Google Play Store App Ratings Attribution Analysis

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Executive Summary

As the technology industry continues to expand, the mobile gaming app industry is showing major strides in consumer growth, revenue expansion and profit opportunities. In this report, we analyzed the predictors of mobile gaming app ratings and recommended app improvements for increasing ratings for a paid gaming app called Speedy Hedgehog.

Our method for approaching this business problem includes examining multiple variables that potentially predict app ratings and formulating them into a model. We use a data set from the Google Play Store that included 8,619 apps with over 30 different categories. We filtered this data to include only gaming apps with ratings at or above 3.5. For our model, we ran an analysis on the variables in the data set and found that the number of reviews, storage size and type of app (free or paid) would be the best variables to include to predict ratings. While we first conducted a KNN clustering technique, we ultimately ran a linear regression to analyze how these variables would predict ratings. Our results showed that while size was not a significant predictor for app rating and number of reviews had a minimal impact, whether or not an app was free had a significant impact on rating.

Based on these results, we determined that the company should continue charging for their app. The company should also try to increase their number of reviews, which could be done by incentivizing users with in-app rewards. In terms of app size, because we found that size was not a significant predictor, we determined that the company should not take the size of their app into consideration when determining strategies for increasing the rating or popularity of the app.

The lack of certain variables in our data set limited the scope of our model and our recommendations. Overall, our model predicted the general effects of the variables that we concluded and opened opportunities for further investigation into the gaming app industry.

Introduction

Currently, there are over 2.8 million different apps available in the Google Play marketplace alone.[1] In particular, the mobile gaming industry has made large impacts on the economy worldwide, with an estimated worth of $68.5 billion as of 2019. This number is only expected to grow in the coming years. Gaming apps account for 33% of all app downloads and 74% of consumer spending.[2]

As the mobile gaming space increases, so does competition and the desire of firms to understand why users rate some apps higher than others and how these firms can improve user ratings. [3] Each app can be categorized into specific descriptors (e.g., Food, Games, Photography, etc.). However, this categorical breakdown still leaves thousands of similar apps for users to choose from when deciding to download an app of a certain category. Competition within these app categories can directly affect the profitability of the apps. Companies from large tech firms to venture capital start-ups are competing to push their apps towards the top of app category lists. These companies often examine factors like app price, app descriptions, number of user reviews, user engagement and app updates to inform business decisions on app improvements that will ideally result in higher ratings.[4]

In this report, we will explore different factors that could potentially drive Google Play Store app ratings. The motivation for this exploration comes from a specific company: Speedy Hedgehog,

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[1] "Google Play Store: Number of Apps 2019." Statista. Accessed December 5, 2019. https://www.statista.com/statistics/266210/number-of-available-applications-in-the-google-play-store.
[2] Kaplan, Omer. "Mobile Gaming Is a $68.5 Billion Global Business, and Investors Are Buying In." TechCrunch. TechCrunch, August 22, 2019. https://techcrunch.com/2019/08/22/mobile-gaming-mints-money/.
[3] Salz, Peggy Anne. "The Changing Economics of App Development." Harvard Business Review, December 28, 2015. https://hbr.org/2015/11/the-changing-economics-of-app-development.
[4] Kübler, Raoul, Koen Pauwels, Gökhan Yildirim, and Thomas Fandrich. "App Popularity: Where in the World Are Consumers Most Sensitive to Price and User Ratings?" *Journal of Marketing* 82, no. 5 (2018): 20–44. https://doi.org/10.1509/jm.16.0140.

who is interested in improving their app's ratings. Speedy Hedgehog is a gaming app that costs $2.99 to install. It has a size of 37MB and 8,014 reviews on the Google Play Store.

Problem Formulation

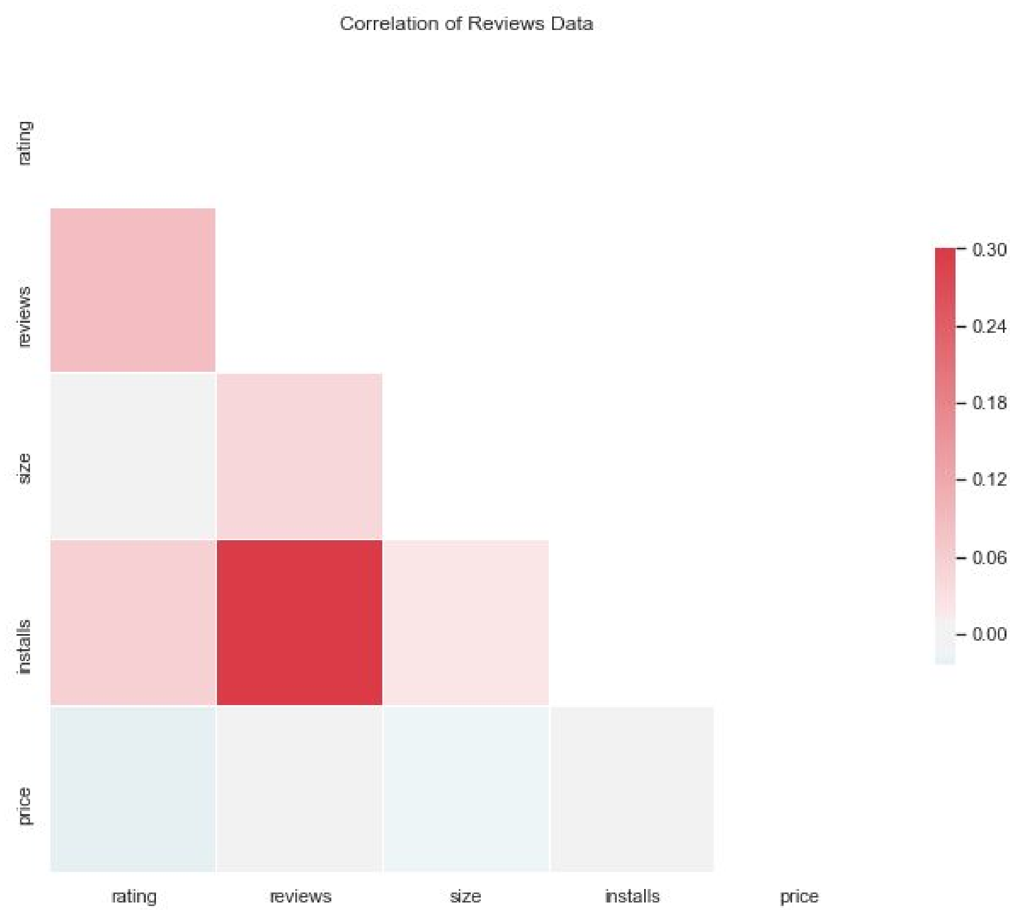
In order to better understand how Speedy Hedgehog could improve their mobile gaming app ratings, we wanted to determine the impact that different variables such as size, price, and number of reviews have on the gaming app. The app is currently 37MB, and we wanted to examine if there exists a relationship between the size of the app and its ratings. Gaming apps typically have rich graphics and dynamic features, which usually results in a bigger app. We want to validate if these elements that potentially add to the user experience take away from the overall app ratings. We also want to understand if the price has any impact on ratings. Typically users wouldn't mind paying for apps if they believe these offer a better gaming experience but we do not know how ratings respond to a change in price and this is what we want to examine. Additionally, the app currently has only 8,014 reviews. We want to understand if efforts to increase the number of reviews has the potential of improving the rating of the app, because then we can recommend strategies to drive reviews.

Data Characteristics

The data we chose to analyze included 8,619 different apps from the Google Play Store. However, these observations spanned over 30 different app categories. Because Speedy Hedgehog fell into the specific category of gaming, we felt that we could minimize inter-category variation and filter our data to include only gaming apps. We could then provide more accurate results to recommend improvements for a gaming app like Speedy Hedgehog.

Our ratings variable showed the ratings of apps on a scale of 1 to 5, with 5 being the best ratings and 1 being the worst. In order to use ratings as our dependent variable, we examined the data and found that ratings were skewed (Figure 1), so we adjusted our data to exclude observations with ratings below 3.5, which is only about 2% of the whole dataset.

Next, we looked at independent variables we wanted to include in our model, such as number of reviews, size, number of installs, and price. We ran a correlation analysis on these variables along with ratings, shown below:



We created a new variable called type: when the price is 0, type is 0; when the price is greater than 0, type is 1. We conducted this transformation because the price was highly skewed (Figure 2). We chose to use type in our model in order to gauge how much type explained ratings.

We also decided not to include installs in our model because the installs variable had categorical data (e.g. 100,000+ installs), which did not make sense for our business question, because we would want to look at number of installs as interval data, and we do not know how greatly the number of installs actually differs within the same level. Moreover, we would expect that if the ratings are higher, then so would the number of installs be. If this was the case, there could be endogeneity in our model, which is another reason to exclude installs in our analysis. We were therefore left with ratings as our dependent variable and reviews, size and type as our independent variables to use in our model.

Model Development, Estimation and Results

The first attempt to create a predictive model to gain insight into app ratings was a supervised clustering technique. Using a K-Nearest-Neighbor (KNN) approach, a model using the number of installations, as a factor, and the size of the applications as variables. In order to perform this clustering, these two values for each app in the dataset were graphed against one another. Each app's ratings was then categorized by its quartile (1,2,3, or 4) based on the descriptive quartiles of all game app ratings in the dataset. Quartiles were used instead of the continuous ratings to better the accuracy of the clustering and to account for the skewness within the ratings towards higher scores on a one to five scale. Below is a graph showing the relationship between the factorized number of downloads (i.e., 1,000 means 1,000-4,999, etc.) and the numeric size of the app in terms of megabytes. Each point on the graph is color coded to correlate with the quartile within which that app's rating falls (i.e., quartile 1 contains app with ratings in the lowest 25%, quartile 2 contains apps that fall within 25% and 50%, etc.).

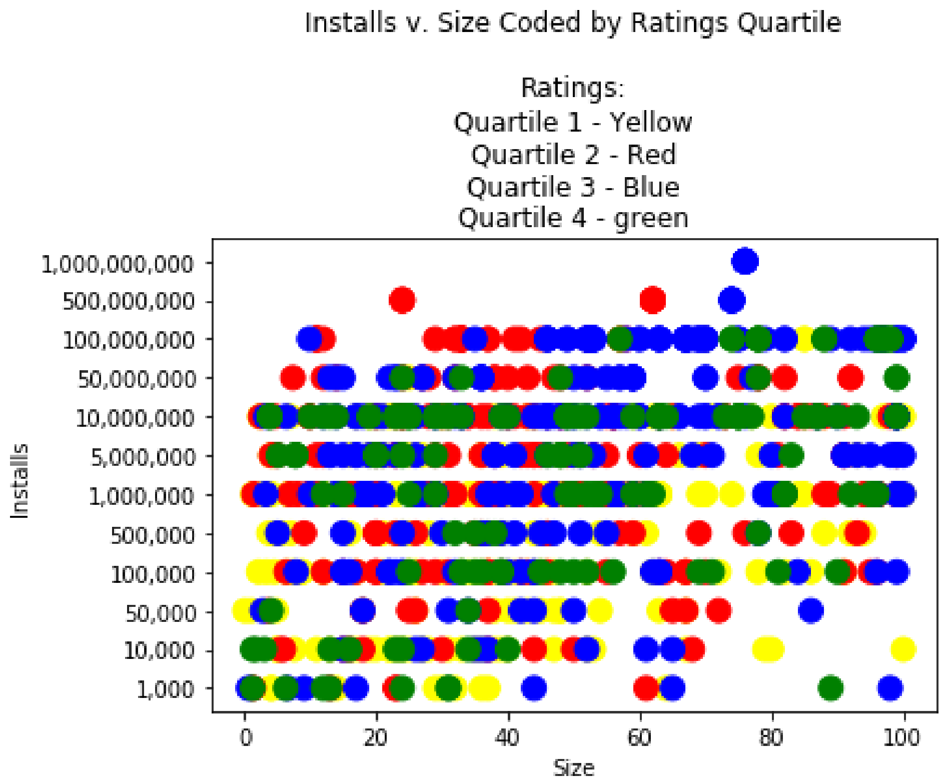


Figure 3: Graphing output of potential clustering model

As the above visualization shows, and our KNN output confirms (Appendix), there are no visually distinguishable clusters using the parameters, and therefore we determined clustering using this dataset will not provide useful insight.

Moving away from supervised clustering, we decided to use linear regression to gain insight about how reviews, size and type affect Speedy Hedgehog's app ratings. We used ratings as the dependent variable and we use the number of reviews, size, and app type (paid vs. free) as the independent variables to see how they influence ratings. As shown in Table 1, the regression model is significant. For every 1% increase in the number of reviews, the ratings increase by 0.02. Moreover, the model tells us that paid apps have 0.18 higher ratings than those for free apps. It also tells us that the app size does not significantly impact ratings.

Recommendations

As stated previously, the model results indicate that for gaming apps, paid apps are rated higher than non paid apps. This relationship could be possible because many free apps make money using in-app advertisements, which may impact user experience and result in lower ratings.[5] Additionally, paid apps might offer a better product and experience which might lead to users ratings them better. Therefore, the company can continue charging the current price of $2.99. We cannot however offer specific price recommendations, as we were unable to use the price variable due to skewness.

The model also tells us that app ratings and reviews are correlated and hence the company can employ different approaches to increase the number of reviews and examine if that has an effect on the Google Play Store ratings. Specifically, they can incentivize users to leave a review by offering in-app rewards such credits in exchange, but this strategy should be implemented carefully as repeatedly asking users to rate the app might bother them and result in them uninstalling the app, or even leaving a poor rating.

We also found that for gaming apps, the app size does not impact ratings. While this might be counterintuitive, as users usually do not prefer bigger apps, it is possible that a bigger gaming apps offer more exciting product features and rich graphics, which in turn could improve the user

[5] Manifest, T. (2018, March 7). How In-App Advertising Works for App Monetization. Retrieved from https://medium.com/@the_manifest/how-in-app-advertising-works-for-app-monetization-2cce20497cf.

experience in the game.[6] Thus, the company should not adjust their app size. However, they should be considerate about what features they add and how that impacts the size of the app.

Another thing the company can focus on to improve app ratings is platform stability to minimize bugs and app crashes, which disrupt the user experience and could negatively impact the app's ratings. The Google Play Store also downrates apps that have many bugs and issues, so platform stability is integral to app ratings.[7]

Limitations

This model only looks as data from the Google Play Store and doesn't take into consideration data from Apple's App Store. Hence the aforementioned recommendations might only be applicable for the Android version of the app. There is also the issue of biases in the data as it is likely that only very happy or unhappy users rate the app. Moreover, since we don't have the specific number of installs, the report doesn't include the quantitative relationship between installs and other variables, and hence we can't offer any insights on the relationship between installs and ratings. Lastly the model only shows a correlation between review and ratings which does not imply causation and hence we're not certain that increasing the reviews will indeed increase the app rating.[8]

[6] Reinhardt, P. (n.d.). Effect of Mobile App Size on Downloads. Retrieved from https://segment.com/blog/mobile-app-size-effect-on-downloads/.
[7] Perez, S. (2017, August 3). Google Play will now downrank poorly performing apps. Retrieved from https://techcrunch.com/2017/08/03/google-play-will-now-downrank-poorly-performing-apps/.
[8] Vigen, Tyler. *Spurious Correlations*. London: Hachette Books, 2015.

Conclusion

This report has explored the potential impacts of different app features on the ratings of a gaming app named Speedy Hedgehog. The analysis of this report aimed to assess how the app ratings would be affected by these other variables. This analysis shows that paid apps have higher ratings than free apps, so the Speedy Hedgehog app can continue charging the current price of $2.99. We also noticed that the app size does not significantly impact ratings, but we do not recommend making the app be any larger than what it needs to be in order to avoid a non-delightful user experience. Finally, the analysis shows that for every 1% increase in the number of reviews, the ratings increase by 0.02, which means that Speedy Hedgehog should encourage its users to leave as many reviews as possible.

Appendix

Primary Model

Rating = $\beta 0 + \beta 1 * \log(\text{Reviews}) + \beta 2 * \text{Size} + \beta 3 * \text{Type} + \varepsilon$

Figure 2: Histogram of Rating before being filtered

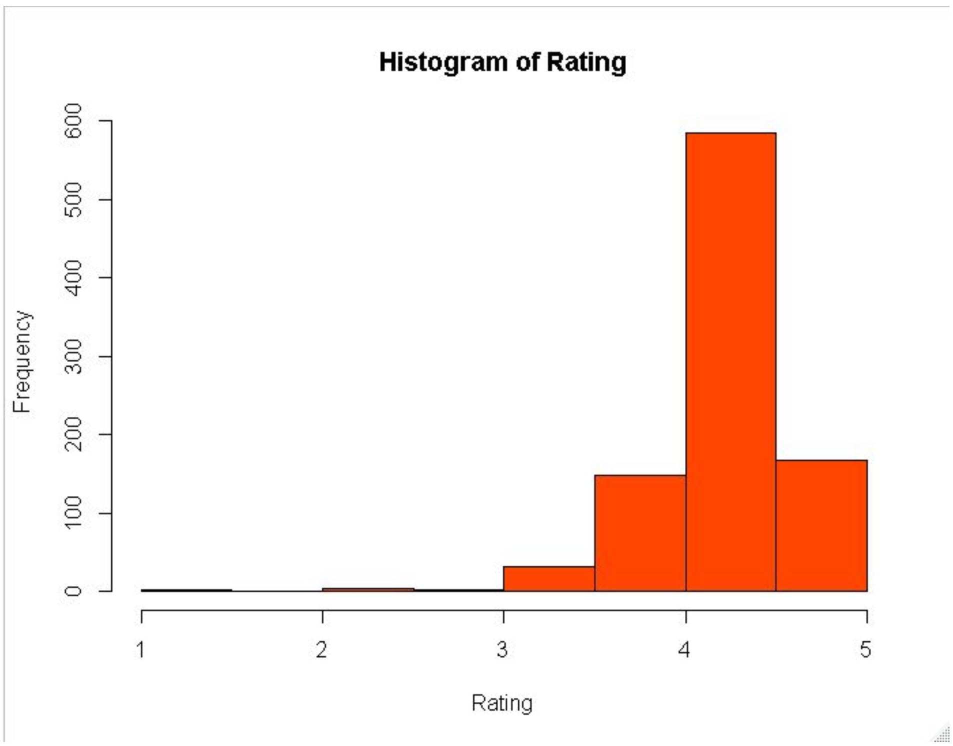


Figure 3: Histogram of Price

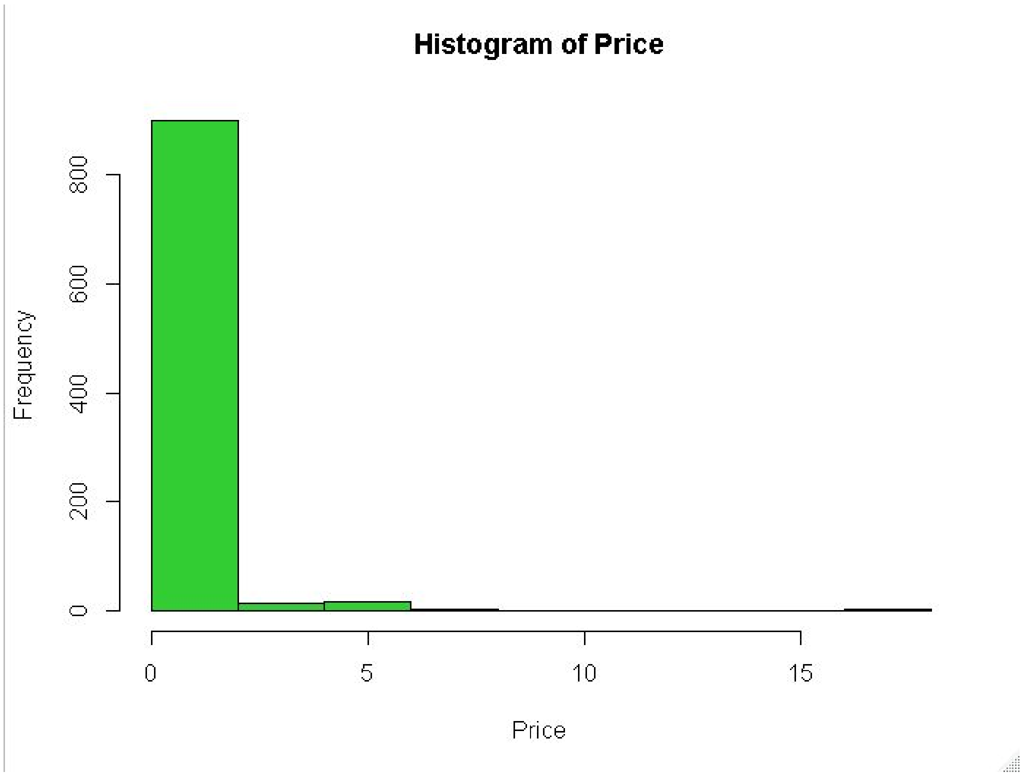


Table 1: The result of linear regression model

Call:

lm(formula = Rating ~ log(Reviews) + Size + Type)

Residuals:

Min 1Q Median 3Q Max

-0.80292 -0.14908 0.01412 0.16636 0.96081

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 4.0290763 0.0313845 128.378 < 2e-16 *** log(Reviews) 0.0231139 0.0028422 8.133 1.38e-15 ***

Size 0.0004214 0.0003520 1.197 0.232

Type 0.1827374 0.0357848 5.107 4.00e-07 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2707 on 906 degrees of freedom

Multiple R-squared: 0.09182, Adjusted R-squared: 0.08881

F-statistic: 30.53 on 3 and 906 DF, p-value: < 2.2e-16

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