Analysis of Nintendo Video Game Sales

**Introduction:**

The video game industry is one of the largest in entertainment. Numerous companies develop software and hardware including Microsoft, Sony and Nintendo. Sales can achieve tens of millions for software and over a hundred million for hardware. Development costs for a triple A game (like a movie blockbuster) are typically large and in one case exceeded half a billion dollars. Investments into software titles like this are because of how lucrative the industry is. GTA V was the fastest multimedia product to achieve a billion dollars in revenue. With this in mind, it is my aim to try to understand what makes a successful video game release. For a video game company, the main reason to develop video games or the related hardware is for profit which can vary depending on the research and development costs of the video game. Sales data serve as a good proxy for success, as they indicate profit. Due to data availability, I have chosen to use Nintendo as a case study. Nintendo are known for famous video game franchises, Mario, The Legend of Zelda and Pokémon and for their hardware such as the Wii, DS, Game Boy and Switch to name a few.

So, what makes a video game published on a Nintendo platform sell the most? Is this due to the release platform or the genre of the video game? Do high review scores correlate with high sales? I aim to try to answer these questions in this analysis. Moreover, I would like to know if the combination of review scores and sales data is able to predict a video game genre or platform. This information could be useful for an independent developer to decide their game genre and platform to develop for to ensure profit.

**Methods:**

Preparing the data

Before any analysis, the data needed to be prepared. Firstly, the two data frames containing the sales data (“list-of-best-selling-video-games.csv”) and the review scores (“all\_games.csv”) needed to be merged. This was done by platform and game name; the inclusion of platform was to ensure that the review score for a platform release was not accidentally paired with the game since some games are released on multiple platforms. The names of the platforms were standardised, and the video game genres were also grouped into a general list of 11 genres that encompass all games released. After these steps had been completed, the data could be analysed.

Analysis 1 – Regression

To analyse the categorical data with a regression, dummy columns were needed. These convert each category into a column with a 0 or 1 to represent if it was that category or not. The Metacritic scores were divided by 10 to put them out of 10, thus making them easier to compare to the user reviews which are also out of 10. The sales figures were put into millions for ease of comparison. For full clarity, the first regression conducted did not have these scaled changes, but only reported the model score. The model score for the regression which had the variables scaled was also reported to show there was no difference in the model fit, just how easy it is to interpret the coefficients. Sci-Kit Learn was used for the regression by using a training and testing data split. The regression line was plotted, and full model summary output displayed.

Analysis 2 – K- Nearest Neighbours (KNN)

To determine if the sales and review scores could be used to predict the platform or genre of the game, a nearest neighbour analysis was conducted. The genres and platforms were converted to numbers and a PCA was performed on the review scores. The first principal component was used to represent the review scores. The sales were logged to separate the data into more discernible clusters. The best value of K was determined by searching through models fitted with different values of k between 1 and 60.

**Results:**

Analysis 1 – Regression

The results of the regression suggested the model was in fact statistically significant (p<0.001) and had an adjusted R squared value of 0.203 so 20.3% of the data variation was explained by the model. But the model fit was not good with a model score of -0.048 and the confidence intervals grew as sales increased (see figure 3). The model estimated that the Switch platform predicted the best sales at 3.528 million more than the intercept. The racing genre predicted the highest sales increase of all genres at 8.642 million. Critic scores predicted a positive relationship with sales, but user scores predicted a negative relationship.

­Analysis 2 – KNN

Neither the KNN model for platform or genre produced a good fit with model scores of 0.316 and 0.228 respectively despite hyperparameter optimisation which yielded a k value of 7 and 13 respectively. The platform model showed that the highest selling games were released on the Switch, Wii and DS but the best reviewed games were on the Nintendo 64, GameCube, Switch and Wii (see figure 2). The first PC was negatively correlated with the review scores, so a good review score is a negative PC score. For genre, the highest selling genres were predicted as platformers, racing games and party games but the best reviewed games were action-adventure games and platformers (see figure 1). The figures below show the three models graphically.

Chart, scatter chart

Description automatically generatedGraphical user interface

Description automatically generatedGraphical user interface, chart, scatter chart

Description automatically generated**Figures:**

2) KNN plot showing predicted platform for logged sales and Principal Component 1

3) Regression line and confidence for predicted sales vs actual sales calculated with the regression model

**Conclusion:**

1) KNN plot showing predicted genre for logged sales and Principal Component 1

The regression showed that the Nintendo switch platform significantly predicted an increase in sales of over 3.5 million and that if the genre was racing it had the biggest change in predicted sales, an increase of over 8 million. These results indicate that the latest console and the racing genre are the best combination for predicting higher sales. The Mario Kart series is often one of the highest selling games on a system, so it is not necessarily surprising that there is a link between racing games and high sales. A more surprising result was that although a positive critic score predicted an increase in sales, a positive user score also predicted a decrease in sales. For every 1-point increase in user score, the sales decreased by 1.5 million in contrast for every 1-point increase in critic review score, the predicted sales increase by 2.8 million. This indicates a clear disparity between user and critic scores where you would expect them to be at least similar. However, during the KNN analysis, the two scores appeared distinctly correlated when graphed so were combined into a principal component. Using the principal component and sales, the KNN analysis was able to determine that the best sales came from racing, party, and platformer games. While other genres such as action-adventure faired better with reviews. On the other hand, the highest sales were predicted in 3 platforms, the Wii, Switch, and DS. These three consoles are the best-selling Nintendo consoles bar the Game Boy; it is likely increased console sales have driven the higher software sales.

These results come with the caveat that the predictive models were not good fits so, the results cannot be trusted. There were inherent issues with the data that likely contributed to this. For future developments of this analysis it will be imperative to collect a wider range of data that expands beyond just Nintendo publishing and beyond the top in sales. To understand what makes a successful game it will be useful to determine what makes an unsuccessful game too. Moreover, analysis into the differences between critic and user scores may be relevant. Users buy the products that contribute to sales whereas critics do not. However, user reviews should be after they have bought a game (and contributed to sales), the decision to buy the game first may have been related to critic reviews. Perhaps critic reviews by themselves make a better metric. Lastly, it would be interesting to introduce a metric such as percentage of consoles that have the game to understand success. This will control the differences due to different console sales figures.

Full analysis on github at: https://github.com/JaimieBarnes/python-assessment