

NATIONAL UNIVERSITY OF SINGAPORE

FACULTY OF SCIENCE



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Term Paper

Title:

Analysis of Video Game Sales

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Summary:

In this analysis, we explored the determinants of video game sales using a multifaceted approach. A linear mixed-effects model captured the hierarchical data structure and assessed platform and genre effects while accounting for publisher variability. Furthermore, we predicted sales through regression methods, incorporating critic and user scores, and employed multiple regression to directly examine the publishers' impact on sales. This combination of methods offered a comprehensive understanding of factors influencing video game sales, yielding valuable insights for strategic decision-making in the gaming industry.

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Introduction

The video game sector has witnessed substantial expansion in recent years, emerging as a prominent player in the worldwide entertainment industry (Pashkov, 2021). As the volume of games launched across diverse platforms and genres continues to grow - including the rising popularity of esports, it becomes increasingly important to identify the factors driving sales and ratings. Both sales and ratings act as key determinants of a game's triumph and its acceptance among the intended audience. Analyzing the relationship between game features, critical assessments, user opinions, and sales achievements empowers industry participants to make well-informed choices, finetune marketing strategies, and ultimately deliver superior gaming experiences for enthusiasts across the globe.

Description of Data

For this paper, we will be using a Kaggle dataset - "Video Game Sales with Ratings" (Kirubi, 2016), containing information on various aspects of video games released from 2007 to 2016, including their sales performance, ratings, and general characteristics. The dataset encompasses 16,719 games released across different platforms, including PC, PlayStation, Xbox, and Nintendo consoles. Each game entry includes information on the game's name, platform, release year, genre, publisher, sales figures in North America, Europe, Japan, and other regions, as well as global sales. Additionally, the dataset features Critic_Score and User_Score from Metacritic, along with the ESRB¹ rating for each game. From this dataset, we will explore the factors that influence video game sales and examine relationships between game characteristics, ratings, and sales performance.

Initial Data Cleaning and Exploratory Data Analysis (EDA)

After dropping observations with missing values in certain columns, we are left with 7,017 games with fully-filled rows to perform our analysis with. This is done especially to ensure that if necessary, statistical models can be run accurately without ambiguity when considering all of the variables in the

¹ The Entertainment Software Rating Board (ESRB) functions as a self-governing body responsible for assigning age and content classifications to consumer video games within the United States and Canada. (Wikipedia, 2022)

dataset. We then plot a correlation plot to measure the collinearity of the numeric variables in the dataset, as shown in Figure 1 below:

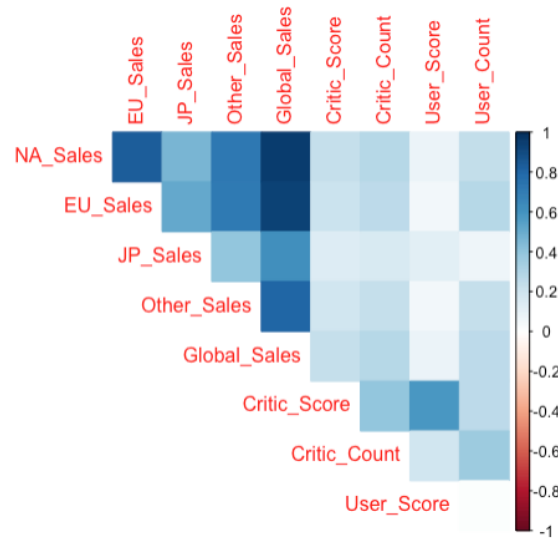


Figure 1: Collinearity plot of numerical variables in cleaned dataset

As evident in Figure 1 above, there appears to be very high collinearity between Global_Sales and the various (location)_Sales variables, which is understandably obvious as the sum of these variables add up to provide the Global_Sales value for each game. Another unique finding would be the high collinearity between Critic_Score and User_Score, confirming that professional critics and consumers alike generally have similar grading preferences when evaluating the enjoyment of a video game, despite certain anomalies with polarizing reviews such as Call of Duty: Infinite Warfare and Mass Effect 3 (Phillips, 2012), where consumers in particular have varied their opinions of these games - especially when comparing the contexts of their initial release and a few years afterwards.

Using Multiple Regression to Investigate Impact of Publishers on Global Sales

In this section, we shall investigate the impact of the various publishers on global video game sales. For this, we first perform data cleaning of the original dataset, where we remove observations with missing values for Critic_Score, User_Score, Rating and Publisher. With 8,137 games remaining in the dataset,

we next perform one-hot encoding on the Publisher variable, before fitting a multiple regression model to identify the top publishers based on their regression coefficients:

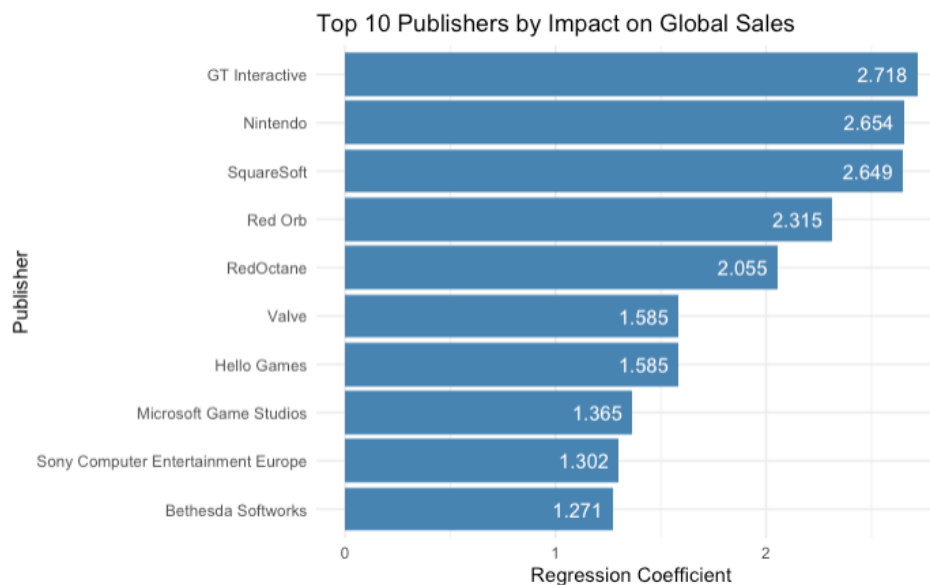


Figure 2: Bar chart representing top 10 publishers by impact on global sales, based on regression coefficient

From Figure 2 above, we can identify the top 10 publishers with the greatest impact on Global_Sales, including popular publishers today such as Valve, Sony, and Microsoft. In particular, Nintendo's dominance as a top publisher can be accredited to the successful launch of the Wii console, with Wii Sports unanimously being the top contributor in Global_Sales during the late 2000s (Figure 4 in Appendix, if required).

Using Various Regression Methods to Predict Global Sales using Critic Score and User Score

Using the cleaned dataset from the EDA section, we will attempt various regression methods: namely multiple linear regression (MLR), random forest (RF) and XGBoost - to assess if Critic_Score and User_Score are indeed good predictors of Global_Sales. This can be done by comparing the evaluation metrics of the 3 models, assuming that 10-fold cross-validation is applied, with the summarized results evident in Table 1 below:

| Evaluation Metric/Model | MLR | RF | XGBoost |
|--------------------------------|------------|------------------|------------|
| Mean RMSE | 1.766241 | 1.730558 | 1.76862 |
| Mean R-squared | 0.07863555 | 0.1105488 | 0.06202084 |
| Mean MAE | 0.760865 | 0.6995031 | 0.7022947 |

Table 1: Evaluation metrics of respective regression models

Based on Table 1 above, it appears that the RF model performs the best across all three evaluation metrics. However, the R-squared values for all three models are relatively low, indicating that these models do not explain a substantial portion of the variance in Global_Sales. To improve model performance, we shall normalize the predictors and make use of a 80-20 train-test split before running the 3 models again with 10-fold cross validation. The results are tabulated in Table 2 below:

| Evaluation Metric/Model | MLR | RF | XGBoost |
|--------------------------------|------------|-----------|------------------|
| Mean RMSE | 1.496797 | 1.684257 | 1.476058 |
| Mean R-squared | 0.05374856 | 0.0286819 | 0.0888855 |
| Mean MAE | 0.717222 | 0.7204104 | 0.6358971 |

Table 2: Evaluation metrics of respective regression models - with normalization

It appears that the MR and RF models have been adversely impacted based on all three evaluation metrics. However, normalizing the predictors did significantly improve the XGBoost model, as evident in the improvements in RMSE and R-squared scores. In short, despite Critic_Score and User_Score not being strong predictors, XGBoost is still the optimal model to use when normalization is used.

Using Linear Mixed-Effects Model to Investigate Impact of Publishers, Platform and Genres on Global Sales

In this analysis, we used a linear mixed-effects model to account for the hierarchical nature of the data, with video games nested within publishers. The model included fixed effects for platform and genre, as well as random intercepts for publishers. Our results from the ANOVA table (Figure 3D) revealed significant effects of platform and genre on global video game sales. Based on t-values (Figure 3A), the platforms PS, PS2, PS3, PS4, Wii, and X360, as well as the shooter and strategy genres, were found to

have notable influences on sales. In particular, strategy games have a negative effect on global sales, presumably because they were not as popular globally in the 1990s and 2000s compared to today. This model allowed us to account for variability in sales performance across different publishers. Model diagnostics, including a residual plot (Figure 3B) and a Q-Q plot (Figure 3C), suggested that our linear mixed-effects model was an appropriate choice for the data, with only minor deviations from normality in the tails of the residual distribution.

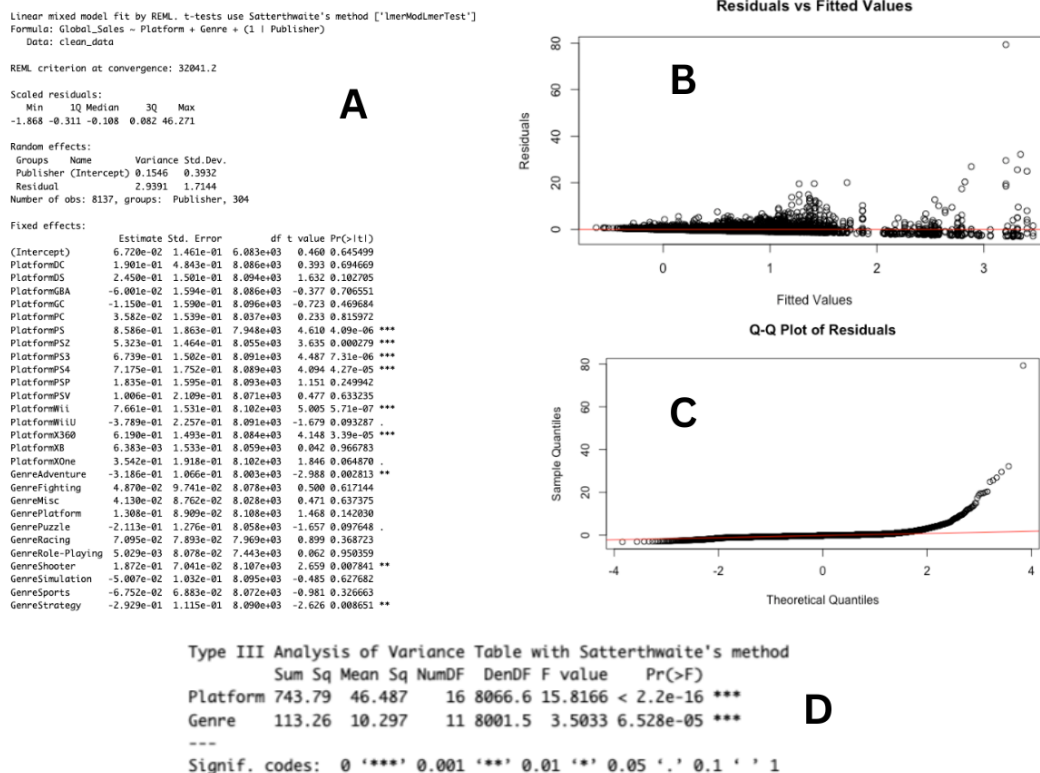


Figure 3: (A) Model summary indicating significant platforms and genres based on t-value; (B) Residual plot to assess linearity and homoscedasticity; (C) Q-Q Plot to assess normality; (D) ANOVA table indicating high significance of platform and genre

Conclusion

In summary, we conducted a comprehensive analysis of the video game sales dataset using three distinct approaches. By combining these approaches, we gained a deeper understanding of the factors that drive video game sales and provided valuable insights that can inform strategic decisions within the gaming industry.

References

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Appendix

| Column Name | Column Type | Description |
|-----------------|-------------|--|
| Name | String | The title of the video game. |
| Platform | String | The gaming console or system on which the game is available (e.g., PC, PlayStation, Xbox). |
| Year_of_Release | Integer | The year the game was released. |
| Genre | String | The game's genre (e.g., action, adventure, sports, strategy). |
| Publisher | String | The company responsible for publishing the game. |
| NA_Sales | Float | Total sales of the game in North America, in millions of units. |
| EU_Sales | Float | Total sales of the game in Europe, in millions of units. |
| JP_Sales | Float | Total sales of the game in Japan, in millions of units. |
| Other_Sales | Float | Total sales of the game in other regions, in millions of units. |
| Global_Sales | Float | Total worldwide sales of the game, in millions of units. |
| Critic_Score | Float | Average score given by professional critics, as aggregated Metacritic (range: 0-100). |
| Critic_Count | Integer | Number of critics who reviewed the game. |
| User_Score | Float | Average score given by users, as aggregated by Metacritic (range: 0-10). |
| User_Count | Integer | Number of users who reviewed the game. |
| Developer | String | The company responsible for developing the game. |
| Rating | String | The ESRB rating assigned to the game (e.g., E for Everyone, T for Teen, M for Mature). |

Table 3: Schema of "Video Game Sales with Ratings" dataset, sourced from Kaggle

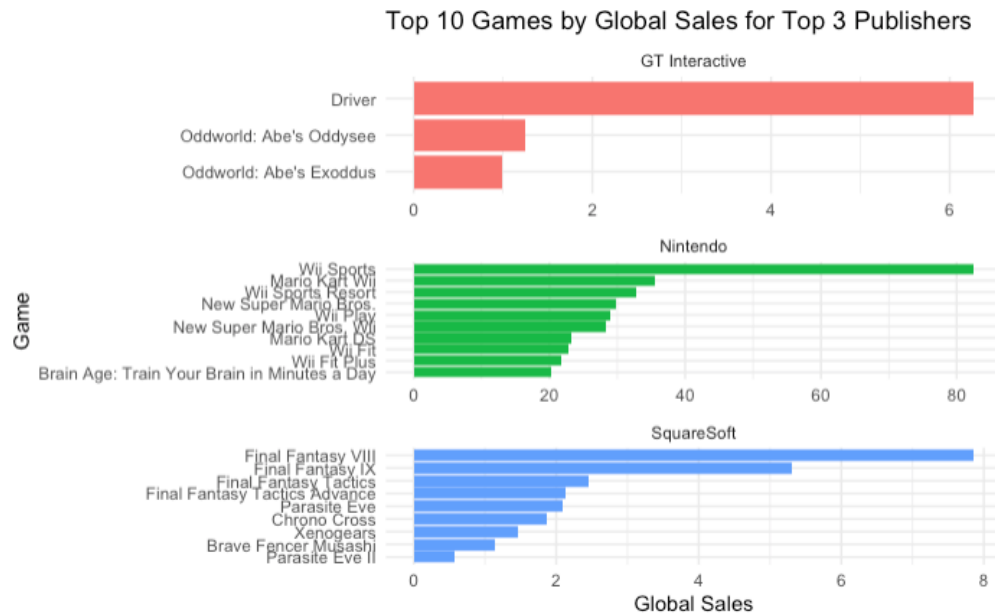


Figure 4: Faceted bar chart representing top 10 games by global sales for Top 3 most impactful publishers, based on regression coefficient