



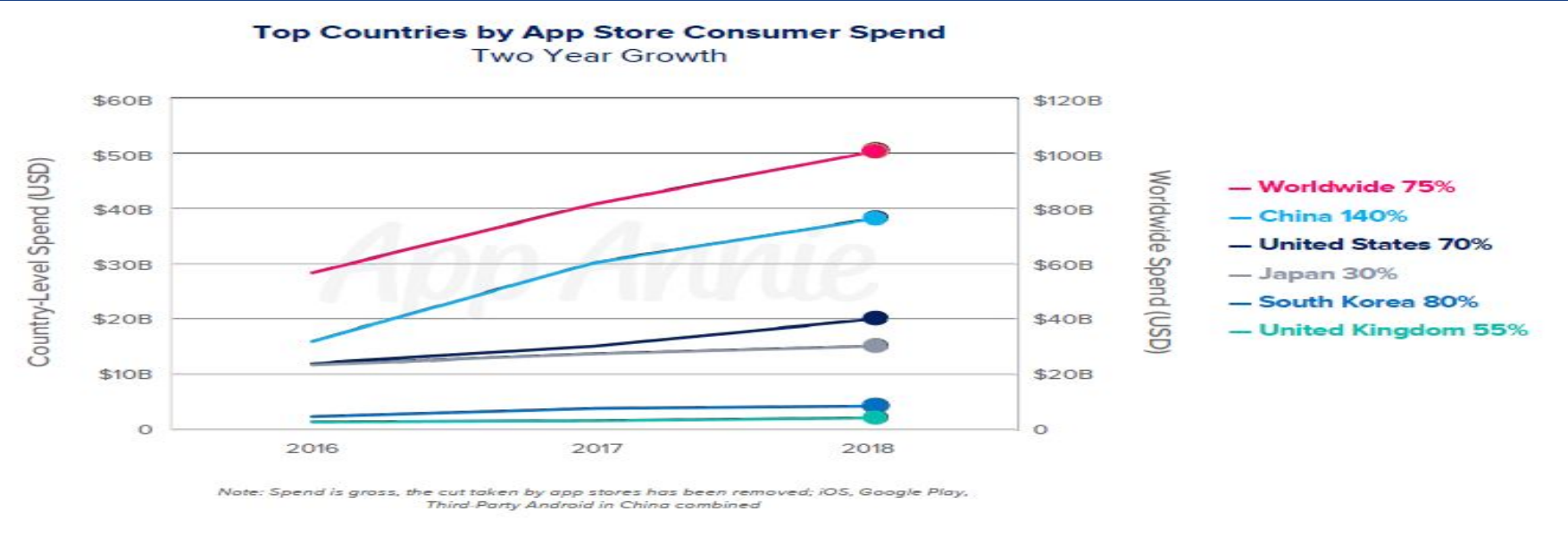
What Determines an App’s Rating?

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Background

- High Usage**
- According to *Statista*, mobile phones generated **52.2%** of all website traffic worldwide in 2018.
- High Profitability**
- As a result of this growth, the profitability of apps has also increased significantly. Just as of April 2019, global app revenue reached **\$19.5 billion**, an increase of **17%** from April 2018 (Nelson).
- User Rating**
- It is clear that app creation has the potential to be a highly lucrative venture, and one of the factors playing into whether an app becomes successful is its overall **user rating**. In fact, user ratings are often the first thing new customers look at to determine if an app is worth installing.
- Useful for any App Developers**
- For large companies or small developers looking to create successful apps, our findings could be greatly useful. Even developers just looking to make useful apps with no intention of making money could use our findings to better satisfy app users.



Data Summary

Source

- Our dataset comes from the Google Play Store, obtained from Kaggle.
- The dataset contains data for **over 267,000 apps** from the Google Play Store from April 2019.
- The data was extracted from the Google Play Store using Python web scraping tools. Since the data comes directly from Google, we can be reasonably sure of its validity.

Response Variable

To determine an app’s success, we wish to predict an app’s average **user rating** on the Google Play Store (**0-5 stars**). Since the response variable is an average of each app’s ratings, the variable is continuous.

Explanatory Variables

- Installs:** Number of installations for the app, split into <1 million, 1-10 million, and 10 million+ installs
- Price:** Price of the app in dollars
- Reviews:** Total number of reviews for the app
- Genre:** Primary genre of the app, ranging between entertainment, lifestyle, media, and productivity
- Content Rating:** Age recommendation for the app, ranging between E (Everyone) and Teen

E vs Teen

We chose to only to investigate apps that had a content rating of E or Teen, to make our large dataset more manageable.

Analysis

Three Stage Model

Stage 1 Model (Quantitative)

$$\text{Predicted Rating} = \beta_0 + \beta_1 \cdot \ln(\text{price}) + \beta_2 \cdot \ln(\text{reviews})$$

Global F Test	0.0007 < .1
Adjusted R-sq	0.0611

$$\text{Predicted Rating} = 4.15688 + (0.02632) \cdot \ln(\text{price}) + (0.03950) \cdot \ln(\text{reviews})$$

Stage 2 Model (Stage 1 + Qualitative)

$$\begin{aligned} \text{Predicted Rating} = & \beta_0 + \beta_1 \cdot \ln(\text{price}) + \beta_2 \cdot \ln(\text{reviews}) + \beta_3 \cdot \text{DummyContentB} + \\ & \beta_4 \cdot \text{DummyInstallB} + \beta_5 \cdot \text{DummyInstallC} + \beta_6 \cdot \text{DummyCatB} + \beta_7 \cdot \text{DummyCatC} + \beta_8 \cdot \text{DummyCatD} \end{aligned}$$

Global F Test	0.0177 < .1
Adjusted R-sq	0.0530

Nested F- Test

$$F = 0.71859505548$$

$$P = .63607$$

Stage 3 Model (Stage 2 + Interaction)

$$\text{Predicted Rating} = \beta_0 + \beta_1 \cdot \ln(\text{price}) + \beta_2 \cdot \ln(\text{reviews})$$

Global F Test	0.0007 < .1
Adjusted R-sq	0.0611

$$\text{Predicted Rating} = 4.15688 + (0.02632) \cdot \ln(\text{price}) + (0.03950) \cdot \ln(\text{reviews})$$

Final Model

$$\text{Predicted Rating} = 4.15688 + (0.02632) \cdot \ln(\text{price}) + (0.03950) \cdot \ln(\text{reviews})$$

Global F Test	0.0007 < .1
Adjusted R-sq	0.0611

Robust Model

Why Use Robust?

- Data presents non-normality of errors, outliers on x or y axis.

Advantages and Disadvantages

- Robust regression yields estimates for the β ’s that are nearly as good as the least squares estimates when the assumption of normality is satisfied
- Significantly better results for a heavy-tailed distribution

Biggest Differences

- Robust regression is better at dealing with outliers than traditional Multiple Linear Regression.

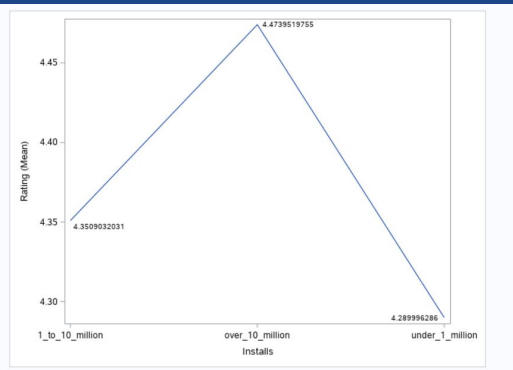
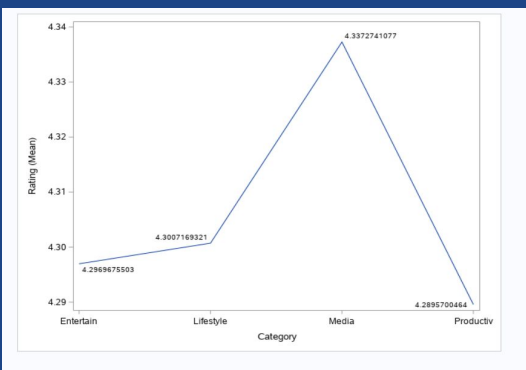
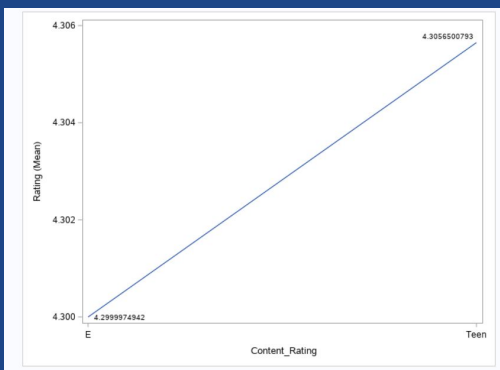
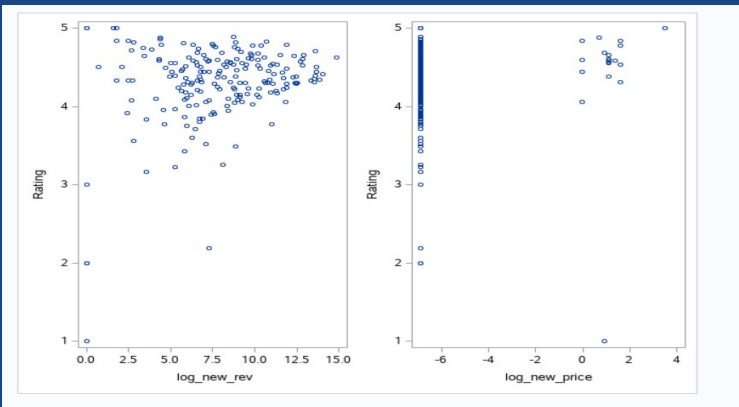
Robust Model:

$$R\text{-Square} = 0.0395$$

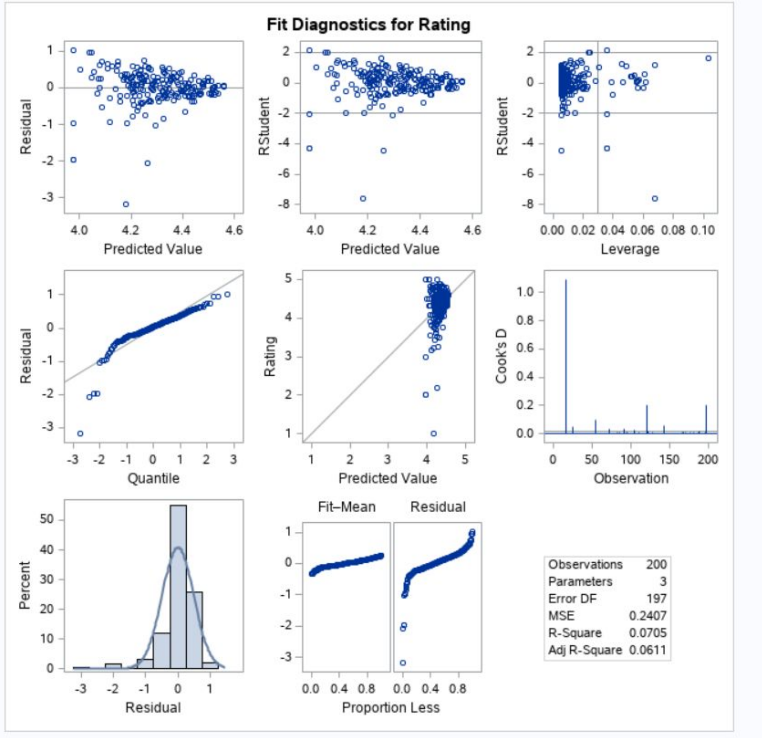
Multiple Linear Regression Model:

$$R\text{-Square} = 0.0705$$

Early Data Analysis



Regression Assumptions



The REG Procedure	
Model: MODEL1	
Dependent Variable: Rating	
Durbin-Watson D	2.201
Pr < DW	0.5214
Pr > DW	0.0786
Number of Observations	200
1st Order Autocorrelation	-0.101

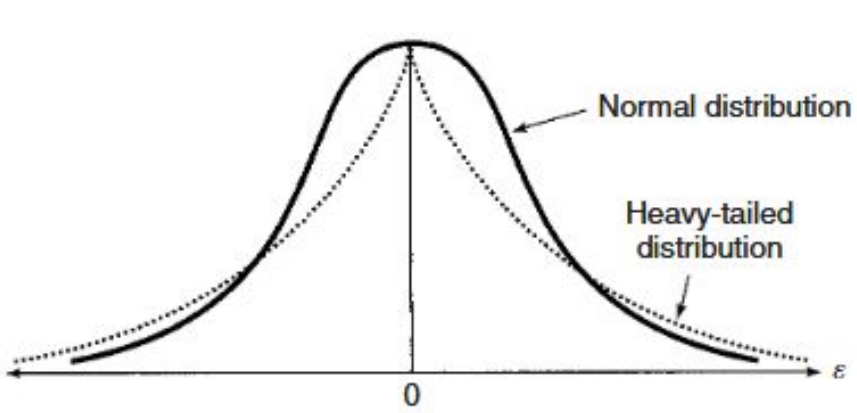
Note: Pr=DW is the p-value for testing positive autocorrelation, and Pr=DW is the p-value for testing negative autocorrelation.

Conclusion

- Utilizing the log transformation on our quantitative variables favored our overall statistical significance in the model
- We were not able to produce a good fit for our model
- This might have been due to missing variables / model misspecification

Was Our Research Question Answered?

- The model was not substantially useful in predicting user rating
- Our beta estimation don’t explain the user ratings of apps



Goodness-of-Fit	
Statistic	Value
R-Square	0.0395
AICR	225.0712
BICR	236.3716
Deviance	20.5832