Final Project: Proposal/Dataset Selection

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INTRODUCTION

The entertainment industry, particularly the movie sector, is characterized by the considerable financial investments and uncertainties over return on those investments. This preliminary analysis looks first at the dataset of movies to understand the relationship between the budgets and revenue. The other portion of the analysis focuses on potential correlations between movie features and its user interactions. Utilizing statistical techniques such as descriptive statistics, correlation analysis and regression modeling, we hope to derive the fundamental aspects of what makes a successful movie.

DATASET OVERVIEW

Initial exploration of the dataset revealed a dataset with a variety of movie budgets, popularity, revenue, and other characteristics. The summary statistics provided insight that the budget and revenues of movies range widely and as a result there will be that much variability within our dataset. For instance, the median budget was at $15 million, and the median revenue was approximately at $19.17 million. User responses to the movies in the data set also show large ranges in variables like popularity scores and total vote counts per movie. This sort of variability underscores the need for further analysis to understand the key drivers of movie success.

```
> # Summary statistics
> summary(movie_dataset)
     index           budget                genres             homepage                id        
 Min.   :   0   Min.   :        0   Length:4803        Length:4803        Min.   :     5  
 1st Qu.:1200   1st Qu.:   790000   Class :character   Class :character   1st Qu.:  9014  
 Median :2401   Median : 15000000   Mode  :character   Mode  :character   Median : 14629  
 Mean   :2401   Mean   : 29045040                                         Mean   : 57166  
 3rd Qu.:3602   3rd Qu.: 40000000                                         3rd Qu.: 58610  
 Max.   :4802   Max.   :380000000                                         Max.   :459488  

   keywords         original_language  original_title       overview           popularity     
 Length:4803        Length:4803        Length:4803        Length:4803        Min.   :  0.000  
 Class :character   Class :character   Class :character   Class :character   1st Qu.:  4.668  
 Mode  :character   Mode  :character   Mode  :character   Mode  :character   Median : 12.922  
                                                                             Mean   : 21.492  
                                                                             3rd Qu.: 28.314  
                                                                             Max.   :875.581  

 production_companies production_countries  release_date           revenue          
 Length:4803          Length:4803          Min.   :1916-09-04   Min.   :         0  
 Class :character     Class :character     1st Qu.:1999-07-14   1st Qu.:         0  
 Mode  :character     Mode  :character     Median :2005-10-03   Median :  19170001  
                                           Mean   :2002-12-27   Mean   :  82260639  
                                           3rd Qu.:2011-02-16   3rd Qu.:  92917187  
                                           Max.   :2017-02-03   Max.   :2787965087  
                                           NA's   :1                                
    runtime       spoken_languages      status            tagline             title          
 Min.   :  0.0   Length:4803        Length:4803        Length:4803        Length:4803       
 1st Qu.: 94.0   Class :character   Class :character   Class :character   Class :character  
 Median :103.0   Mode  :character   Mode  :character   Mode  :character   Mode  :character  
 Mean   :106.9                                                                              
 3rd Qu.:118.0                                                                              
 Max.   :338.0                                                                              
 NA's   :2                                                                                  
  vote_average      vote_count            cast               crew             director        
 Min.   : 0.000   Min.   :    0.0   Length:4803        Length:4803        Length:4803       
 1st Qu.: 5.600   1st Qu.:   54.0   Class :character   Class :character   Class :character  
 Median : 6.200   Median :  235.0   Mode  :character   Mode  :character   Mode  :character  
 Mean   : 6.092   Mean   :  690.2                                                            
 3rd Qu.: 6.800   3rd Qu.:  737.0                                                            
 Max.   :10.000   Max.   :13752.0                                                            
```

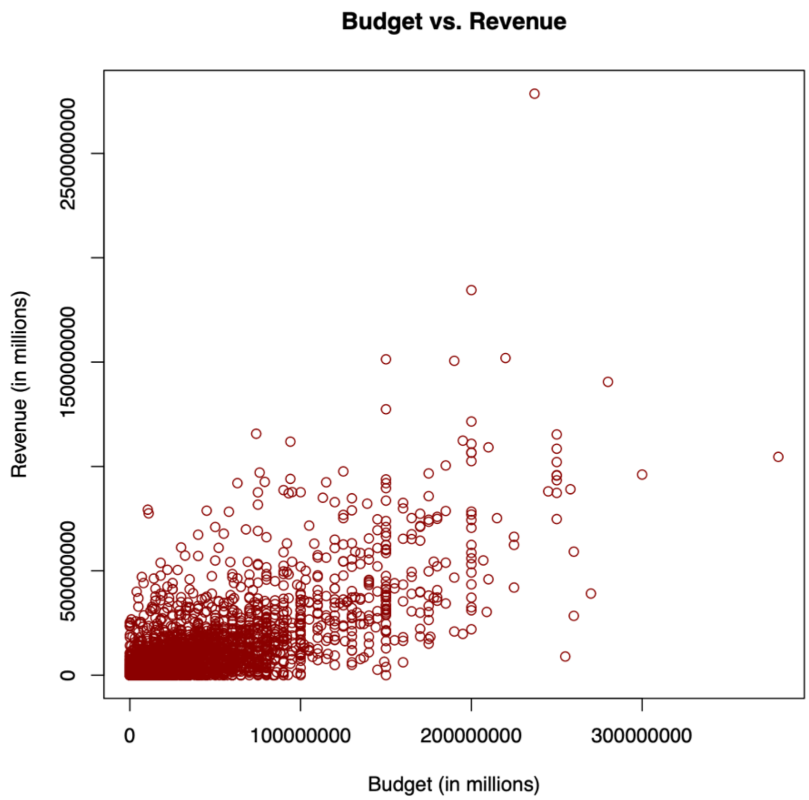
The summary statistics for the other question being studied had one small modification to allow for proper modeling. The variable ‘runtime’ had two observations with missing values, so these were removed for the subsequent heatmap to be executed.

```
R 4.3.2 · C:/Users/seanm/OneDrive/Desktop/McLean_FinalProject_ALY6015/
> #Remove all observations with 'NA' in the 'runtime' variable
> movies <- movie_dataset[complete.cases(movie_dataset$runtime), ]
> #Display the modified dataset
> summary(movies)
```

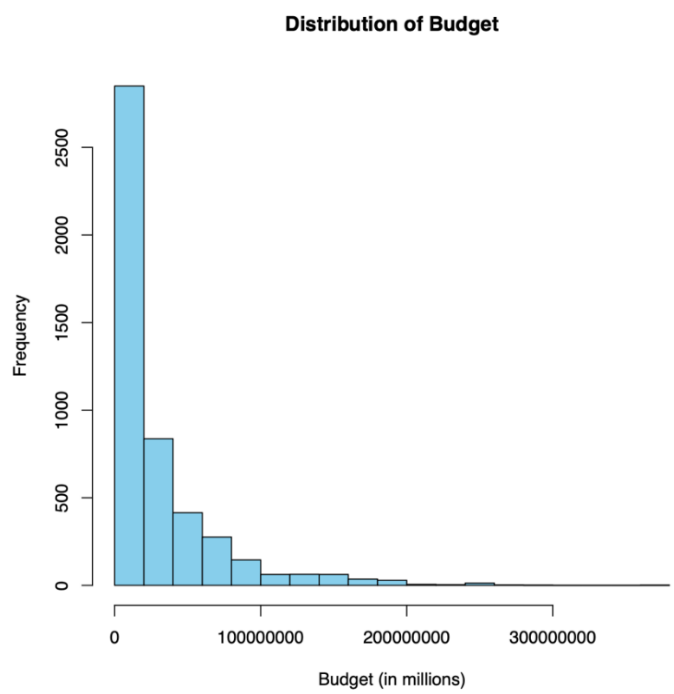
```
R 4.3.2 · C:/Users/seanm/OneDrive/Desktop/McLean_FinalProject_ALY6015/
production_countries release_date          revenue              runtime
Length:4801          Length:4801        Min.   :0.000e+00   Min.   :  0.0
Class :character     Class :character   1st Qu.:0.000e+00   1st Qu.: 94.0
Mode  :character     Mode  :character   Median :1.918e+07   Median :103.0
                                        Mean   :8.229e+07   Mean   :106.9
                                        3rd Qu.:9.292e+07   3rd Qu.:118.0
                                        Max.   :2.788e+09   Max.   :338.0
```

PRELIMINARY ANALYSIS

We started our preliminary analysis of the relationship between movie budget and revenue by examining the Pearson correlation coefficient. Visualization, through histograms and scatter plots, to understand the distribution and relationship between budgets and revenues, helped us get a feel for the data.



Budget vs. Revenue
Revenue (in millions)
0
500000000
1500000000
2500000000
0
100000000
200000000
300000000
Budget (in millions)



Distribution of Budget
Frequency
0
500
1000
1500
2000
2500
0
100000000
200000000
300000000
Budget (in millions)

A linear regression model was fitted to assess the relationship between budget and revenue. The regression analysis indicated a statistically significant positive association between the two variables. The positive correlation between budget and revenue indicates that higher investments in production typically result in higher returns. For each additional unit of currency spent on the budget, revenue increased by approximately 2.9227 units of currency.

```
> # Summary of the regression model
> summary(lm_model)

Call:
lm(formula = revenue ~ budget, data = movie_dataset)

Residuals:
       Min         1Q     Median         3Q        Max 
-653371282  -35365659    2250851    8486969 2097912654 

Coefficients:
                 Estimate    Std. Error t value            Pr(>|t|)    
(Intercept) -2629555.3399  1970427.0736  -1.335               0.182    
budget             2.9227        0.0394  74.188 <0.0000000000000002 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 111200000 on 4801 degrees of freedom
Multiple R-squared:  0.5341,	Adjusted R-squared:  0.534 
F-statistic:  5504 on 1 and 4801 DF,  p-value: < 0.00000000000000022
```

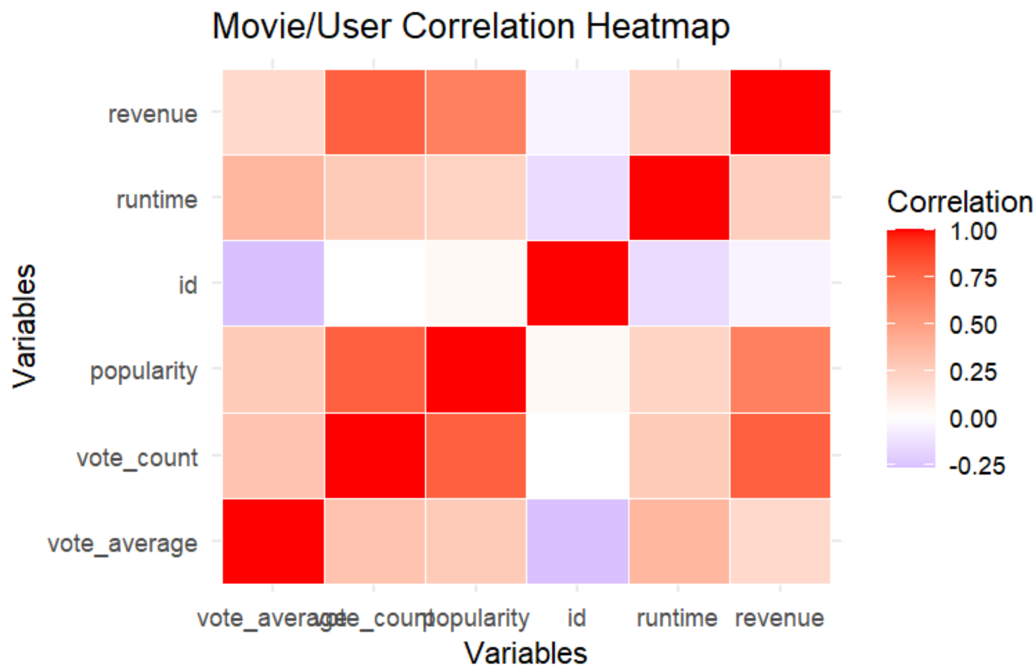
It is important to note, however, that this study naturally has its limitations, and one of them might be the inclusion of factors such as genre, release date, and marketing strategies which could have a significant influence on a movie's success.

The other question in the final project looked at the correlation between user interactions and movie features in the data set. Six numerical variables were selected for a correlation analysis that pertained to movie characteristics and user actions like voting ratings. A correlation matrix was constructed to identify any positive linear relationships among the chosen variables.

```
untime", "revenue")])
> correlation_matrix
             vote_average  vote_count popularity          id    runtime     revenue
vote_average    1.0000000  0.31342259  0.2741711 -0.26820034  0.3750457  0.19728596
vote_count      0.3134226  1.00000000  0.7780978 -0.00320646  0.2719442  0.78146223
popularity      0.2741711  0.77809783  1.0000000  0.03243460  0.2255021  0.64467729
id             -0.2682003 -0.00320646  0.0324346  1.00000000 -0.1535360 -0.04975024
runtime         0.3750457  0.27194420  0.2255021 -0.15353603  1.0000000  0.25109314
revenue         0.1972860  0.78146223  0.6446773 -0.04975024  0.2510931  1.00000000
> 
```

Interpreting the matrix, there are several strong relationships with ‘revenue’, ‘popularity’ and ‘vote_count’ standing out among the variables. The revenue variable has a high association with the ‘vote_count’ and ‘popularity’ variables, suggesting that it affects user responses in some capacity. Another strong relationship among the matrix is the ‘popularity’ and’vote_count’ variables which could indicate that the number of votes for a movie can have an immense effect on its popularity score. The ‘id’ variable could be eliminated from the mix due to having negative or indifferent correlations with all the other variables.

A heatmap is used to visualize correlation matrices and identify trends and patterns in the data. The darker shades of red reflect the strong correlations mentioned in the matrix.



To understand the relationships between two variables with strong positive linear correlations, a pair of scatterplots are built for visual representation of the interactions. To avoid the issue of over dense plotting and cluttering with a large data set, a sample was taken and split into training and testing sets to assess the performance and generalization ability of the model. The 'id' variable was eliminated from the previous dataset because of its irrelevancy toward the other variables. A linear regression model was then used to analyze the coefficients of each independent variable.

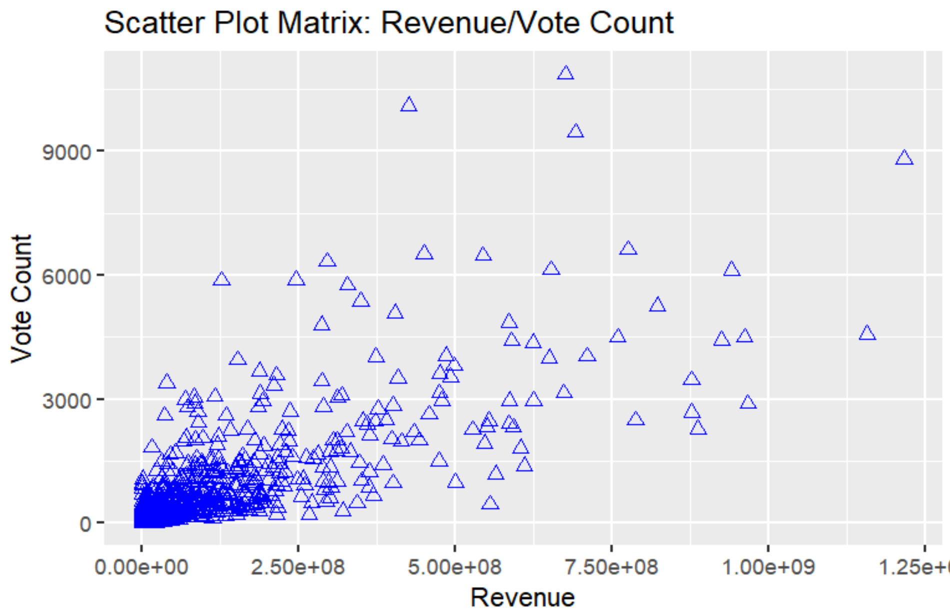
```
Call:
lm(formula = vote_count ~ ., data = training_set)

Coefficients:
 (Intercept)  vote_average    popularity       runtime       revenue
  -5.485e+02     7.233e+01     2.421e+01     4.421e-01     2.955e-06
```

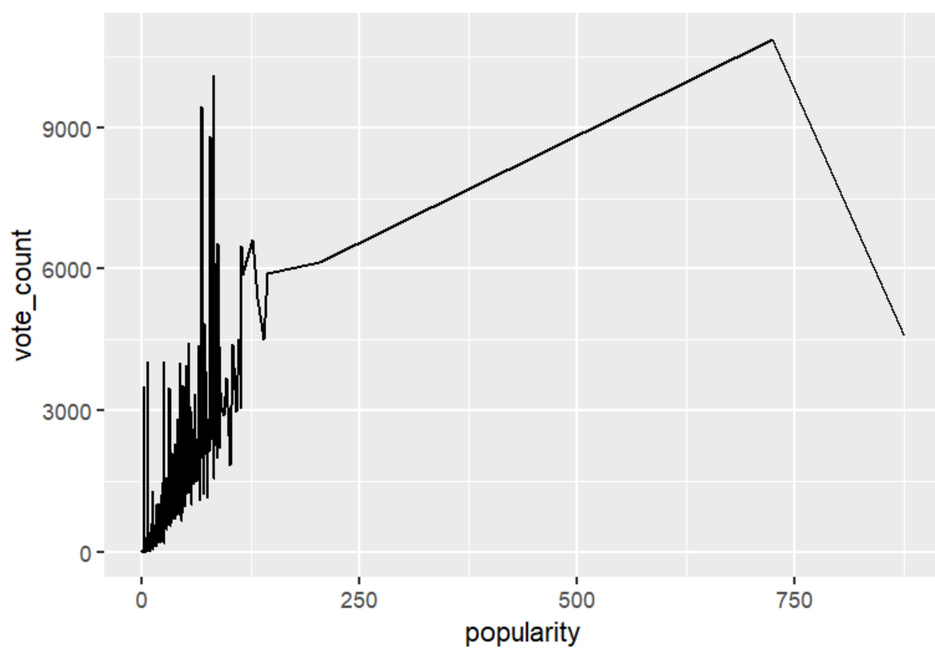
Positive coefficients indicate a positive association, and negative coefficients suggest a negative association, and the magnitude of the coefficients indicates the strength of the effect. All four variables show a positive correlation to the vote counts of the movies in the data set. A k-fold cross validation is then conducted to assess how well the model will popularize to an independent data set.

```
Call:
lm(formula = .outcome ~ ., data = dat)

Residuals:
    Min      1Q  Median      3Q     Max 
-5923.5  -175.9   -36.2    75.1  7152.6 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  -5.485e+02  5.533e+01  -9.912   <2e-16 ***
vote_average  7.233e+01  8.372e+00   8.640   <2e-16 ***
popularity    2.421e+01  4.487e-01  53.955   <2e-16 ***
runtime       4.421e-01  4.416e-01   1.001    0.317    
revenue       2.955e-06  7.689e-08  38.431   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 559.4 on 3837 degrees of freedom
Multiple R-squared:  0.798,	Adjusted R-squared:  0.7978 
F-statistic:  3790 on 4 and 3837 DF,  p-value: < 2.2e-16
```

An analysis of the summary shows that the ‘runtime variable’ has a higher p-value (0.317), suggesting that it may not be a statistically significant predictor in the model. The F-statistic that shows the overall significance of the model is large, and the associated p-value is very small (< 2.2e-16), indicating that the overall model is statistically significant. Overall, the model is well-fitted with statistically significant predictors.

The models of the samples conducted are plotted to show the relationships between the response variable ‘vote_count’ and the independent variables ‘revenue’ and ‘popularity’ which showed the strongest correlations in the correlation matrix. Most of the observations in the scatterplot are under 3000 votes and $250 million in revenue. The outliers in the plot are heading in a positive direction, indicating that the higher the revenue for a movie, the higher the vote count for that movie. The analysis of the line plot between the variables ‘vote_counts’ and ‘popularity’ is similar with the popularity score being high when the vote count for the movie is also high. The few outliers in the plot also demonstrate the same patterns.

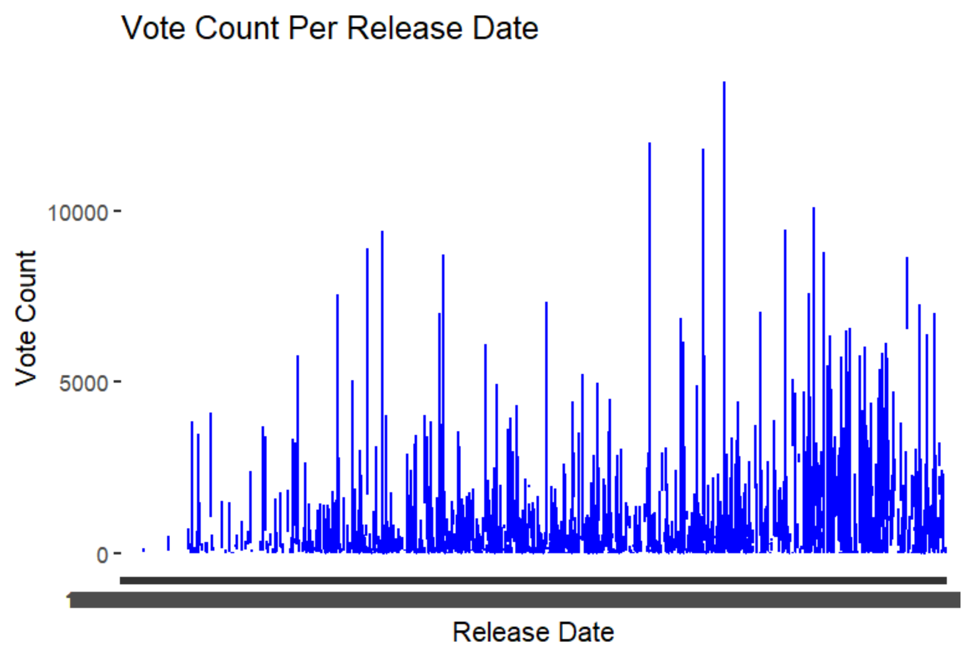




Additional categorical variables that were explored using Analysis of Variance (ANOVA) testing were release dates and whether there were significant differences between them. To again alleviate the concern of over dense plotting and cluttering with the data set, a sample was taken and split into training and testing sets to assess the performance and generalization ability of the model.

```
> summary(anova_model)
               Df    Sum Sq Mean Sq F value  Pr(>F)    
release_date 3279 5.487e+09 1673498   1.368 2.2e-12 ***
Residuals    1485 1.817e+09 1223626                    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> 
```

Examining the ANOVA model, the p-value is very small (2.2e-12), suggesting that there is a significant association between ‘release_date’ and the response variable. The table also suggests that the variable ‘release_date’ is statistically significant in explaining the variability in the voting count totals. The line plot is created to show this relationship and the analysis shows that movies released more recently have slightly higher voting counts than older movies. The top movies by vote count are all more recent, but because of the plot not showing a strong association might mean this will need to be evaluated more to see if this relationship is strong despite the low p-value in the ANOVA model.



For the final submission, we will expand our investigation by including additional variables, such as genre, release date, and marketing expenditure. These will enable us to build out our regression model and account more fully for multiple factors that influence a movie's revenue. Furthermore, an in-depth analysis would include the chi-square test, ANOVA, and other advanced statistical methodologies, which will allow us to gain insights into relationships present within the dataset.

CONCLUSION

Our preliminary analysis from the first question indicates that budget plays a significant role in determining movie revenue. While it’s true that higher investments are generally aimed at higher returns, there are several other success factors for filmmakers and industry stakeholders to consider. The correlations involving movie and user relationships show mainly positive associations, with certain aspects of movies like revenue and vote counts having an impact on its popularity and vote average. By conducting further analysis and utilizing more advanced statistical techniques, we can identify actionable insights that can help decision-making in the dynamic and hyper-competitive movie business.

REFERENCES

Bluman, A. (2018). Elementary statistics: A step by step approach (10th ed.). McGraw Hill.

Kabacoff, R. I. (2022). R in action: Data analysis and graphics with R and tidyverse (3rd ed.). Manning Publications.

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APPENDIX

```
#Question 1: Correlation between Movie Budget and Popularity

# Load necessary libraries

library(readr)

library(ggplot2)

# Load the dataset

movie_dataset <- read_csv("/Users/m.joubert/Documents/Final Project: Initial Analysis Report - Joubert/movie_dataset.csv")

# Explore the structure of the dataset

str(movie_dataset)
```

```r
#Summary statistics

summary(movie_dataset)

# Histogram of budget

hist(movie_dataset$budget, breaks = 20, col = "skyblue", main = "Distribution of Budget", xlab = "Budget (in millions)")

# Scatter plot of budget vs. revenue

plot(movie_dataset$budget, movie_dataset$revenue,

     main = "Budget vs. Revenue",

     xlab = "Budget (in millions)",

     ylab = "Revenue (in millions)",

     col = "darkred")

# Fit linear regression model

lm_model <- lm(revenue ~ budget, data = movie_dataset)

# Summary of the regression model

summary(lm_model)



#Question: Correlation between user interactions and movie features

#Loading necessary libraries

library(readr)
```

```
library(dplyr)

library(ggplot2)

library(caret)

 #Importing the dataset

movie_dataset <- read.csv("movie_dataset.csv", header = TRUE)

movie_dataset

 #Summary statistics of the dataset

summary(movie_dataset)

View(movie_dataset)

 #Remove all observations with 'NA' in the 'runtime' variable

dataset <- movie_dataset[complete.cases(movie_dataset$runtime), ]

 #Display the modified dataset

summary(dataset)

 #Perform correlation analysis

correlation_matrix <- cor(dataset[c("vote_average", "vote_count", "popularity", "id",
"runtime", "revenue")])

correlation_matrix

 # Reshape the correlation matrix to long format for heatmap

library(tidyr)
```

```
cor_long <- as.data.frame(as.table(correlation_matrix))

names(cor_long) <- c("Var1", "Var2", "Correlation")

 # Create a heatmap using ggplot2

heatmap_plot <- ggplot(data = cor_long, aes(x = Var1, y = Var2)) +

  geom_tile(aes(fill = Correlation), color = "white") +

  scale_fill_gradient2(low = "blue", high = "red", mid = "white", midpoint = 0) + # Adjust
color scale

  labs(title = "Movie/User Correlation Heatmap",

       x = "Variables",

       y = "Variables") +

  theme_minimal()

print(heatmap_plot)

 #Create a new variable from dataset for sampling

movies <- dataset %>%

  select(vote_average, vote_count, popularity, runtime, revenue)

summary(movies)

 # Split the dataset into training and testing sets

set.seed(456)

trainIndex <- createDataPartition(movies$vote_count, p = 0.8, list = FALSE)
```

```
training_set <- movies[trainIndex, ]

testing_set <- movies[-trainIndex, ]

 # Create a linear regression model

model <- lm(vote_count ~ ., data = training_set)

model

 # Make predictions on the test set

predictions <- predict(model, newdata = testing_set)

 # Evaluate the model

rmse <- sqrt(mean((predictions - testing_set[["vote_count"]])^2))

print(paste("Root Mean Squared Error:", rmse))

 # Perform k-fold cross-validation

ctrl <- trainControl(method = "cv", number = 10)

cv_model <- train(vote_count ~ ., data = training_set, method = "lm", trControl = ctrl)

 # Print cross-validation results

print(cv_model)

 # Access the mean performance metrics across folds

summary(cv_model)

 #Individual Scatter Plots Showing Relationship Between Vote Count and Revenue.

scatter_plot_matrix <- ggplot(testing_set, aes(x = revenue, y = vote_count)) +
```

```
  geom_point(shape = 2, color = "blue", size = 2) +
  labs(title = "Scatter Plot Matrix: Revenue/Vote Count",
       x = "Revenue",
       y = "Vote Count")
scatter_plot_matrix
 #Individual Line Plots Showing Relationship Between Vote Count and Popularity.
ggplot(testing_set, aes(x = popularity, y = vote_count)) +
  geom_line()
 #Perform ANOVA testing
#Create a new variable from dataset for testing
anovas <- dataset %>%
  select(vote_count, release_date)
summary(anovas)
 #Split dataset into a training set and a test set.
set.seed(123)
index <- createDataPartition(anovas$release_date, p = 0.8, list = FALSE)
train_data <- anovas[index, ]
test_data <- anovas[-index, ]
 #Create ANOVA model
```

```
anova_model <- aov(vote_count ~ release_date, data = train_data)

summary(anova_model)

 #Conduct post-hoc tests

TukeyHSD(anova_model)

 #Lineplot for one-way ANOVA

ggplot(train_data, aes(x = release_date, y = vote_count)) +

  geom_line(color = "blue") +

  labs(title = "Vote Count Per Release Date",

       x = "Release Date",

       y = "Vote Count")
```