
The University of Chicago Booth School of Business

BUSN 41201 - Big Data - Final Project

# PROJECT TITLE

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Note: The full the code used in all the questions can be found in the appendix.

## 1. Executive Summary

[REDO AFTER WE COMPLETE THE REPORT]

In this report, we present a comprehensive analysis of the "Google Play Store dataset" to gain insights into the characteristics and success factors of mobile applications. By examining various aspects related to app details, including categories, ratings, reviews, sizes, installations, and pricing, we aim to identify patterns and trends that contribute to an app's success on the Google Play Store.

We begin by exploring the general statistics of apps, focusing on the distribution of app categories, ratings, and reviews. This provides a foundational understanding of the data and highlights key areas of interest. Next, we delve into specific analyses to understand the relationship between app size, installs, and pricing, exploring how these factors influence an app's popularity and user engagement.

Our study also includes a sentiment analysis of user reviews, examining the polarity and subjectivity of feedback to understand how user sentiments correlate with app ratings and success. Additionally, we develop predictive models to forecast app ratings based on various features, and we investigate potential causal relationships between app characteristics and their performance metrics.

By leveraging data visualization, feature engineering, and predictive modeling techniques, we aim to provide actionable insights for potential app developers. These insights can help optimize app features, improve user satisfaction, and ultimately enhance the app's visibility and success on the Google Play Store.

## 2. Introduction

[WE CAN CHANGE THE QUESTIONS, THESE ARE JUST EXAMPLES]

In this paper, we aim to analyze the Google Play Store dataset to gain a comprehensive understanding of the factors that contribute to the success of mobile applications. The dataset includes details of apps such as categories, ratings, reviews, sizes, installations, and pricing, as well as user reviews with sentiment analysis. Our objective is to uncover patterns and trends that can help app developers optimize their offerings and improve user satisfaction.

The Google Play Store dataset, available on Kaggle, consists of two files: `googleplaystore.csv`, which contains detailed information about the apps, and `googleplaystore_user_reviews.csv`, which includes user reviews and sentiment data.

Our analysis will focus on the following research questions:

- **What factors affect the number of installs an app receives?** Specifically, what is the relationship between app size, type (free or paid), price, and the number of installs?
- **What are the key features that influence an app's rating?** How do factors like category, price, and number of reviews contribute to the overall rating of an app?
- **How does user sentiment in reviews correlate with app ratings?**
  Can sentiment analysis of user reviews provide additional insights into user satisfaction and app performance?

We will begin by loading and cleaning the dataset, followed by a thorough exploratory data analysis to uncover initial insights. Subsequently, we will perform detailed analyses to address our research questions, culminating in the development of predictive models and the identification of causal relationships. We will end by making concluding remarks from our research.

## 3. Dataset

### a) Understanding the data

For `googleplaystore.csv` there are the following columns:

- App: Application Name
- Category: Category Type (e.g. Family, Game, Art)
- Rating: User rating review
- Reviews: Number of reviews
- Size: Download size of application
- Installs: Number of user downloads 0.. - Type: Paid or Free
- Price: Price of App
- Content.Rating: Age group that app is targeted at (E.g. Everyone, Teen, Child)
- Genres: Other categories the app belongs to, other than the main category
- Last.Updated: Date when app was last updated
- Current.Ver: Current app version available
- Android.Ver: Minimum required Android version for app

There are a total of 10841 rows (applications).

For `googleplaystore_user_reviews.csv` there are the following columns:

- App: Application Name
- Translated_Review: User review, translated to English
- Sentiment: Positive / Negative / Neutral (Preprocessed)
- Sentiment_Polarity: Sentiment polarity score (Preprocessed)
- Sentiment_Subjectivity: Sentiment subjectivity score (Preprocessed)

This dataset contains the first 100 'most relevant' review for each app, with some prepocessing already done to add the last 3 features.

There are a total of 64295 rows (reviews).

### b) Data Cleaning

For the `googleplaystore` dataset, we first process the variables by converting columns to the appropriate datatype. For example Installs, Size, Reviews Price, and Android.Ver are converted to numerics,

Last.Updated is converted to date. Then we filter out apps with Type 0 or NA, and remove duplicated rows.

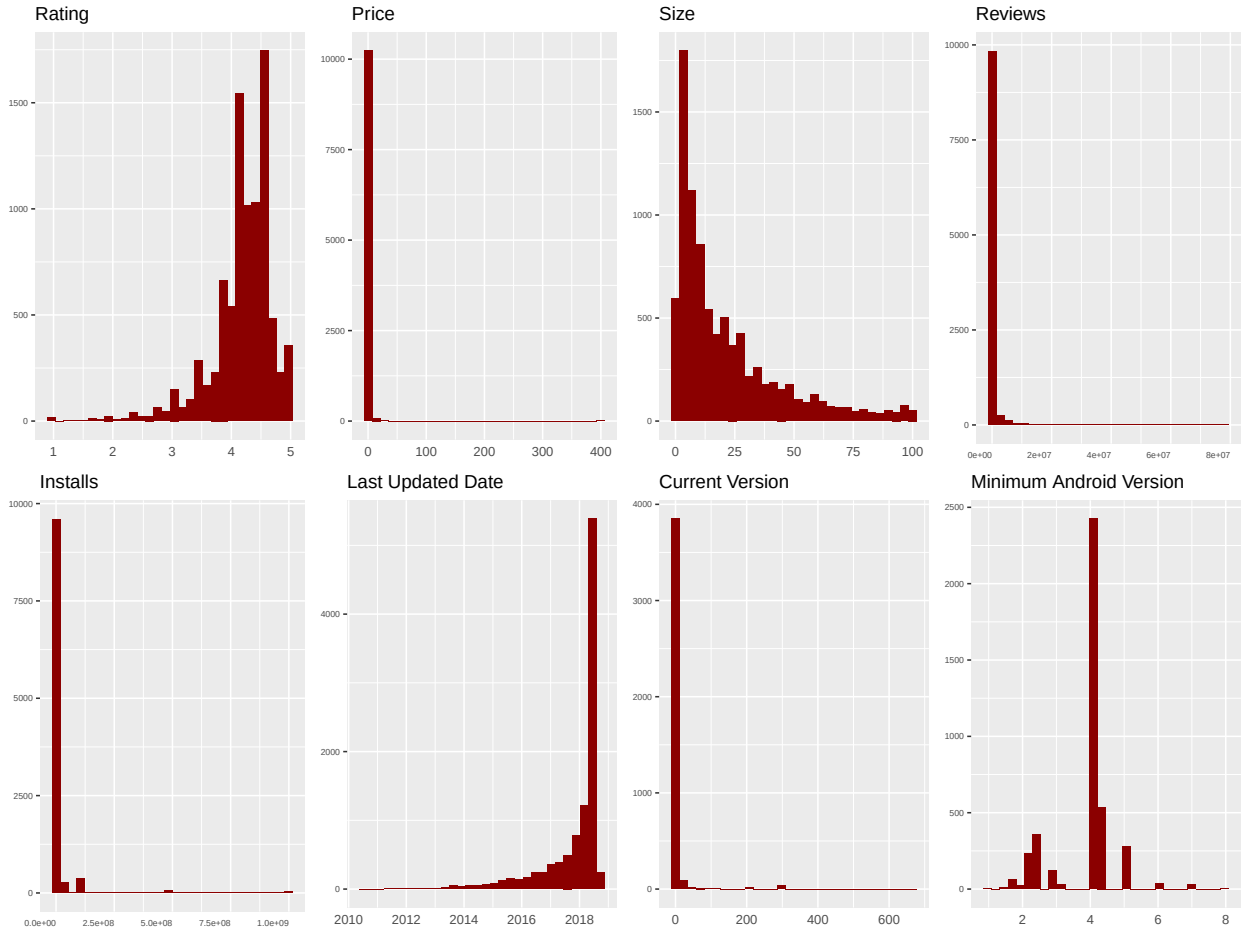
After this, we are left with 10356 rows.

With the `googleplaystore_user_reviews` dataset, the variables were already well structured, but we noticed there were many rows with "nan"s. After filtering these out, we were left with 37432 rows.

## 4. Exploratory Analysis

### a) Numerical Features

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




According to the histograms, most apps have high ratings, peaking around 4 to 5, with fewer apps rated below 3, indicating generally positive user feedback. The majority of apps have a low number of installs, while a few apps have extremely high install numbers, showing a highly skewed distribution. Since installs are highly skewed, we will perform a log transformation on it in later analysis.

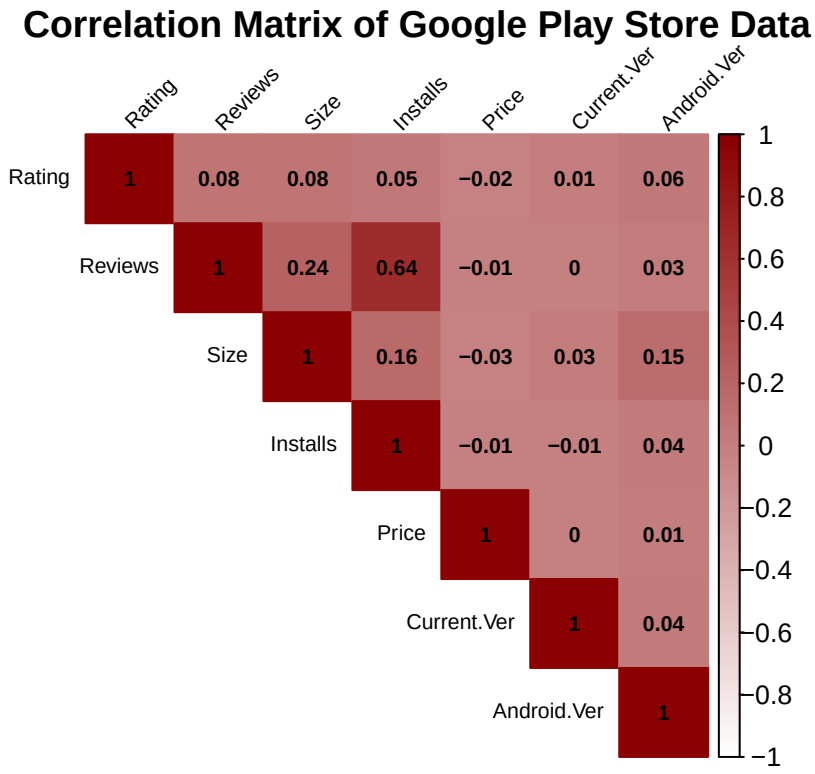
Regarding other numerical variables, the vast majority of apps are free, with the few paid apps showing a wide price range, including some very expensive ones. Most apps are small in size, with a significant drop-off as size increases. The majority are less than 25 MB, with very few exceeding 100 MB. Similarly, most apps have a low number of reviews, with a small number having extremely high reviews, indicating a skewed

distribution where a few apps are very popular while many are not widely reviewed. Most apps have been updated recently, with a notable increase in updates around 2018, suggesting the dataset is current and apps are actively maintained. Most apps are on version 1 or 2, with a sharp decrease in the number of apps as the version number increases, indicating that many apps do not undergo numerous versions.

Most apps require Android version 4 or 4.5, with fewer requiring higher versions, suggesting developers aim for compatibility with older Android versions to reach a wider audience. However, the data for these version variables is not clean and contains extreme outliers even after cleaning, making it difficult to interpret. Therefore, we might exclude these variables from later analysis.

**b) Correlation Matrix**

We begin by analysing the correlation matrix of all the numeric variables for googleplaystore:

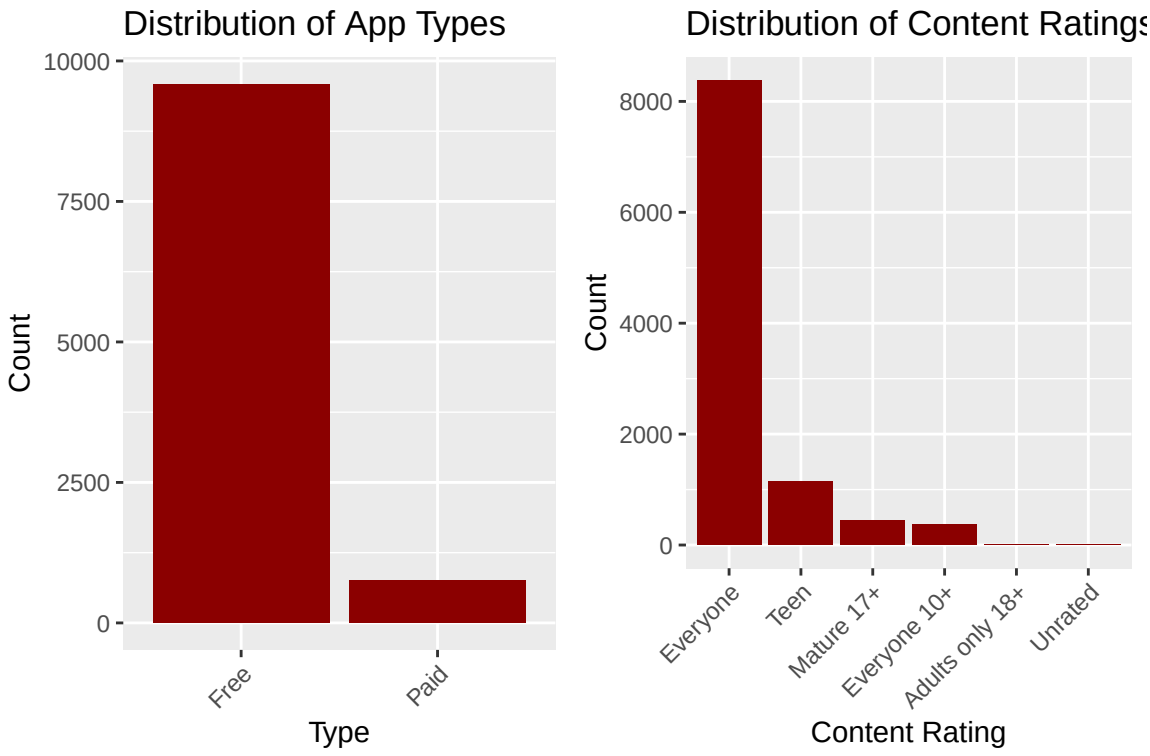



This seems surprising initially as the variables appear to be fairly uncorrelated with eachother, except for the fact that "Installs" and "Reviews" which are highly correlated with a score of 0.64, which would make sense as one would expect a more popular app with a greater number of installs to also have a higher number of reviews. One surprising variable that is somewhat positively correlated with others is "Size", with small

positive correlations with "Reviews" and "Installs". This might perhaps be due to the fact with apps with a larger download size are more 'complicated' and may perform more functions, and thus lead to a greater number of installations and thus reviews too.

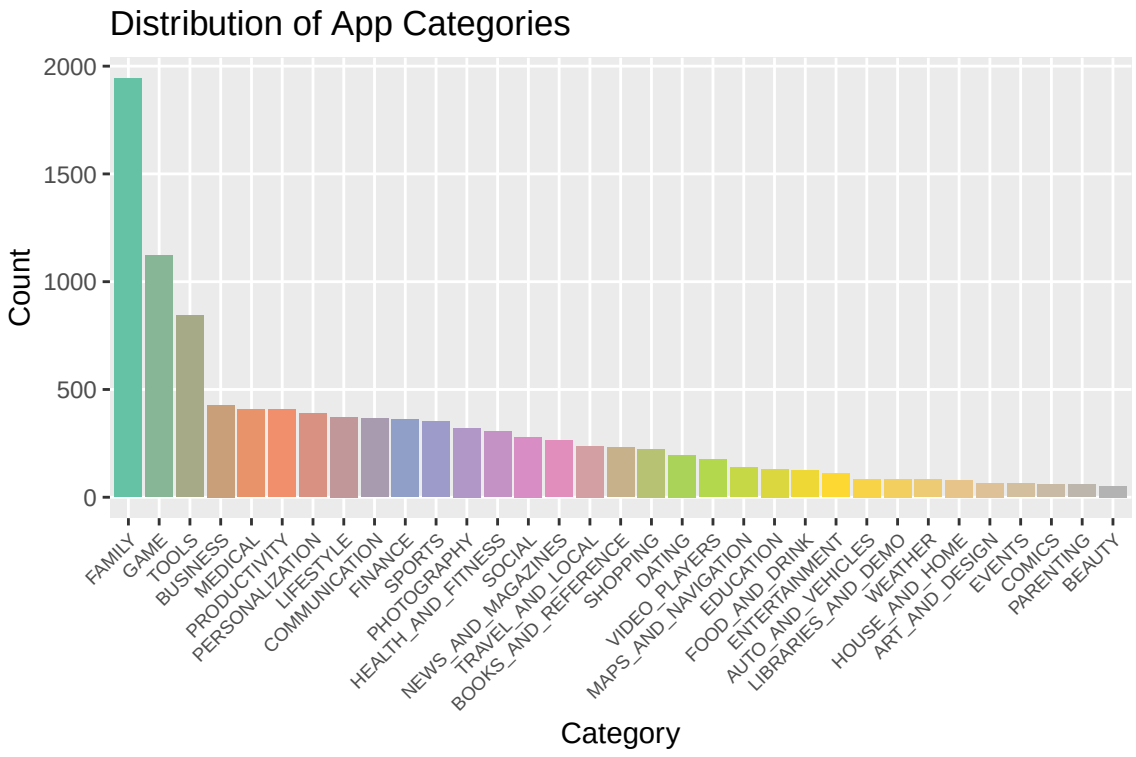
**c) Categorical Features**

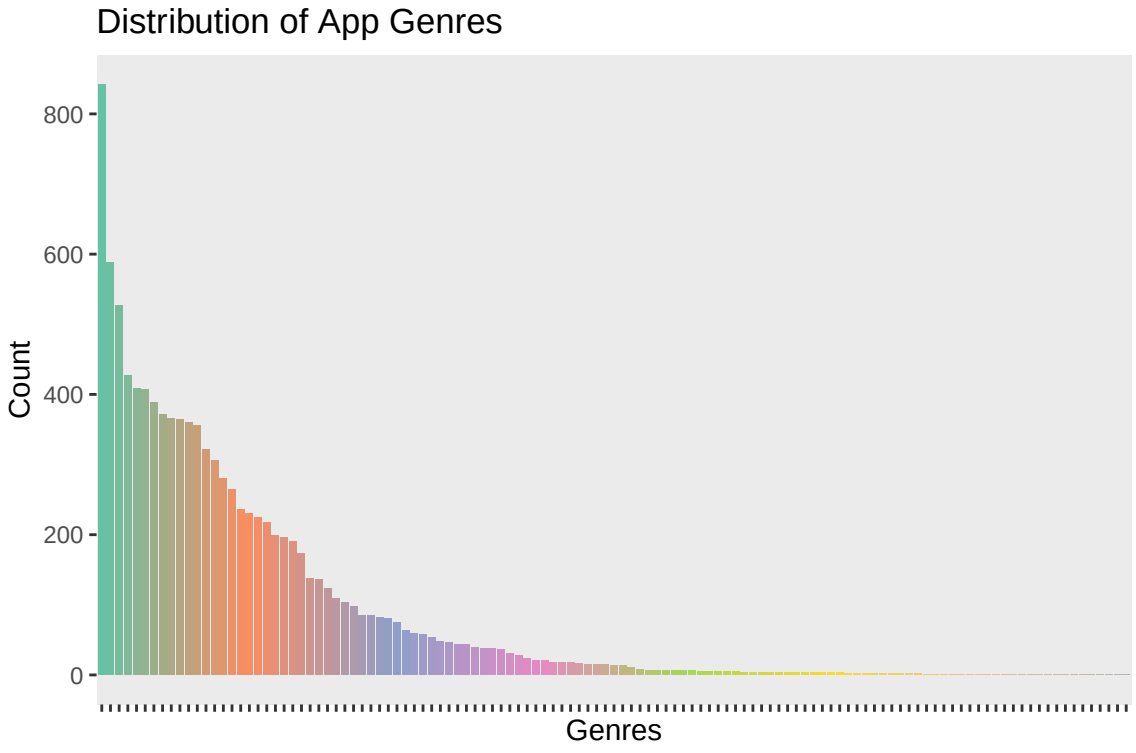
We also look at the distribution of the categorical features in our dataset:




So immediately we observe that there is a much greater proportion of free apps than paid, this aligns with the common "freemium" model where apps are free to download but may offer in-app purchases. This model also lowers the barrier to entry to users.

The content rating distribution shows that the the significant majority of apps are aimed at is "Everyone". This indicates that most apps are designed to be accessible for a general audience, which makes sense if developers want the largest possible user base for their app.




Next, looking at the distribution of category, sorted by count, we see that distribution is very heavily skewed to the right. In particular the first 3 categories (Family, Game, and Tools) have a very large number

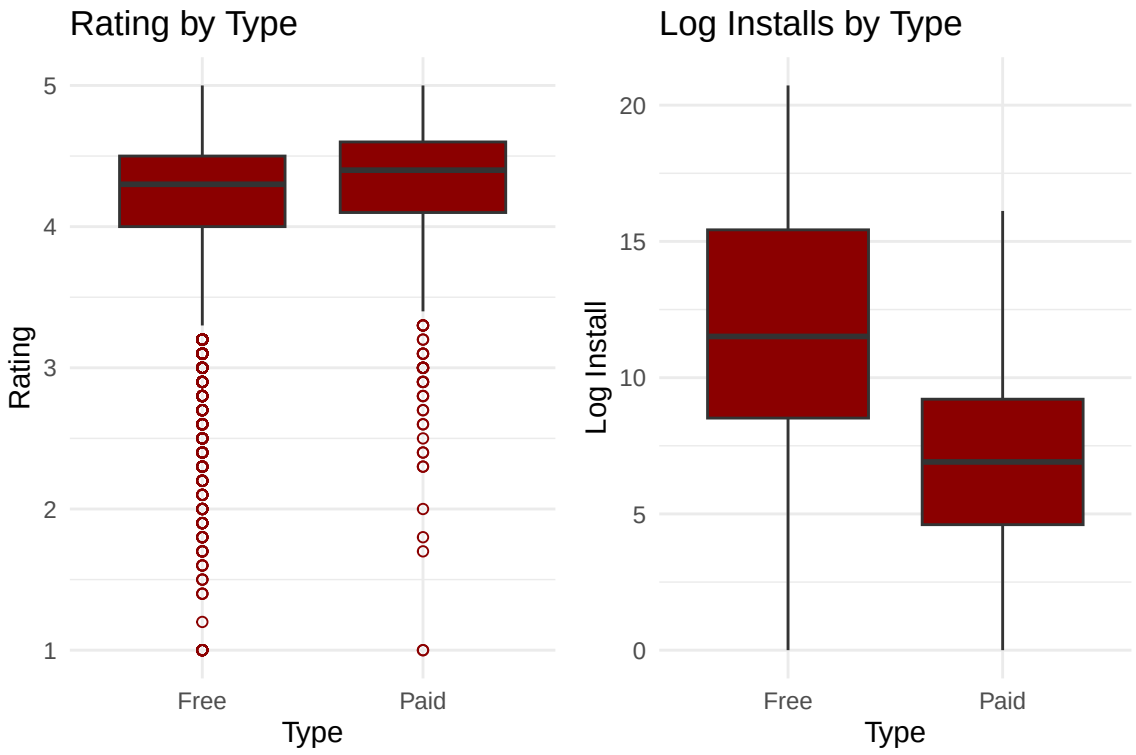
of apps, after which the count per category drops and falls slowly for the remaining categories.

Secondly, from the genre distribution (recalling that genres are additional categories that apps can be listed as), we observe the same skewness. However the top 30-40% of genres contain most of the count, whereas afterwards the genres listed have a count of almost 0 which suggests that there are many genres with very few apps, suggesting either niche markets or less popular app types.

Table 1: Top 10 Genres and Categories

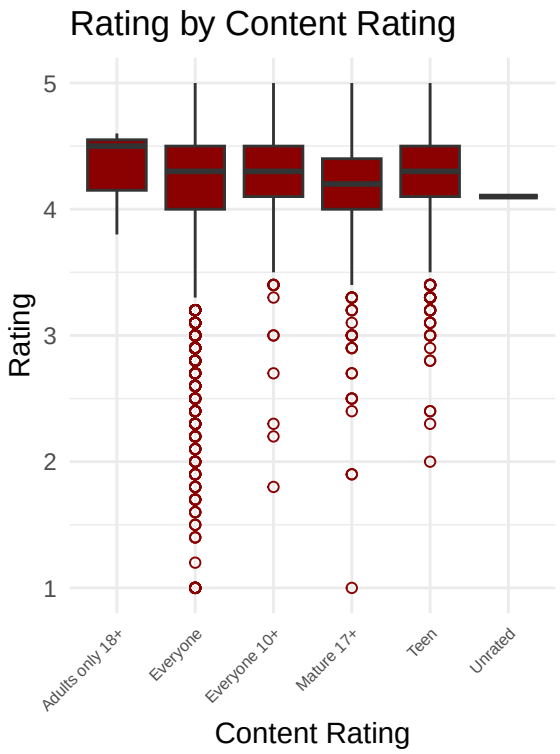
| Rank | Category | Category_Count | Genre | Genre_Count |
|---|---|---|---|---|
| 1 | FAMILY | 1942 | Tools | 842 |
| 2 | GAME | 1121 | Entertainment | 588 |
| 3 | TOOLS | 843 | Education | 527 |
| 4 | BUSINESS | 427 | Business | 427 |
| 5 | MEDICAL | 408 | Medical | 408 |
| 6 | PRODUCTIVITY | 407 | Productivity | 407 |
| 7 | PERSONALIZATION | 388 | Personalization | 388 |
| 8 | LIFESTYLE | 373 | Lifestyle | 372 |
| 9 | COMMUNICATION | 366 | Communication | 366 |
| 10 | FINANCE | 360 | Sports | 364 |

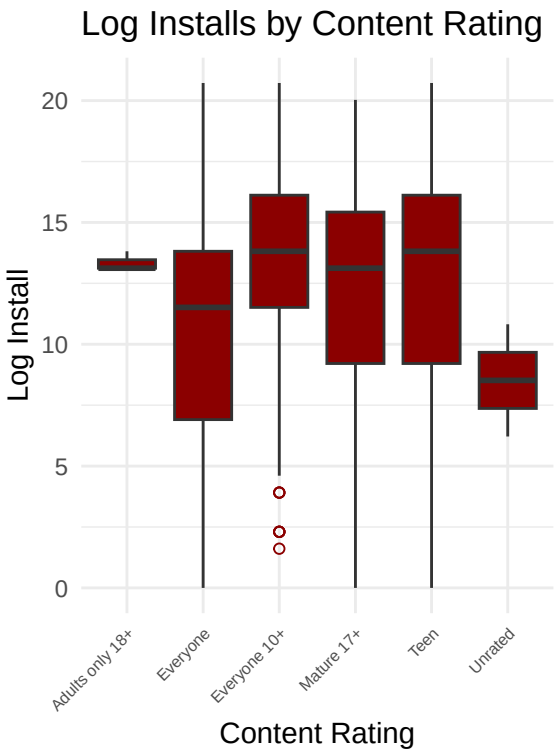
**d) Exploring Categorical Features vs Y**



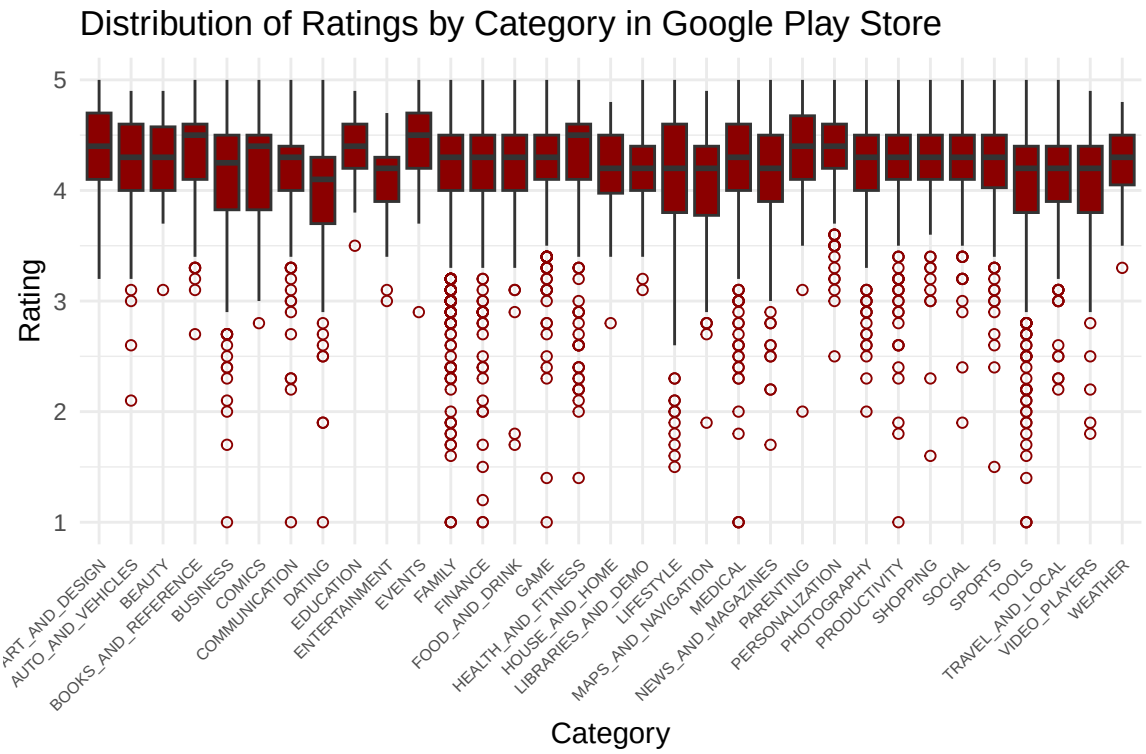

The rating of free Apps display a broad range of ratings from 1 to 5, with most ratings clustered around 4. There are many outliers on the lower end, suggesting some free apps are rated poorly. Similar to free apps, ratings mainly cluster around 4. However, there are fewer lower outliers compared to free apps, indicating generally higher satisfaction among users who purchase apps. Both free and paid apps have a median rating close to 4, showing that overall user satisfaction is high across both app types. The presence of more lower outliers in free apps might indicate variability in quality, where some free apps may not meet user expectations, perhaps due to ads or less functionality.

The rating of free Apps have a broader distribution of log installs, with the median around 15. The range of installs is wide, showing that some free apps achieve significantly higher installs. The distribution of installs is noticeably more constrained and lower than that of free apps. The median log install is lower, and the range (IQR) is narrower, indicating less variation in the number of installs. Thus, free apps tend to reach more users, reflected by the higher median installs and wider distribution. This is expected as the barrier to try a free app is lower than for a paid app. Paid apps, while having fewer installs, tend to have a more consistent range of installs. This could suggest a dedicated user base willing to pay for apps that potentially offer higher quality or unique features not found in free apps.

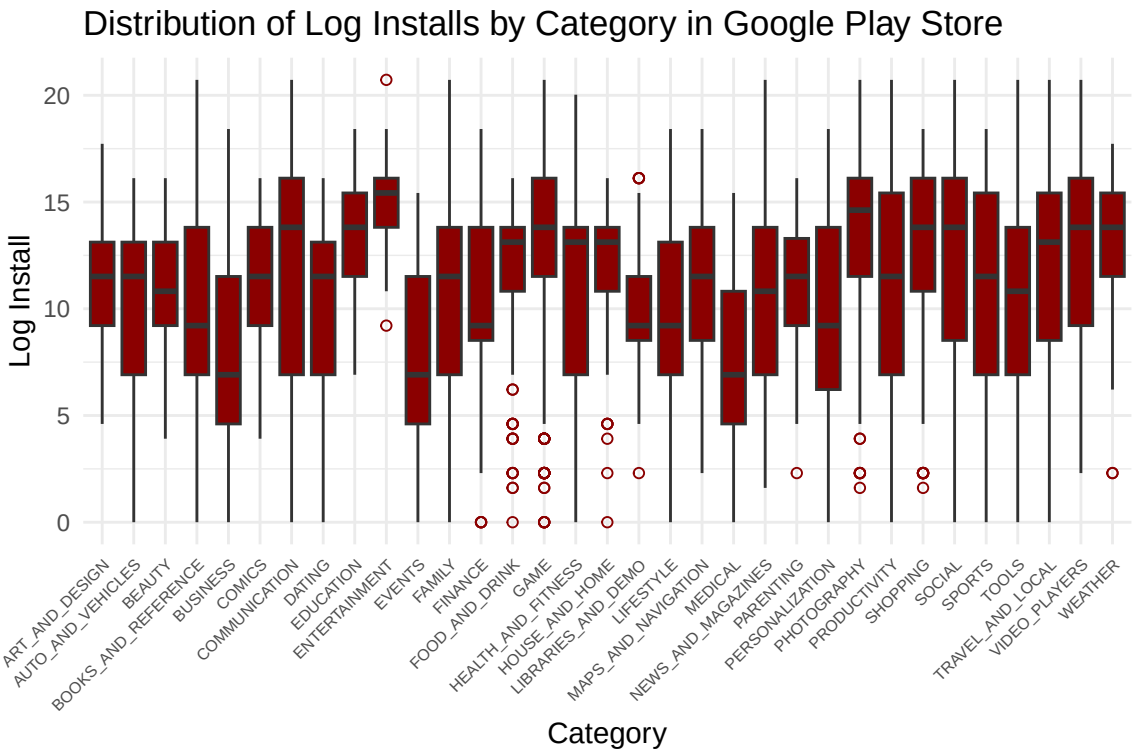



Content ratings such as "Everyone" and "Teen" cover a broad audience, resulting in higher downloads. Categories with restricted audiences like "Adults Only 18+" have both fewer downloads and lower ratings, possibly due to content restrictions or niche market appeal. Thus, Apps aimed at a general audience ("Everyone") might expect higher installations and generally favorable ratings, whereas apps targeted at adults or mature audiences might face more challenges in both downloads and user acceptance.



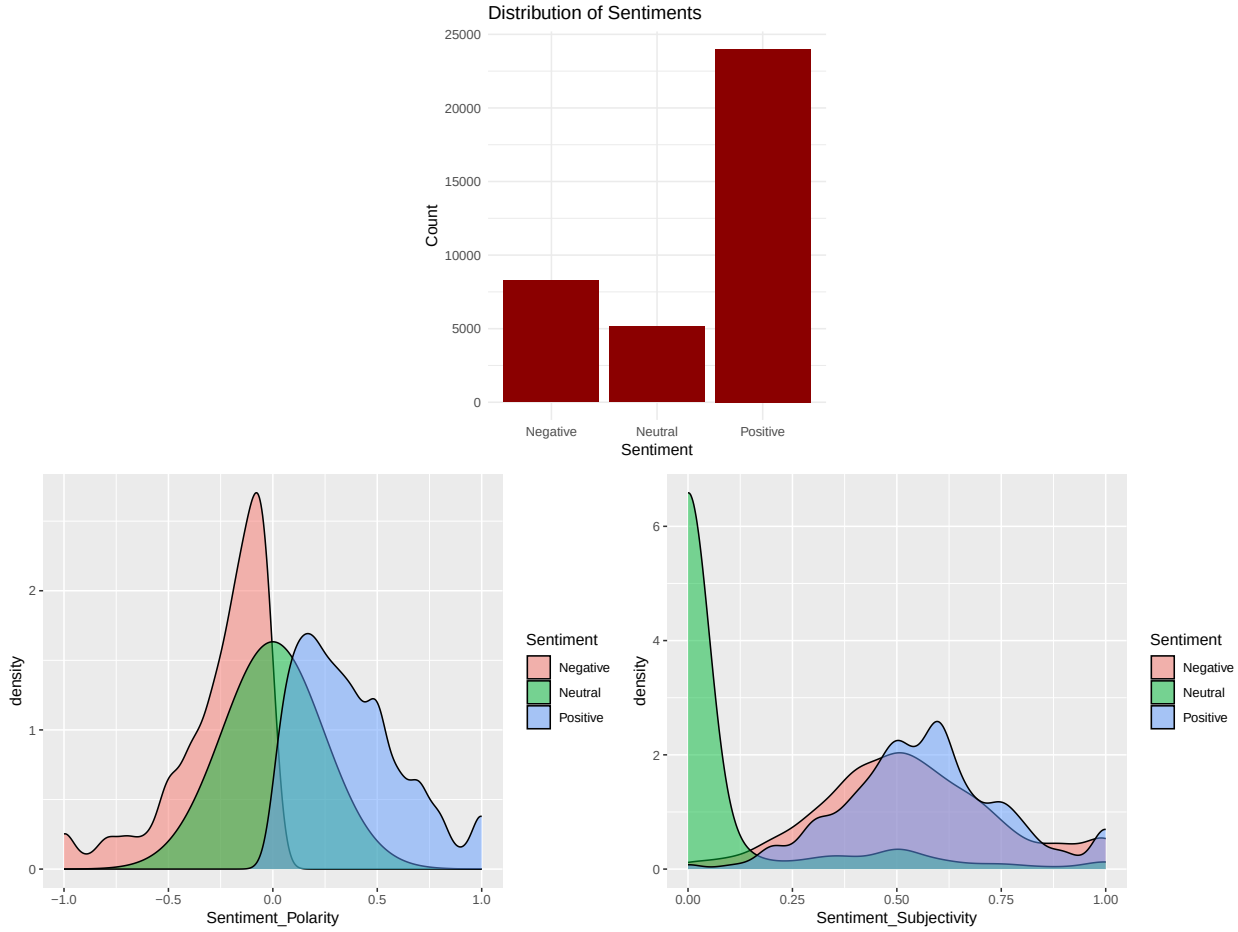

Most categories have median ratings close to 4.0, suggesting a generally positive rating across the board. The boxes are mostly concentrated in the higher rating range (around 3.5 to 4.5), indicating overall good ratings across various categories. Categories like “Art & Design” and “Books & Reference” show less variability in ratings, as indicated by shorter boxes, meaning that ratings in these categories are more consistent. In contrast, categories like “Business” and “Health & Fitness” show wider boxes, indicating more variability in how users rate apps in these categories. Several categories have a significant number of outliers, particularly on the lower side (ratings below 3), such as “Business”, “Education”, and “Health & Fitness”. This could indicate that while many apps in these categories perform well, there are also a considerable number of apps that users are not satisfied with.




The plot shows a wide range of variability in installations across different categories. Categories like "Games" and "Family" show a broad range of installations, evident from the height of their boxes and whiskers, indicating a diverse set of app popularity within these categories. Most categories have their median log installations around the middle of the box, indicating a balanced distribution of data. However, some categories might show a skewed distribution if the median is closer to the top or bottom. Several categories exhibit numerous outliers, especially on the lower side (lower log install counts). This could indicate specific apps in these categories that are significantly less popular than the majority.

**e) Sentiment dataset**

In the "googleplaystore_user_reviews" dataset, there are already pre-processed features indicating the Sentiment of the review, its polarity, and its subjectivity. Below we visualize the distributions of these features:




Hence, we observe that the majority of reviews have a positive sentiment, which suggests that users tend to leave reviews when they are happy / satisfied with the app. However the number of negative reviews is greater than the number of neutrals which might indicate that users are more likely to leave a review if they feel strongly (either positive or negative) as opposed to being indifferent about it.

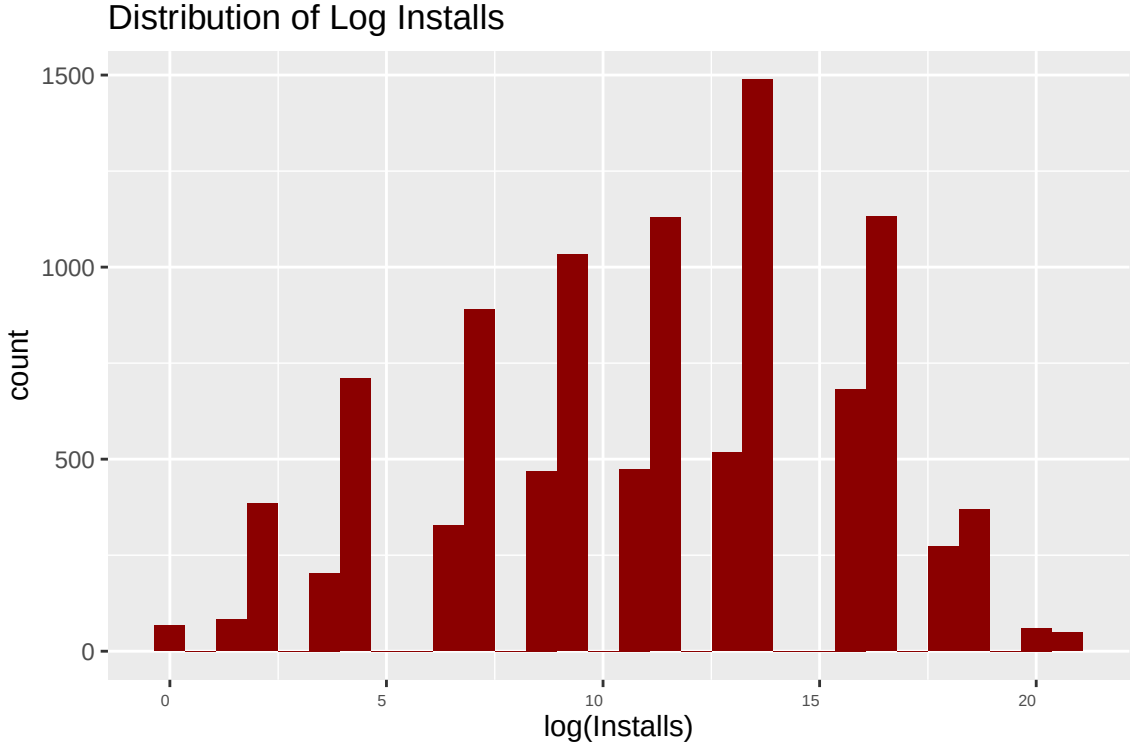
The density plot for polarities are as expected, as negative sentiments are clustered around negative polarity values, neutral sentiments around 0, and positive sentiments are spread across positive values.

Finally the subjectivity plot shows that a large right skew for neutral sentiments, which suggests that neutral reviews tend to be more objective. Interestingly, both negative and positive sentiments seem to be centered around a positive subjectivity score of around 0.5, which suggests that these reviews are more subjective and opinion-based.

## 5. What factors affect the number of installs an app receives?

### A. Data Preparation and Initial Investigation

Firstly, we eliminate all the null values. Then, we decided to create a new feature called "Days_Since_Update" as this may be more useful than just a specific date of update, and has the added advantage of being a numeric value. The original data was scraped in August 2018, with the latest update for an app being 8th August 2018. The original dataset had no specific day from which it was scraped, so we decided to use 15th August 2018 as an intermediary value, and calculated the different between this date and the "Last.Updated" to create the new feature. As we mention in the EDA section, we perform log transformation on the Installs variable. We result in a much more normal distribution after transformation.




###

B. Analysis #### Lasso

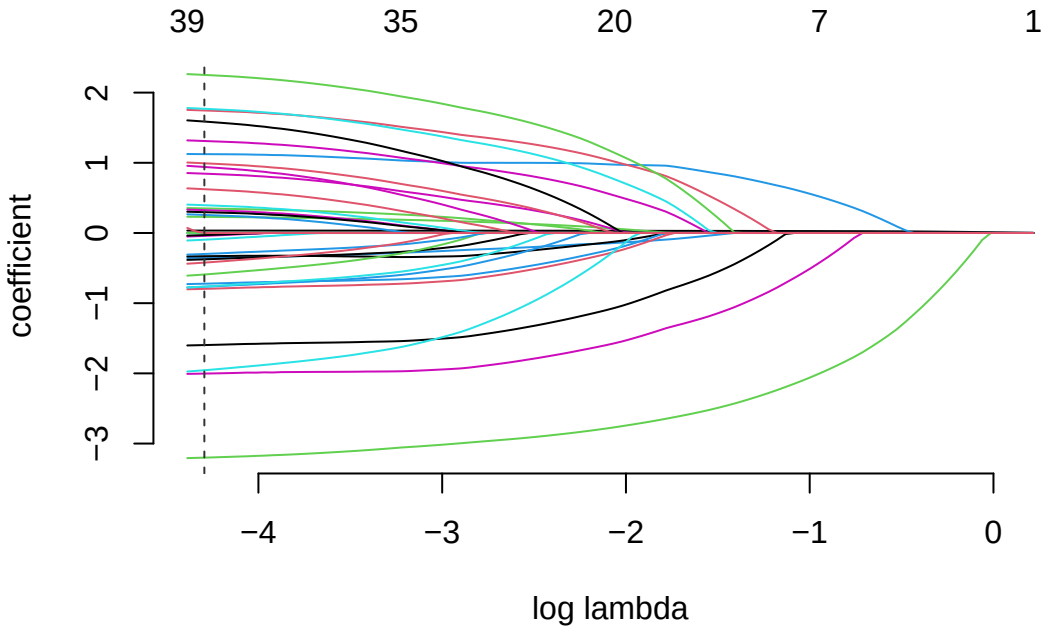
```
## Loading required package: Matrix
```

```
##
```

```
## Attaching package: 'Matrix'
```

```
## The following objects are masked from 'package:tidyr':
```

```
##
##     expand, pack, unpack
```




```
##
## gaussian gamlr with 44 inputs and 100 segments.
```

Table 2: Highest and Lowest Coefficients from LASSO Model

| Feature | Coefficient | Impact |
|---|---|---|
| CategoryENTERTAINMENT | 2.2522446 | Positive |
| CategoryEDUCATION | 1.7695382 | Positive |
| CategoryPHOTOGRAPHY | 1.7456409 | Positive |
| CategoryWEATHER | 1.5878266 | Positive |
| CategorySHOPPING | 1.3106124 | Positive |
| CategoryFINANCE | -0.7959939 | Negative |
| CategoryBUSINESS | -1.5968459 | Negative |

| | | |
|---|---|---|
| CategoryEVENTS | -1.9552108 | Negative |
| CategoryMEDICAL | -2.0030610 | Negative |
| TypePaid | -3.2005830 | Negative |

The LASSO model analysis reveals distinct patterns regarding the impact of app categories and monetization strategies on app performance within the Google Play Store. Categories such as Entertainment, Education, Photography, Weather, and Shopping positively influence app performance, indicating high user engagement or downloads, with Entertainment apps showing the highest positive effect.

Conversely, Medical, Events, Business, and Finance apps demonstrate negative impacts, suggesting challenges in user acceptance or market competition, particularly for Medical apps, which show the most significant negative influence.

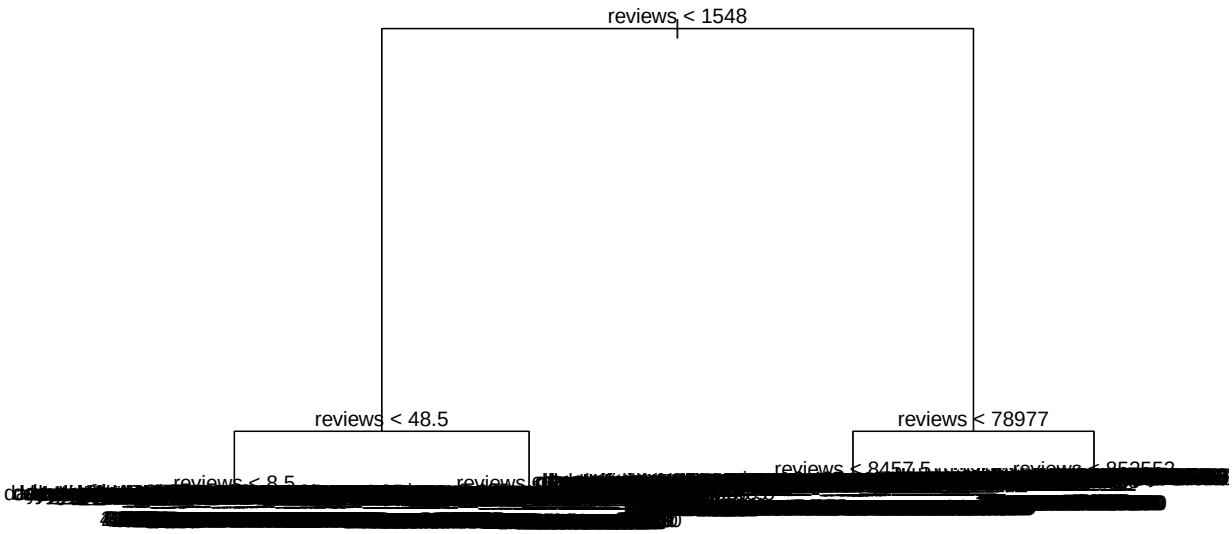
The model also highlights a strong negative effect associated with paid apps, suggesting a distinct user preference for free apps, likely due to hesitancy to incur upfront costs without guaranteed value.

These insights provide valuable guidance for app developers and marketers, emphasizing the importance of category choice and the critical impact of pricing strategies on market success.

```
## [1] "In-sample R^2: 0.298913804277731"
```

The value of 0.299 suggests a moderate level of explanatory power. This is neither particularly high nor low but indicates that while the model has captured a significant portion of the available explanatory information, there remains a substantial amount of variability that is not explained by the model. Despite not explaining more than half of the variance, the model could still be useful depending on the context and the complexity of the data.

**Decision Tree**

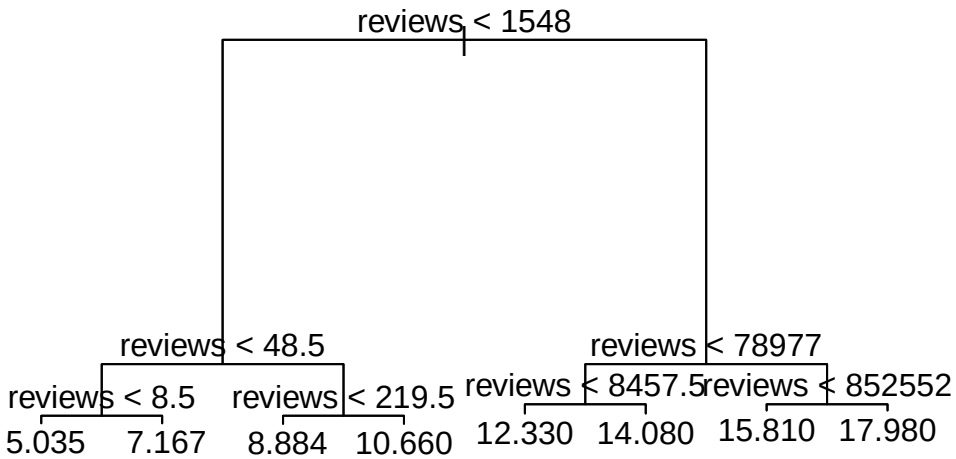



The decision tree visualization centered on the 'reviews' feature provides insightful details on its significant role in the predictive model. The tree structure displays multiple decision points based on the number of reviews, with initial and deeper splits at various thresholds, such as 1548, 48.5, 845.5, and 78977 reviews. These splits demonstrate that the number of reviews is a critical predictor in the model, influencing the predicted outcomes substantially.

```
## In-sample R^2: 0.9647982
## Mean Squared Error: 0.4799728
```

The results presented from the analysis of a predictive model using a decision tree approach indicate robust performance metrics, with an in-sample $R^2$ value of 0.9647982 and a Mean Squared Error (MSE) of 0.4799728. Such a high $R^2$ value suggests that the model explains approximately 96.48% of the variance within the training dataset, indicating a very good fit to the data. The low MSE further supports the model's efficacy, highlighting its accuracy in predicting the dependent variable by showing a small average squared difference between the predicted and actual values.

However, despite the promising performance metrics, caution should be exercised regarding potential overfitting.To address this concern, we will perform Cross Validation to prune the tree.

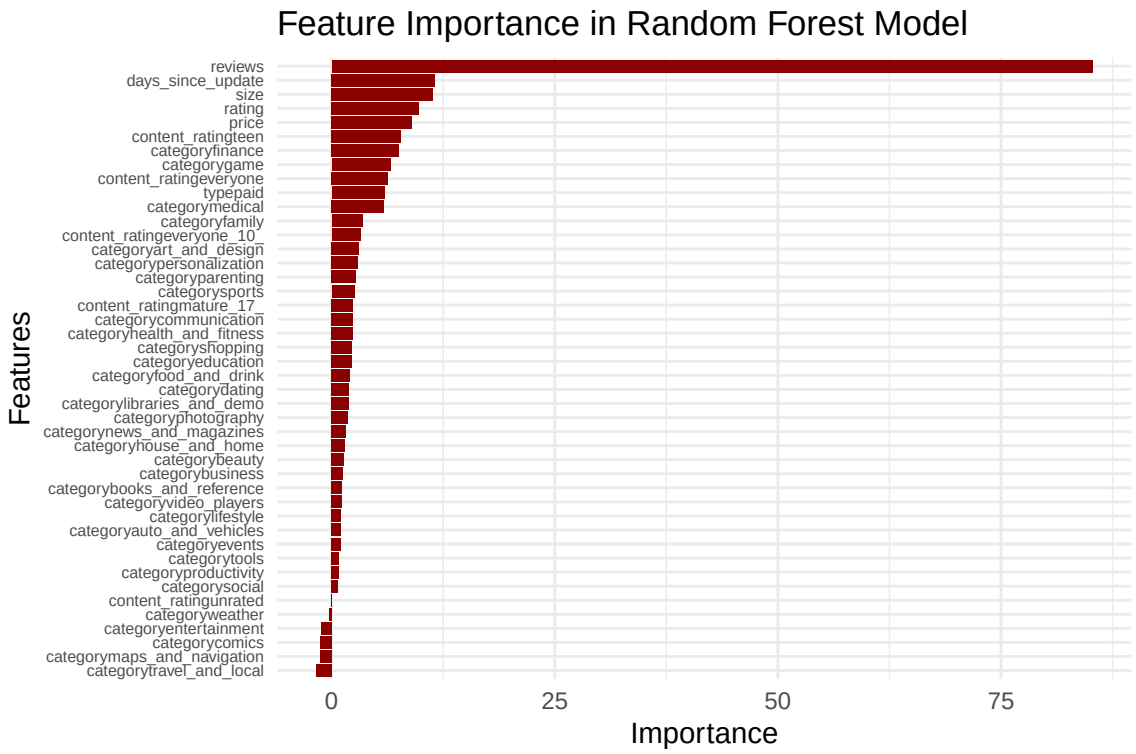



The decision tree's structure, which categorizes outputs based on the number of reviews, underscores the critical role of user reviews in influencing the model's predictions. This not only highlights the importance of this feature but also reflects how critical user engagement metrics are in predicting app performance.

```
## In-sample R^2: 0.8981282
## Mean Squared Error: 1.389012
```

The decision tree model exhibits a strong fit, as indicated by an in-sample $R^2$ of 0.8981282 from the cross-validation process. This value demonstrates that the model explains approximately 89.81% of the variance in the dependent variable, confirming its effectiveness in capturing the underlying relationships between the predictors and the response variable. However, the Mean Squared Error (MSE) has increased to 1.389012. While this still represents a relatively low error rate, the increase compared to earlier results suggests some variability in predictive accuracy when the model is subjected to different subsets of data. This could be indicative of a slight overfitting to the training data, where the model performs exceptionally well on training data but less consistently on unseen data.

**Random Forest.**




Similarly with decision tree, the random forest model reveals that the number of reviews is the most significant determinant, indicating that user engagement, as measured by review volume, plays a pivotal role in app success. This suggests that apps with higher review counts likely see greater visibility and popularity, which significantly impacts the model's predictions.

Following reviews, the 'days_since_update' feature stands out as the second most important factor, highlighting the importance of recent updates in app performance. This feature's prominence suggests that apps regularly updated with new features or bug fixes tend to be favored by users, reflecting ongoing development commitment and app reliability.

Other notable features include app size, user ratings, and whether an app is free or paid. These aspects moderately influence app performance, with size and ratings likely affecting user download and retention decisions, and the app's type (paid or free) reflecting user purchasing behavior. Additionally, pricing and specific content ratings like 'everyone' and 'teen' show varying degrees of impact, indicating differences in target demographics and their preferences.

The importance of various app categories such as 'finance', 'medical', 'sports', and 'game' also varies, which may reflect distinct market dynamics, user base sizes, and usage patterns inherent to each cate-

gory. This differentiation underscores the need for developers to consider category-specific strategies when designing and marketing their apps.

```
## In-sample R^2: 0.9829158
## Mean Squared Error: 0.2329418
```

**C. Conclusion**

## 6. What are the key features that influence an app's rating?

### A. Introduction

### B. Analysis

**Model 1.**

**Model 2.**

**Model 3.**

### C. Conclusion

## 7. How does user sentiment in reviews correlate with app ratings?

### A. Introduction

### B. Analysis

**Model 1.**

**Model 2.**

**Model 3.**

### C. Conclusion

## 8. Conclusion

## 9. Appendix

```
########################################
# Setup
########################################

knitr::opts_chunk$set(
    echo = FALSE,
    fig.height = 4,
    fig.width = 6,
    warning = FALSE,
    cache = TRUE,
    digits = 3,
    width = 48
)

# Required Packages
library(tidyverse)
library(ggplot2)
library(dplyr)
library(corrplot)
library(grid)
library(gridExtra)
library(RColorBrewer)
library(kableExtra)
library(gamlr)
library(bestNormalize)
library(tree)
library(janitor)
library(randomForest)
library(rsample)
########################################
# 3. a) Understanding the datasets
########################################
# Load the datasets
googleplaystore_raw <- read.csv("data/googleplaystore.csv")
googleplaystore_user_reviews_raw <- read.csv("data/googleplaystore_user_reviews.csv")

# Check the column names
colnames(googleplaystore_raw)
colnames(googleplaystore_user_reviews_raw)

# Check the dimensions
dim(googleplaystore_raw)
dim(googleplaystore_user_reviews_raw)
########################################
# 3. b) Data Cleaning
########################################

# Convert the variables to the appropriate data type
googleplaystore <- googleplaystore_raw |>
```

```r
  mutate(
    # Transform Installs and size to numeric
    Installs = gsub("\\+", "", as.character(Installs)),
    Installs = as.numeric(gsub(",", "", Installs)),
    Size = gsub("M", "", Size),
    # Convert apps with size < 1MB to 0, and transform to numeric
    Size = ifelse(grepl("k", Size), 0, as.numeric(Size)),
    # Transform reviews to numeric
    Reviews = as.numeric(Reviews),
    # Change currency numeric
    Price = as.numeric(gsub("\\$", "", as.character(Price))),
    # Convert Last.Updated to date
    Last.Updated = mdy(Last.Updated),
    # Change version number to 1 decimal, and add NAs where appropriate
    Android.Ver = gsub("Varies with device", NaN, Android.Ver),
    Android.Ver = as.numeric(substr(Android.Ver, start = 1, stop = 3)),
    Current.Ver = gsub("Varies with device", NaN, Current.Ver),
    Current.Ver = as.numeric(substr(Current.Ver, start = 1, stop = 3)),
  ) |>
  # Remove apps with Type 0 or NA
  filter(Type %in% c("Free", "Paid")) |>
  # Convert Category, Type, Content.Rating and Genres to factors
  mutate(
    App = as.factor(App),
    Category = as.factor(Category),
    Type = as.factor(Type),
    Content.Rating = as.factor(Content.Rating),
    Genres = as.factor(Genres)
  ) |>
  # Remove duplicate rows
  distinct()

# Remove all rows with nans
googleplaystore_user_reviews <- googleplaystore_user_reviews_raw |>
  filter(Translated_Review != "nan") |>
  # Convert Sentiment to factor
  mutate(Sentiment = as.factor(Sentiment))
########################################
# 4. a) Overall Histogram Overview
########################################
common_theme <- theme(
  axis.ticks.x = element_blank(), # Optional: Remove x-axis ticks if not needed
  axis.title.x = element_blank(), # Removes x-axis title for cleaner look
  axis.text.y = element_text(size = 6), # Y-axis text size for uniformity
  axis.title.y = element_blank(), # Removes x-axis title for cleaner look
)

# Determine the top 10 values for categorical data
top_categories <- googleplaystore %>%
  count(Category) %>%
  top_n(10) %>%
  pull(Category)
```

```
filtered_google <- googleplaystore %>%
  filter(Category %in% top_categories) %>%
    mutate(Category = factor(Category, levels = names(sort(table(Category), decreasing = TRUE))))

p1 <- ggplot(filtered_google, aes(x = Category)) +
  geom_bar(fill = "darkred") +
  ggtitle("Top 10 of 33 Categories")+
  theme(axis.text.x = element_text(size = 8,angle = 45, hjust = 1)) +
  common_theme
#########
p2 <- ggplot(googleplaystore, aes(x = Rating)) +
  geom_histogram(bins = 30, fill = "darkred") +
  ggtitle("Rating")+common_theme
#########
p3 <- ggplot(googleplaystore, aes(x = Reviews)) +
  geom_histogram(bins = 30, fill = "darkred") +
  ggtitle("Reviews")+
  theme(axis.text.x = element_text(size = 6,angle = 0, hjust = 1, vjust = 0.5)) +
  common_theme
#########
p4 <- ggplot(googleplaystore, aes(x = Size)) +
  geom_histogram(bins = 30, fill = "darkred") +
  ggtitle("Size")+common_theme
#########
p5 <- ggplot(googleplaystore, aes(x = Installs)) +
  geom_histogram(bins = 30, fill = "darkred") +
  ggtitle("Installs")+
  theme(axis.text.x = element_text(size = 6,angle = 0, hjust = 1, vjust = 0.5)) +
  common_theme
#########
p6 <- ggplot(filtered_google, aes(x = Type)) +
  geom_bar(fill = "darkred") +
  ggtitle("Type")+common_theme
#########
p7 <- ggplot(googleplaystore, aes(x = Price)) +
  geom_histogram(bins = 30, fill = "darkred") +
  ggtitle("Price")+common_theme
#########
filtered_google <- googleplaystore %>%
    mutate(Content.Rating = factor(Content.Rating,
                                   levels = names(sort(table(Content.Rating),
                                                       decreasing = TRUE))))
p8 <- ggplot(filtered_google, aes(x = Content.Rating)) +
  geom_bar(fill = "darkred") +
  ggtitle("Content Rating")+
  theme(axis.text.x = element_text(size = 10,angle = 45, hjust = 1)) +
  common_theme
#########
top_genres <- googleplaystore %>%
  count(Genres) %>%
  top_n(10) %>%
  pull(Genres)
filtered_google <- googleplaystore %>%
```

```
  filter(Genres %in% top_genres) %>%
  mutate(Genres = factor(Genres, levels = names(sort(table(Genres), decreasing = TRUE))))
p9 <- ggplot(filtered_google, aes(x = Genres)) +
  geom_bar(fill = "darkred") +
  ggtitle("Top 10 of 119 Genres") +
  theme(axis.text.x = element_text(size = 10,angle = 45, hjust = 1))+common_theme
#########
p10 <- ggplot(googleplaystore, aes(x = Last.Updated)) +
  geom_histogram(bins = 30, fill = "darkred") +
  ggtitle("Last Updated Date")+common_theme
#########
# top_CurrentVer <- googleplaystore %>%
#   count(Current.Ver) %>%
#   top_n(10) %>%
#   pull(Current.Ver)
# filtered_google <- googleplaystore %>%
#   filter(Current.Ver %in% top_CurrentVer) %>%
  # mutate(Current.Ver = factor(Current.Ver,
  #                             levels = names(sort(table(Current.Ver), decreasing = TRUE))))
p11 <- ggplot(filtered_google, aes(x = Current.Ver)) +
  geom_histogram(fill = "darkred") +
  ggtitle("Current Version") +common_theme
#########
# top_AndroidVer <- googleplaystore %>%
#   count(Android.Ver) %>%
#   top_n(10) %>%
#   pull(Android.Ver)
# filtered_google <- googleplaystore %>%
#   filter(Android.Ver %in% top_AndroidVer) %>%
  # mutate(Android.Ver = factor(Android.Ver,
  #                             levels = names(sort(table(Android.Ver), decreasing = TRUE))))
p12 <- ggplot(filtered_google, aes(x = Android.Ver)) +
  geom_histogram(fill = "darkred") +
  ggtitle("Minimum Android Version")+common_theme
grid.arrange(p2, p7, p4, p3, p5, p10, p11, p12,
             nrow = 2, ncol = 4, heights = rep(1, 2), widths = rep(1, 4))
########################################
# 4. b) Correlation Matrix
########################################
# google_cleaned <- googleplaystore %>%
#   select(Rating, Reviews, Size, Installs, Price)
#
# # Calculate correlation matrix
# cor_matrix <- cor(google_cleaned, use = "complete.obs")  # using complete observations
#
# # Plot the correlation matrix
# corrplot(cor_matrix, method = "color", col = colorRampPalette(c("white", "darkred"))(200),
#          type = "upper", order = "hclust",
#          addCoef.col = "black", # Adding correlation coefficients
#          tl.col = "black", tl.srt = 45, # Text label color and rotation
#          diag = FALSE) # Remove diagonal
########################################
# 4. b) Correlation Matrix
```

```
##########################################
# Select only the numeric columns for the correlation matrix
numeric_columns <- googleplaystore[, sapply(googleplaystore, is.numeric)]

# Compute the correlation matrix
cor_matrix <- cor(numeric_columns, use = "complete.obs")

# Visualize the correlation matrix using a heatmap
corrplot(cor_matrix, method = "color", type = "upper",
         col = colorRampPalette(c("white", "darkred"))(200),
         tl.col = "black", tl.srt = 45,
         addCoef.col = "black", number.cex = 0.7,tl.cex = 0.7,
         title = "Correlation Matrix of Google Play Store Data",
         mar = c(0, 0, 1, 0))
##########################################
# 4. c) Categorical Features
##########################################
# Distribution of Types (Free vs. Paid)
p1 <- ggplot(googleplaystore, aes(x = Type, fill = Type)) +
  geom_bar(fill = "darkred") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  labs(title = "Distribution of App Types", x = "Type", y = "Count") +
  theme(legend.position = "none")

# Distribution of Content Ratings
filtered_google <- googleplaystore %>%
    mutate(Content.Rating = factor(Content.Rating,
                                   levels = names(sort(table(Content.Rating), decreasing = TRUE))))
p2 <- ggplot(filtered_google, aes(x = `Content.Rating`, fill = `Content.Rating`)) +
  geom_bar(fill = "darkred") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  labs(title = "Distribution of Content Ratings", x = "Content Rating", y = "Count") +
  theme(legend.position = "none")

# Arrange the plots in a grid
grid.arrange(p1, p2, ncol = 2)
# Count the number of apps in each category
category_counts <- googleplaystore |>
  count(Category) |>
  arrange(desc(n))

# Convert Category to a factor with levels ordered by count
category_counts$Category <- factor(category_counts$Category,
                                   levels = category_counts$Category)

# Plot the distribution of app categories sorted by count
p3 = ggplot(category_counts, aes(x = n, y = Category, fill = Category)) +
  geom_bar(stat = "identity") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 7)) +
  labs(title = "Distribution of App Categories", x = "Count", y = "Category") +
  theme(legend.position = "none") +
  scale_fill_manual(values = colorRampPalette(brewer.pal(8, "Set2"))(nrow(category_counts))) +
  theme(panel.grid.minor = element_blank()) +
```

```
  coord_flip()

# Count the number of apps in each genre
genre_counts <- googleplaystore |>
  count(Genres) |>
  arrange(desc(n))

# Convert Genres to a factor with levels ordered by count
genre_counts$Genres <- factor(genre_counts$Genres, levels = genre_counts$Genres)

# Plot the distribution of app genres sorted by count
p4 = ggplot(genre_counts, aes(x = n, y = Genres, fill = Genres)) +
  geom_bar(stat = "identity") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  labs(title = "Distribution of App Genres", x = "Count", y = "Genres") +
  theme(legend.position = "none") +
  scale_fill_manual(values = colorRampPalette(brewer.pal(8, "Set2"))(nrow(genre_counts))) +
  theme(panel.grid.minor = element_blank(),
        panel.grid.major = element_blank(),
        axis.text.x = element_blank()) +
  coord_flip()

p3
p4
# Combine the dataframes
combined_df <- data.frame(
  Rank = 1:10,
  Category = category_counts[1:10,]$Category,
  Category_Count = category_counts[1:10,]$n,
  Genre = genre_counts[1:10,]$Genres,
  Genre_Count = genre_counts[1:10,]$n
)

# Print the combined dataframe using kable
kable(combined_df, caption = "Top 10 Genres and Categories", align = 'c') %>%
  kable_styling(bootstrap_options = c("striped", "hover", "condensed"))
##########################################
# 4. d) Categorical Features
##########################################
# Create the box plot
b1<-ggplot(googleplaystore, aes(x = Type, y = Rating)) +
  geom_boxplot(outlier.color = "darkred", outlier.shape = 1
               ,fill = "darkred") +  # Red for outliers
  labs(title = "Rating by Type",
       x = "Type",
       y = "Rating") +
  theme_minimal()

b2<-ggplot(googleplaystore, aes(x = Type, y = log(Installs))) +
  geom_boxplot(outlier.color = "darkred", outlier.shape = 1,
               fill = "darkred") +  # Red for outliers
  labs(title = "Log Installs by Type",
       x = "Type",
```

```
       y = "Log Install") +
  theme_minimal()

grid.arrange(b1, b2, ncol = 2)
b1<-ggplot(googleplaystore, aes(x = Content.Rating, y = Rating)) +
  geom_boxplot(outlier.color = "darkred", outlier.shape = 1,
               fill = "darkred") +  # Red for outliers
  labs(title = "Rating by Content Rating",
       x = "Content Rating",
       y = "Rating") +
  theme_minimal() +
  theme(axis.text.x = element_text(size = 6,angle = 45, hjust = 1, vjust = 1))

b2<-ggplot(googleplaystore, aes(x = Content.Rating, y = log(Installs))) +
  geom_boxplot(outlier.color = "darkred", outlier.shape = 1,
               fill = "darkred") +  # Red for outliers
  labs(title = "Log Installs by Content Rating",
       x = "Content Rating",
       y = "Log Install") +
  theme_minimal() +
  theme(axis.text.x = element_text(size = 6,angle = 45, hjust = 1, vjust = 1))

grid.arrange(b1, b2, ncol = 2)
# Create the box plot
ggplot(googleplaystore, aes(x = Category, y = Rating)) +
  geom_boxplot(outlier.color = "darkred", outlier.shape = 1,
               fill = "darkred") +  # Red for outliers
  labs(title = "Distribution of Ratings by Category in Google Play Store",
       x = "Category",
       y = "Rating") +
  theme_minimal() +
  theme(axis.text.x = element_text(size = 6,angle = 45, hjust = 1, vjust = 1))
# Create the box plot
ggplot(googleplaystore, aes(x = Category, y = log(Installs))) +
  geom_boxplot(outlier.color = "darkred", outlier.shape = 1,
               fill = "darkred") +  # Red for outliers
  labs(title = "Distribution of Log Installs by Category in Google Play Store",
       x = "Category",
       y = "Log Install") +
  theme_minimal() +
  theme(axis.text.x = element_text(size = 6, angle = 45, hjust = 1, vjust = 1))
########################################
# 4. e) Sentiment dataset
########################################

# Distribution of Sentiments
p1 = ggplot(googleplaystore_user_reviews, aes(x = Sentiment)) +
  geom_bar(fill = "darkred") +
  labs(title = "Distribution of Sentiments", x = "Sentiment", y = "Count") +
  theme_minimal()

p2 = googleplaystore_user_reviews |>
  ggplot(aes(x=Sentiment_Polarity, group=Sentiment, fill=Sentiment)) +
```

```
  geom_density(adjust=1.5, alpha=0.5)

p3 = googleplaystore_user_reviews |>
  ggplot(aes(x=Sentiment_Subjectivity, group=Sentiment, fill=Sentiment)) +
  geom_density(adjust=1.5, alpha=0.5)

# Arrange the plots in a grid
# Arrange the plots in the specified layout
p1_centered <- arrangeGrob(nullGrob(), p1, nullGrob(), ncol = 3)
p2_p3_row <- arrangeGrob(p2, p3, ncol = 2)
grid.arrange(p1_centered, p2_p3_row, nrow = 2)
installs_data <- googleplaystore |> na.omit()

# The data is scraped from August 2018
installs_data$Days_Since_Update <- as.numeric(as.Date("2018-08-15") - installs_data$Last.Updated)

# Log transform Installs, Size, and Reviews to remove skewness
installs_data <- installs_data |>
  mutate(log_Installs = log(installs_data$Installs))

# Create dummy variables using model.matrix
x <- model.matrix(log_Installs ~ Reviews + Size  + Price + Days_Since_Update +
                    Category + Type + Content.Rating + Rating - 1, data = installs_data)
# Response variable
y <- installs_data$log_Installs
ggplot(googleplaystore, aes(x = log(Installs))) +
  geom_histogram(bins = 30, fill = "darkred") +
  ggtitle("Distribution of Log Installs")+
  theme(axis.text.x = element_text(size = 6,angle = 0, hjust = 1, vjust = 0.5))
library(gamlr)
set.seed(1024)
lasso_model <- gamlr(x, y, alpha = 1, nfolds = 100, type.measure = "mse")
plot(lasso_model)
# best_lambda <- cv_model$lambda.min  # Lambda that minimizes MSE
# lasso_model <- glmnet(x, y, alpha = 1, lambda = best_lambda)
# # Extracting coefficients at the lambda that minimizes the MSE
# coefficients_lasso <- coef(lasso_model, s = best_lambda)  # returns a matrix
# # Simplify to vector and remove intercept if present
# coefficients_lasso <- coefficients_lasso[-1, 1]  # Assuming the intercept is the first entry, adjust
#
# # Find the highest and lowest coefficients
# highest_coefs <- sort(coefficients_lasso, decreasing = TRUE)[1:5]
# lowest_coefs <- sort(coefficients_lasso, decreasing = FALSE)[1:5]
#
# # Convert them to data frames
# highest_df = data.frame(Feature = names(highest_coefs),
#                         Coefficient = highest_coefs, Impact = "Positive")
# lowest_df = data.frame(Feature = names(lowest_coefs),
#                        Coefficient = lowest_coefs, Impact = "Negative")
# coefficients_df <- rbind(highest_df, lowest_df)
#
# # Ordering the dataframe by coefficient magnitude for clearer interpretation
# coefficients_df <- coefficients_df[order(abs(coefficients_df$Coefficient), decreasing=TRUE),]
```

```r
# library(knitr)
# library(kableExtra)
# kable(coefficients_df, caption = "Highest and Lowest Coefficients from LASSO Model",
#       row.names = FALSE) %>%
#   kable_styling(bootstrap_options = c("striped", "hover"))

# Find the index with lowest AICc
summary_output = summary(lasso_model)
best_aicc_index <- which.min(summary_output$aicc)

coefficients_lasso <- lasso_model$beta[, best_aicc_index]
highest_coefs <- head(sort(coefficients_lasso, decreasing = TRUE), 5)
lowest_coefs <- head(sort(coefficients_lasso, decreasing = FALSE), 5)

# Convert them to data frames
highest_df = data.frame(Feature = names(highest_coefs),
                        Coefficient = highest_coefs, Impact = "Positive")
lowest_df = data.frame(Feature = names(lowest_coefs),
                       Coefficient = lowest_coefs, Impact = "Negative")
coefficients_df <- rbind(highest_df, lowest_df)

# Ordering the dataframe by coefficient magnitude for clearer interpretation
coefficients_df <- coefficients_df[order(coefficients_df$Coefficient, decreasing=TRUE),]
kable(coefficients_df,
      caption = "Highest and Lowest Coefficients from LASSO Model",
      row.names = FALSE) |>
  kable_styling(bootstrap_options = c("striped", "hover"))
print(paste("In-sample R^2:", summary_output$r2[best_aicc_index]))
clean_column_names <- function(data) {
    names(data) <- tolower(names(data))
    names(data) <- gsub("[^[:alnum:]_]", "_", names(data))
    names(data) <- make.names(names(data), unique = TRUE)
    return(data)
}

x <- clean_column_names(as.data.frame(x))
tree_model <- tree(y ~ ., data = x, mindev = 0.00001)
plot(tree_model)
text(tree_model, pretty = 0)
evaluate_tree_model <- function(model, x, y) {
    predictions <- predict(model, x)
    SSR <- sum((y - predictions)^2)
    mean_rating <- mean(y)
    SST <- sum((y - mean_rating)^2)
    R_squared <- 1 - (SSR / SST)
    mse <- mean((y - predictions)^2)
    cat("In-sample R^2:", R_squared, "\n")
    cat("Mean Squared Error:", mse, "\n")
}

evaluate_tree_model(tree_model, x, y)
# Cross Validation
cv_tree_model <- cv.tree(tree_model, K=50)
```

```r
# Find the last index corresponding to minimum deviance
tree_index = max(which(cv_tree_model$dev == min(cv_tree_model$dev)))

# Find the tree size
tree_size = cv_tree_model$size[tree_index]

# Prune the tree
pruned_tree <- prune.tree(tree_model, best=tree_size)
plot(pruned_tree)
text(pruned_tree, pretty = 1)
evaluate_tree_model(pruned_tree, x, y)
rf_model <- randomForest(y ~ ., data=x, importance = TRUE, ntree=50)
importance <- importance(rf_model)  # Get importance
importance_df <- data.frame(Feature = rownames(importance), Importance = importance[,1])
# Plotting feature importance using ggplot2
ggplot(importance_df, aes(x = reorder(Feature, Importance), y = Importance)) +
  geom_col(fill = "darkred") +
  labs(title = "Feature Importance in Random Forest Model", x = "Features", y = "Importance") +
  theme_minimal() +
  coord_flip()+
  theme(axis.text.y = element_text(size = 6))  # Flip coordinates for easier reading of feature names
evaluate_tree_model(rf_model, x, y)
```