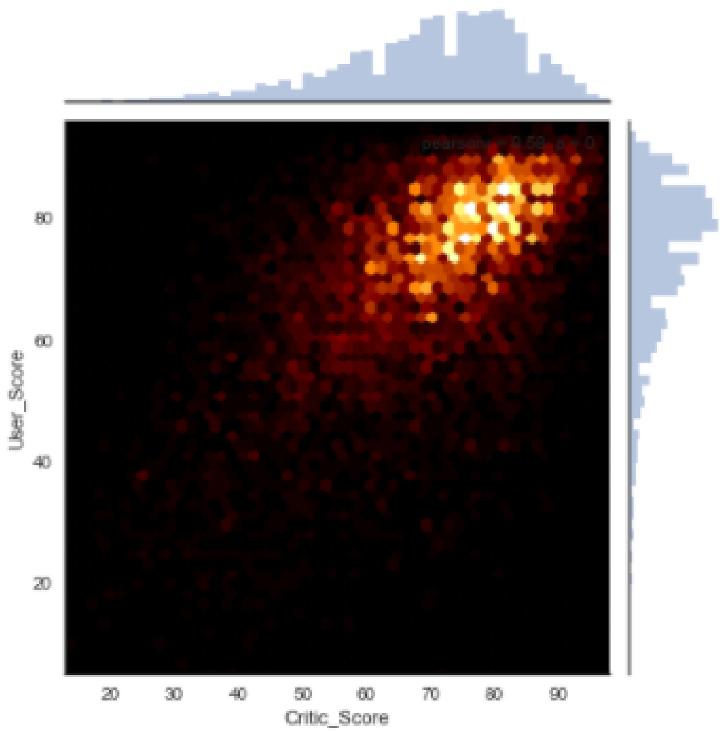

Figure 3: Heat Map of Critic Score vs User Score

A heat map visualizing the correlation between the User Scores and the Critic Scores given to games is shown in Fig. 3. A notable thing to note is that User Scores are generally more lenient and more positive than Critic Scores, which tend to be on average lower and thus more strict. Further heatmaps were done comparing other variables, but they did not produce significant results.

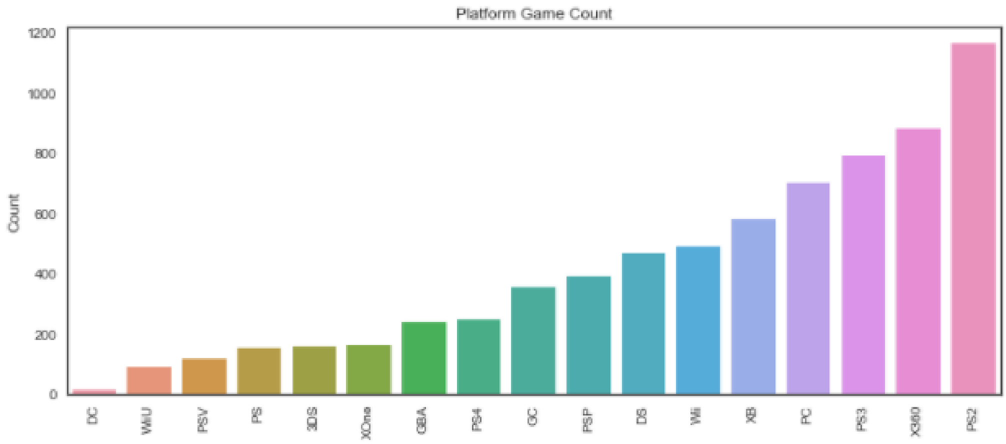

Figure 4: Number of Games Per Platform

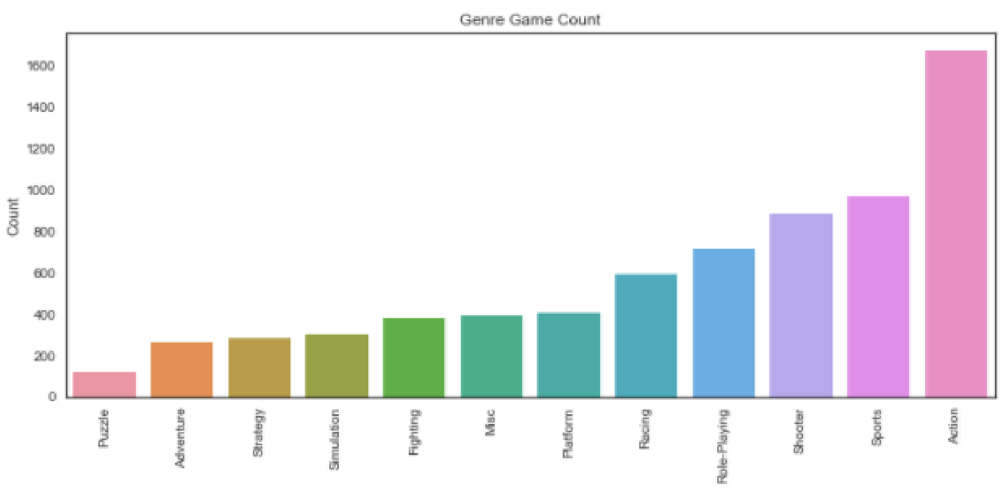

Figure 5: Number of Games Per Genre

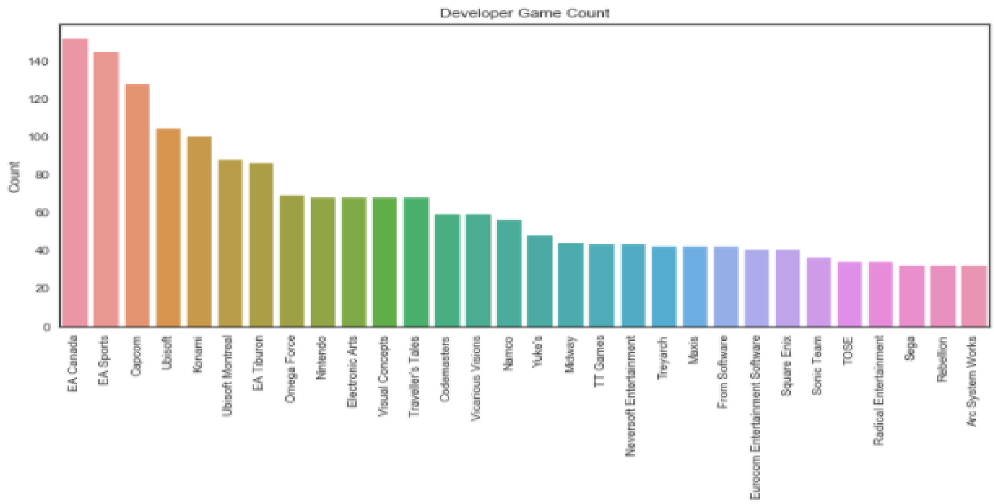

Figure 6: Number of Games Per Developer

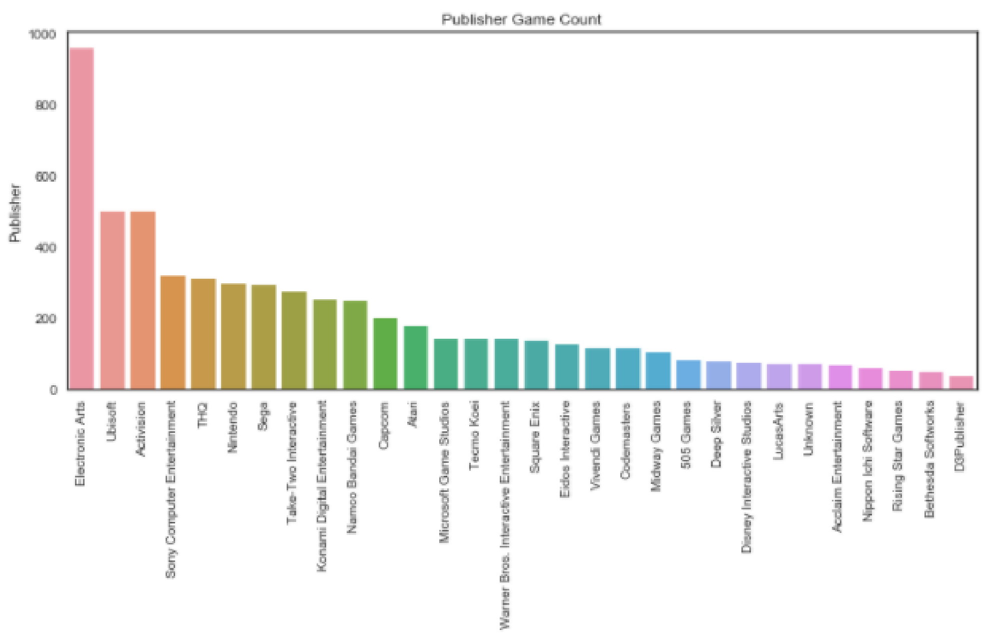

Figure 7: Number of Games Per Publisher

The following four bar graphs show the video game counts for Platform, Genre, Developer, and Publisher respectively. This is to see who are the dominant companies in the video game industry, which turns tells us the most popular and most active people.

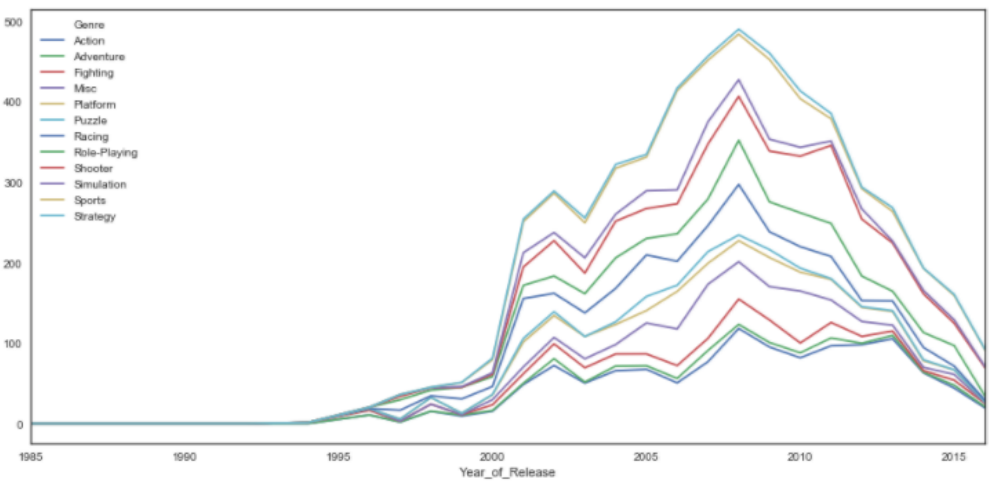

Figure 8: Number of Games Per Year

The final data visualization I did was a line graph of the number of video games sold per year per genre. Action video games are pretty dominant as shown in both graphs however, it is good to note that the average video game produced per year is slowly decreasing. This can be explained by the advancement of mobile technology. Mobile games are becoming extremely popular so people who once gamed on consoles like the PS2, Gamecube, Xbox and so forth are now able to game on a mobile platform which is more convenient and cheaper than gaming on PC or on a console.

4.3 Clustering

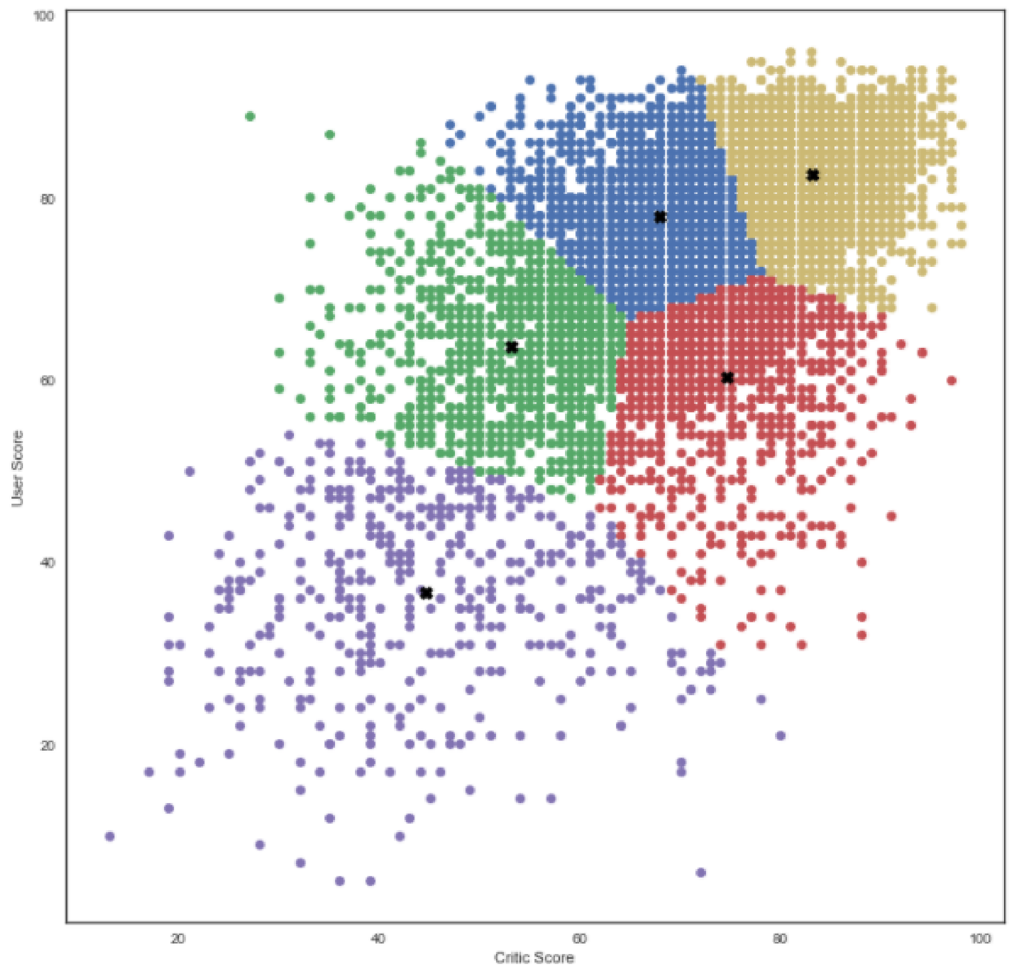

Figure 9: Clustering Groups using K-Means for Critic Scores vs User Scores

I decided to apply a K-means clustering algorithm to the scatter plot mentioned before comparing Critic Score and User Score. This is to discern the possible groups of video games critic scores for both professional critics and the average critic. With the yellow group, green group, and the purple group, one can see the correlation that these are great, average, and bad games respectively. It becomes a bit more vague once we see the blue and red clusters. With the red group, the professional critics gave a more generous response while the users did not. This implies that the critics enjoyed the game but the majority of the user population didn't. This brings into consideration whether or not professional game critics know what they are talking about. The blue group cluster says the same thing but for the opposite aspect, where users are more generous in their critics than professionals.

4.4 Linear Regression Analysis

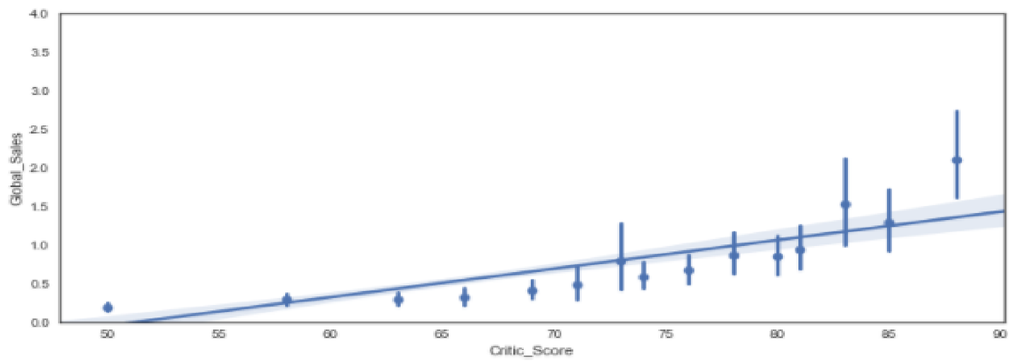

Figure 10: Linear Regression for Critic Scores vs Global Sales

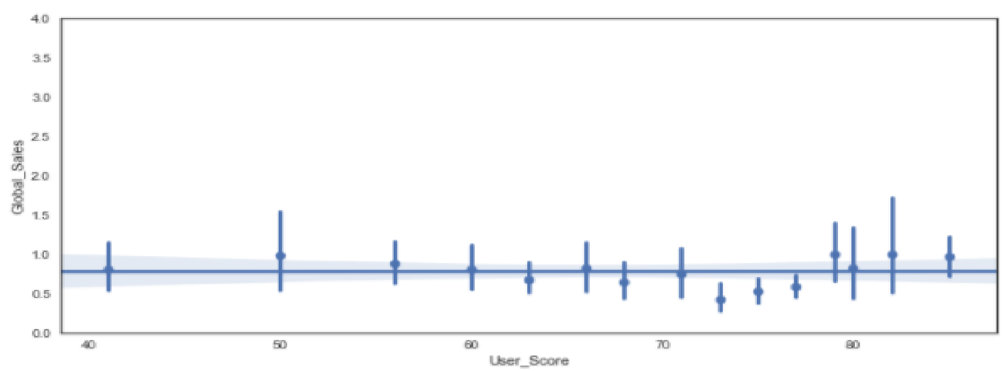

Figure 11: Linear Regression for User Scores vs Global Sales

Looking at the linear regression for Critic Scores vs Global Sales and User Scores vs Global Sales, it is clear to see that Critic Scores are more important for video game sales in general. Further analysis gives Critic Scores a Pearson

Score of 0.24 while User Score gets a Pearson Score of 0.089. For now, it seems strongly favorable towards Critic Scores being a strong influencer and predictor in video game sales.

4.5 Predictive Models

	Name	Platform	Genre	Publisher	Year_of_Release	User_Score	Global_Sales	Hit_Probability
1710	Titanfall 2	PS4	Shooter	Electronic Arts	2016.0	84.0	0.75	0.578512
1408	Kirby: Planet Robobot	3DS	Action	Nintendo	2016.0	87.0	0.93	0.554916
6881	Fast Racing Neo	WiiU	Action	Nintendo	2016.0	85.0	0.01	0.550898
3035	Star Fox: Zero	WiiU	Shooter	Nintendo	2016.0	74.0	0.36	0.538158
2512	Plants vs. Zombies: Garden Warfare 2	XOne	Shooter	Electronic Arts	2016.0	81.0	0.48	0.514371
2482	Plants vs. Zombies: Garden Warfare 2	PS4	Shooter	Electronic Arts	2016.0	77.0	0.49	0.511284
2165	Titanfall 2	XOne	Shooter	Electronic Arts	2016.0	80.0	0.57	0.504677
2999	BioShock The Collection	PS4	Shooter	Take-Two Interactive	2016.0	85.0	0.37	0.463367
3358	Mario Party: Star Rush	3DS	Misc	Nintendo	2016.0	68.0	0.30	0.452181
4570	BioShock The Collection	XOne	Shooter	Take-Two Interactive	2016.0	83.0	0.16	0.409224

Figure 12: Predictive Model for User Scores vs Global Sales

	Name	Platform	Genre	Publisher	Year_of_Release	Critic_Score	Global_Sales	Hit_Probability
1710	Titanfall 2	PS4	Shooter	Electronic Arts	2016.0	89.0	0.75	0.753510
4769	Skylanders Imaginators	PS4	Platform	Activision	2016.0	80.0	0.14	0.618349
2482	Plants vs. Zombies: Garden Warfare 2	PS4	Shooter	Electronic Arts	2016.0	81.0	0.49	0.601155
2165	Titanfall 2	XOne	Shooter	Electronic Arts	2016.0	87.0	0.57	0.578110
2999	BioShock The Collection	PS4	Shooter	Take-Two Interactive	2016.0	84.0	0.37	0.545768
1408	Kirby: Planet Robobot	3DS	Action	Nintendo	2016.0	81.0	0.93	0.535150
1974	Dishonored 2	PS4	Action	Bethesda Softworks	2016.0	88.0	0.64	0.531433
6881	Fast Racing Neo	WiiU	Action	Nintendo	2016.0	81.0	0.01	0.527781
2953	Deus Ex: Mankind Divided	PS4	Role-Playing	Square Enix	2016.0	84.0	0.38	0.513600
3104	Mirror's Edge Catalyst	PS4	Platform	Electronic Arts	2016.0	69.0	0.35	0.462702

Figure 13: Predictive Model for Critic Scores vs Global Sales

As shown in Fig 12. and Fig 13., I created two predictive models using logarithmic regression in order to predict which games would be hits in the year 2016. Using Critic Score generates a higher average in probability confidence while using User Score generates barely more than 50 percent confidence. Knowing which games are popular today given it is 2017, both predictive models are successful in predicting popular games and their sales but using Critic Scores produces a more confident model to use. Further work was done to use Random Forest as well as Naive Bayes learning models in order to determine whether or not this correlates and it was shown that it too as well supports the fact that Critic Scores are more successful in predicting video game success.

5 Conclusion

In conclusion, it is clear to see that Critic Scores play an important part in determining video game success. As stated in the article *Steam Gauge: Do strong reviews lead to stronger sales on Steam?* by Orland, games who do not even break a 60 on the MetaCritic scale won't even become successful. Though this may seem a bit harsh, it proves to be true. Further work can be done on this by analyzing more variables. There are many outliers that show that video games don't have to be from big producers in order to be successful. Many indie-games like Undertale and so forth have become immensely successful due to the optimistic and supportive player base.

6 Bibliography

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