SLHW2

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```
# Install necessary libraries if not installed
#install.packages(c("ggplot2", "dplyr", "scales", "lubridate"))
# install.packages("caret")
# install.packages("GGally")
# install.packages("tidyverse")
#install.packages("randomForest")
# install.packages("gbm")
# install.packages("fastshap")
#install.packages("effects")
#install.packages("ROCR")
```

```
# Load libraries
library(ggplot2)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(scales)
library(lubridate)
```

```
## Warning: package 'lubridate' was built under R version 4.3.3

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v forcats 1.0.0     v stringr 1.5.0
## v purrr   1.0.2     v tibble  3.2.1
## v readr   2.1.4     v tidyr   1.3.0

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x readr::col_factor() masks scales::col_factor()
## x purrr::discard()    masks scales::discard()
## x dplyr::filter()     masks stats::filter()
## x dplyr::lag()        masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become error
```

```r
library(GGally)
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```

```r
library(caret)
```

```
## Loading required package: lattice
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
##
##     lift
```

```r
library(rpart)
library(rpart.plot)
library(nnet)
library(gbm)
```

```
## Warning: package 'gbm' was built under R version 4.3.3
```

```
## Loaded gbm 2.2.2
## This version of gbm is no longer under development. Consider transitioning to gbm3, https://github.c
```

```r
library(MASS)
```

```
##
## Attaching package: 'MASS'
##
## The following object is masked from 'package:dplyr':
##
##     select
```

```r
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 4.3.3
```

```
## randomForest 4.7-1.2
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:dplyr':
##
##     combine
##
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```r
library(pdp)
```

```
## Warning: package 'pdp' was built under R version 4.3.3

##
## Attaching package: 'pdp'
##
## The following object is masked from 'package:purrr':
##
##     partial
```

```
library(fastshap)
```

```
##
## Attaching package: 'fastshap'
##
## The following object is masked from 'package:dplyr':
##
##     explain
```

```
library(effects)
```

```
## Loading required package: carData

## Warning in check_dep_version(): ABI version mismatch:
## lme4 was built with Matrix ABI version 1
## Current Matrix ABI version is 0
## Please re-install lme4 from source or restore original 'Matrix' package

## Use the command
##     lattice::trellis.par.set(effectsTheme())
##   to customize lattice options for effects plots.
## See ?effectsTheme for details.
```

```
library(e1071)
```

About the Data

Import Data

```
#tuesdata <- tidytuesdayR::tt_load('2022-11-01')
tuesdata <- tidytuesdayR::tt_load(2022, week = 44)
```

```
## ---- Compiling #TidyTuesday Information for 2022-11-01 ----
## --- There is 1 file available ---
##
##
## -- Downloading files -----------------------------------------------------------
##
##   1 of 1: "horror_movies.csv"
```

```
horror <- tuesdata$horror_movies
```

```
glimpse(horror)
```

```
## Rows: 32,540
## Columns: 20
## $ id                   <dbl> 760161, 760741, 882598, 756999, 772450, 1014226, 717~
## $ original_title       <chr> "Orphan: First Kill", "Beast", "Smile", "The Black P~
## $ title                <chr> "Orphan: First Kill", "Beast", "Smile", "The Black P~
## $ original_language <chr> "en", "en", "en", "en", "es", "es", "en", "en", "en"~
## $ overview          <chr> "After escaping from an Estonian psychiatric facilit~
## $ tagline           <chr> "There's always been something wrong with Esther.", ~
## $ release_date      <date> 2022-07-27, 2022-08-11, 2022-09-23, 2022-06-22, 202~
## $ poster_path       <chr> "/pHkKbIRoCe7zIFvqan9LFSaQAde.jpg", "/xIGr7UHsKf0URW~
## $ popularity        <dbl> 5088.584, 2172.338, 1863.628, 1071.398, 1020.995, 93~
## $ vote_count        <dbl> 902, 584, 114, 2736, 83, 1, 125, 1684, 73, 1035, 637~
## $ vote_average      <dbl> 6.9, 7.1, 6.8, 7.9, 7.0, 1.0, 5.8, 7.0, 6.5, 6.8, 7.~
## $ budget            <dbl> 0, 0, 17000000, 18800000, 0, 0, 20000000, 68000000, ~
## $ revenue           <dbl> 9572765, 56000000, 45000000, 161000000, 0, 0, 289259~
## $ runtime           <dbl> 99, 93, 115, 103, 0, 0, 88, 130, 90, 106, 98, 89, 97~
## $ status            <chr> "Released", "Released", "Released", "Released", "Rel~
## $ adult             <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FAL~
## $ backdrop_path     <chr> "/5GA3vV1aWWHTSDO5eno8V5zDo8r.jpg", "/2k9tBql5GYH328~
## $ genre_names       <chr> "Horror, Thriller", "Adventure, Drama, Horror", "Hor~
## $ collection        <dbl> 760193, NA, NA, NA, NA, NA, 94899, NA, NA, 950289, N~
## $ collection_name   <chr> "Orphan Collection", NA, NA, NA, NA, NA, "Jeepers Cr~
```

Data Dictionary

1. The `id` variable is an integer that serves as a unique identifier for each movie.
2. The `original_title` variable is a character string representing the movie's original title.
3. The `title` variable is a character string containing the localized or alternative movie title.
4. The `original_language` variable is a character field indicating the language in which the movie was originally made.
5. The `overview` variable is a character field providing a brief description or synopsis of the movie.
6. The `tagline` variable is a character field capturing the movie's catchphrase or slogan.
7. The `release_date` variable is a date field that records the date when the movie was first released.
8. The `poster_path` variable is a character field containing the URL to the movie's poster image.
9. The `popularity` variable is a numerical value representing the movie's popularity score based on audience interactions.
10. The `vote_count` variable is an integer field that records the total number of audience votes received.
11. The `vote_average` variable is a numerical field that represents the average audience rating on a scale from 0 to 10.
12. The `budget` variable is an integer field capturing the movie's production budget in USD.
13. The `revenue` variable is an integer field indicating the total revenue earned by the movie in USD.
14. The `runtime` variable is an integer field that specifies the duration of the movie in minutes.
15. The `status` variable is a character field that indicates the current status of the movie, such as "Released."
16. The `adult` variable is a boolean that indicates whether the movie is intended for adult audiences.
17. The `backdrop_path` variable is a character field that provides the URL to the backdrop image for the movie.
18. The `genre_names` variable is a character field listing the genres associated with the movie, separated by commas.
19. The `collection` variable is a numerical field containing the unique ID of the collection the movie belongs to, which may be null for movies not part of a collection.
20. The `collection_name` variable is a character field representing the name of the collection, which may also be null if the movie does not belong to one.

Available Data

The dataset contains detailed information on a wide range of horror movies, about ~35,000 pieces of entertainment, including various features such as title, genre, release date, runtime, popularity, budget, and revenue. Additional details include the movie's runtime, vote count, average vote, genre names, and collection association. Notably, the dataset also contains the poster and backdrop image URLs for each movie, as well as whether the movie is intended for adults. These data points provide a comprehensive view of each movie's performance, reception, and thematic elements, enabling further analysis on trends, movie popularity, and financial success within the horror genre. These features will be used to train a classification model to predict whether each entry is a successful movie or not. The objective is to leverage these data points to build an accurate classification model, focusing on identifying the key predictors that contribute most to the classification process.

Motivation

As the entertainment industry expands, identifying the success of a movie is critical to content platforms and production companies. Success in the entertainment industry is typically measured by revenue, budget, and audience reception. Predicting whether a movie is likely to be successful or not can help guide investment decisions, optimize content strategies, and improve user recommendations. However, accurately predicting success is a challenge due to the multifaceted nature of what contributes to a movie's success, including budget, genre, release time, and audience engagement factors.

In this context, predicting a movie's success involves analyzing historical data and identifying patterns that correlate with positive outcomes. By doing so, production teams and platforms can better allocate resources, strategize marketing efforts, and predict the potential success of future movies. The motivation behind this project is to build a classification model that can predict whether a movie will be successful based on various features, thus improving decision-making processes in the entertainment industry.

Goal

The primary goal of this project is to develop a classification model that predicts whether a given movie is successful or not. The project will focus on feature selection, model interpretation, and the comparison of predictor sets to determine the most significant factors contributing to a movie's success. By analyzing a variety of features such as budget, revenue, genre, and popularity, the goal is to build a model that classifies movies as "successful" or "unsuccessful" with high accuracy. This will allow content platforms and production companies to make data-driven decisions and better understand the elements that contribute to the success of a movie.

Data Preprocessing and Visualization Tools

```
summary(horror)
```

```
##        id          original_title        title           original_language
##  Min.   :     17   Length:32540       Length:32540       Length:32540
##  1st Qu.: 146495   Class :character   Class :character   Class :character
##  Median : 426521   Mode  :character   Mode  :character   Mode  :character
##  Mean   : 445911
##  3rd Qu.: 707534
##  Max.   :1033095
##
##    overview           tagline           release_date        poster_path
##  Length:32540       Length:32540       Min.   :1950-01-01   Length:32540
##  Class :character   Class :character   1st Qu.:2000-10-20   Class :character
##  Mode  :character   Mode  :character   Median :2012-12-09   Mode  :character
##                                        Mean   :2007-02-18
##                                        3rd Qu.:2018-10-03
##                                        Max.   :2022-12-31
##
##    popularity         vote_count        vote_average        budget
##  Min.   :   0.000   Min.   :    0.00   Min.   : 0.000   Min.   :        0
##  1st Qu.:   0.600   1st Qu.:    0.00   1st Qu.: 0.000   1st Qu.:        0
##  Median :   0.840   Median :    2.00   Median : 4.000   Median :        0
##  Mean   :   4.013   Mean   :   62.69   Mean   : 3.336   Mean   :   543127
##  3rd Qu.:   2.243   3rd Qu.:   11.00   3rd Qu.: 5.700   3rd Qu.:        0
##  Max.   :5088.584   Max.   :16900.00   Max.   :10.000   Max.   :200000000
##
##     revenue             runtime          status             adult
##  Min.   :        0   Min.   :  0.00   Length:32540       Mode :logical
##  1st Qu.:        0   1st Qu.: 14.00   Class :character   FALSE:32540
##  Median :        0   Median : 80.00   Mode  :character
##  Mean   :  1349747   Mean   : 62.14
##  3rd Qu.:        0   3rd Qu.: 91.00
##  Max.   :701842551   Max.   :683.00
##
##  backdrop_path      genre_names          collection      collection_name
##  Length:32540       Length:32540       Min.   :    656   Length:32540
##  Class :character   Class :character   1st Qu.: 155421   Class :character
##  Mode  :character   Mode  :character   Median : 471259   Mode  :character
##                                        Mean   : 481535
##                                        3rd Qu.: 759067
##                                        Max.   :1033032
##                                        NA's   :30234
```

Data Cleanup

Handling NA Values

We will look at how many NA values are in each column to better understand our data set.

```
na_counts <- colSums(is.na(horror))

print(na_counts)
```

```
##                id    original_title             title original_language
##                 0                 0                 0                 0
##          overview           tagline      release_date       poster_path
##              1286             19833                 0              4474
##        popularity        vote_count      vote_average            budget
##                 0                 0                 0                 0
##           revenue           runtime            status             adult
##                 0                 0                 0                 0
##     backdrop_path       genre_names        collection   collection_name
##             18995                 0             30234             30234
```

```
sum(horror$revenue == 0)
```

```
## [1] 30964
```

```
sum(horror$budget == 0)
```

```
## [1] 27339
```

```
sum(horror$budget != 0 & horror$revenue != 0)
```

```
## [1] 1098
```

```
sum(horror$budget == 0 & horror$revenue == 0)
```

```
## [1] 26861
```

For numeric columns, we will fill missing values with the median values of that column. These include id, release_date, popularity, vote_count, vote_average, revenue, and runtime. We will then fill missing character columns with “Unknown.” These include original_title, title, original_language, tagline, overview, poster_path, status, adult, and backdrop_path.

```
numeric_cols <- sapply(horror, is.numeric)
horror[numeric_cols] <- lapply(horror[numeric_cols], function(x) {
  ifelse(is.na(x), median(x, na.rm = TRUE), x)
})

char_cols <- sapply(horror, is.character)
horror[char_cols] <- lapply(horror[char_cols], function(x) {
  ifelse(is.na(x), "Unknown", x)
})
```

Drop Columns

We will remove the columns ids and paths as these are not needed for our overall analysis.

```
#horror <- horror |> select(-id, -poster_path, -backdrop_path, -collection, -collection_name)

horror <- dplyr::select(horror, -id, -poster_path, -backdrop_path, -collection, -collection_name)
```

Feature Engineering

As part of feature engineering we need to create our boolean-like columns to logical data types. We will do so for the adult column. If the observation is FALSE, then it will convert to a logical operator of 0. If the observation is TRUE for this column, then it will be converted to 1. We must also convert categorical columns to factors. This includes original_language, status, and genre_names. Finally, we will extract year from release_date because this will help in further analysis.

```
horror$adult <- as.logical(horror$adult)

categorical_cols <- c("original_language", "status", "genre_names")
horror[categorical_cols] <- lapply(horror[categorical_cols], as.factor)

horror$release_year <- as.numeric(substr(horror$release_date, 1, 4))
```

Handling Outliers

We will replace some outliers. Specifically, for runtime we will replace runtime with the 0 if there is a runtime that is defined as an outlier, we will replace it with 0. We will also remove rows with outliers regarding popularity that is defined as popularity above 10000. We will also categorize budget levels. We categorize movies into “Low”, “Medium”, or “High” budget based on the budget column:

```
runQ1 <- quantile(horror$runtime, 0.25, na.rm = TRUE)
runQ3 <- quantile(horror$runtime, 0.75, na.rm = TRUE)
IQR <- runQ3 - runQ1
lower_bound <- runQ1 - 1.5 * IQR
upper_bound <- runQ3 + 1.5 * IQR
horror$runtime[horror$runtime < lower_bound | horror$runtime > upper_bound] <- 0

#horror$runtime[horror$runtime <= 0 | horror$runtime > 300] <- NA

horror <- horror[!(horror$popularity > 10000), ]
```

```
horror$budget_category <- ifelse(horror$budget == 0, "No Budget",
                           ifelse(horror$budget < 1e7, "Low",
                           ifelse(horror$budget < 5e7, "Medium", "High")))
```

Create Target Variables

We first create a profit variable that is the revenue minus budget of a movie. We then create a success variable: if profit > 0, movie is considered successful

```
horror$profit <- horror$revenue - horror$budget
horror$success <- ifelse(horror$profit > 0, "Success", "No Success")
```

Making data frame with no 0s

Create a new data frame without rows where revenue and budget is 0

```
df_for_class = subset(horror, revenue != 0 & budget != 0)
df_for_class$success = as.factor(df_for_class$success)

head(df_for_class)
```

```
## # A tibble: 6 x 19
##   original_title           title original_language overview tagline release_date
##   <chr>                    <chr> <fct>             <chr>    <chr>   <date>
## 1 Smile                    Smile en                After w~ Once y~ 2022-09-23
## 2 The Black Phone          The ~ en                Finney ~ Never ~ 2022-06-22
## 3 Jeepers Creepers: Reborn Jeep~ en                Forced ~ Evil R~ 2022-09-15
## 4 Nope                     Nope  en                Residen~ What’s~ 2022-07-20
## 5 X                        X     en                In 1979~ Dying ~ 2022-03-17
## 6 Dahmer                   Dahm~ en                On Febr~ The mi~ 2002-06-21
## # i 13 more variables: popularity <dbl>, vote_count <dbl>, vote_average <dbl>,
## #   budget <dbl>, revenue <dbl>, runtime <dbl>, status <fct>, adult <lgl>,
## #   genre_names <fct>, release_year <dbl>, budget_category <chr>, profit <dbl>,
## #   success <fct>
```

```
dim(df_for_class)
```

```
## [1] 1098   19
```

Split the Data

Train and Test Data

We will split the data into training (60%) and testing (40%) sets. We will then look at the new data by checking the number of rows in training and testing sets and looking at the summary of the training set.

```
set.seed(123)

in_train <- createDataPartition(df_for_class$budget_category, p = 0.6, list = FALSE)
training <- df_for_class[in_train, ]
testing <- df_for_class[-in_train, ]

nrow(training)
```

```
## [1] 659
```

```r
nrow(testing)
```

```
## [1] 439
```

```r
summary(training)
```

```
##  original_title        title           original_language    overview
##  Length:659         Length:659         en     :560       Length:659
##  Class :character   Class :character   ja     : 16       Class :character
##  Mode  :character   Mode  :character   es     : 14       Mode  :character
##                                        hi     : 14
##                                        ko     : 10
##                                        de     :  8
##                                        (Other): 37
##    tagline           release_date          popularity          vote_count
##  Length:659         Min.   :1953-06-05   Min.   :   0.600   Min.   :    0.0
##  Class :character   1st Qu.:1994-12-12   1st Qu.:   7.186   1st Qu.:   98.5
##  Mode  :character   Median :2007-01-19   Median :  15.516   Median :  543.0
##                     Mean   :2003-08-09   Mean   :  27.011   Mean   : 1206.6
##                     3rd Qu.:2015-01-28   3rd Qu.:  31.030   3rd Qu.: 1544.5
##                     Max.   :2022-09-29   Max.   :1071.398   Max.   :16900.0
##
##   vote_average        budget             revenue             runtime
##  Min.   : 0.000   Min.   :        1   Min.   :        1   Min.   :  0.00
##  1st Qu.: 5.300   1st Qu.:  1000000   1st Qu.:   675326   1st Qu.: 87.50
##  Median : 6.000   Median :  5000000   Median : 11642254   Median : 95.00
##  Mean   : 5.797   Mean   : 12769148   Mean   : 39044327   Mean   : 91.09
##  3rd Qu.: 6.600   3rd Qu.: 15000000   3rd Qu.: 45023606   3rd Qu.:103.00
##  Max.   :10.000   Max.   :200000000   Max.   :701842551   Max.   :153.00
##
##              status      adult                          genre_names
##  In Production  :  0   Mode :logical   Horror, Thriller         :103
##  Planned        :  0   FALSE:659       Horror                   : 99
##  Post Production:  0                   Horror, Mystery, Thriller: 52
##  Released       :659                   Comedy, Horror           : 36
##                                        Horror, Science Fiction  : 29
##                                        Drama, Horror, Thriller  : 27
##                                        (Other)                  :313
##   release_year  budget_category        profit                   success
##  Min.   :1953   Length:659         Min.   :-194775779   No Success:212
##  1st Qu.:1994   Class :character   1st Qu.:    -99162   Success   :447
##  Median :2007   Mode  :character   Median :   3400000
##  Mean   :2003                      Mean   :  26275179
##  3rd Qu.:2015                      3rd Qu.:  30288153
##  Max.   :2022                      Max.   : 666842551
##
```

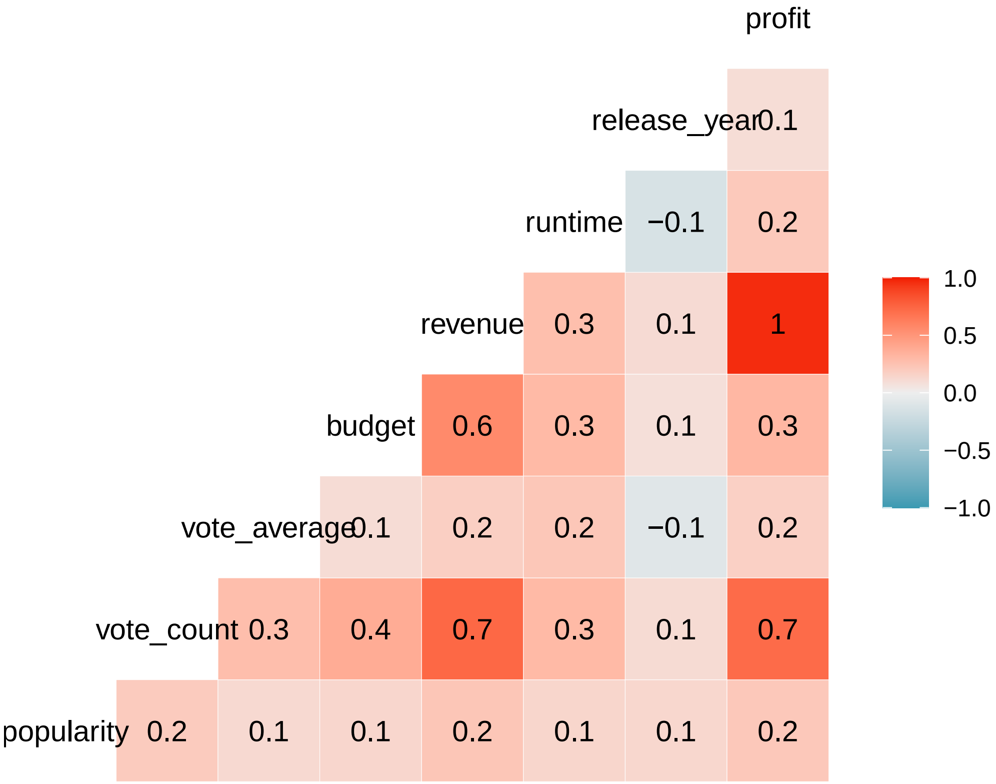
Distribution of Target Variable

```r
table(training$success) / length(training$success)
```

```
##
## No Success    Success
##  0.3216995  0.6783005
```

Correlation Analysis

```
ggcorr(df_for_class[ , sapply(df_for_class, is.numeric)], label = TRUE)
```

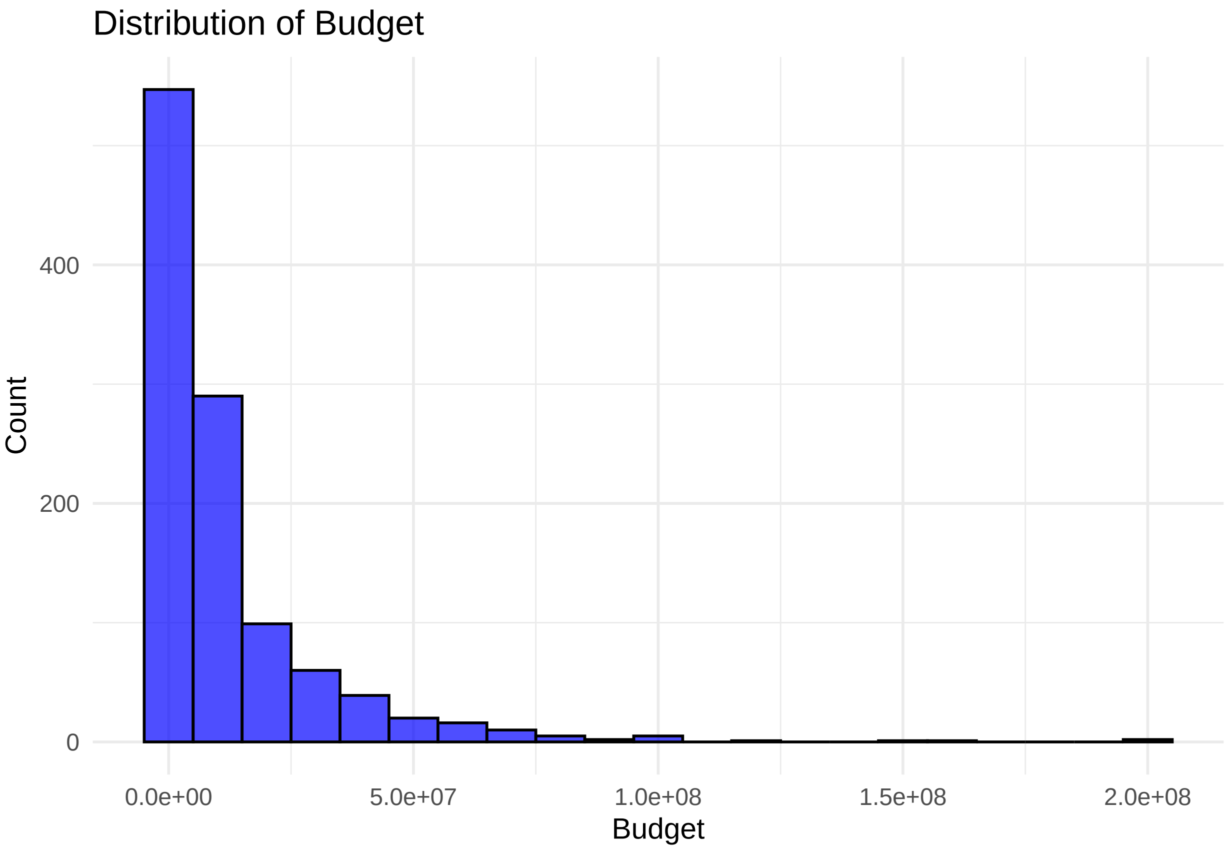


Visualization Tools

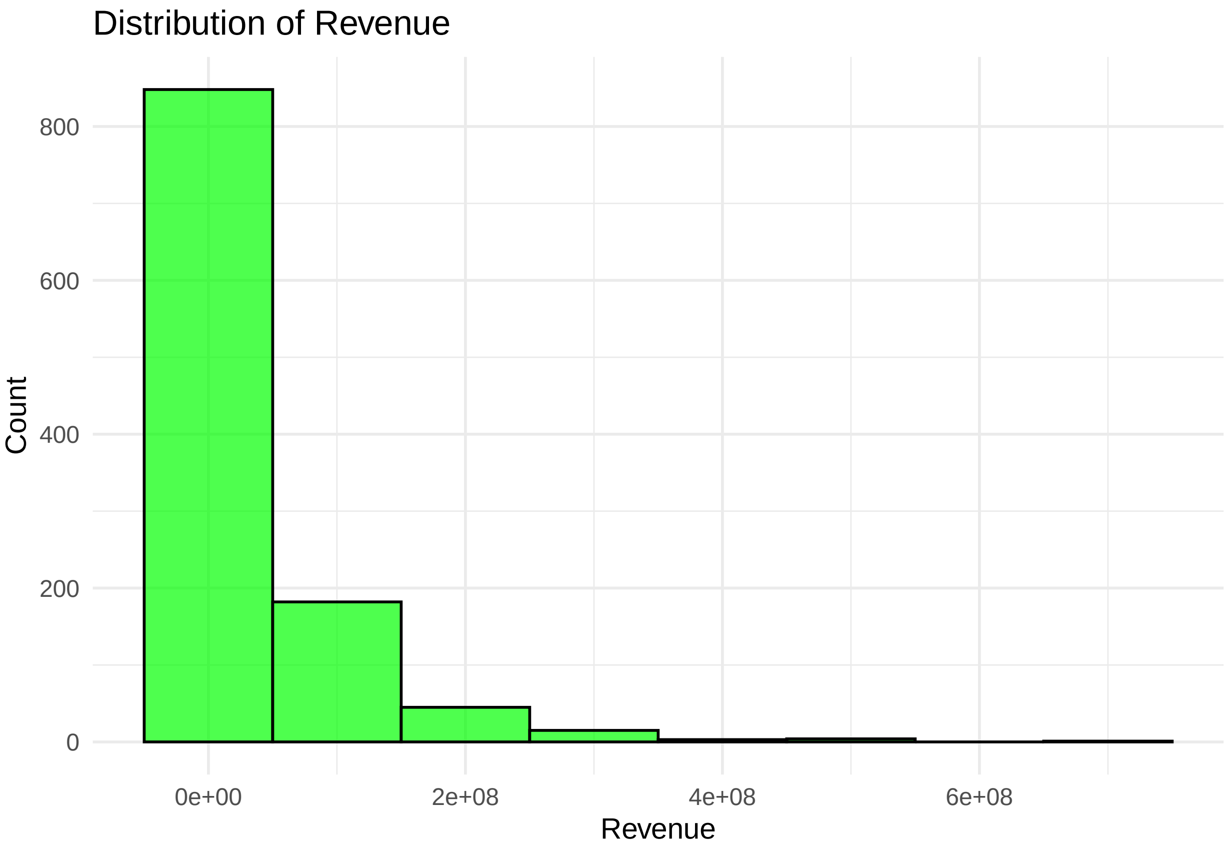
Distribution of Numeric Features

We will plot the distributions of numeric features, specifically budget, revenue, and runtime.

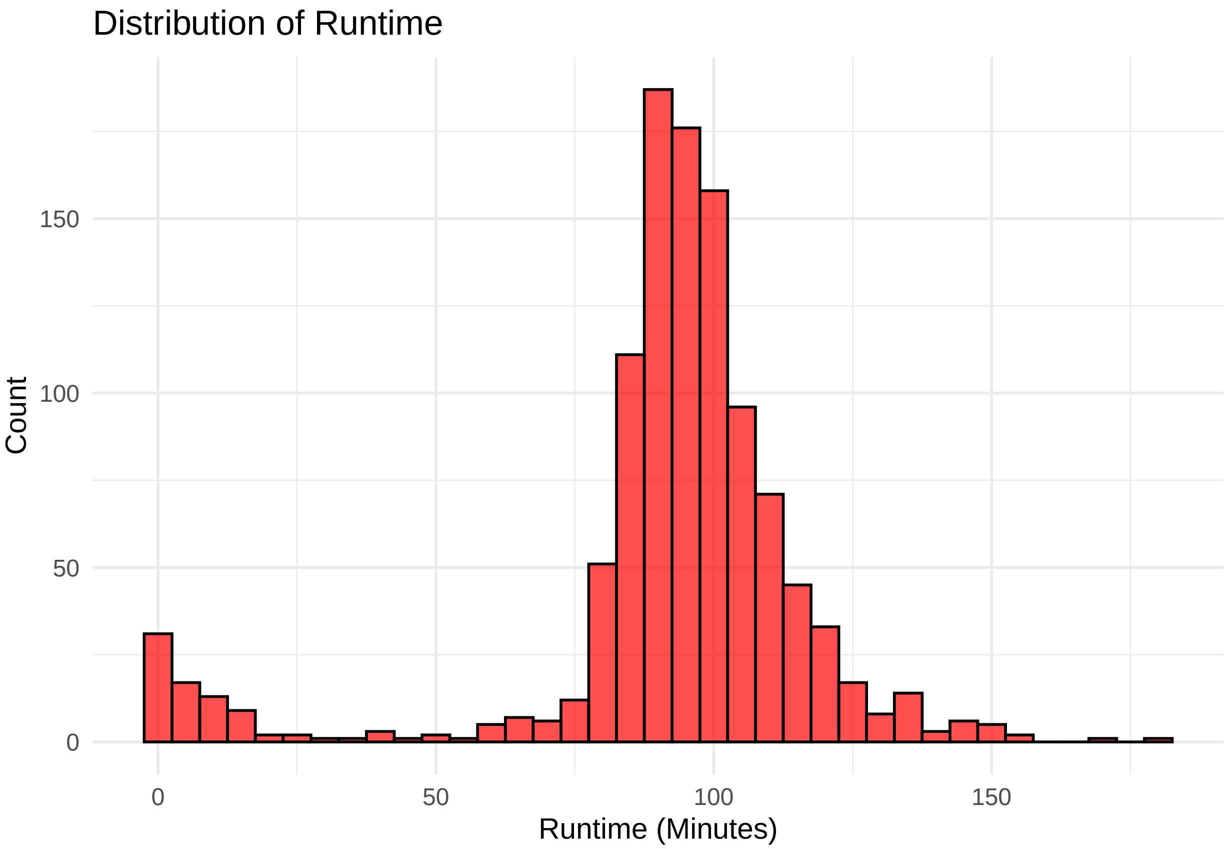
```
ggplot(df_for_class, aes(x = budget)) +
  geom_histogram(binwidth = 1e7, fill = "blue", color = "black", alpha = 0.7) +
  labs(title = "Distribution of Budget", x = "Budget", y = "Count") +
  theme_minimal()
```



```r
ggplot(df_for_class, aes(x = revenue)) +
  geom_histogram(binwidth = 1e8, fill = "green", color = "black", alpha = 0.7) +
  labs(title = "Distribution of Revenue", x = "Revenue", y = "Count") +
  theme_minimal()
```



```r
ggplot(df_for_class, aes(x = runtime)) +
  geom_histogram(binwidth = 5, fill = "red", color = "black", alpha = 0.7) +
  labs(title = "Distribution of Runtime", x = "Runtime (Minutes)", y = "Count") +
  theme_minimal()
```

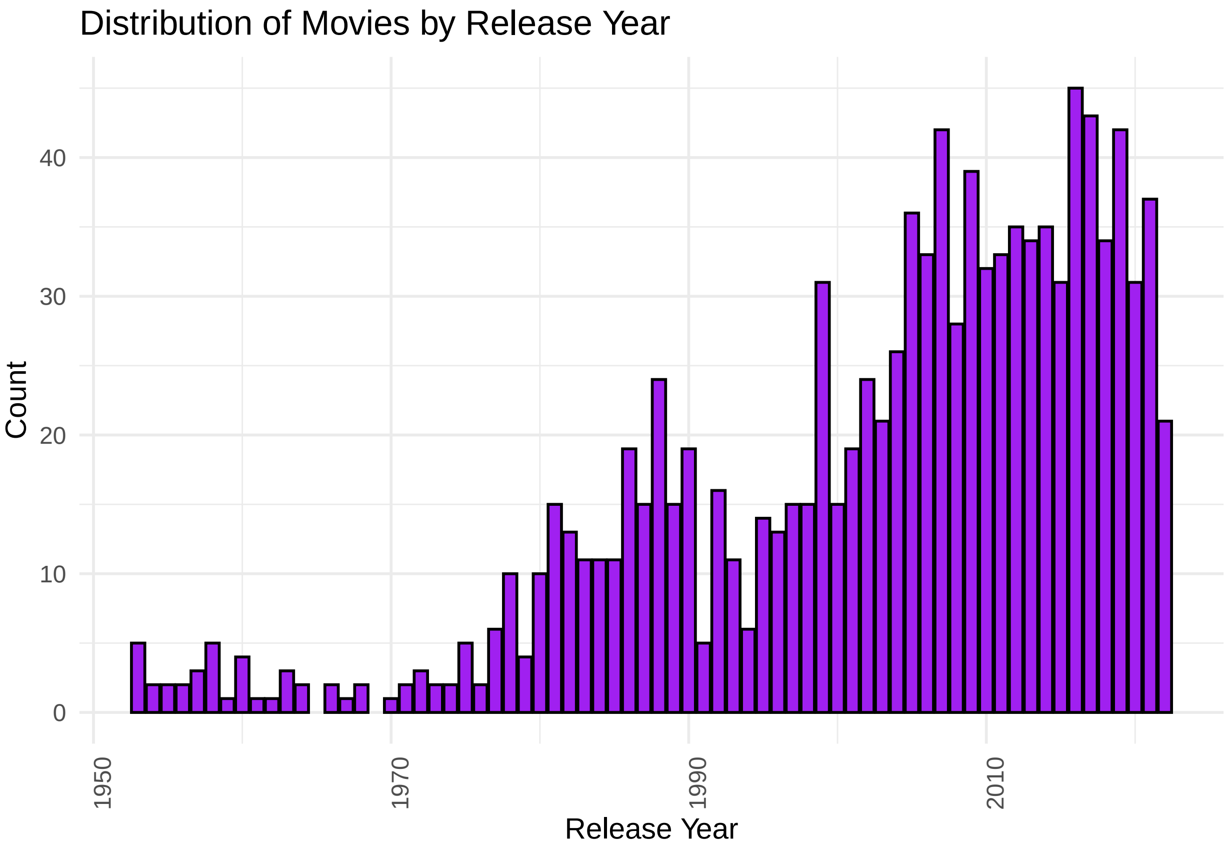


Budget and revenue are both right skewed and unimodal. Runtime is also right skewed, but could be considered to be bimodal.

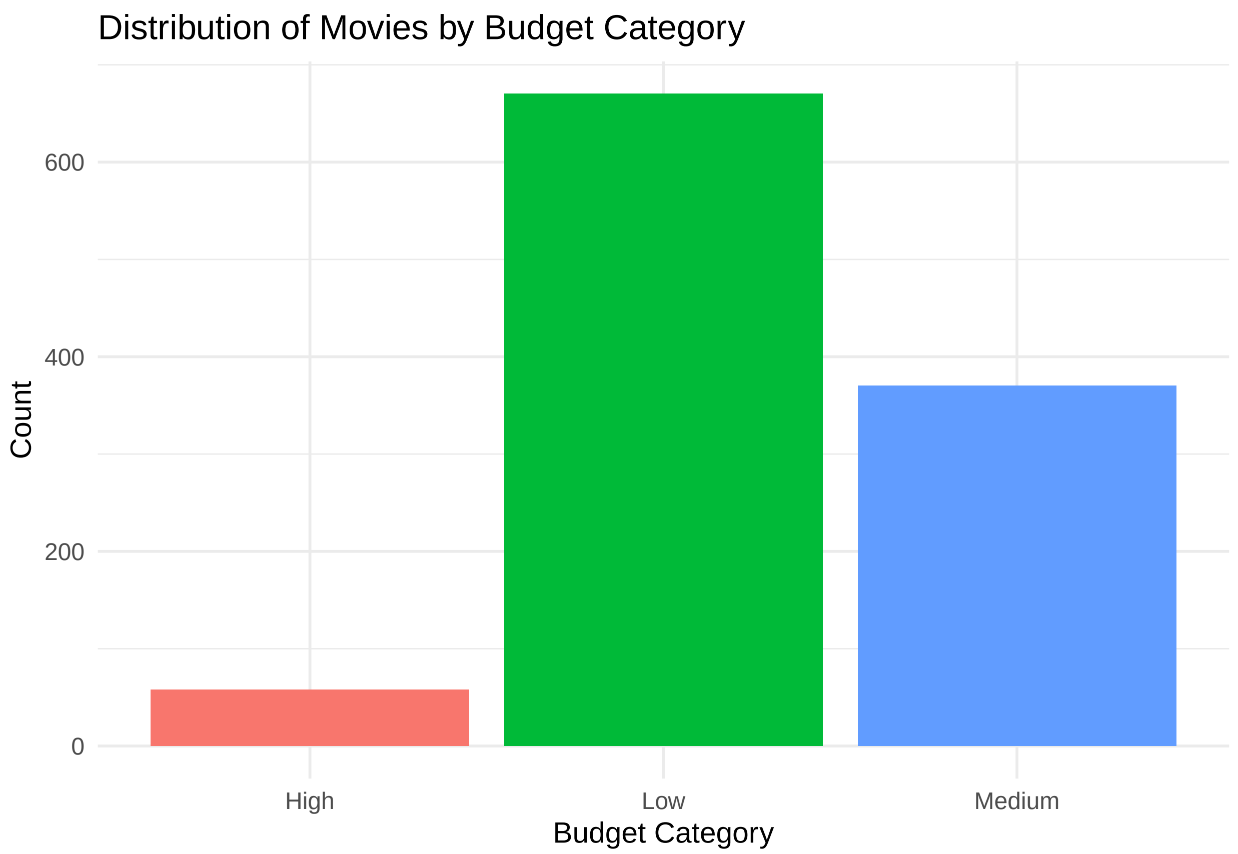
Distribution of Some Categorical Features

We will plot the distributions of some categorical features, specifically release_year and budget_category.

```r
ggplot(df_for_class, aes(x = release_year)) +
  geom_bar(fill = "purple", color = "black") +
  labs(title = "Distribution of Movies by Release Year", x = "Release Year", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



```
ggplot(df_for_class, aes(x = budget_category, fill = budget_category)) +
  geom_bar() +
  labs(title = "Distribution of Movies by Budget Category", x = "Budget Category", y = "Count") +
  theme_minimal() +
  theme(legend.position = "none")
```



Release year is left skewed and unimodal. Most movies were made with a low budget and only very few movies were made with a high budget.

Distribution of Target Variable

We will now look at the distribution of our target variable, show_or_movie.

```
sum(df_for_class$success == "Success")
```

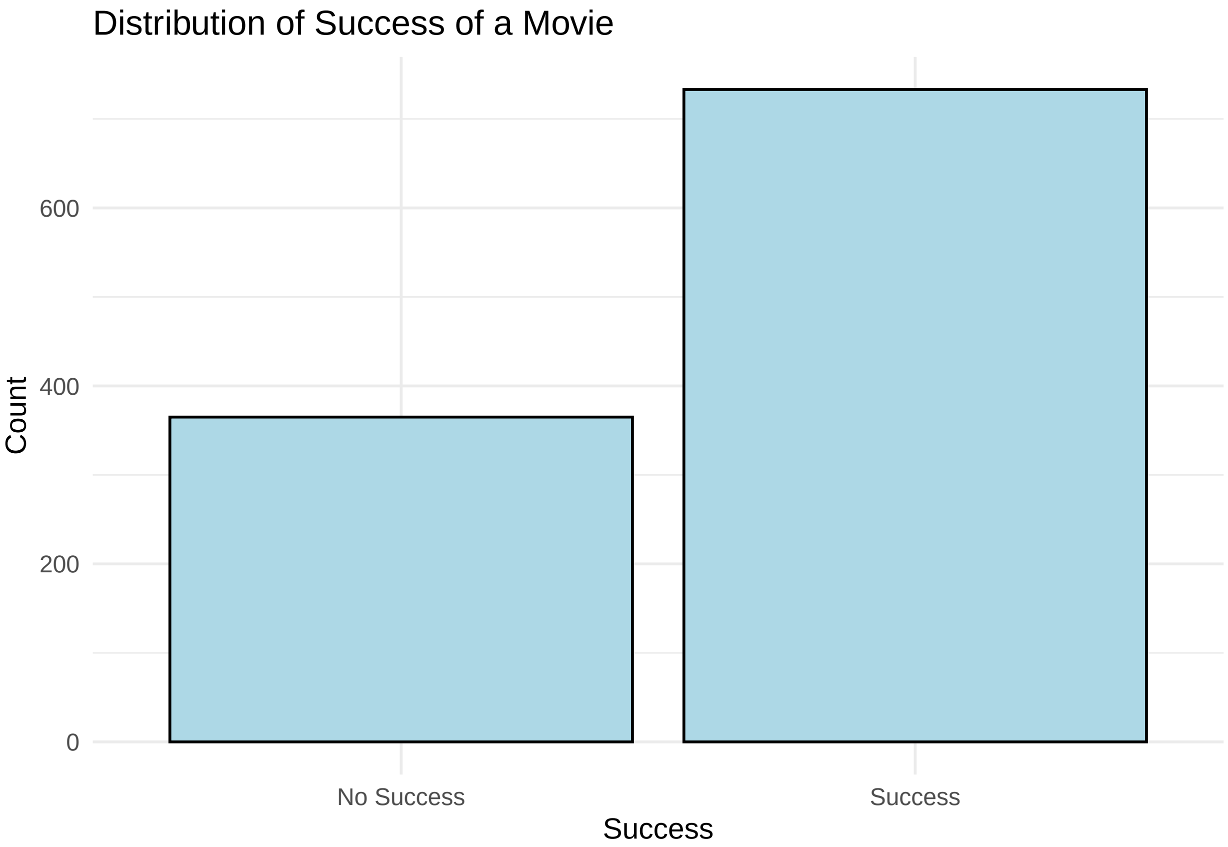
```
## [1] 733
```

```
sum(df_for_class$success == "No Success")
```

```
## [1] 365
```

66.7% successful movies, 33.3% unsuccessful movies: unbalanced dataset

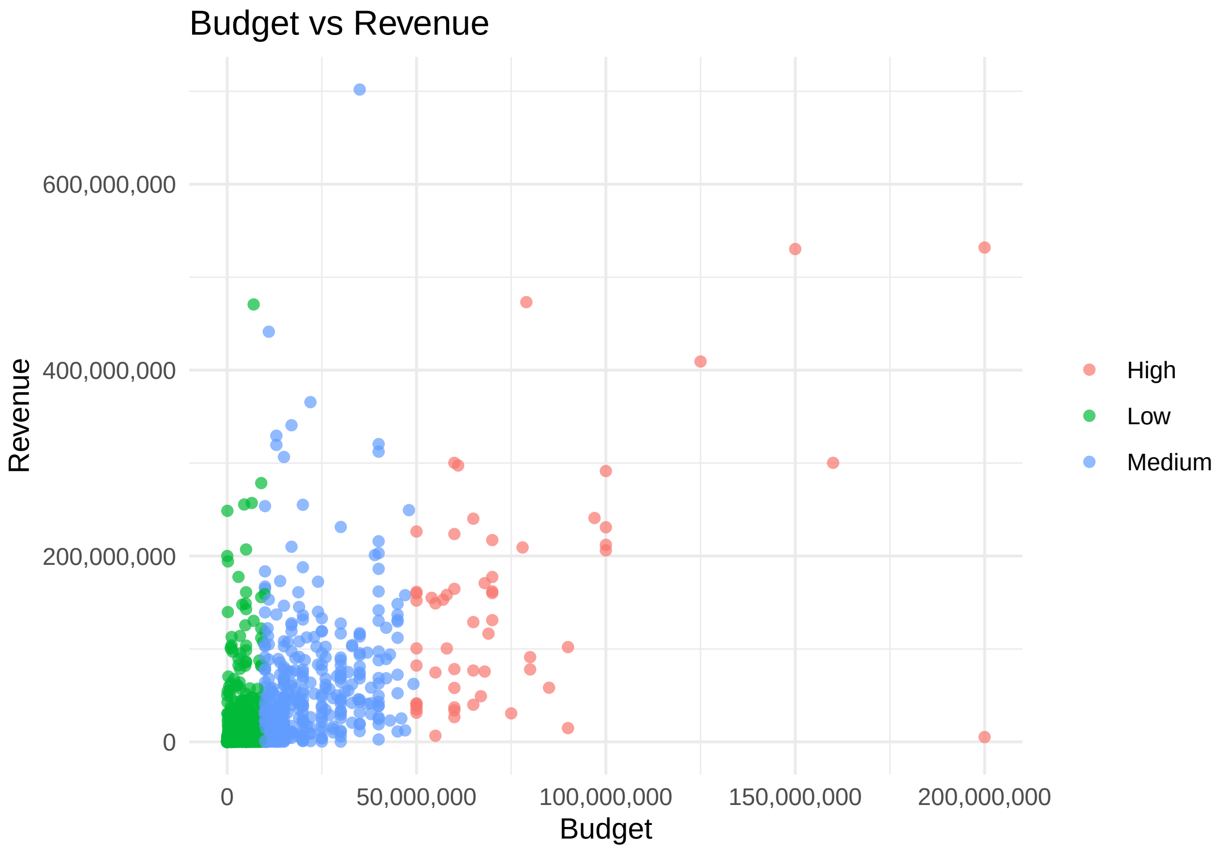
```
ggplot(df_for_class, aes(x = success)) +
  geom_bar(fill = "lightblue", color = "black") +
  labs(title = "Distribution of Success of a Movie", x = "Success", y = "Count") +
  theme_minimal()
```



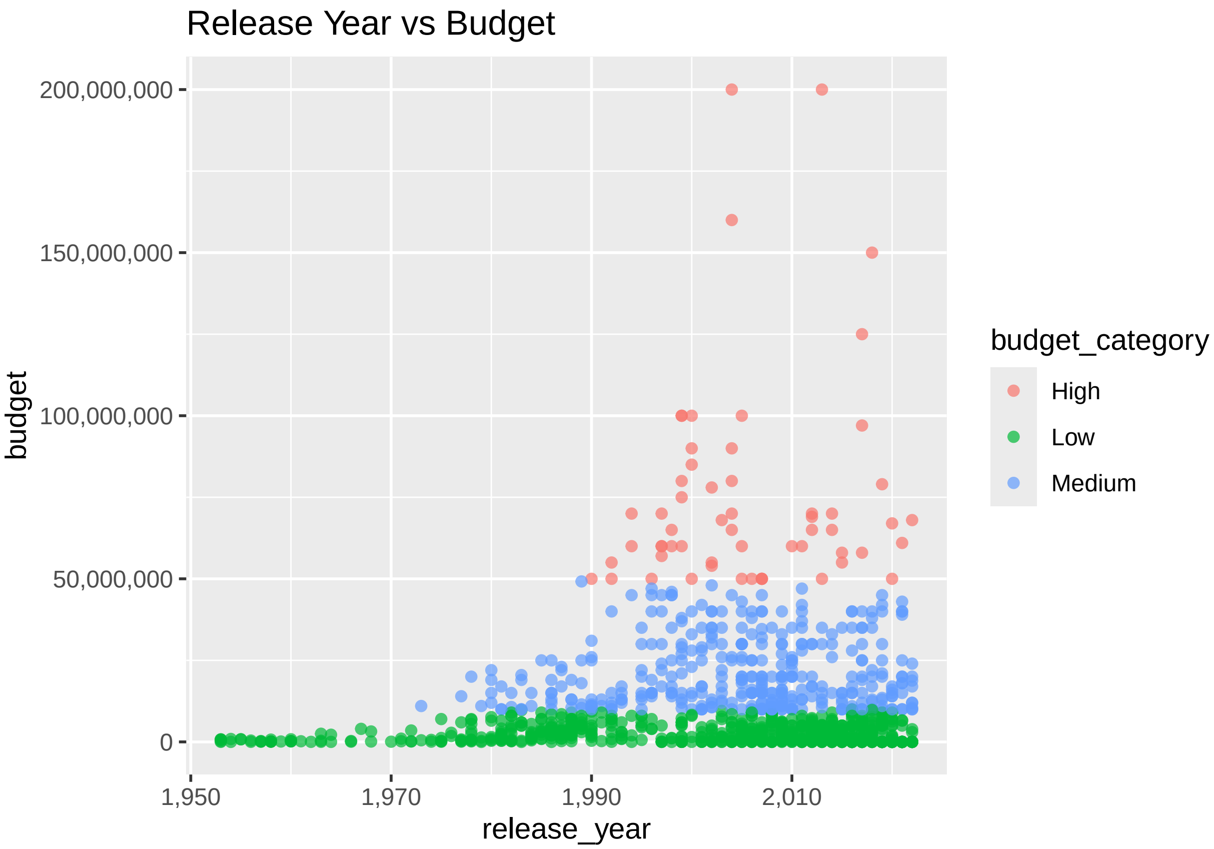
Variable Relationships

We first examine the relationship between budget and revenue for each horror movie, with points colored by their budget category, helping to identify patterns and outliers in how budget impacts revenue. We can also visualize how the budget has evolved over the years by plotting release_year versus budget. We then examine the relationship between `popularity` and `vote_average` to see if there's a trend in how movies' popularity correlates with their ratings. We also examine the relationship between `budget` and `profit`. Each point represents a movie, and the color differentiates between successful and non-successful movies. The idea is to see if movies with higher budgets tend to generate more profit. Finally we show how the `profit` distribution differs between successful and non-successful movies. This boxplot shows the distribution of `profit` for movies categorized as "Success" or "No Success". The plot helps visualize how profits are distributed across these categories, revealing if successful movies tend to have higher profits.

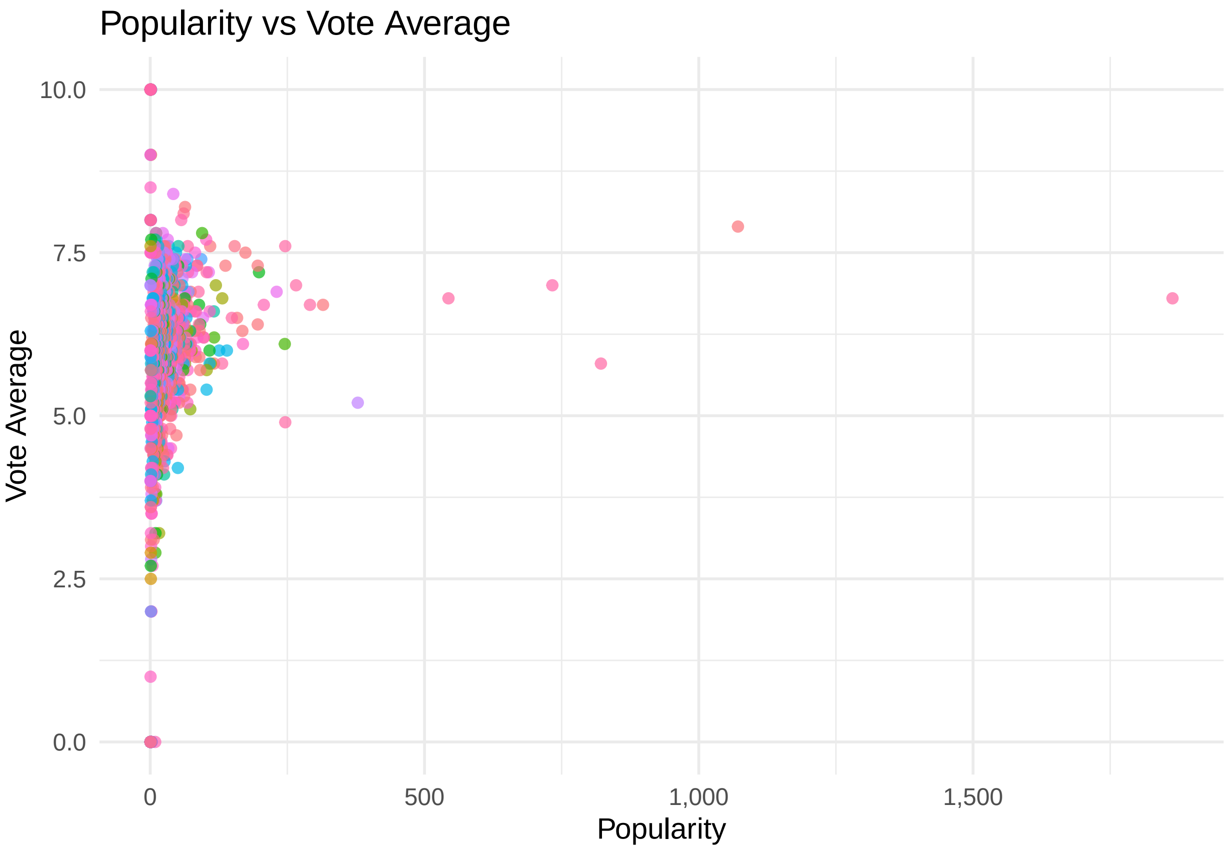
```r
ggplot(df_for_class, aes(x = budget, y = revenue)) +
  geom_point(aes(color = budget_category), alpha = 0.7) +
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma) +
  labs(title = "Budget vs Revenue", x = "Budget", y = "Revenue") +
  theme_minimal() +
  theme(legend.title = element_blank())
```



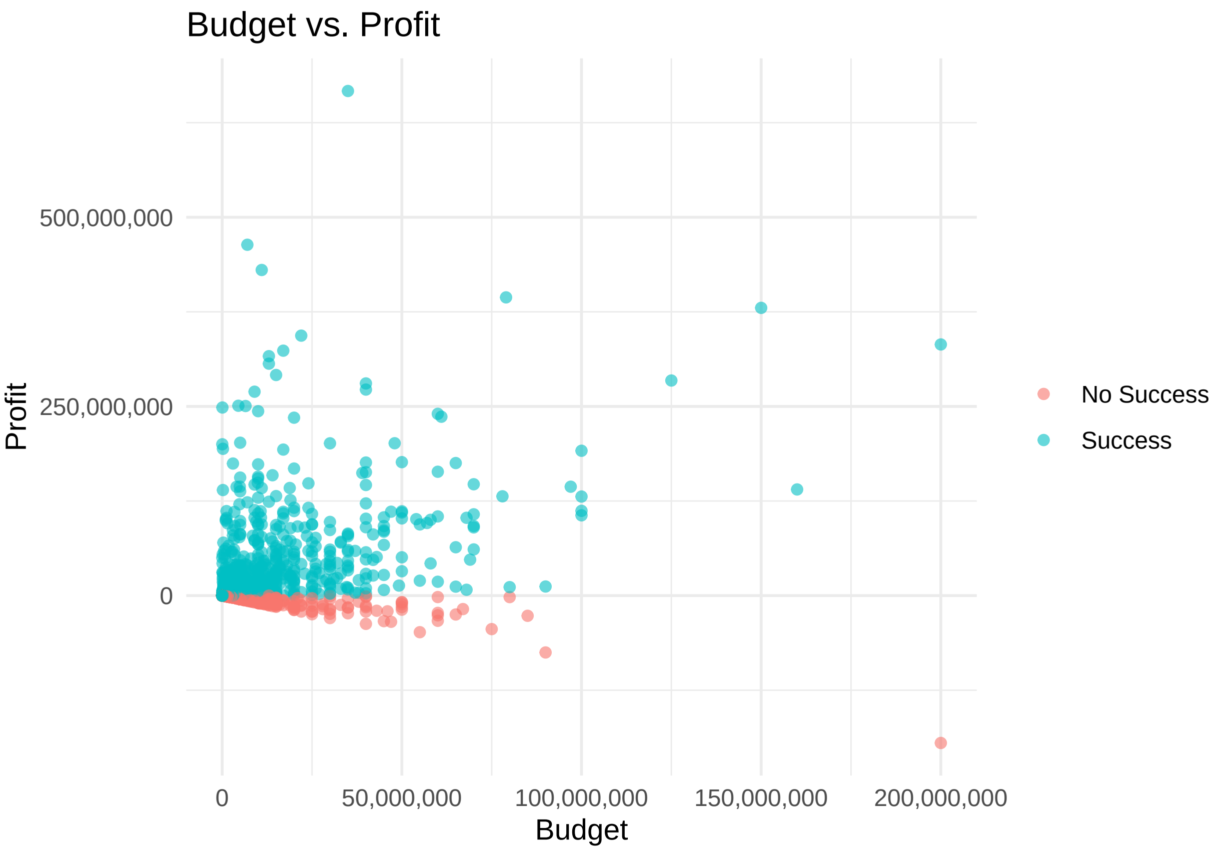
```r
ggplot(df_for_class, aes(x = release_year, y = budget)) +
  geom_point(aes(color = budget_category), alpha = 0.7) +
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma) +
  labs(title = "Release Year vs Budget")
```



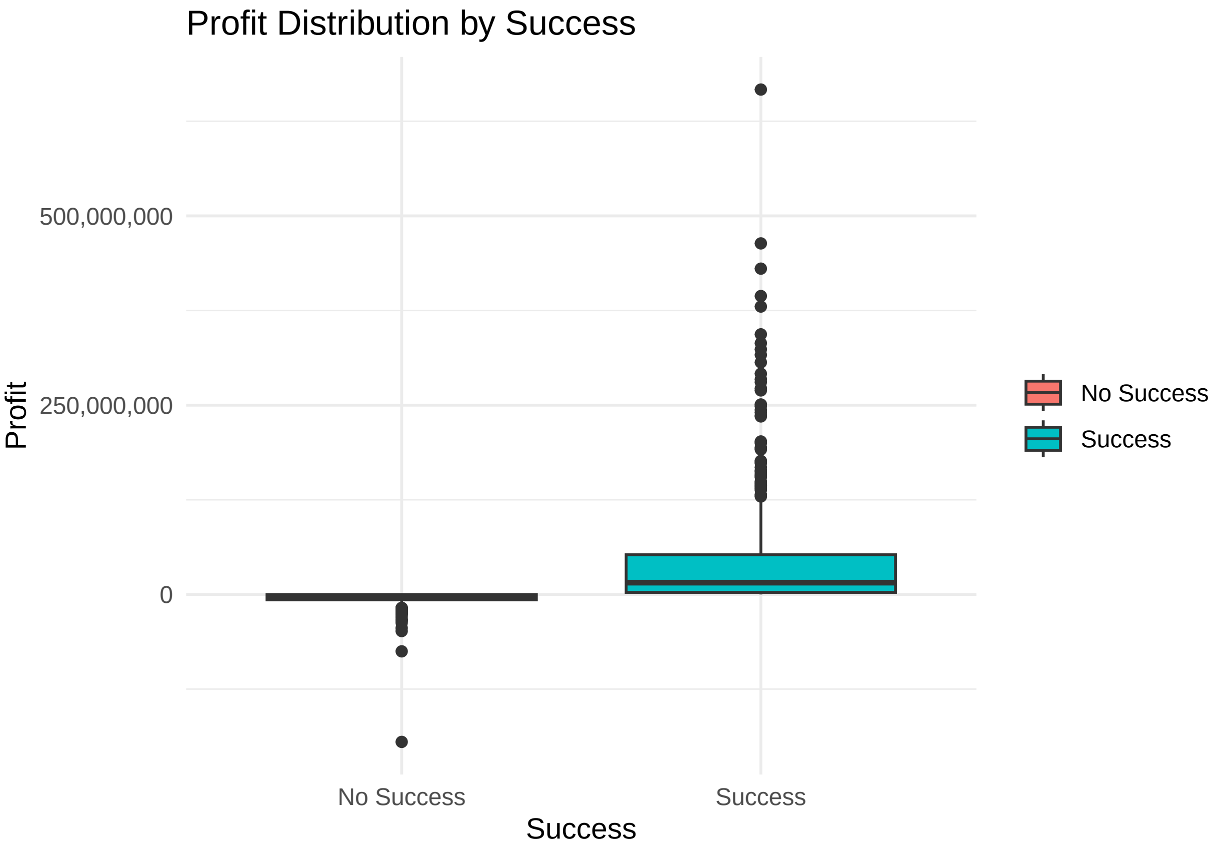
```
ggplot(df_for_class, aes(x = popularity, y = vote_average)) +
  geom_point(aes(color = genre_names), alpha = 0.7) +
  scale_x_continuous(labels = scales::comma) +
  labs(title = "Popularity vs Vote Average", x = "Popularity", y = "Vote Average") +
  theme_minimal() +
  theme(legend.position = "none")
```



```
ggplot(df_for_class, aes(x = budget, y = profit)) +
  geom_point(aes(color = success), alpha = 0.6) +
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma) +
  labs(title = "Budget vs. Profit", x = "Budget", y = "Profit") +
  theme_minimal() +
  theme(legend.title = element_blank())
```



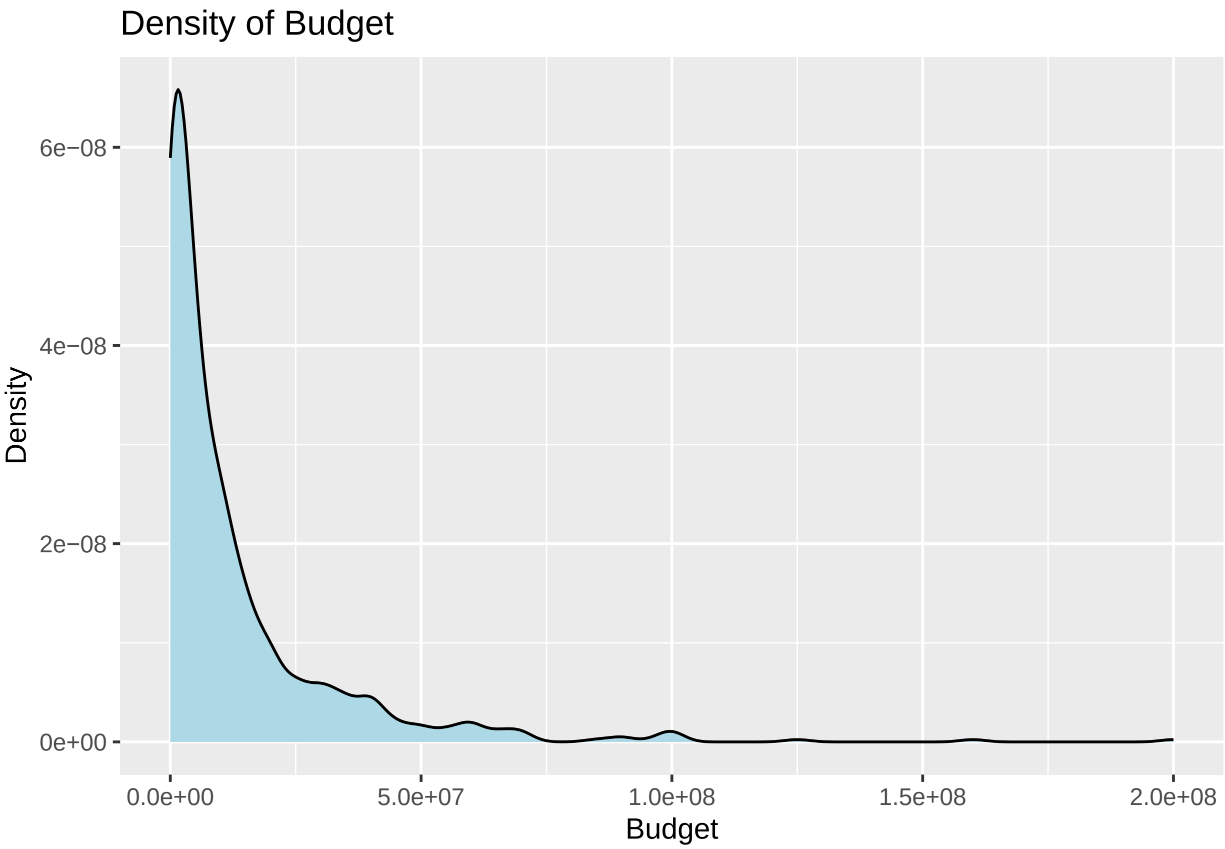
```r
ggplot(df_for_class, aes(x = success, y = profit, fill = success)) +
  geom_boxplot() +
  scale_y_continuous(labels = scales::comma) +
  labs(title = "Profit Distribution by Success", x = "Success", y = "Profit") +
  theme_minimal() +
  theme(legend.title = element_blank())
```



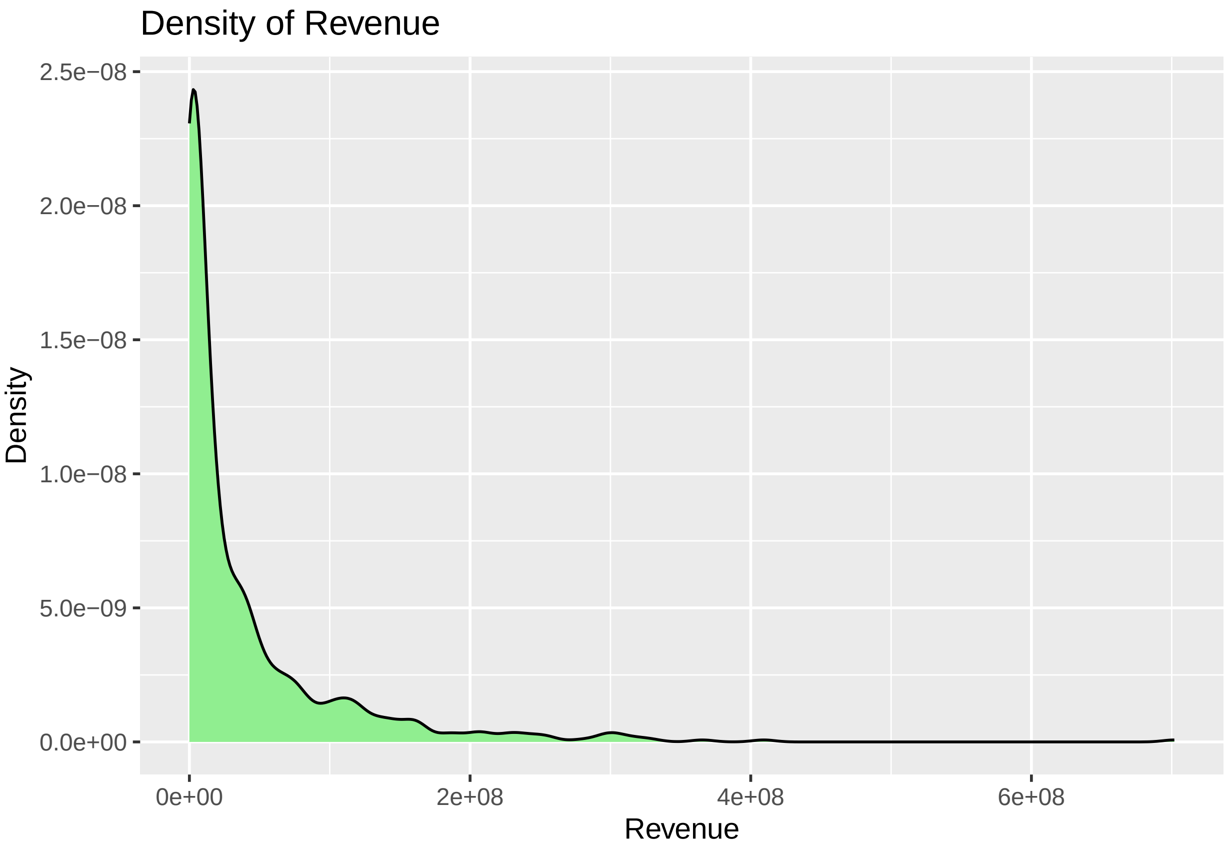
Training Visuals

We will now do EDA but for data in the training data set instead of the original data set to see how the ditrubutions change or not for each variable.

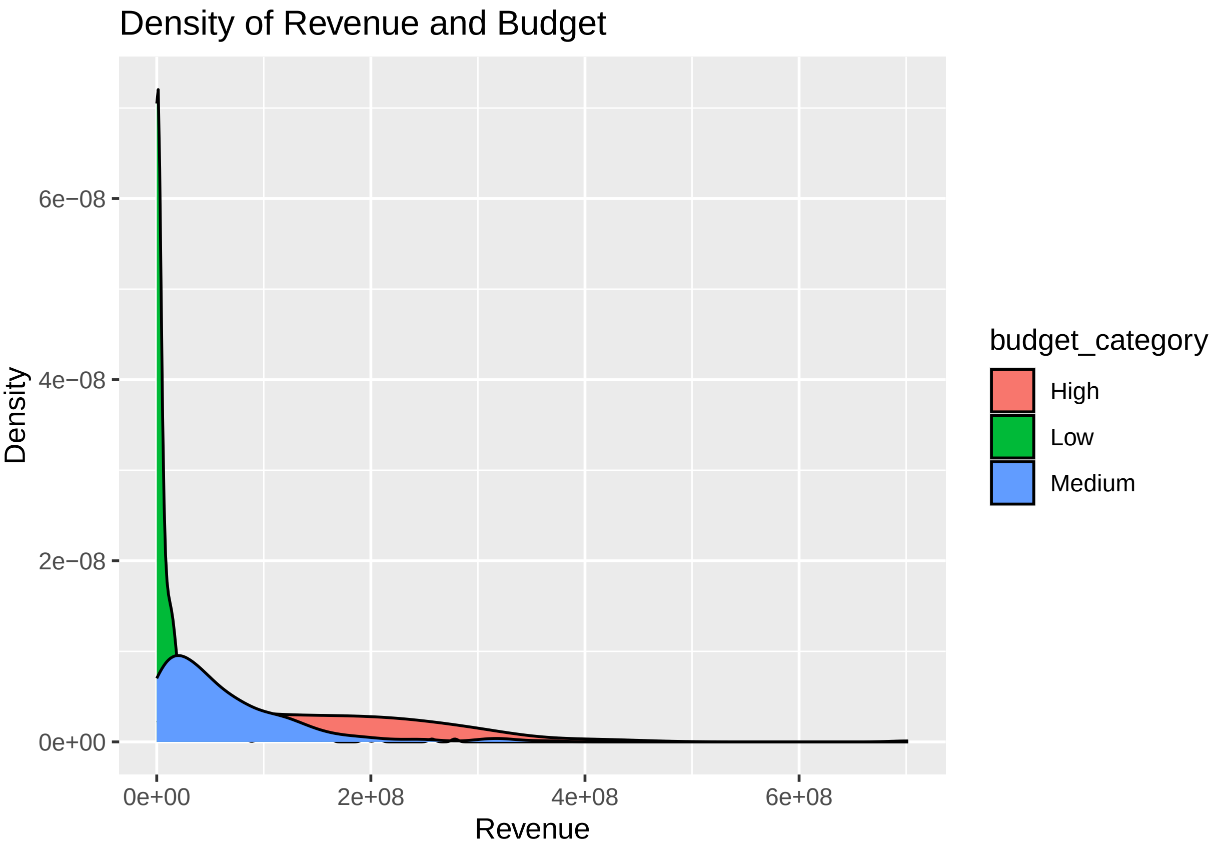
```r
ggplot(training, aes(x = budget)) +
  geom_density(fill = "lightblue") +
  labs(title = "Density of Budget", x = "Budget", y = "Density")
```



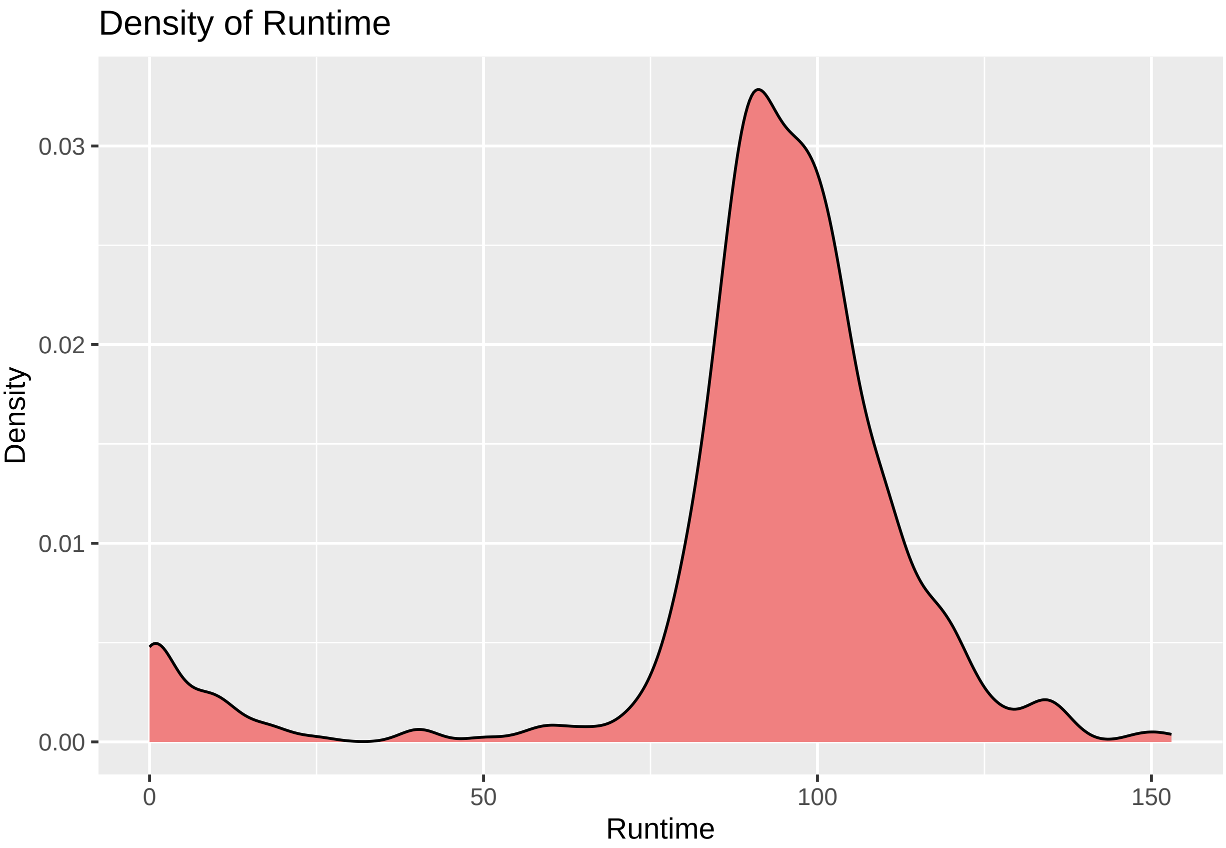
```r
ggplot(training, aes(x = revenue)) +
  geom_density(fill = "lightgreen") +
  labs(title = "Density of Revenue", x = "Revenue", y = "Density")
```



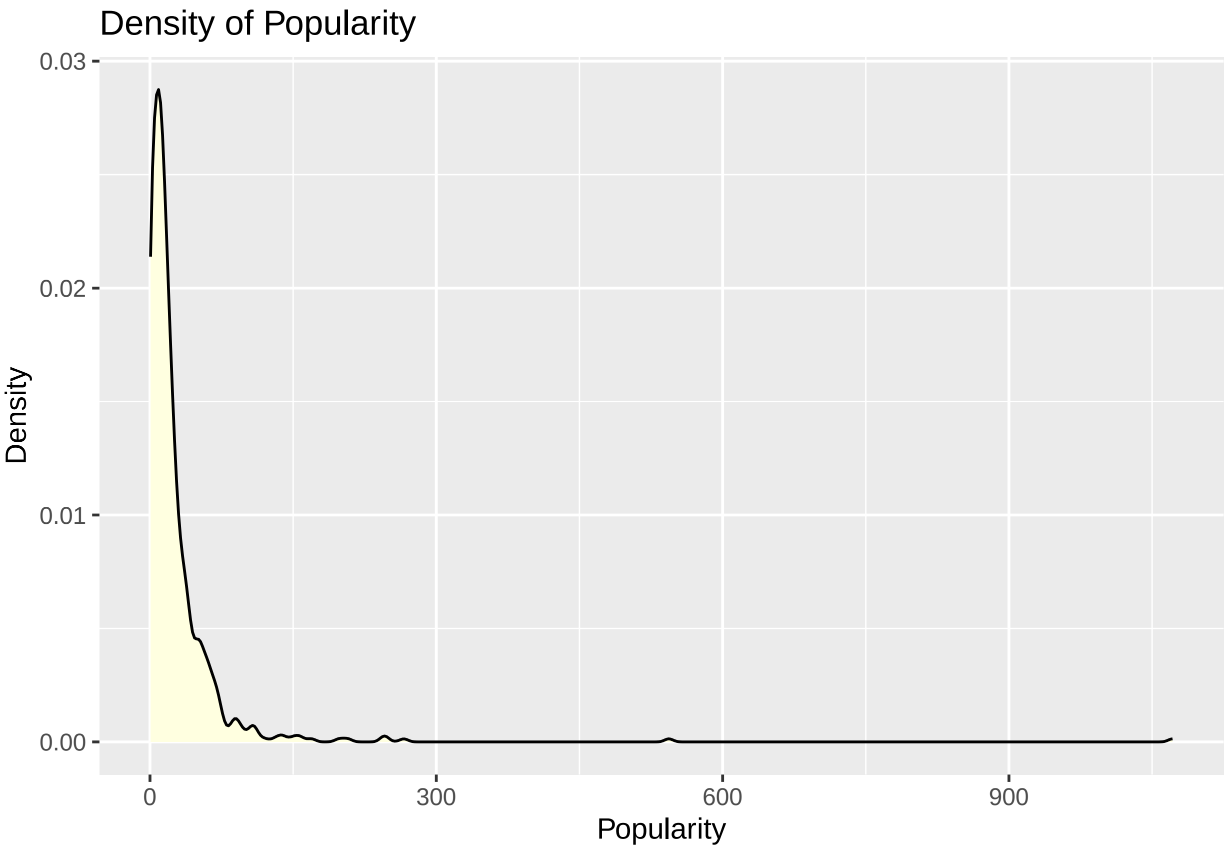
```r
ggplot(training, aes(fill = budget_category, x = revenue)) +
  geom_density() +
  labs(title = "Density of Revenue and Budget", x = "Revenue", y = "Density")
```



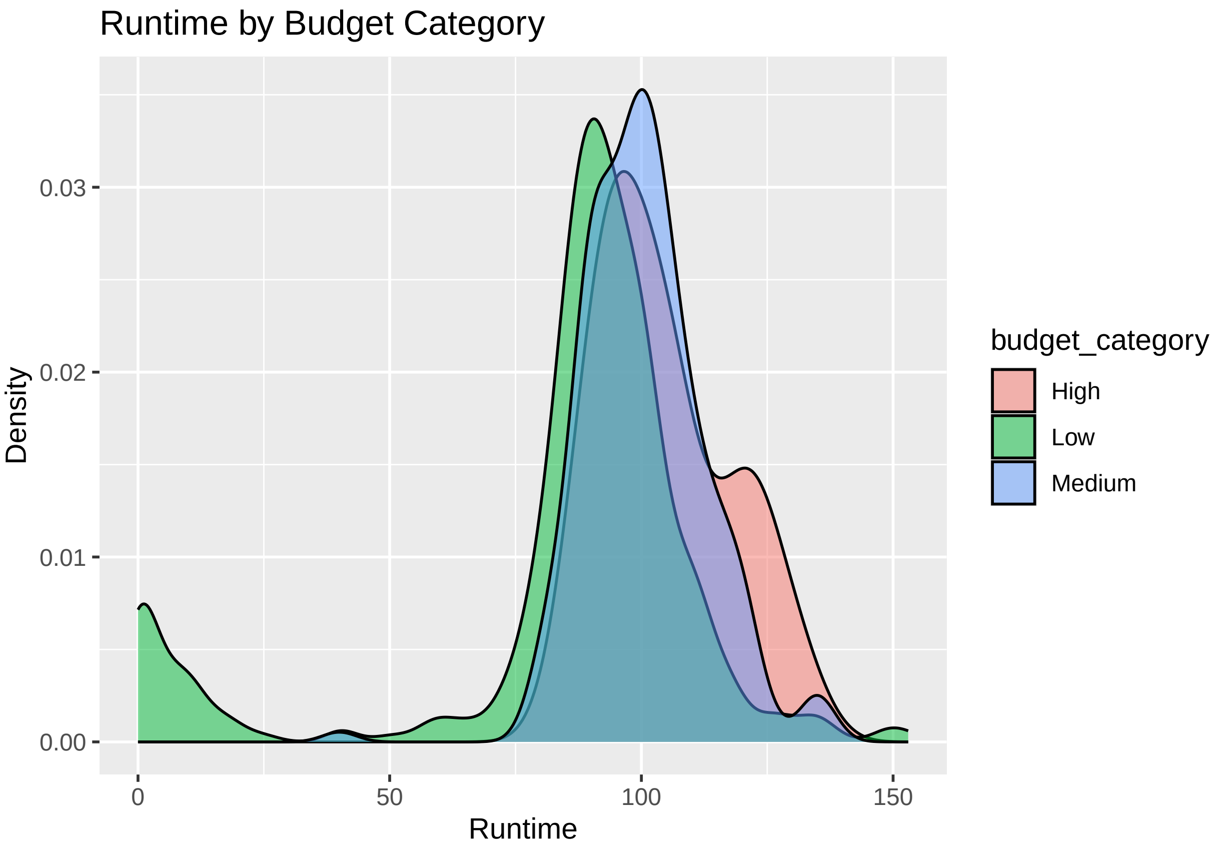
```r
ggplot(training, aes(x = runtime)) +
  geom_density(fill = "lightcoral") +
  labs(title = "Density of Runtime", x = "Runtime", y = "Density")
```



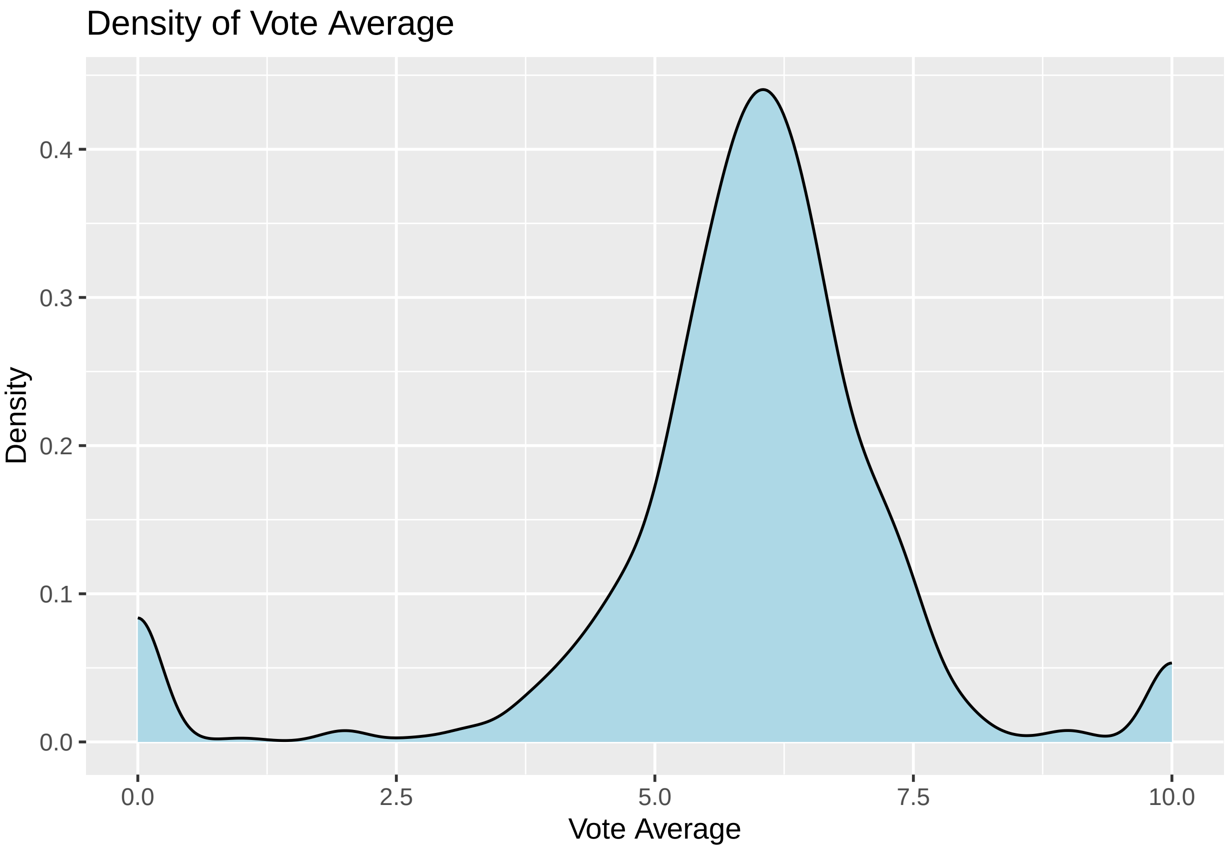
```
ggplot(training, aes(x = popularity)) +
  geom_density(fill = "lightyellow") +
  labs(title = "Density of Popularity", x = "Popularity", y = "Density")
```



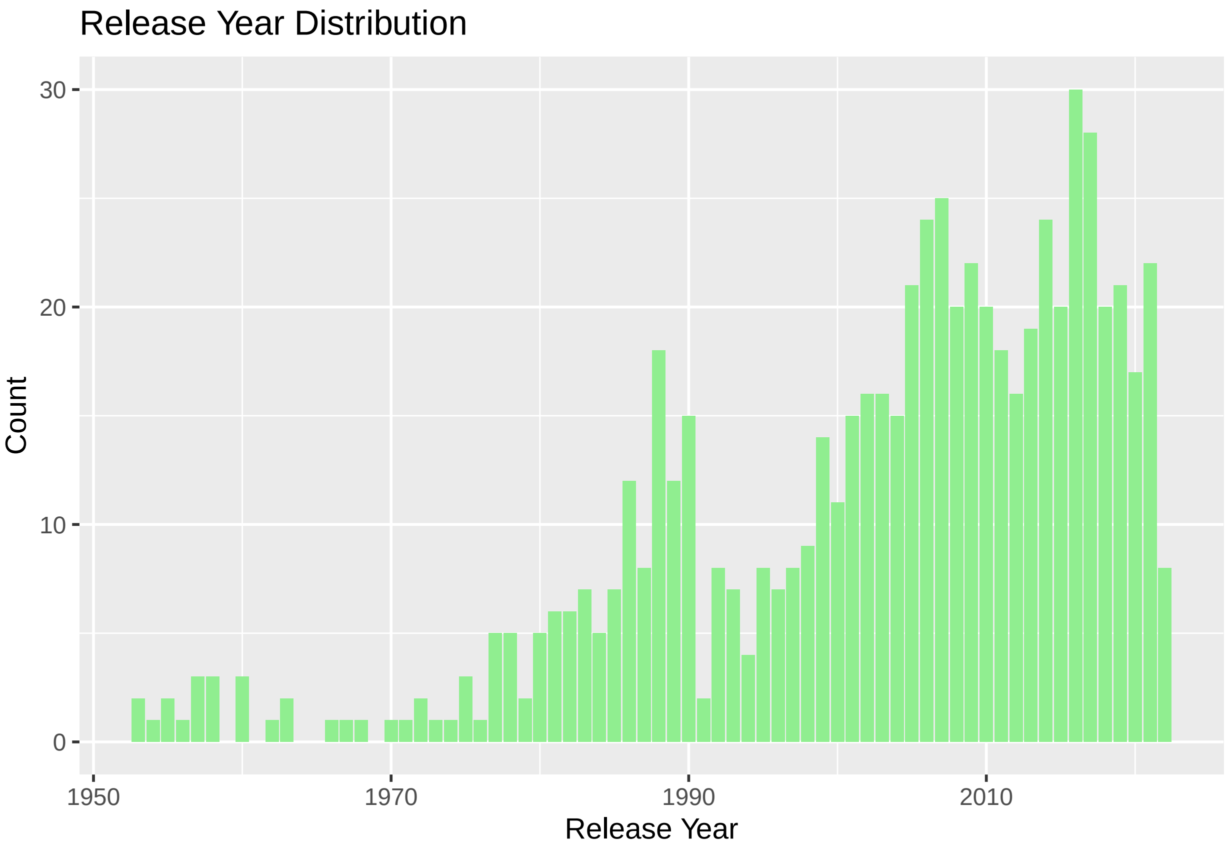
```
ggplot(training, aes(x = runtime, fill = budget_category)) +
  geom_density(alpha = 0.5) +
  labs(title = "Runtime by Budget Category", x = "Runtime", y = "Density")
```



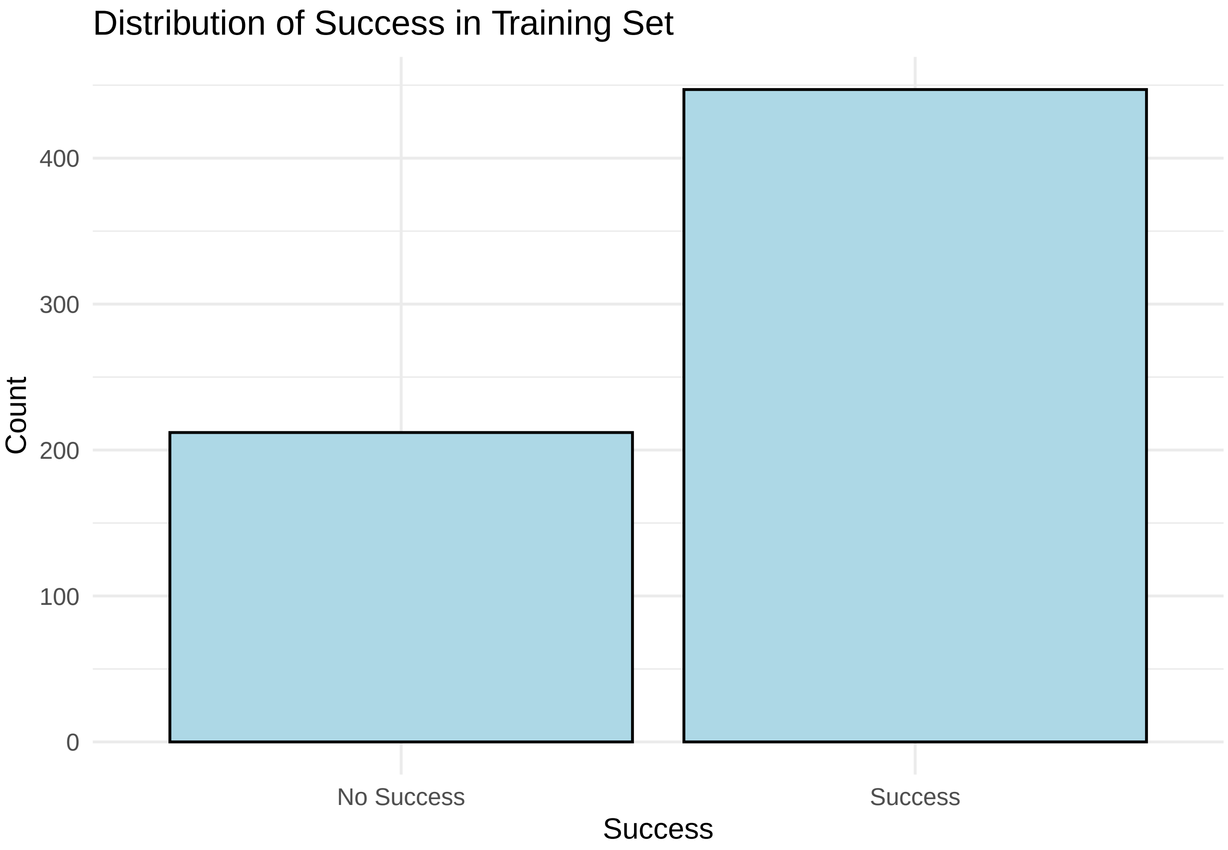
```r
ggplot(training, aes(x = vote_average)) +
  geom_density(fill = "lightblue") +
  labs(title = "Density of Vote Average", x = "Vote Average", y = "Density")
```



```
ggplot(training, aes(x = release_year)) +
  geom_bar(fill = "lightgreen") +
  labs(title = "Release Year Distribution", x = "Release Year", y = "Count")
```



```r
ggplot(training, aes(x = success)) +
  geom_bar(fill = "lightblue", color = "black") +
  labs(title = "Distribution of Success in Training Set", x = "Success", y = "Count") +
  theme_minimal()
```



Classification with Emphasis on Prediction

Questions We Aim to Answer:

1. "How well can we predict a movie's revenue based on its budget, popularity, and release year?" (Regression)
2. Predicting popularity (Regression)
3. "Can we predict whether a movie will be profitable?" (QDA and LDA)
4. "Predicting success categories (hit, average, flop) (QDA and LDA)
5. Predicting Budget using logistic regression
6. Predicting whether a movie was a success or not is our main objective.

Normalizing the Data

We will normalize the data with the min-max normalization function which will later be split into training and testing and used for models that need normalized data.

```
# Columns to normalize
columns_to_normalize <- c("budget", "release_year", "runtime", "popularity")
# Min-max normalization function
min_max_normalize <- function(x) {
  (x - min(x, na.rm = TRUE)) / (max(x, na.rm = TRUE) - min(x, na.rm = TRUE))
}
# Create a copy of the original data frame
df_normal <- df_for_class
# Normalize only the specified columns
df_normal[columns_to_normalize] <- lapply(df_for_class[columns_to_normalize], min_max_normalize)
```

```r
# Check the structure to confirm normalization
str(df_normal)
```

```
## tibble [1,098 x 19] (S3: tbl_df/tbl/data.frame)
##  $ original_title   : chr [1:1098] "Smile" "The Black Phone" "Jeepers Creepers: Reborn" "Nope" ...
##  $ title            : chr [1:1098] "Smile" "The Black Phone" "Jeepers Creepers: Reborn" "Nope" ...
##  $ original_language: Factor w/ 97 levels "af","am","ar",..: 19 19 19 19 19 19 19 19 19 19 ...
##  $ overview         : chr [1:1098] "After witnessing a bizarre, traumatic incident involving a patien
##  $ tagline          : chr [1:1098] "Once you see it, it's too late." "Never talk to strangers." "Evil
##  $ release_date     : Date[1:1098], format: "2022-09-23" "2022-06-22" ...
##  $ popularity       : num [1:1098] 1 0.575 0.441 0.393 0.291 ...
##  $ vote_count       : num [1:1098] 114 2736 125 1684 1035 ...
##  $ vote_average     : num [1:1098] 6.8 7.9 5.8 7 6.8 5.2 6.7 6.7 7 4.9 ...
##  $ budget           : num [1:1098] 0.085 0.094 0.1 0.34 0.05 ...
##  $ revenue          : num [1:1098] 4.50e+07 1.61e+08 2.89e+06 1.71e+08 1.43e+07 ...
##  $ runtime          : num [1:1098] 0.642 0.575 0.492 0.726 0.592 ...
##  $ status           : Factor w/ 4 levels "In Production",..: 4 4 4 4 4 4 4 4 4 4 ...
##  $ adult            : logi [1:1098] FALSE FALSE FALSE FALSE FALSE FALSE ...
##  $ genre_names      : Factor w/ 772 levels "Action, Adventure, Animation, Comedy, Drama, Fantasy, Hor
##  $ release_year     : num [1:1098] 1 1 1 1 1 ...
##  $ budget_category  : chr [1:1098] "Medium" "Medium" "Medium" "High" ...
##  $ profit           : num [1:1098] 28000000 142200000 -17107406 102800000 4257609 ...
##  $ success          : Factor w/ 2 levels "No Success","Success": 2 2 1 2 2 1 2 2 2 1 ...
```

Splitting training and testing for normalized data

```r
in_train_n <- createDataPartition(df_normal$budget_category, p = 0.6, list = FALSE)
training_n <- df_normal[in_train, ]
testing_n <- df_normal[-in_train, ]

nrow(training_n)
```

```
## [1] 659
```

```r
nrow(testing_n)
```

```
## [1] 439
```

```r
summary(training_n)
```

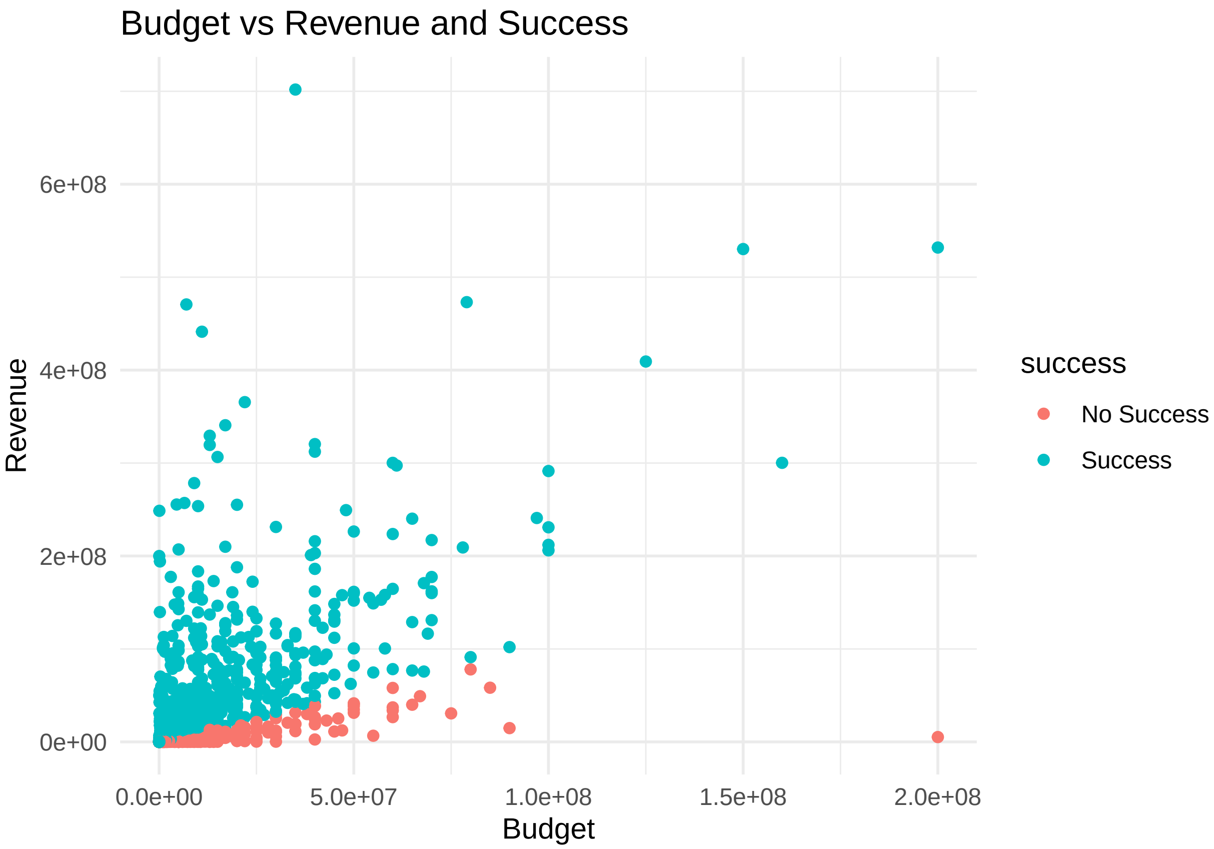
```
##  original_title        title           original_language   overview        
##  Length:659         Length:659         en     :560       Length:659        
##  Class :character   Class :character   ja     : 16       Class :character  
##  Mode  :character   Mode  :character   es     : 14       Mode  :character  
##                                        hi     : 14                         
##                                        ko     : 10                         
##                                        de     :  8                         
##                                        (Other): 37                         
##    tagline           release_date         popularity          vote_count     
##  Length:659         Min.   :1953-06-05   Min.   :0.000000   Min.   :    0.0  
##  Class :character   1st Qu.:1994-12-12   1st Qu.:0.003535   1st Qu.:   98.5  
##  Mode  :character   Median :2007-01-19   Median :0.008006   Median :  543.0  
##                     Mean   :2003-08-09   Mean   :0.014176   Mean   : 1206.6  
##                     3rd Qu.:2015-01-28   3rd Qu.:0.016334   3rd Qu.: 1544.5  
##                     Max.   :2022-09-29   Max.   :0.574762   Max.   :16900.0  
```

```
##
##   vote_average        budget           revenue             runtime
##  Min.   : 0.000   Min.   :0.00000   Min.   :        1   Min.   :0.0000
##  1st Qu.: 5.300   1st Qu.:0.00500   1st Qu.:   675326   1st Qu.:0.4888
##  Median : 6.000   Median :0.02500   Median : 11642254   Median :0.5307
##  Mean   : 5.797   Mean   :0.06385   Mean   : 39044327   Mean   :0.5089
##  3rd Qu.: 6.600   3rd Qu.:0.07500   3rd Qu.: 45023606   3rd Qu.:0.5754
##  Max.   :10.000   Max.   :1.00000   Max.   :701842551   Max.   :0.8547
##
##              status      adult                            genre_names
##  In Production  :  0   Mode :logical   Horror, Thriller         :103
##  Planned        :  0   FALSE:659       Horror                   : 99
##  Post Production:  0                   Horror, Mystery, Thriller: 52
##  Released       :659                   Comedy, Horror           : 36
##                                        Horror, Science Fiction  : 29
##                                        Drama, Horror, Thriller  : 27
##                                        (Other)                  :313
##   release_year    budget_category        profit                success
##  Min.   :0.0000   Length:659         Min.   :-194775779   No Success:212
##  1st Qu.:0.6014   Class :character   1st Qu.:    -99162   Success   :447
##  Median :0.7826   Mode  :character   Median :   3400000
##  Mean   :0.7259                      Mean   :  26275179
##  3rd Qu.:0.8986                      3rd Qu.:  30288153
##  Max.   :1.0000                      Max.   : 666842551
##
```

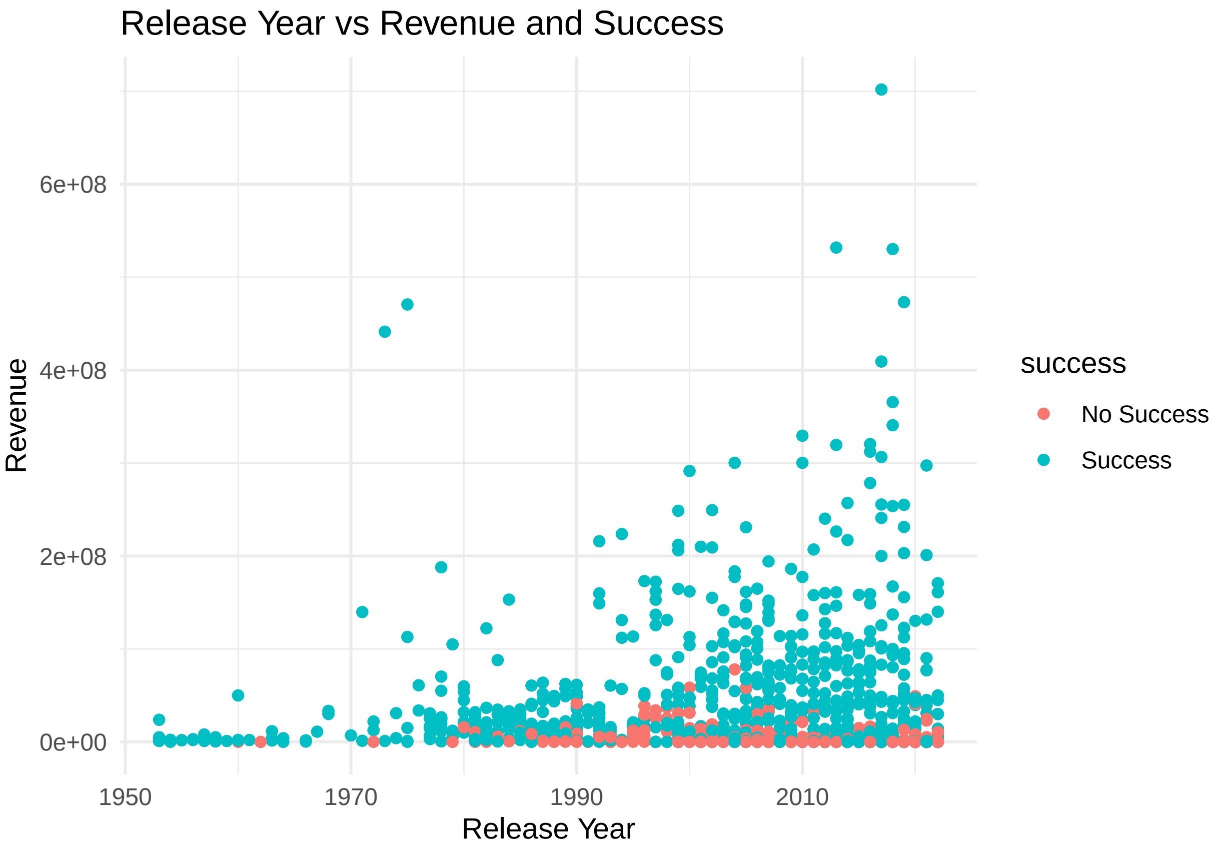
Visualizing the Relationships

We will visualize the relationships between the variables we chose to use to revenue, colored by success.

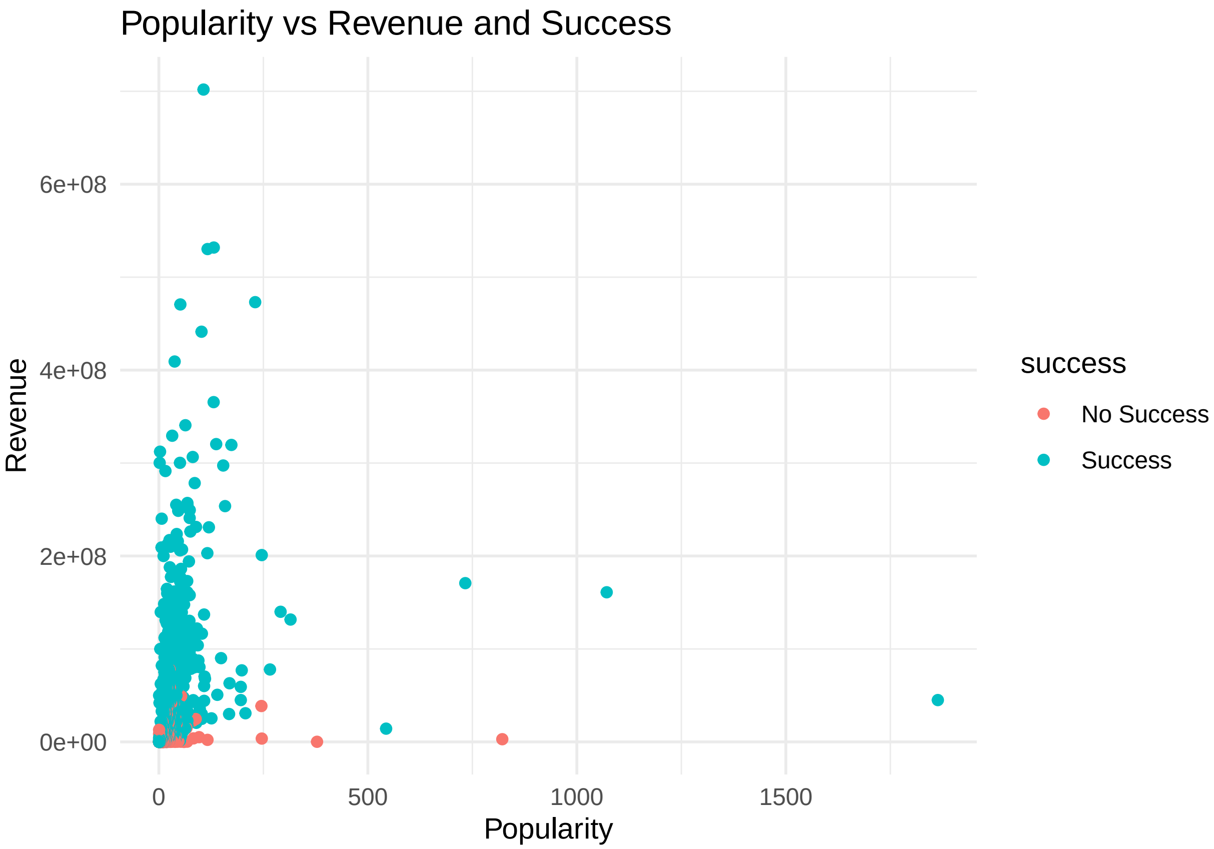
```
library(ggplot2)

ggplot(df_for_class, aes(x = budget, y = revenue, color = success)) +
  geom_point() +
  labs(title = "Budget vs Revenue and Success", x = "Budget", y = "Revenue") +
  theme_minimal()
```



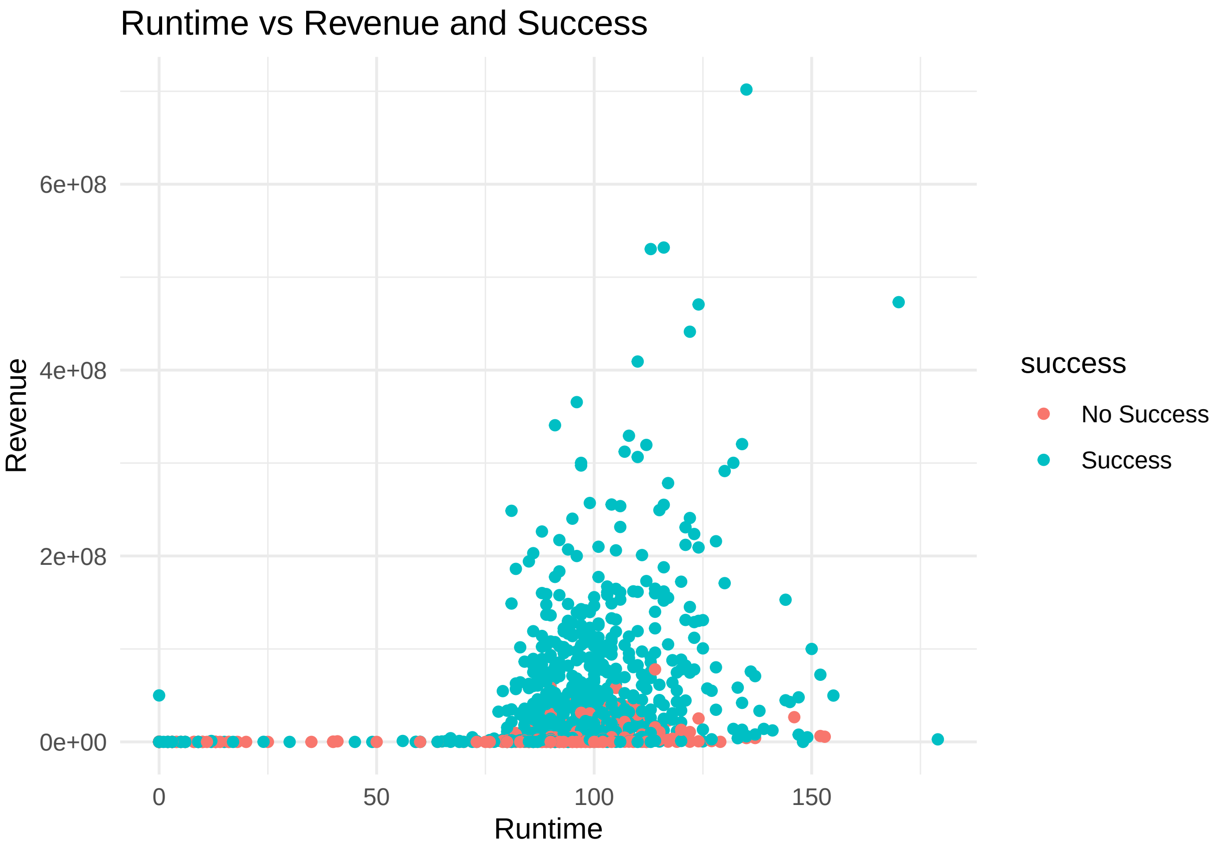
```
ggplot(df_for_class, aes(x = release_year, y = revenue, color = success)) +
  geom_point() +
  labs(title = "Release Year vs Revenue and Success", x = "Release Year", y = "Revenue") +
  theme_minimal()
```



```r
ggplot(df_for_class, aes(x = popularity, y = revenue, color = success)) +
  geom_point() +
  labs(title = "Popularity vs Revenue and Success", x = "Popularity", y = "Revenue") +
  theme_minimal()
```



```r
ggplot(df_for_class, aes(x = runtime, y = revenue, color = success)) +
  geom_point() +
  labs(title = "Runtime vs Revenue and Success", x = "Runtime", y = "Revenue") +
  theme_minimal()
```



Classifying Success with LDA:

Training the model

```
lda_model <- lda(success ~ budget + release_year + runtime + popularity, data = training_n)
lda_model
```

```
## Call:
## lda(success ~ budget + release_year + runtime + popularity, data = training_n)
##
## Prior probabilities of groups:
## No Success    Success
##  0.3216995  0.6783005
##
## Group means:
##                 budget release_year   runtime  popularity
## No Success 0.05370571    0.7686628 0.4738326 0.006290148
## Success    0.06865487    0.7056058 0.5254771 0.017916457
##
## Coefficients of linear discriminants:
##                    LD1
## budget        1.005574
## release_year -2.732860
## runtime       2.633095
## popularity   23.712963
```

Predicting

We will first predict success categories and then add the predictions to the LDA dataset for visualizing the predictions.

```r
lda_predictions <- predict(lda_model, newdata = testing_n)$class

prediction_counts_lda <- table(lda_predictions)
print(prediction_counts_lda)
```

```
## lda_predictions
## No Success    Success
##         35        404
```

Evaluating the Model

We will use the confusion matrix and accuracy calculations to show the accuracy of the model.

```r
confusion_matrix_lda <- table(Predicted = lda_predictions, Actual = testing_n$success)
print(confusion_matrix_lda)
```

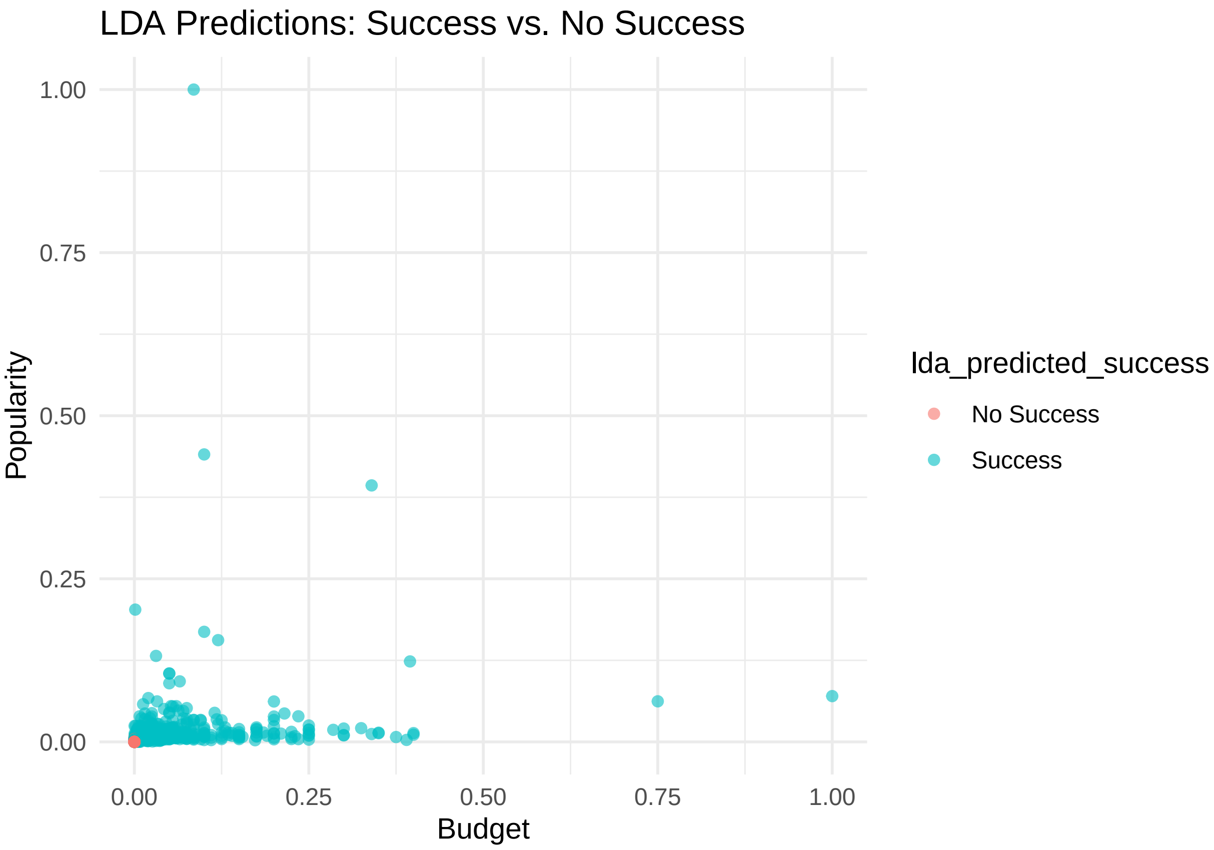
```
##             Actual
## Predicted    No Success Success
##   No Success         19      16
##   Success           134     270
```

```r
accuracy_lda <- sum(lda_predictions == testing_n$success) / length(lda_predictions)
print(paste("Accuracy: ", round(accuracy_lda * 100, 4), "%"))
```

```
## [1] "Accuracy:  65.8314 %"
```

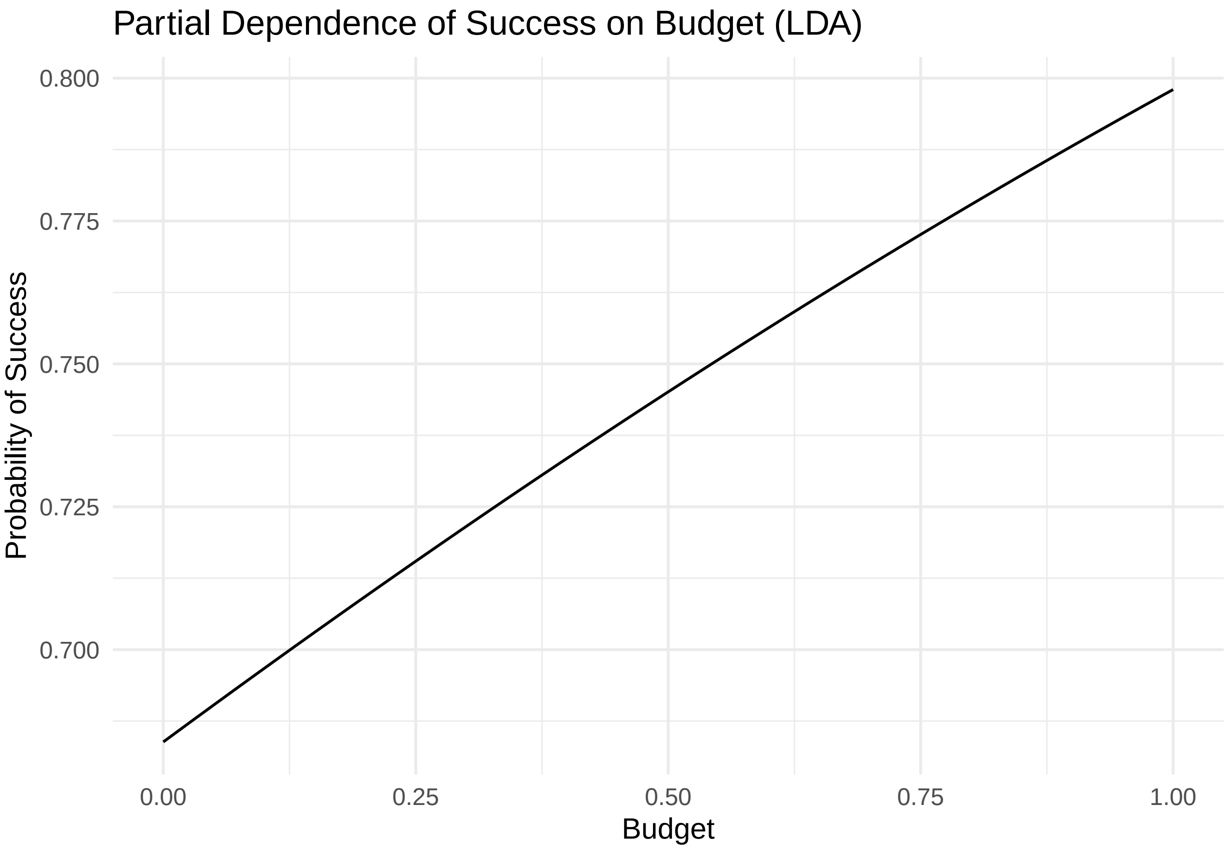
Visualizing Decision Boundaries

```r
testing_n$lda_predicted_success <- lda_predictions

library(ggplot2)
ggplot(testing_n, aes(x = budget, y = popularity, color = lda_predicted_success)) +
  geom_point(alpha = 0.6) +
  labs(title = "LDA Predictions: Success vs. No Success", x = "Budget", y = "Popularity") +
  theme_minimal()
```

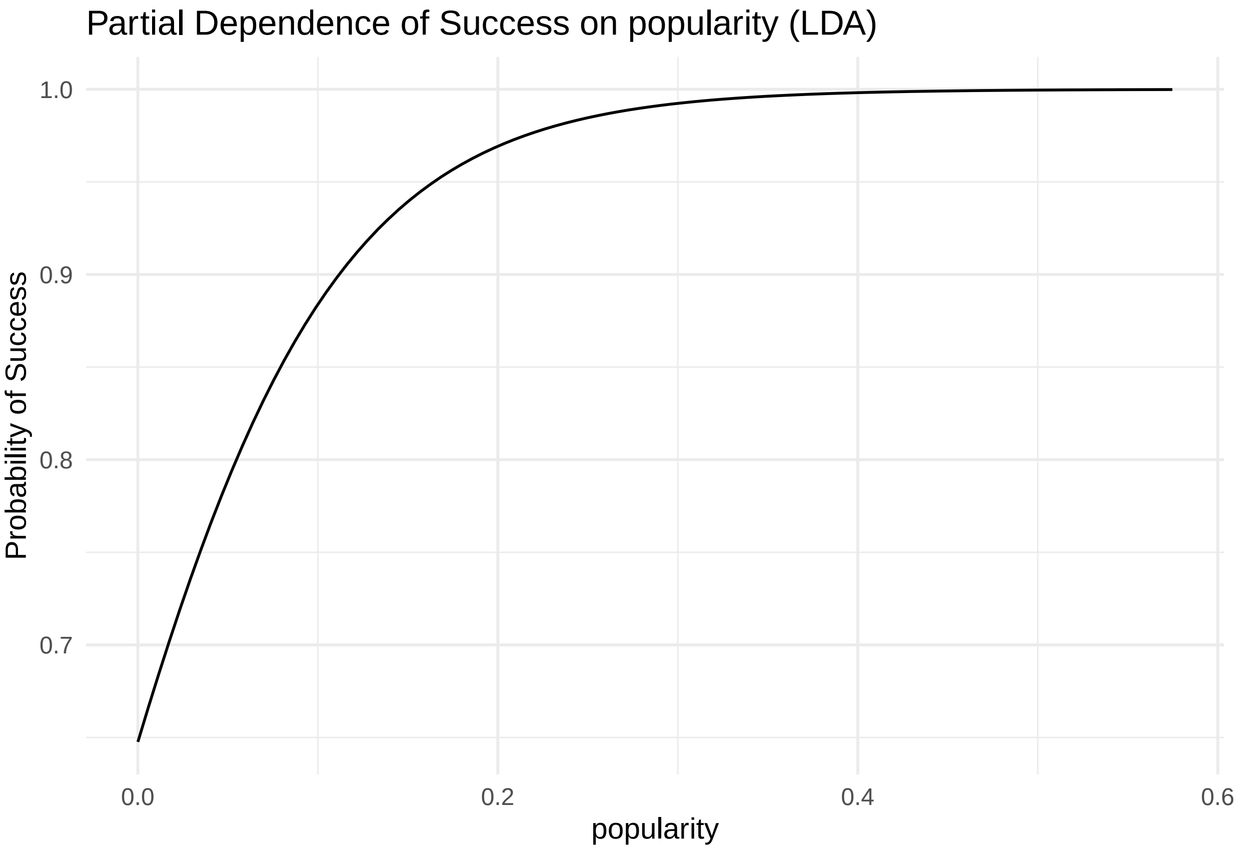


PDP

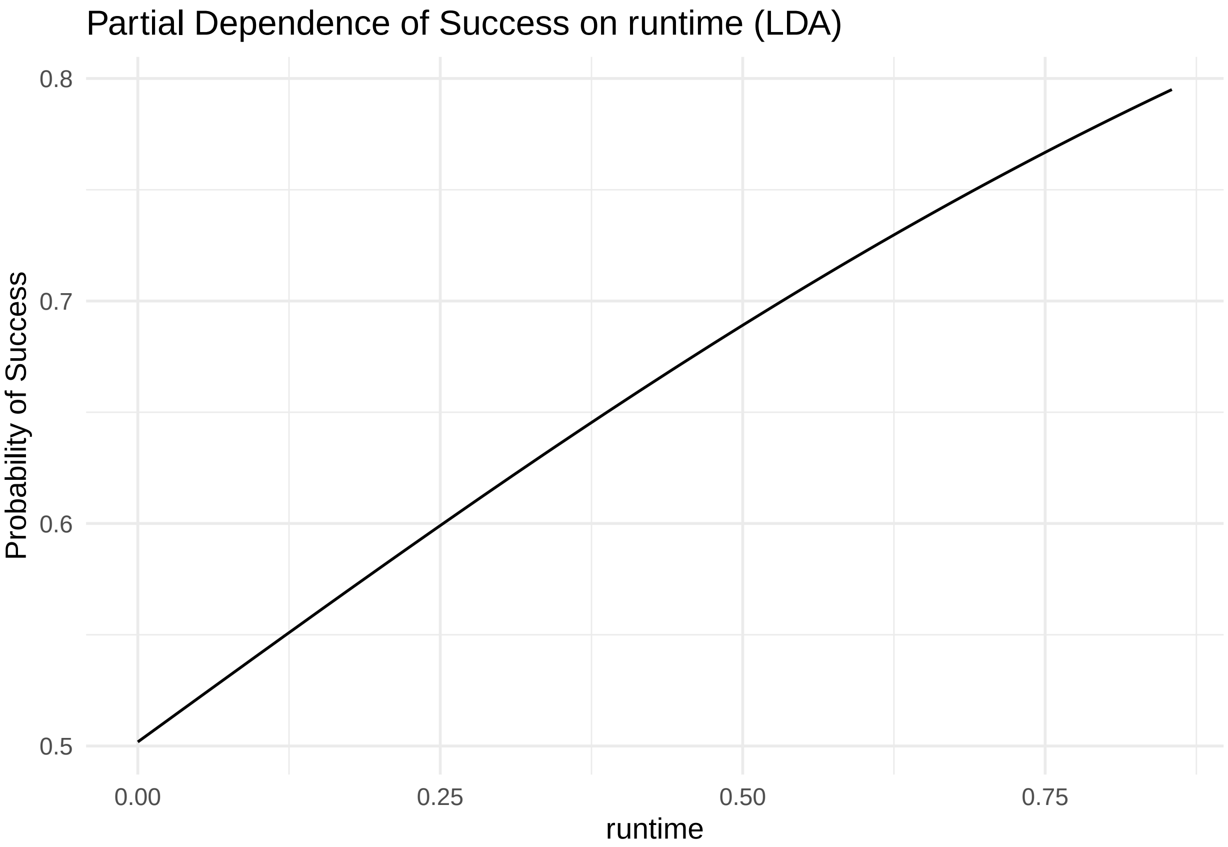
```
budget_range <- seq(from = min(training_n$budget, na.rm = TRUE),
                    to = max(training_n$budget, na.rm = TRUE),
                    length.out = 100)

pdp_data <- data.frame(
  budget = budget_range,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100)
)

pred_probs <- predict(lda_model, newdata = pdp_data, type = "response")$posterior[,2]

pdp_data$success_probability <- pred_probs

ggplot(pdp_data, aes(x = budget, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on Budget (LDA)",
       x = "Budget",
       y = "Probability of Success") +
  theme_minimal()
```



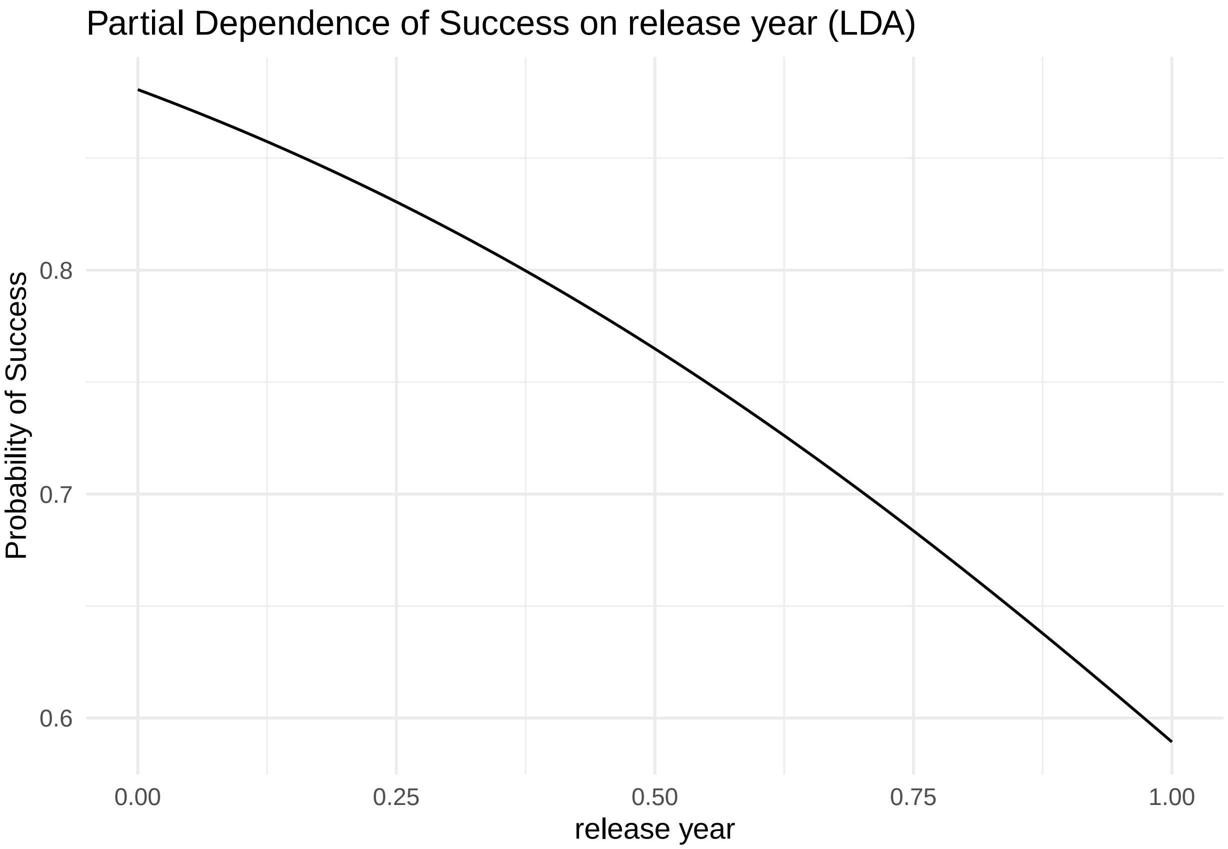
```r
pop_range <- seq(from = min(training_n$popularity, na.rm = TRUE),
                    to = max(training_n$popularity, na.rm = TRUE),
                    length.out = 100)

pdp_data2 <- data.frame(
  popularity = pop_range,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs2 <- predict(lda_model, newdata = pdp_data2, type = "response")$posterior[,2]

pdp_data2$success_probability <- pred_probs2

ggplot(pdp_data2, aes(x = popularity, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on popularity (LDA)",
       x = "popularity",
       y = "Probability of Success") +
  theme_minimal()
```



```
rt_range <- seq(from = min(training_n$runtime, na.rm = TRUE),
                    to = max(training_n$runtime, na.rm = TRUE),
                    length.out = 100)

pdp_data3 <- data.frame(
  runtime = rt_range,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs3 <- predict(lda_model, newdata = pdp_data3, type = "response")$posterior[,2]

pdp_data3$success_probability <- pred_probs3

ggplot(pdp_data3, aes(x = runtime, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on runtime (LDA)",
       x = "runtime",
       y = "Probability of Success") +
  theme_minimal()
```



```r
ry_range <- seq(from = min(training_n$release_year, na.rm = TRUE),
                    to = max(training_n$release_year, na.rm = TRUE),
                    length.out = 100)

pdp_data4 <- data.frame(
  release_year = ry_range,
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs4 <- predict(lda_model, newdata = pdp_data4, type = "response")$posterior[,2]

pdp_data4$success_probability <- pred_probs4

ggplot(pdp_data4, aes(x = release_year, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on release year (LDA)",
       x = "release year",
       y = "Probability of Success") +
  theme_minimal()
```



Classifying Success with QDA

Training the model

```
qda_model = qda(success ~ budget + release_year + runtime + popularity, data = training_n)

qda_model
```

```
## Call:
## qda(success ~ budget + release_year + runtime + popularity, data = training_n)
##
## Prior probabilities of groups:
## No Success    Success
##  0.3216995  0.6783005
##
## Group means:
##                budget release_year   runtime  popularity
## No Success 0.05370571    0.7686628 0.4738326 0.006290148
## Success    0.06865487    0.7056058 0.5254771 0.017916457
```

Predicting

```
qda_predictions = predict(qda_model, newdata = testing_n)$class

prediction_counts_qda <- table(qda_predictions)
print(prediction_counts_qda)
```

```
## qda_predictions
## No Success    Success
##        246        193
```

Evaluating the Model

We will use the confusion matrix and accuracy calculations to show the accuracy of the model.

```r
confusion_matrix_qda <- table(Predicted = qda_predictions, Actual = testing_n$success)
print(confusion_matrix_qda)
```

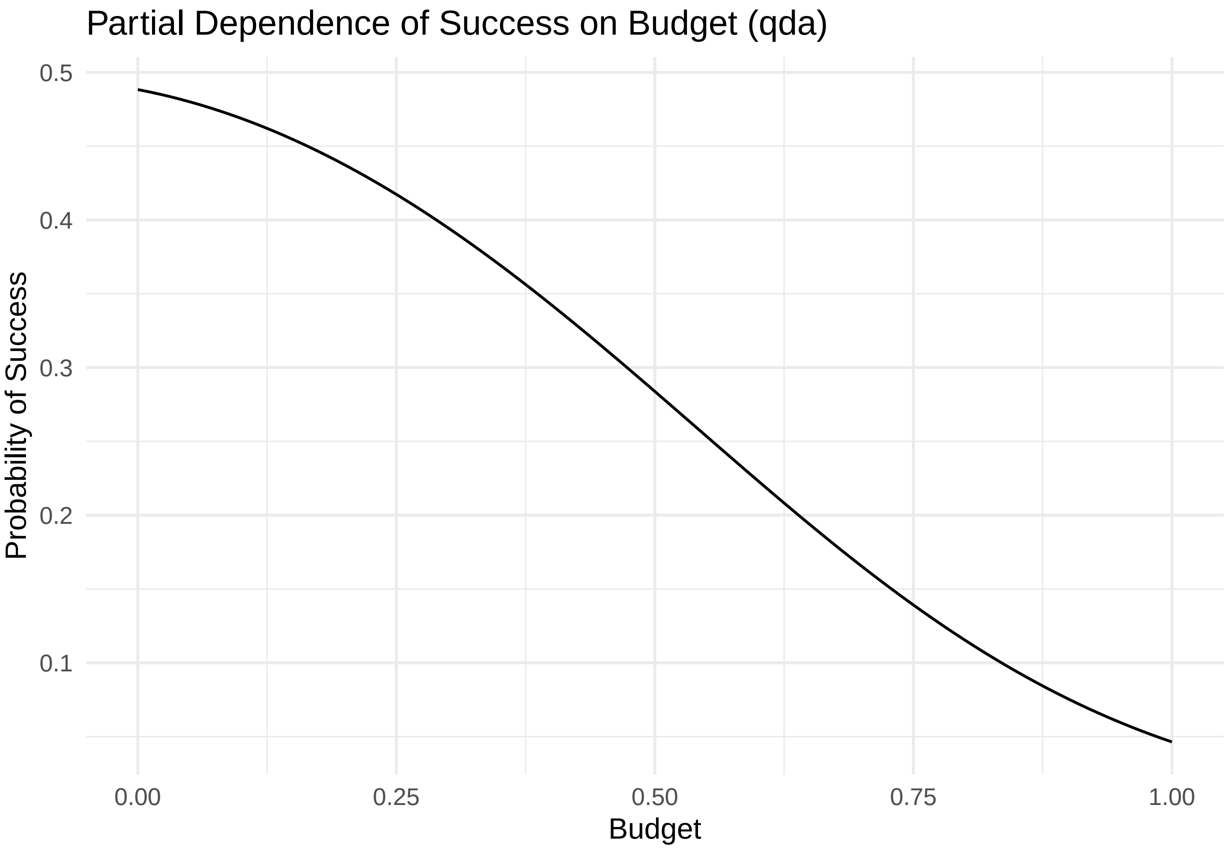
```
##               Actual
## Predicted     No Success Success
##    No Success        117     129
##    Success            36     157
```

```r
accuracy_qda <- sum(qda_predictions == testing_n$success) / length(qda_predictions)
print(paste("Accuracy: ", round(accuracy_qda * 100, 4), "%"))
```

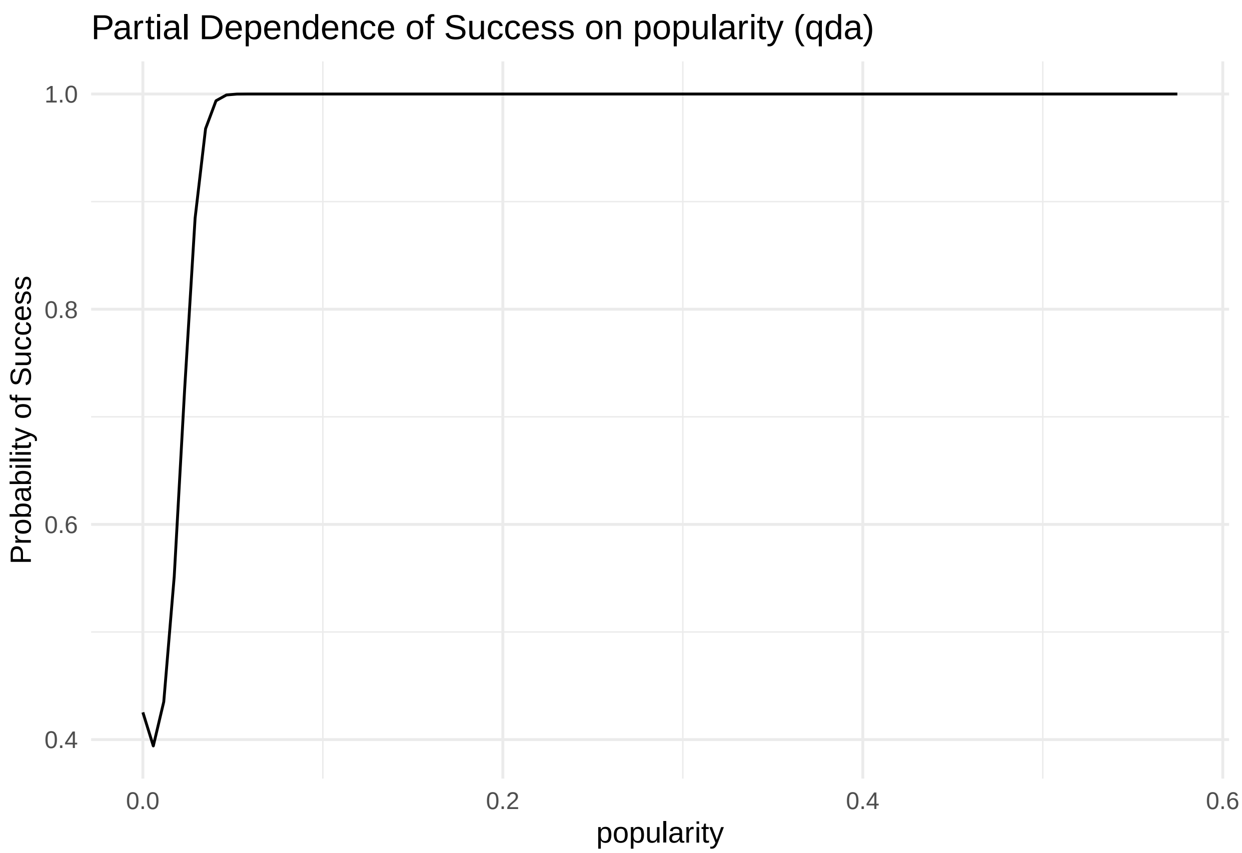
```
## [1] "Accuracy:  62.4146 %"
```

PDP

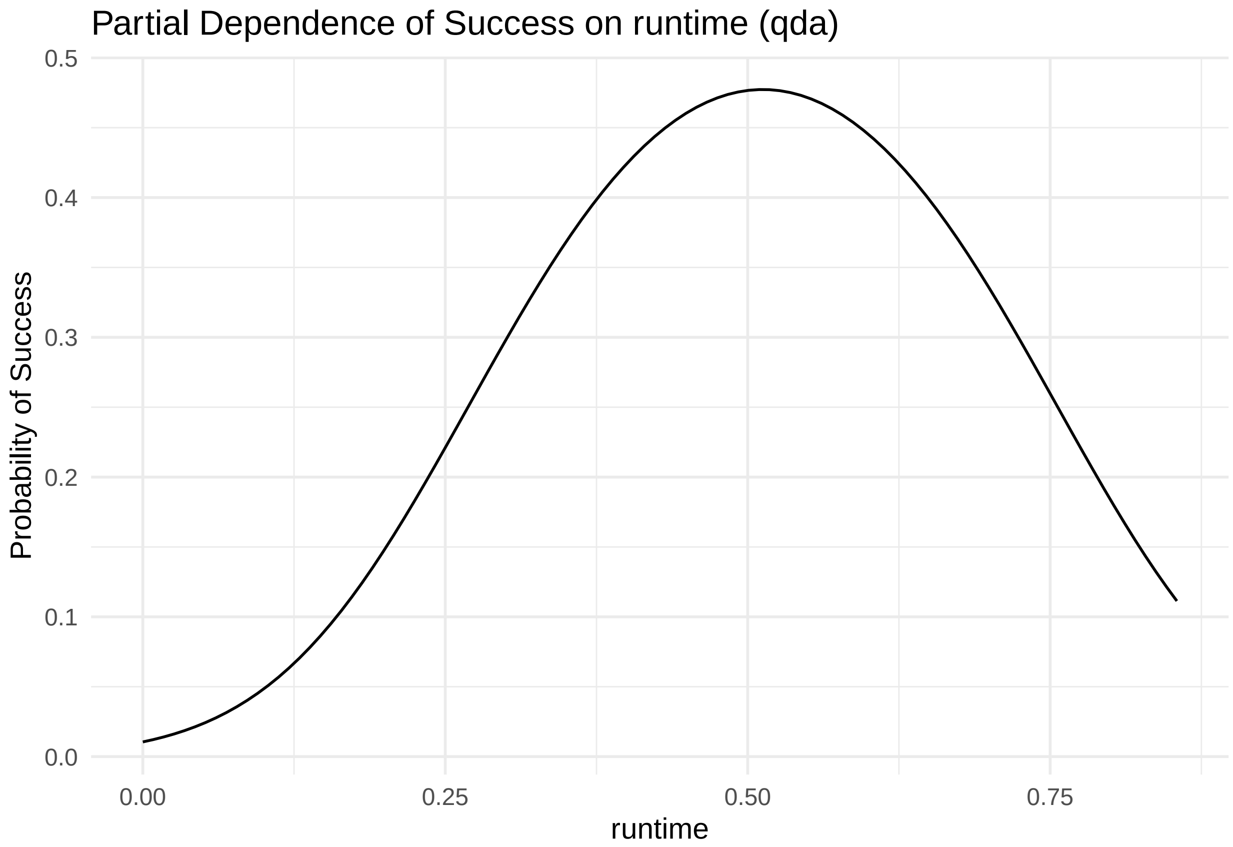
```r
budget_range_qda <- seq(from = min(training_n$budget, na.rm = TRUE),
                    to = max(training_n$budget, na.rm = TRUE),
                    length.out = 100)

pdp_data_qda <- data.frame(
  budget = budget_range_qda,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100)
)

pred_probs_qda <- predict(qda_model, newdata = pdp_data_qda, type = "response")$posterior[,2]

pdp_data_qda$success_probability <- pred_probs_qda

ggplot(pdp_data_qda, aes(x = budget, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on Budget (qda)",
       x = "Budget",
       y = "Probability of Success") +
  theme_minimal()
```



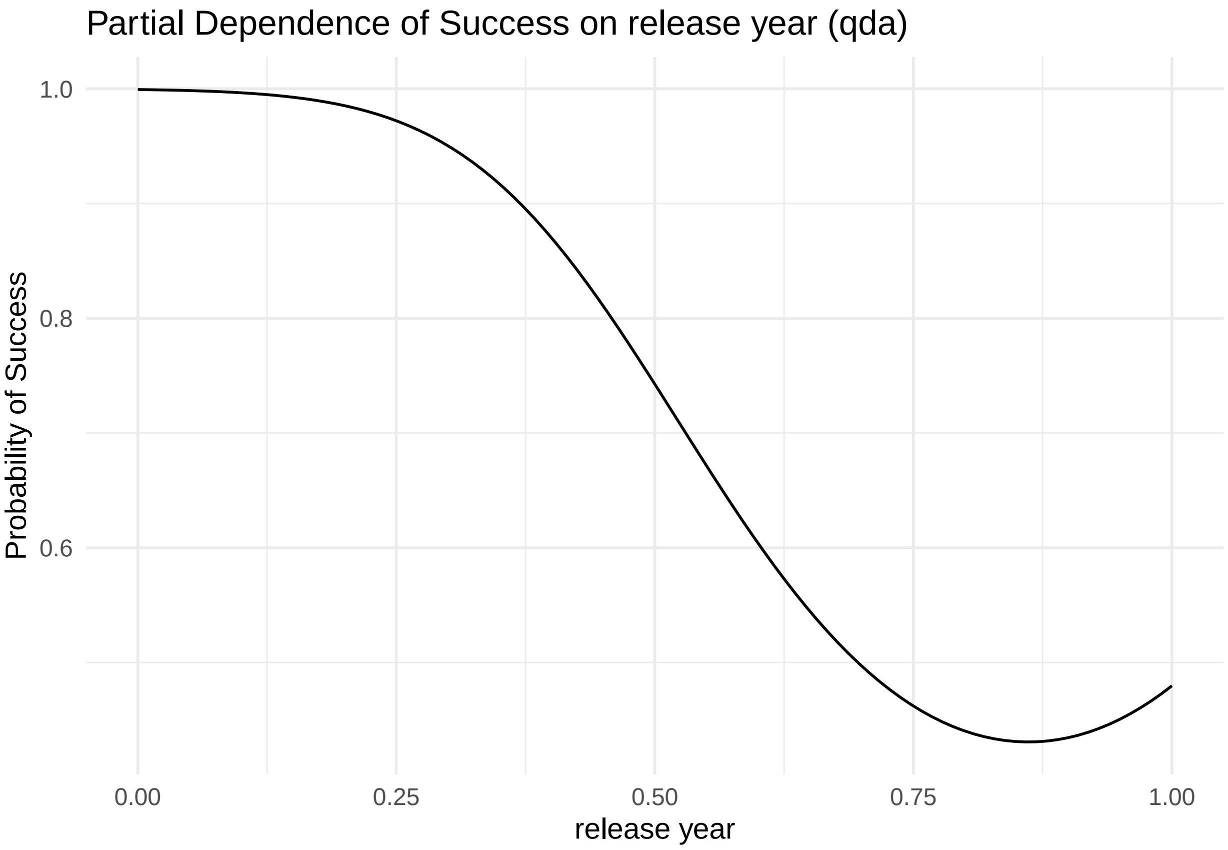
```r
pop_range_qda <- seq(from = min(training_n$popularity, na.rm = TRUE),
                     to = max(training_n$popularity, na.rm = TRUE),
                     length.out = 100)

pdp_data2_qda <- data.frame(
  popularity = pop_range_qda,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs2_qda <- predict(qda_model, newdata = pdp_data2_qda, type = "response")$posterior[,2]

pdp_data2_qda$success_probability <- pred_probs2_qda

ggplot(pdp_data2_qda, aes(x = popularity, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on popularity (qda)",
       x = "popularity",
       y = "Probability of Success") +
  theme_minimal()
```



```
rt_range_qda <- seq(from = min(training_n$runtime, na.rm = TRUE),
                    to = max(training_n$runtime, na.rm = TRUE),
                    length.out = 100)

pdp_data3_qda <- data.frame(
  runtime = rt_range_qda,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs3_qda <- predict(qda_model, newdata = pdp_data3_qda, type = "response")$posterior[,2]

pdp_data3_qda$success_probability <- pred_probs3_qda

ggplot(pdp_data3_qda, aes(x = runtime, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on runtime (qda)",
       x = "runtime",
       y = "Probability of Success") +
  theme_minimal()
```



```
ry_range_qda <- seq(from = min(training_n$release_year, na.rm = TRUE),
                    to = max(training_n$release_year, na.rm = TRUE),
                    length.out = 100)

pdp_data4_qda <- data.frame(
  release_year = ry_range_qda,
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs4_qda <- predict(qda_model, newdata = pdp_data4, type = "response")$posterior[,2]

pdp_data4_qda$success_probability <- pred_probs4_qda

ggplot(pdp_data4_qda, aes(x = release_year, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on release year (qda)",
       x = "release year",
       y = "Probability of Success") +
  theme_minimal()
```



Classifying Success with Naive Bayes:

Naive Bayes is a probabilistic model based on Bayes' Theorem. The model assumes that the features are conditionally independent given the target variable, success.

Training the Model

```
nb_model <- naiveBayes(success ~ budget + release_year + runtime + popularity, data = training)

print(nb_model)
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
## No Success    Success
##  0.3216995  0.6783005
##
## Conditional probabilities:
##             budget
## Y                 [,1]     [,2]
##   No Success 10741143 19918339
##   Success    13730975 19930261
```

```
##
##              release_year
## Y                [,1]     [,2]
##   No Success 2006.038 11.47751
##   Success    2001.687 15.63314
##
##              runtime
## Y                [,1]     [,2]
##   No Success 84.81604 32.49614
##   Success    94.06040 22.54887
##
##              popularity
## Y                [,1]     [,2]
##   No Success 12.31872 20.38792
##   Success    33.97886 64.34544
```

Predicting

```r
predictions_nb <- predict(nb_model, testing)

predictions_nb_counts <- table(predictions_nb)
print(predictions_nb_counts)
```

```
## predictions_nb
## No Success    Success
##        223        216
```

Evaluating the Model

We will use a confusion matrix to show model accuracy.

```r
confusion_matrix_nb <- table(Predicted_NB = predictions_nb, Actual = testing$success)
print(confusion_matrix_nb)
```

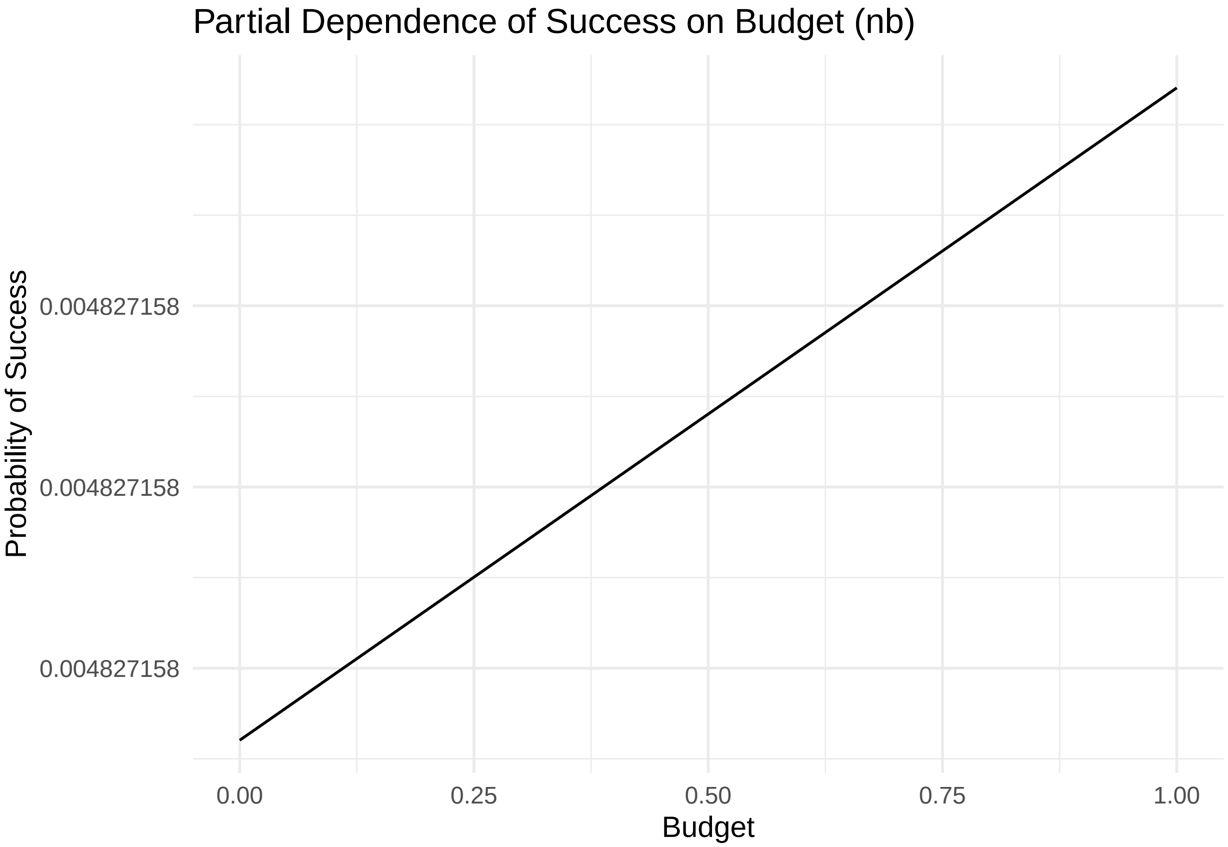
```
##              Actual
## Predicted_NB No Success Success
##   No Success        107     116
##   Success            46     170
```

```r
accuracy_nb <- sum(predictions_nb == testing$success) / nrow(testing)
print(paste("Accuracy: ", round(accuracy_nb *100, 4), "%"))
```

```
## [1] "Accuracy:  63.0979 %"
```

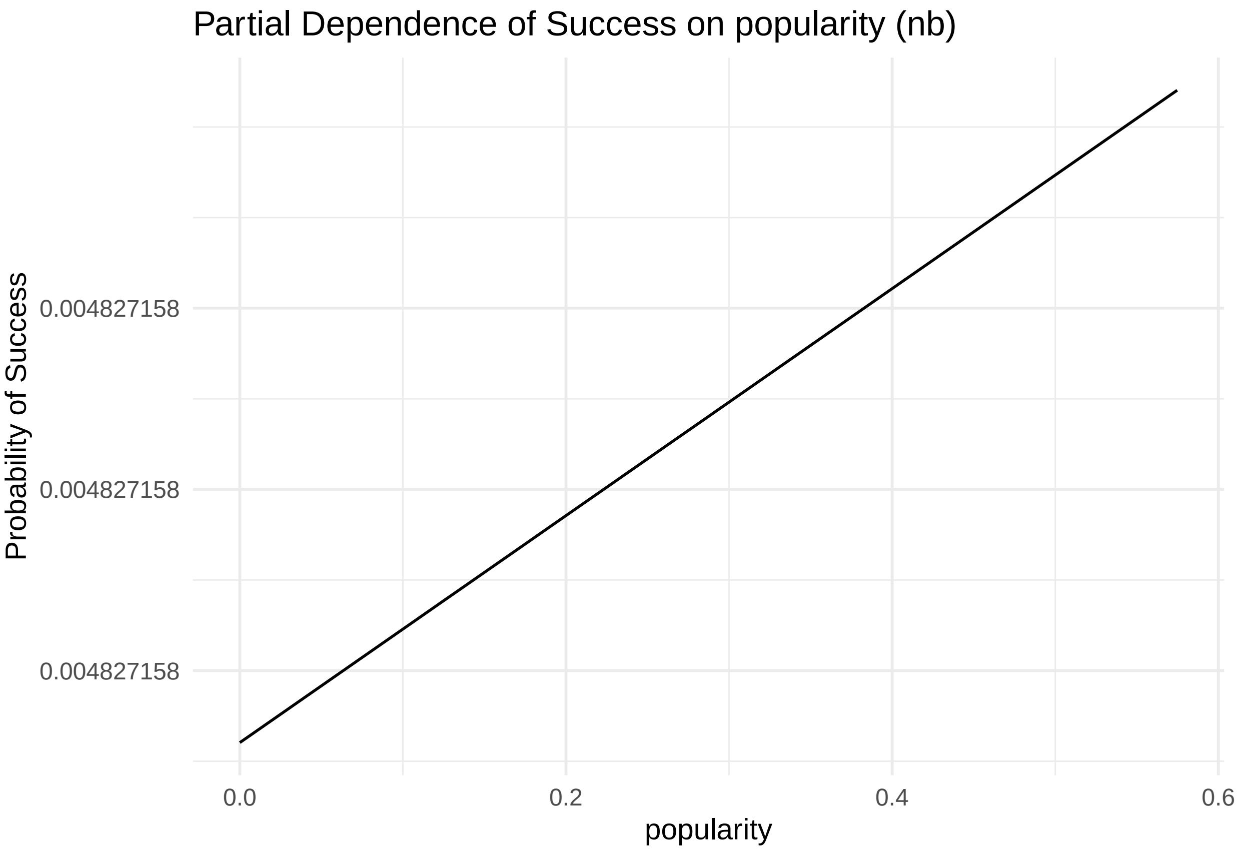
PDP

```r
budget_range_nb <- seq(from = min(training_n$budget, na.rm = TRUE),
                    to = max(training_n$budget, na.rm = TRUE),
                    length.out = 100)

pdp_data_nb <- data.frame(
  budget = budget_range_nb,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100)
)

pred_probs_nb <- predict(nb_model, newdata = pdp_data_nb, type = "raw")

success_probability <- pred_probs_nb[, 2]

pdp_data_nb$success_probability <- success_probability

ggplot(pdp_data_nb, aes(x = budget, y = success_probability)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on Budget (nb)",
       x = "Budget",
       y = "Probability of Success") +
  theme_minimal()
```



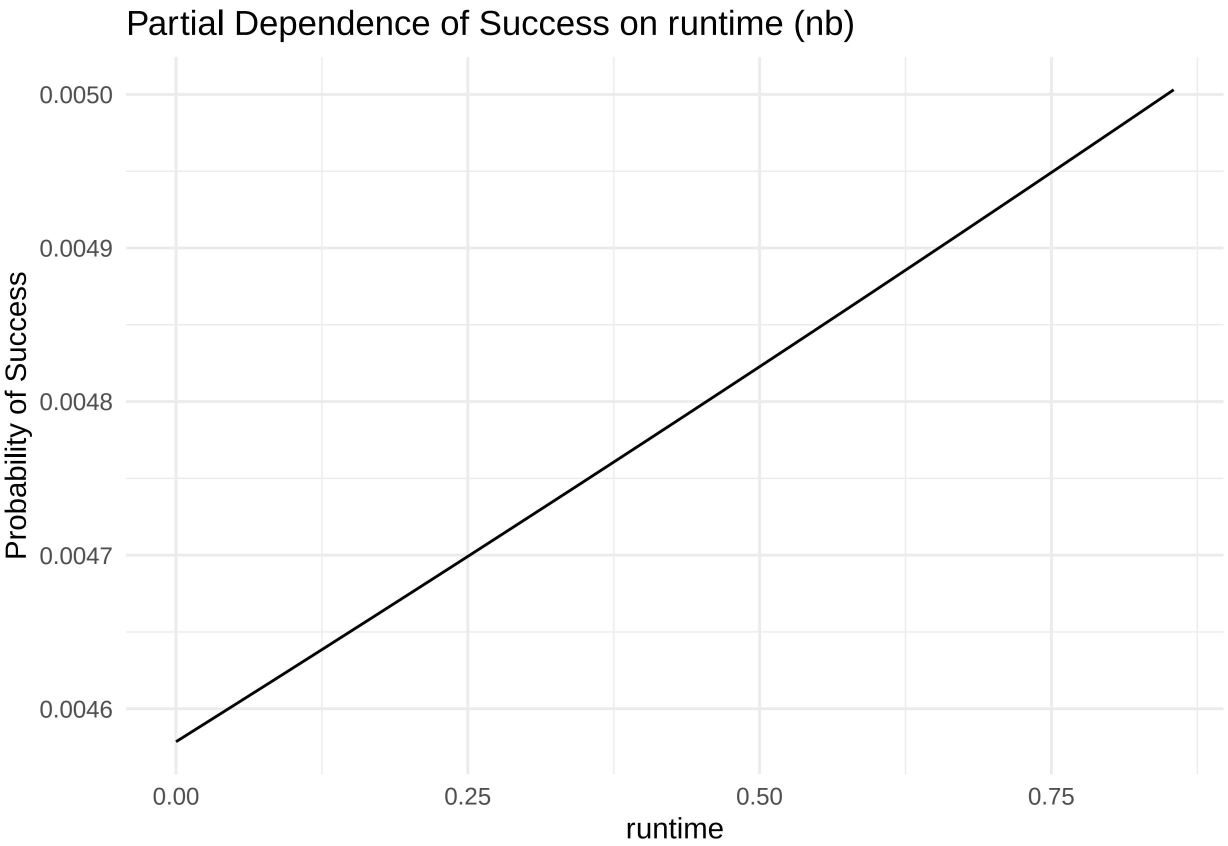
```
pop_range_nb <- seq(from = min(training_n$popularity, na.rm = TRUE),
                    to = max(training_n$popularity, na.rm = TRUE),
                    length.out = 100)

pdp_data2_nb <- data.frame(
  popularity = pop_range_nb,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs_nb2 <- predict(nb_model, newdata = pdp_data2_nb, type = "raw")
```

```
success_probability2 <- pred_probs_nb[, 2]

pdp_data2_nb$success_probability2 <- success_probability2

ggplot(pdp_data2_nb, aes(x = popularity, y = success_probability2)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on popularity (nb)",
       x = "popularity",
       y = "Probability of Success") +
  theme_minimal()
```

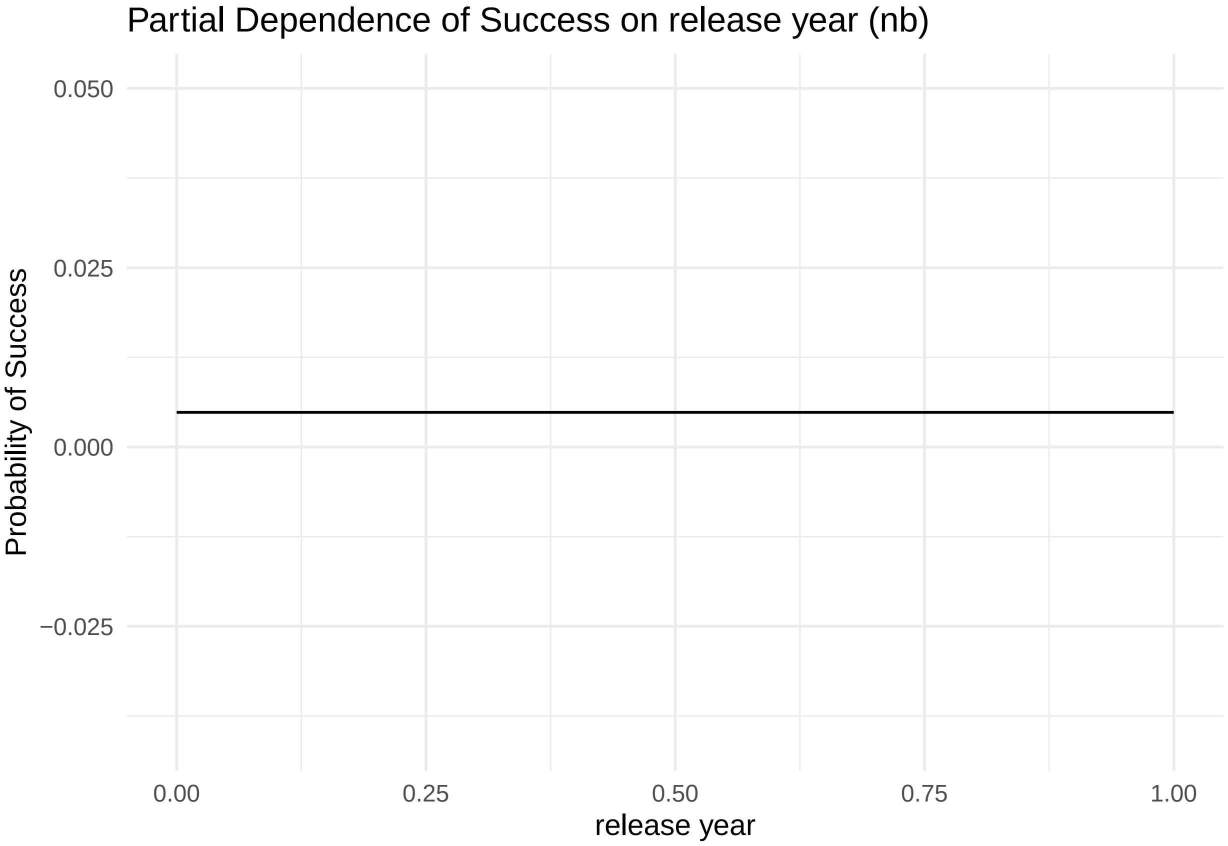


```
rt_range_nb <- seq(from = min(training_n$runtime, na.rm = TRUE),
                    to = max(training_n$runtime, na.rm = TRUE),
                    length.out = 100)

pdp_data3_nb <- data.frame(
  runtime = rt_range_nb,
  release_year = rep(mean(training_n$release_year, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs3_nb <- predict(nb_model, newdata = pdp_data3_nb, type = "raw")

success_probability3 <- pred_probs3_nb[, 2]
```

```r
pdp_data3_nb$success_probability3 <- success_probability3

ggplot(pdp_data3_nb, aes(x = runtime, y = success_probability3)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on runtime (nb)",
       x = "runtime",
       y = "Probability of Success") +
  theme_minimal()
```



```r
ry_range_nb <- seq(from = min(training_n$release_year, na.rm = TRUE),
                   to = max(training_n$release_year, na.rm = TRUE),
                   length.out = 100)

pdp_data4_nb <- data.frame(
  release_year = ry_range_nb,
  runtime = rep(mean(training_n$runtime, na.rm = TRUE), 100),
  popularity = rep(mean(training_n$popularity, na.rm = TRUE), 100),
  budget = rep(mean(training_n$budget, na.rm = TRUE), 100)
)

pred_probs4_nb <- predict(nb_model, newdata = pdp_data4_nb, type = "raw")

success_probability4 <- pred_probs4_nb[, 2]

pdp_data4_nb$success_probability4 <- success_probability4

ggplot(pdp_data4_nb, aes(x = release_year, y = success_probability4)) +
  geom_line() +
  labs(title = "Partial Dependence of Success on release year (nb)",
       x = "release year",
       y = "Probability of Success") +
  theme_minimal()
```



Classifying Success with Shrinkage:

Shrinkage methods we will use are Lasso and Ridge Regression. Lasso helps with feature selection and Ridge Regression helps with handling multicollinearity.

Ridge Regression

Ridge regression reduces variance in the presence of highly correlated predictors like budget and popularity, ensuring effective predictions. Although all predictors are kept, their coefficients are shrunk, reflecting their relative importance. For instance, popularity has a higher coefficient than the, indicating its stronger influence on predicting success. This is useful because some filmmakers may want a holistic view of all contributing factors, even those with smaller effects.

Training the Model We will fit the Ridge model with cross-validation to find the optimal lambda. Then, we will use that best lambda to train the model.

```r
library(glmnet)
```

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

```
##
## Attaching package: 'Matrix'
## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
```

```
## Loaded glmnet 4.1-8
```

```
x <- model.matrix(success ~ budget + release_year + runtime + popularity, data = training_n)[, -1]
y <- ifelse(training_n$success == "Success", 1, 0)

set.seed(123)
ridge_cv <- cv.glmnet(x, y, alpha = 0, family = "binomial")

best_lambda_ridge <- ridge_cv$lambda.min
print(paste("Optimal Lambda for Ridge Regression: ", best_lambda_ridge))
```

```
## [1] "Optimal Lambda for Ridge Regression:  0.00857571602237266"
```

```
ridge_model <- glmnet(x, y, alpha = 0, family = "binomial", lambda = best_lambda_ridge)
```

```


ridge_probabilities <- predict(ridge_model, newx = x, type = "response")

ridge_predictions <- ifelse(ridge_probabilities > 0.5, 1, 0)


ridge_prediction_counts <- table(ridge_predictions)
print(ridge_prediction_counts)
```

Predicting

```
## ridge_predictions
##   0   1
##  70 589
```

Evaluating the Model

We will use a confusion matrix to evaluate the model accuracy.

```
ridge_confusion_matrix <- table(Predicted = ridge_predictions, Actual = y)
print(ridge_confusion_matrix)
```

```
##          Actual
## Predicted   0   1
##         0  40  30
##         1 172 417
```

```
ridge_accuracy <- sum(ridge_predictions == y) / length(y)
print(paste("Accuracy of Ridge Regression: ", round(ridge_accuracy * 100, 4), "%"))
```

```
## [1] "Accuracy of Ridge Regression:  69.3475 %"
```

```
ridge_coefficients <- as.matrix(coef(ridge_model))
print(ridge_coefficients)
```

```
##                      s0
## (Intercept)   1.1558322
## budget       -0.3046535
## release_year -1.7238692
## runtime       0.6027949
## popularity   53.7195835
```

We can see that popularity has a coefficient of about 53.72, while the other variables have coefficients closer to 0. This shows that popularity has the biggest (positive) influence on predicting success. ###

Lasso Regression

Training the Model We will fit the Lasso model with cross-validation to find the optimal lambda. Then, using this best lambda we will train the Lasso model with it.

```
set.seed(123)
lasso_cv <- cv.glmnet(x, y, alpha = 1, family = "binomial")

best_lambda_lasso <- lasso_cv$lambda.min
print(paste("Optimal Lambda for Lasso Regression: ", best_lambda_lasso))
```

```
## [1] "Optimal Lambda for Lasso Regression:  0.000679610828887"
```

```
lasso_model <- glmnet(x, y, alpha = 1, family = "binomial", lambda = best_lambda_lasso)
```

Predicting We will use a threshold of 0.5 to classify a success or not.

```
lasso_probabilities <- predict(lasso_model, newx = x, type = "response")


lasso_predictions <- ifelse(lasso_probabilities > 0.5, 1, 0)

lasso_prediction_counts <- table(lasso_predictions)
print(lasso_prediction_counts)
```

```
## lasso_predictions
##   0   1
## 116 543
```

Evaluating the Model We will use a confusion matrix to evaluate the model accuracy.

```
lasso_confusion_matrix <- table(Predicted = lasso_predictions, Actual = y)
print(lasso_confusion_matrix)
```

```
##          Actual
## Predicted   0   1
##         0  60  56
##         1 152 391
```

```
lasso_accuracy <- sum(lasso_predictions == y) / length(y)
print(paste("Accuracy of Lasso Regression: ", round(lasso_accuracy * 100, 4), "%"))
```

```
## [1] "Accuracy of Lasso Regression:  68.437 %"
```

```
lasso_coefficients <- as.matrix(coef(lasso_model))
print(lasso_coefficients)
```

```
##                      s0
## (Intercept)   1.34153592
## budget       -0.89243201
## release_year -1.94555545
## runtime       0.06609342
## popularity   87.50579005
```

Lasso regression automatically sets some coefficients to zero, removing less important predictors like budget if they do not significantly contribute to the model. By focusing on a smaller set of predictors, Lasso provides a more interpretable model. Lasso confirms Ridge's output by also revealing that the coefficient for popularity is the largest, at about 87.51. This means that popularity has a strong positive relationship on predicting success. This helps filmmakers focus on the most influential factors, reducing unnecessary expenditures on less critical aspects to make a movie successful.

Classifying Success with Logistic Regression:

Objective is to predict whether a movie is successful using logistic regression based on budget, release year, runtime, and popularity.

Training the model

```
testing_lg = testing_n
training_lg = training_n

testing_lg$success <- ifelse(testing_lg$success == "Success", 1, 0)
training_lg$success <- ifelse(training_lg$success == "Success", 1, 0)

lg_model <- glm(success ~ budget + release_year + runtime + popularity,
                data = training_lg,
                family = "binomial")
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

Predicting:

```
probabilities_lg <- predict(lg_model, newdata = testing_lg, type = "response")

predictions_lg <- ifelse(probabilities_lg > 0.5, 1, 0)

prediction_lg_counts <- table(predictions_lg)
print(prediction_lg_counts)
```

```
## predictions_lg
##   0   1
##  78 361
```

Evaluating the model

```
confusion_matrix_lg <- table(Predicted = predictions_lg, Actual = testing_lg$success)
print(confusion_matrix_lg)
```

```
##          Actual
## Predicted   0   1
##         0  39  39
##         1 114 247
```

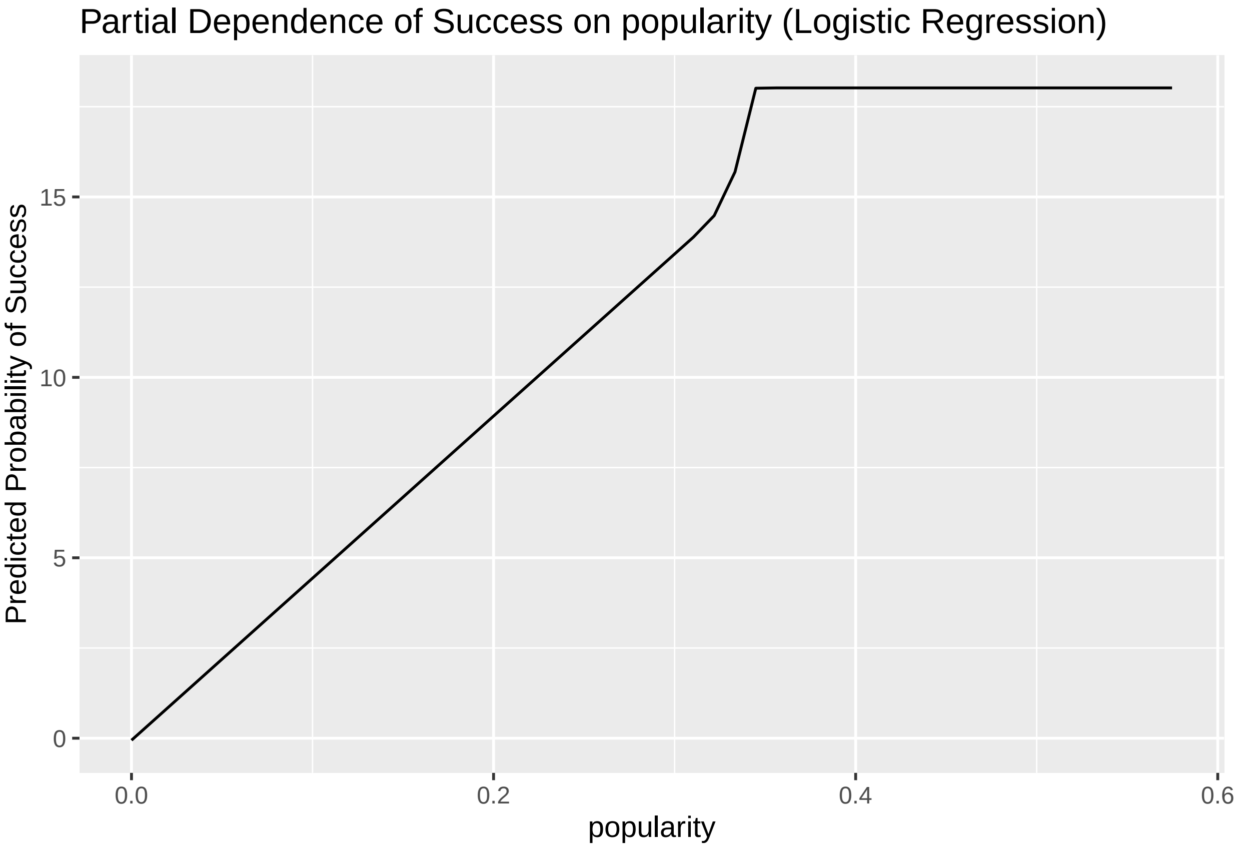
```
accuracy_lg <- sum(predictions_lg == testing_lg$success) / length(predictions_lg)
print(paste("Accuracy: ", round(accuracy_lg * 100, 4), "%"))
```

```
## [1] "Accuracy:  65.1481 %"
```

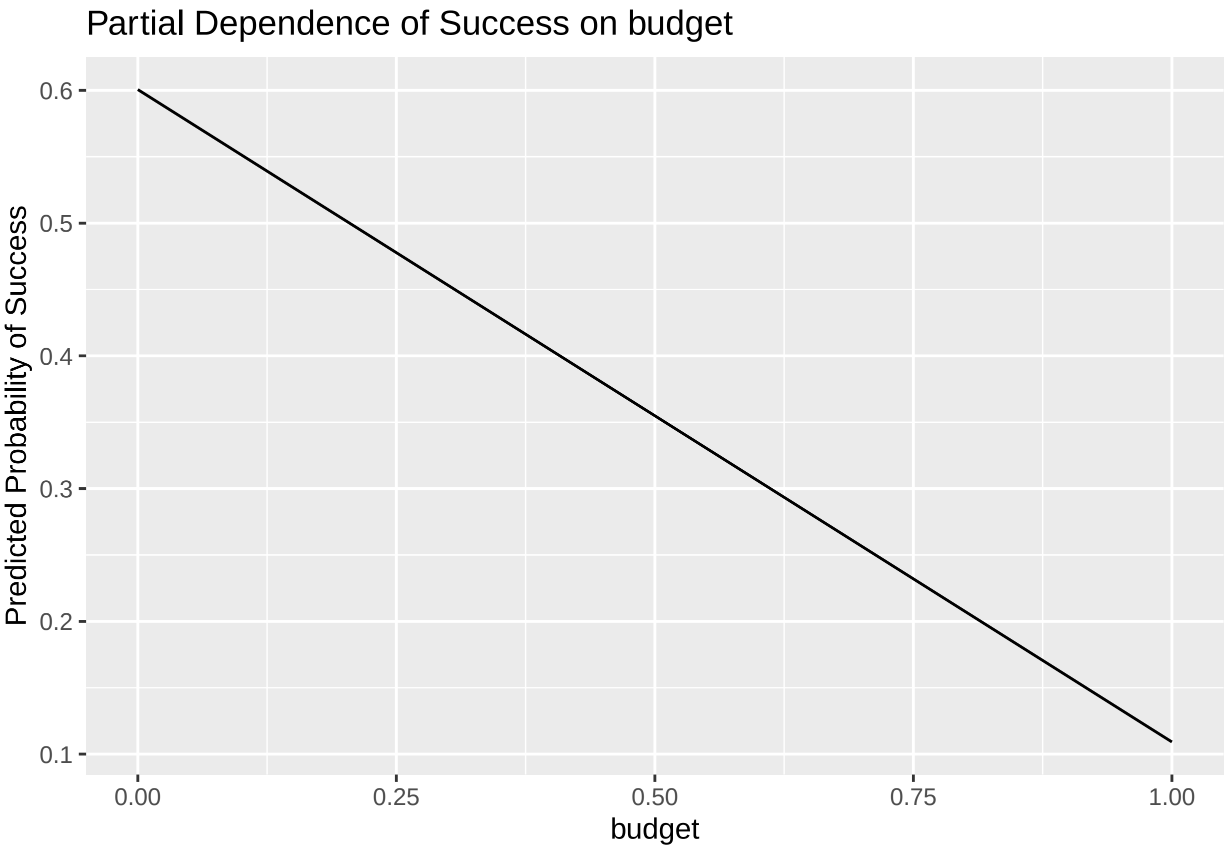
The confusion matrix shows the distribution of correct and incorrect predictions. The accuracy percentage provides a measure of how well the model predicts movie success.

PDP

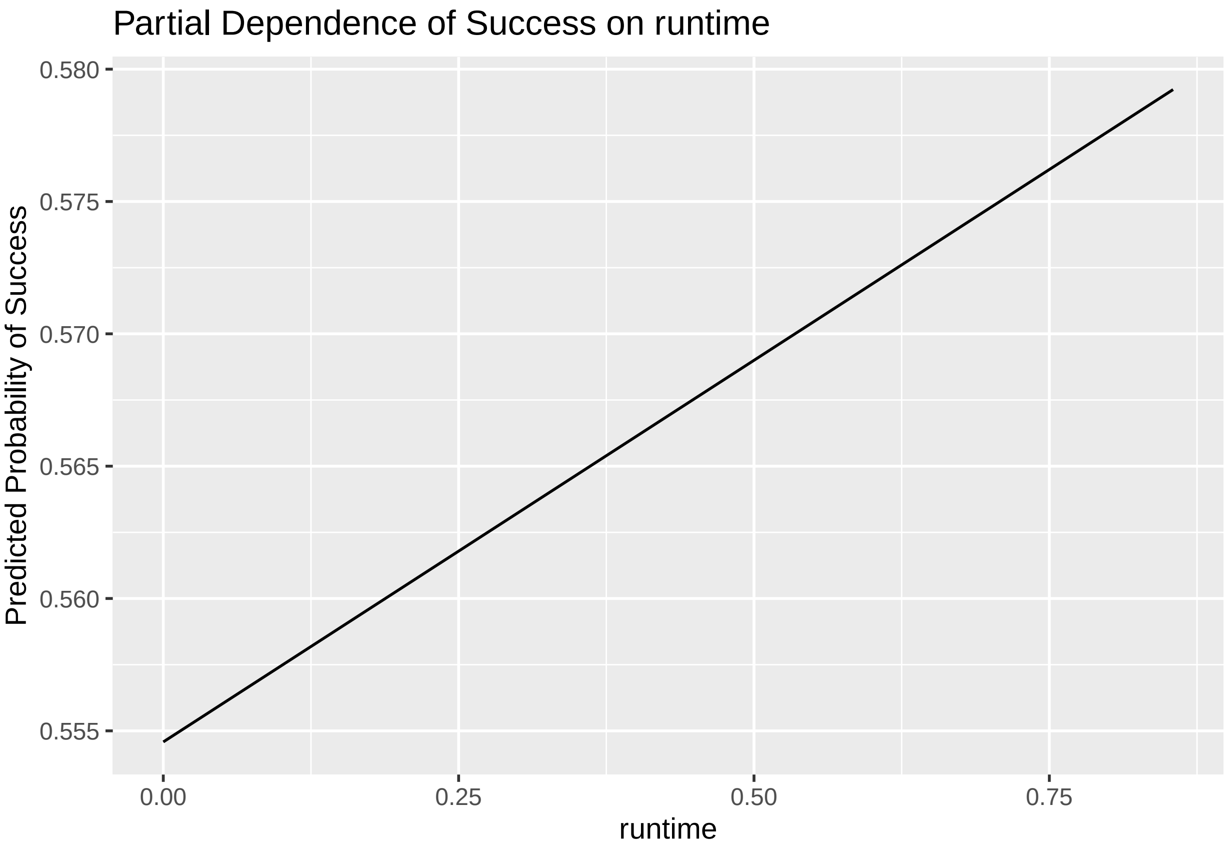
```
pdp_budget_lg <- pdp::partial(lg_model, pred.var = "popularity")

ggplot(pdp_budget_lg, aes(x = popularity, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on popularity (Logistic Regression)") +
  xlab("popularity") +
  ylab("Predicted Probability of Success")
```



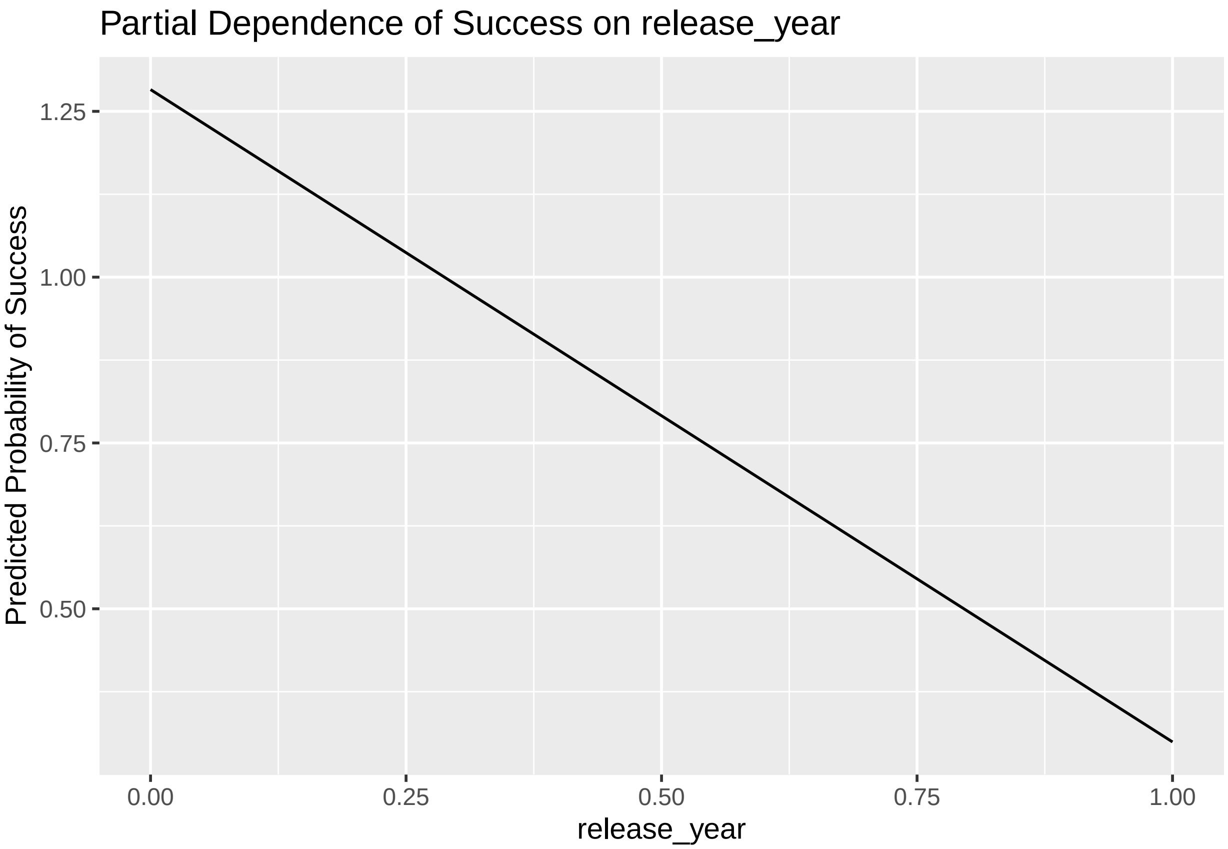
```
pdp_budget_lg2 <- pdp::partial(lg_model, pred.var = "budget")

ggplot(pdp_budget_lg2, aes(x = budget, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on budget") +
  xlab("budget") +
  ylab("Predicted Probability of Success")
```



```
pdp_budget_lg3 <- pdp::partial(lg_model, pred.var = "runtime")

ggplot(pdp_budget_lg3, aes(x = runtime, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on runtime") +
  xlab("runtime") +
  ylab("Predicted Probability of Success")
```



```r
pdp_budget_lg4 <- pdp::partial(lg_model, pred.var = "release_year")

ggplot(pdp_budget_lg4, aes(x = release_year, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on release_year") +
  xlab("release_year") +
  ylab("Predicted Probability of Success")
```



Classifying Budget into four predicted groups with multinomial logistic regression:

```
if (!require("nnet")) install.packages("nnet")
library(nnet)
```

Preparing target

```
budget_quartiles <- quantile(training_n$budget, probs = c(0, 0.25, 0.5, 0.75, 1), na.rm = TRUE)
budget_quartiles <- unique(budget_quartiles)

if (length(budget_quartiles) - 1 != 4) {
  stop("Unable to create exactly 4 quartile groups due to duplicate breaks. Please inspect the data.")
}

# Assign budget categories
training_n$budget_category <- cut(
  training_n$budget,
  breaks = budget_quartiles,
  labels = c("Low", "Medium", "High", "Very High"),
  include.lowest = TRUE
)

table(training_n$budget_category)
```

```
##
##       Low    Medium      High Very High
##       173       161       167       158
```

Fitting the model

```
training_n$budget_category <- as.factor(training_n$budget_category)

multinom_model <- multinom(budget_category ~ revenue + release_year + popularity, data = training_n)
```

```
## # weights:  20 (12 variable)
## initial  value 913.567984
## iter  10 value 799.926103
## iter  10 value 799.926103
## iter  20 value 790.287990
## iter  30 value 789.269648
## final  value 789.267820
## converged
```

Check the model summary

```
summary(multinom_model)
```

```
## Call:
## multinom(formula = budget_category ~ revenue + release_year +
##     popularity, data = training_n)
##
## Coefficients:
##           (Intercept)      revenue release_year  popularity
## Medium     -0.2282491 3.319914e-08   -0.3397700 0.003404545
## High       -0.6738019 5.083066e-08   -0.2738802 0.014257640
## Very High  -1.1782284 6.173187e-08   -0.5745488 0.026366845
##
## Std. Errors:
##            (Intercept)      revenue release_year   popularity
## Medium    2.204654e-16 6.207521e-09 1.501721e-16 3.472101e-18
## High      2.082177e-16 5.953165e-09 1.438903e-16 3.366093e-18
## Very High 1.549093e-16 5.959676e-09 1.077308e-16 2.733015e-18
##
## Residual Deviance: 1578.536
## AIC: 1602.536
```

Predict classifications

```
predicted_categories = predict(multinom_model, newdata = testing_n)

category_counts = table(predicted_categories)
print(category_counts)
```

```
## predicted_categories
##       Low    Medium      High Very High
##       239        41        81        78
```

Evaluating model with confusion matrix and calculating accuracy

```
table(Predicted = predicted_categories, Actual = testing_n$budget_category)
```

```
##              Actual
## Predicted    High Low Medium
##   Low           0 199     40
##   Medium        0  26     15
##   High          6  23     52
##   Very High    17  20     41
```

```
accuracy <- mean(predicted_categories == testing_n$budget_category)
cat("Accuracy: ", round(accuracy * 100, 4), "%")
```

```
## Accuracy:  50.1139 %
```

Classification with Emphasis on Interpretation

Classifying Success with Decision Trees

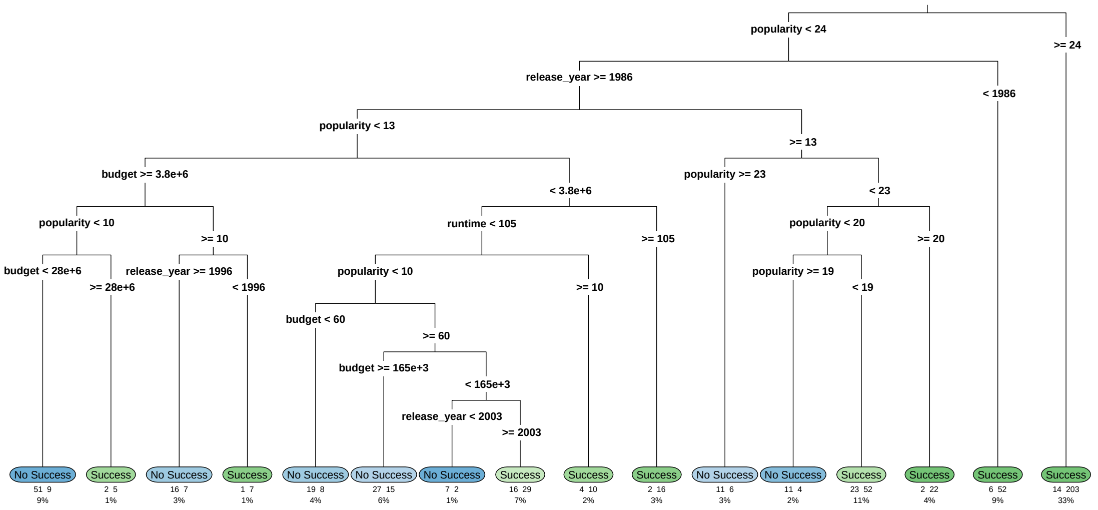
The decision tree structure shows how features like budget and popularity split the data to classify movies. The path from root to leaf highlights the decision rules. This easily identifies the most important features based on the splits.

Fit the Model

```
tree_model <- rpart(success ~ budget + release_year + runtime + popularity, data = training, method = "
```

Visualize the Trees

```
if (!require("rpart.plot")) install.packages("rpart.plot")
library(rpart.plot)
rpart.plot(tree_model, type = 3, extra = 101, under = TRUE, fallen.leaves = TRUE)
```



Predicting

```
tree_predictions <- predict(tree_model, newdata = testing, type = "class")
```

Evaluating the Model

Use the confusion matrix to evaluate the model.

```
tree_confusion <- table(Predicted = tree_predictions, Actual = testing$success)
accuracy_tree <- sum(tree_predictions == testing$success) / nrow(testing)

cat("Decision Tree Confusion Matrix:\n")
```

```
## Decision Tree Confusion Matrix:
```

```
print(tree_confusion)
```

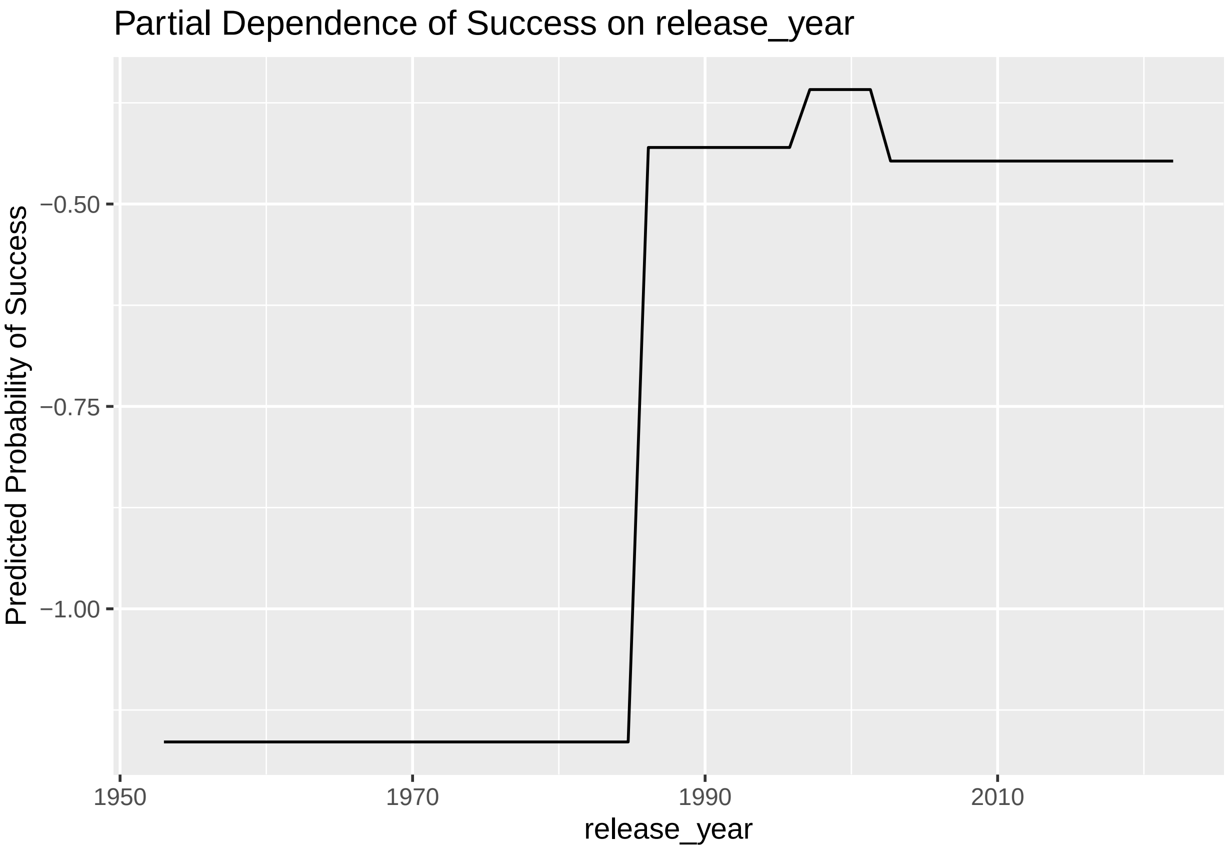
```
##               Actual
## Predicted    No Success Success
##   No Success         57      44
##   Success            96     242
```

```
cat("Decision Tree Accuracy: ", round(accuracy_tree * 100, 4), "%\n")
```

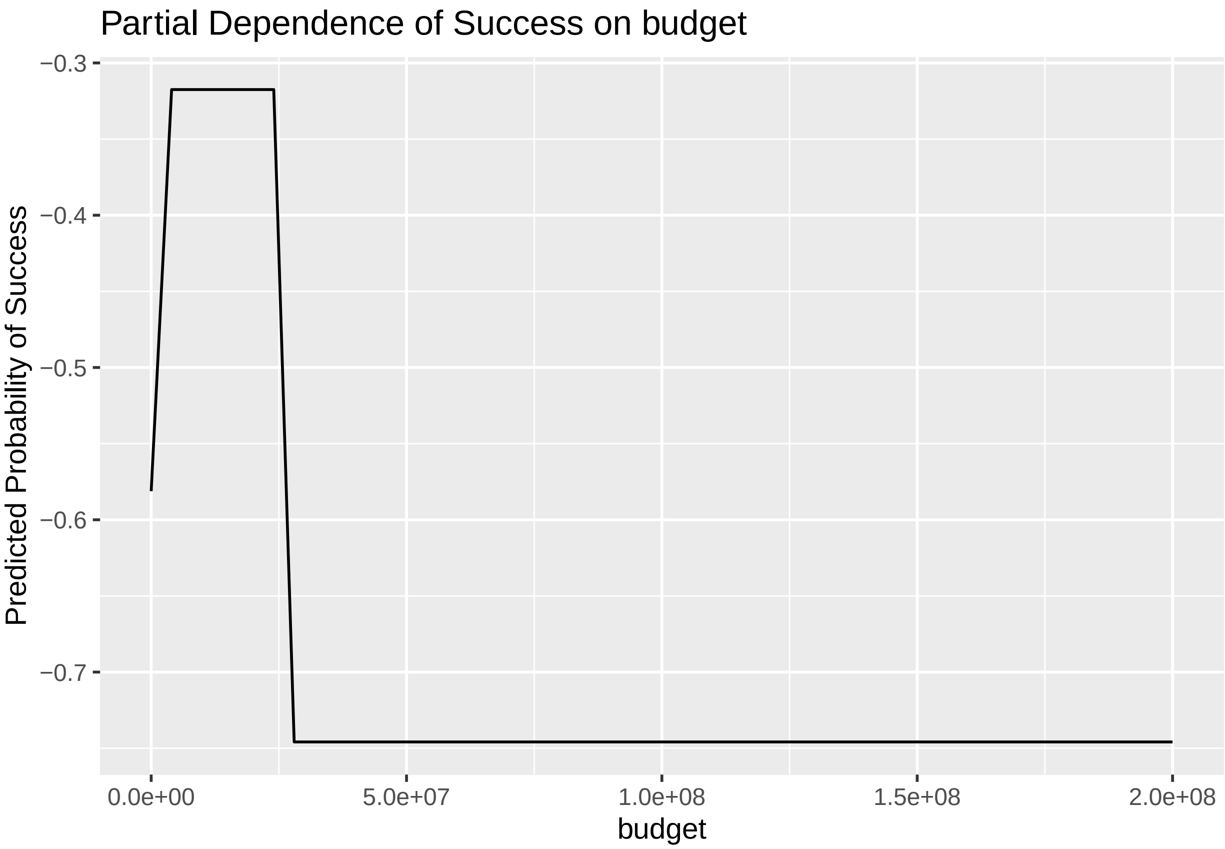
```
## Decision Tree Accuracy:  68.1093 %
```

PDP

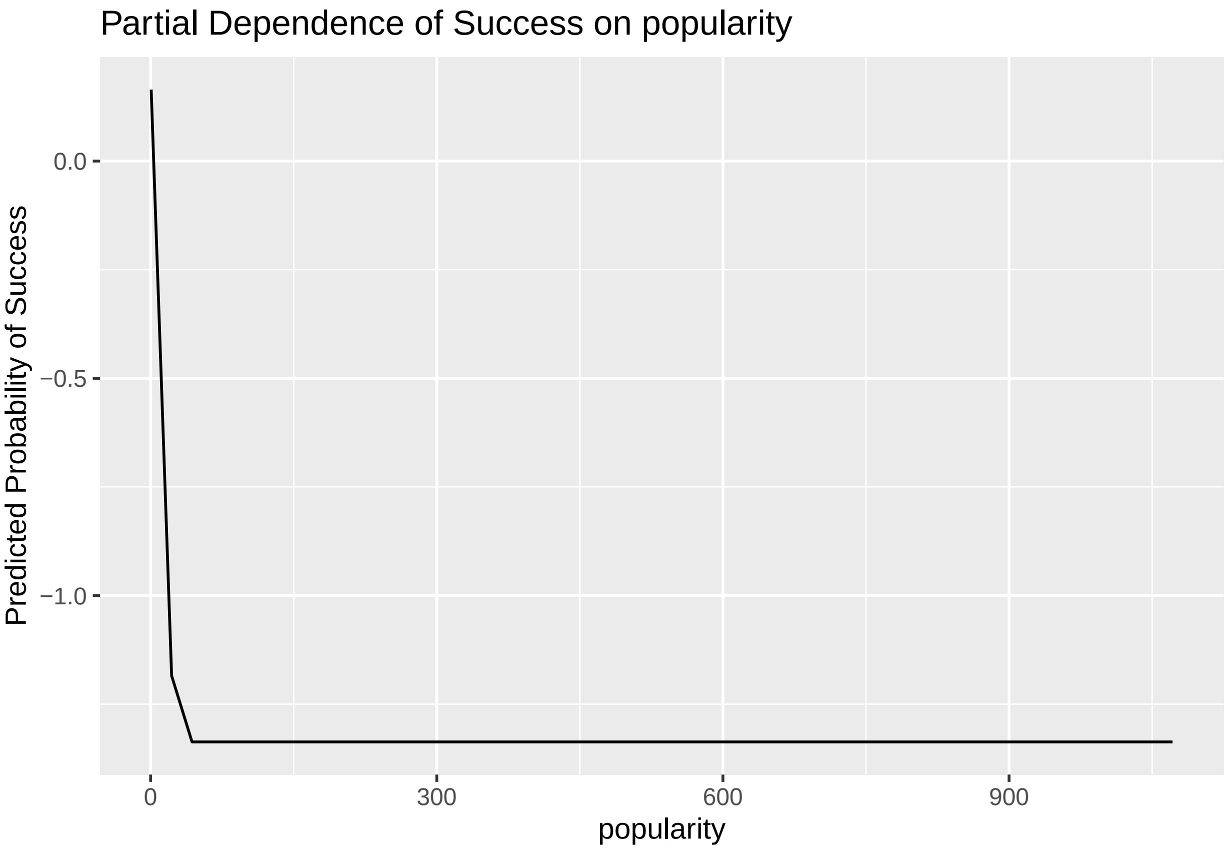
```
pdp_budget_tree <- pdp::partial(tree_model, pred.var = "release_year")

ggplot(pdp_budget_tree, aes(x = release_year, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on release_year") +
  xlab("release_year") +
  ylab("Predicted Probability of Success")
```



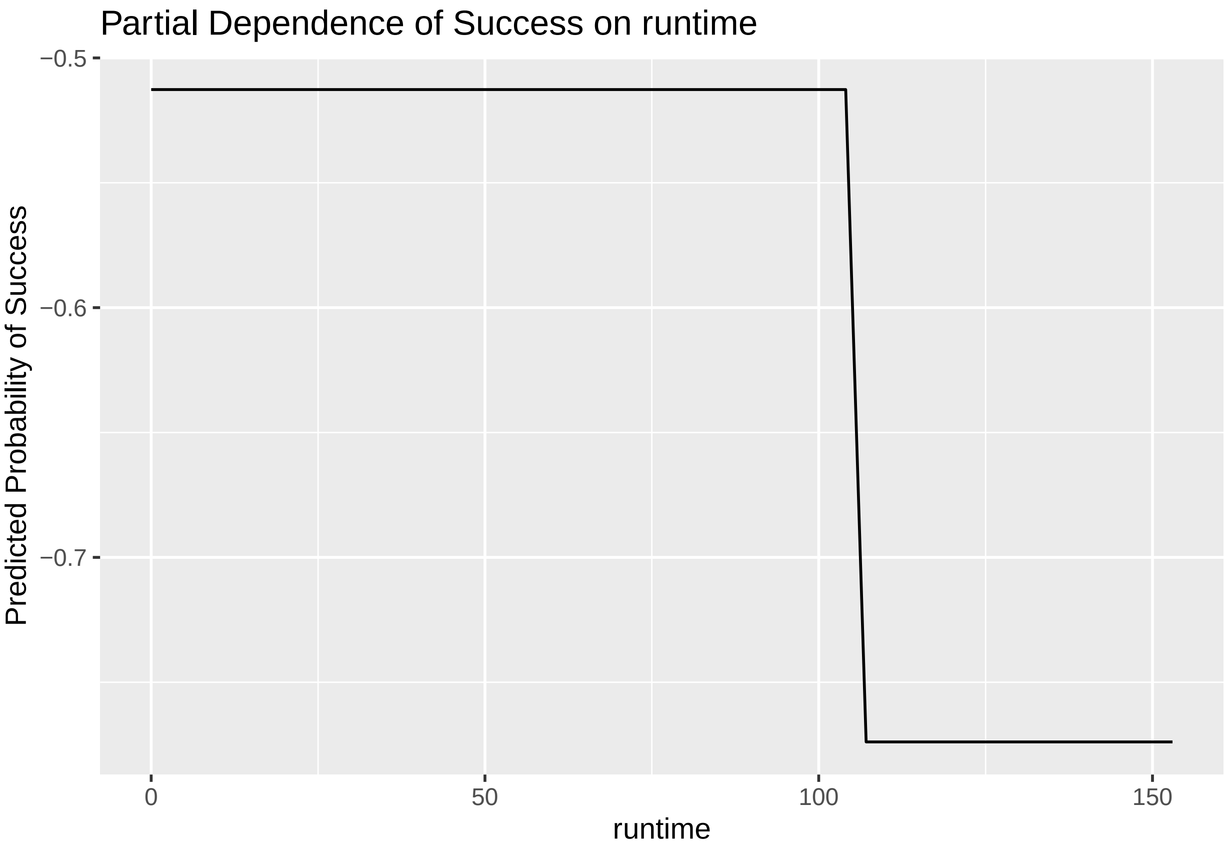
```
pdp_budget_tree2 <- pdp::partial(tree_model, pred.var = "budget")

ggplot(pdp_budget_tree2, aes(x = budget, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on budget") +
  xlab("budget") +
  ylab("Predicted Probability of Success")
```



```
pdp_budget_tree3 <- pdp::partial(tree_model, pred.var = "popularity")

ggplot(pdp_budget_tree3, aes(x = popularity, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on popularity") +
  xlab("popularity") +
  ylab("Predicted Probability of Success")
```



```
pdp_budget_tree4 <- pdp::partial(tree_model, pred.var = "runtime")

ggplot(pdp_budget_tree4, aes(x = runtime, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on runtime") +
  xlab("runtime") +
  ylab("Predicted Probability of Success")
```



Classifying Success with Random Forest (with Feature Importance)

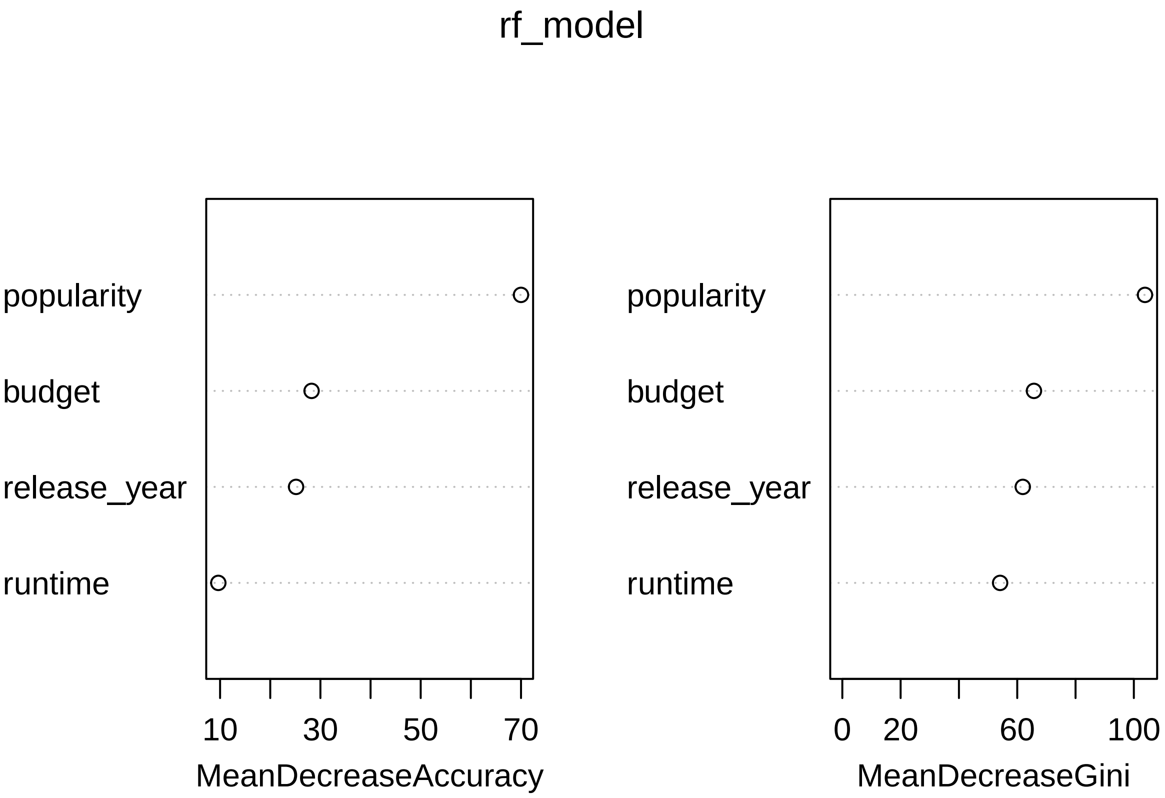
Fit the Model

```
library(randomForest)

rf_model <- randomForest(success ~ budget + release_year + runtime + popularity, data = training, impor
```

View Variable Importance

This shows which features contribute most to the model.

```
importance <- importance(rf_model)
varImpPlot(rf_model)
```



We can see popularity contributes the most to the model with budget next, then release year, and runtime being the least contributable predictor. ### Prediction

```
rf_predictions <- predict(rf_model, newdata = testing)
```

Evaluating the Model

Use a confusion matrix to evaluate the model.

```
rf_confusion <- table(Predicted = rf_predictions, Actual = testing$success)
accuracy_rf <- sum(rf_predictions == testing$success) / nrow(testing)

cat("Random Forest Confusion Matrix:\n")
```

```
## Random Forest Confusion Matrix:
```

```
print(rf_confusion)
```

```
##               Actual
## Predicted     No Success Success
##    No Success         57      41
##    Success            96     245
```

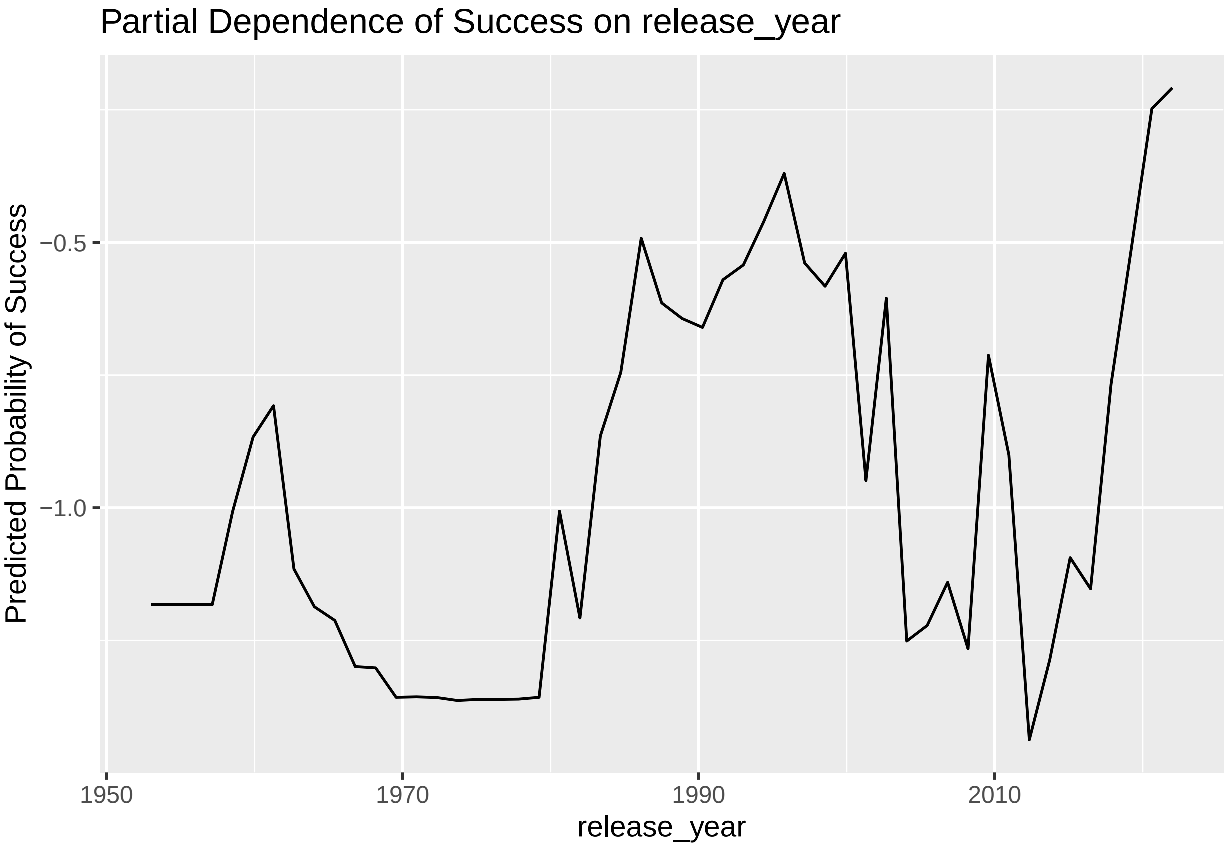
```
cat("Random Forest Accuracy: ", round(accuracy_rf * 100, 4), "%\n")
```

```
## Random Forest Accuracy:  68.7927 %
```

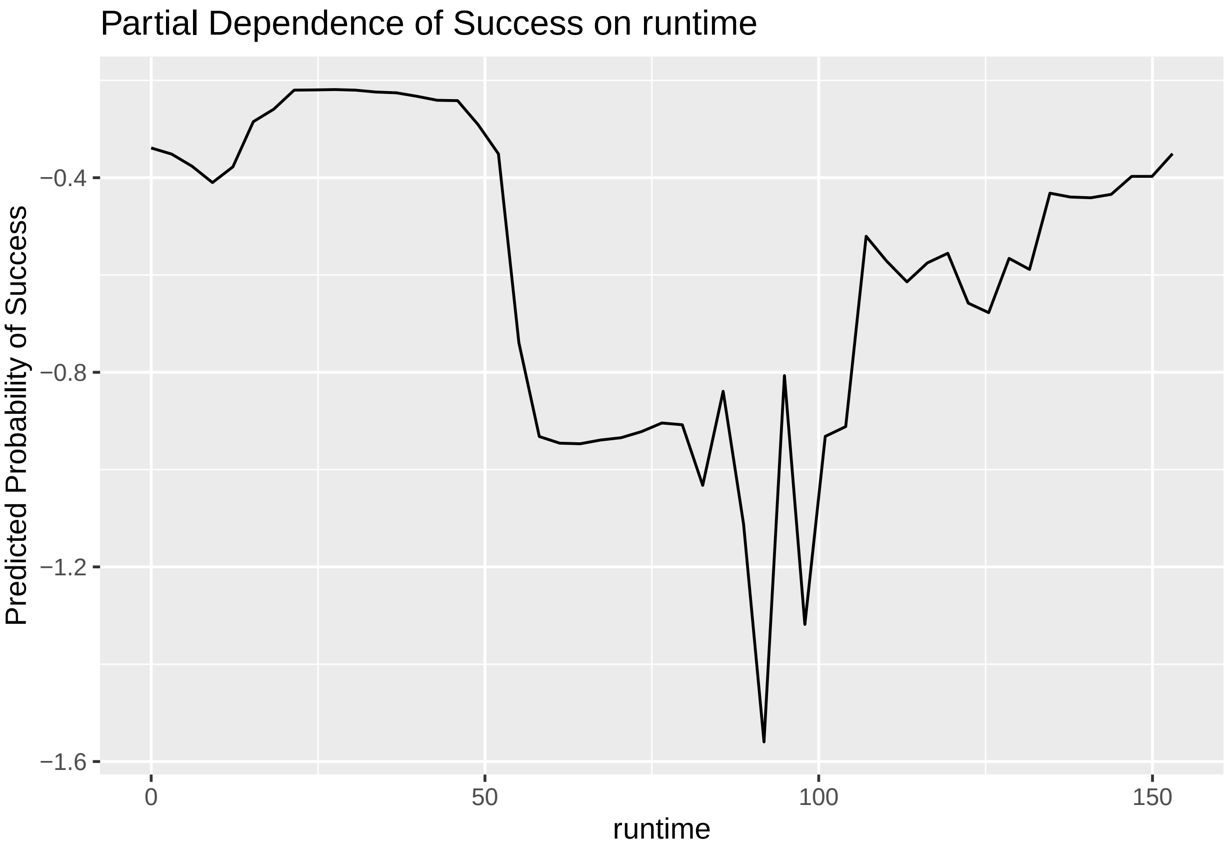
PDP

```
pdp_budget_rf <- pdp::partial(rf_model, pred.var = "release_year")
```

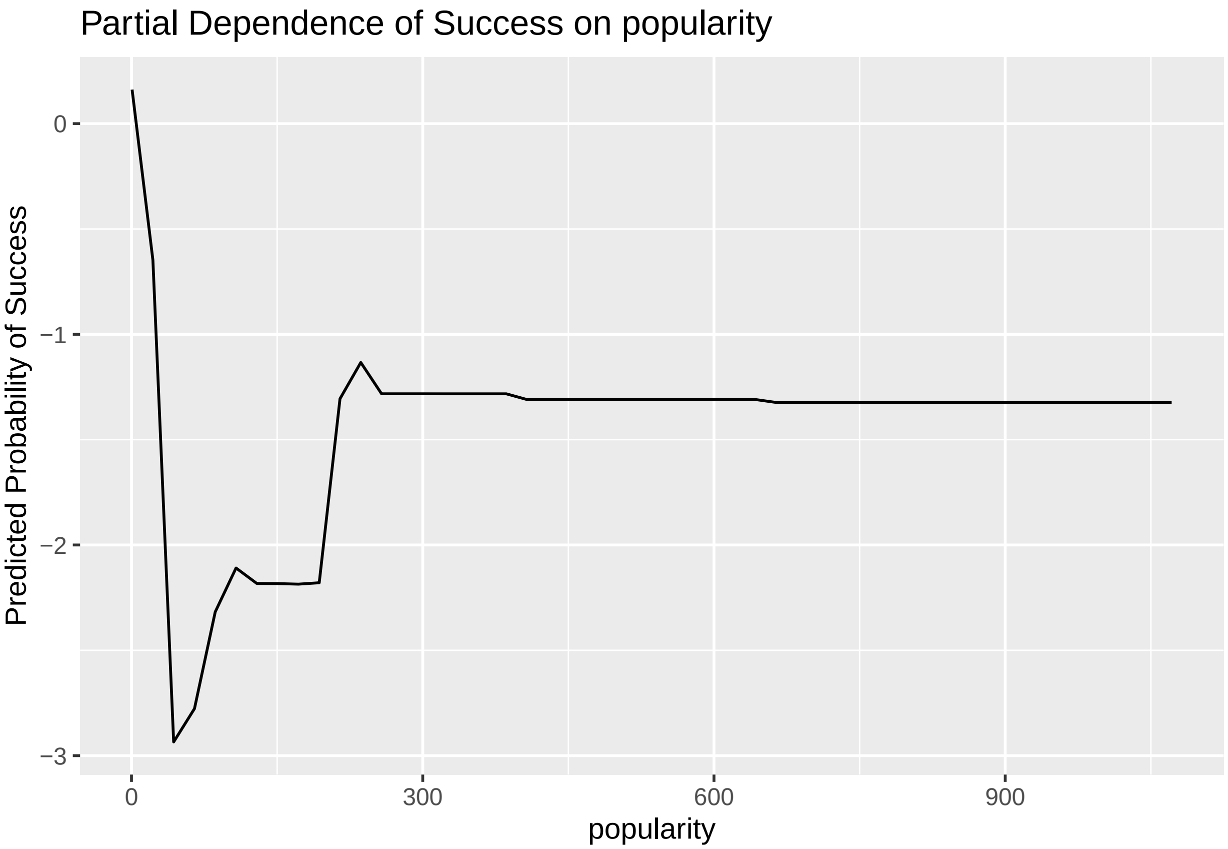
```
ggplot(pdp_budget_rf, aes(x = release_year, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on release_year") +
  xlab("release_year") +
  ylab("Predicted Probability of Success")
```



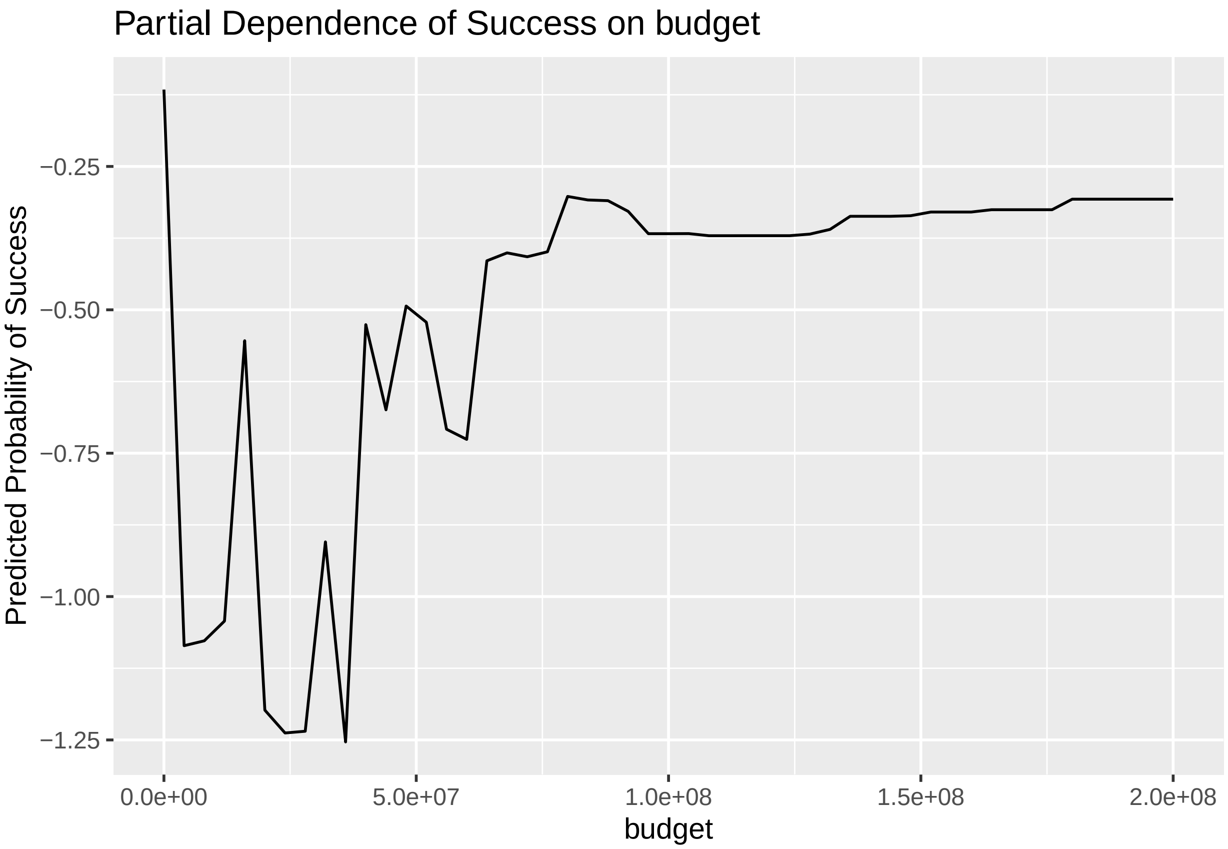
```
pdp_budget_rf2 <- pdp::partial(rf_model, pred.var = "runtime")

ggplot(pdp_budget_rf2, aes(x = runtime, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on runtime") +
  xlab("runtime") +
  ylab("Predicted Probability of Success")
```



```
pdp_budget_rf3 <- pdp::partial(rf_model, pred.var = "popularity")

ggplot(pdp_budget_rf3, aes(x = popularity, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on popularity") +
  xlab("popularity") +
  ylab("Predicted Probability of Success")
```



```
pdp_budget_rf4 <- pdp::partial(rf_model, pred.var = "budget")

ggplot(pdp_budget_rf4, aes(x = budget, y = yhat)) +
  geom_line() +
  ggtitle("Partial Dependence of Success on budget") +
  xlab("budget") +
  ylab("Predicted Probability of Success")
```



Classifying Success with Neural Networks

In the context of movie success classification, the neural network captures nonlinear relationships between features like budget and popularity interacting in unexpected ways.

Fit the Model

```r
set.seed(123)
df_normal$success <- as.factor(df_normal$success)
trainIndex <- createDataPartition(df_normal$success, p = 0.8, list = FALSE)
trainData <- df_normal[trainIndex, ]
testData <- df_normal[-trainIndex, ]

nn_model <- nnet(success ~ budget + release_year + runtime + popularity,
                 data = trainData,
                 size = 5,
                 decay = 0.01,
                 maxit = 500)
```

```
## # weights:  31
## initial  value 677.159206
## iter  10 value 532.657456
## iter  20 value 502.388653
## iter  30 value 492.785405
## iter  40 value 487.961334
## iter  50 value 485.487925
## iter  60 value 484.018116
## iter  70 value 482.830700
## iter  80 value 479.955217
## iter  90 value 479.556221
## iter 100 value 479.419115
## iter 110 value 479.329064
## iter 120 value 479.318553
## final  value 479.317125
## converged
```

```
print(summary(nn_model))
```

```
## a 4-5-1 network with 31 weights
## options were - entropy fitting  decay=0.01
##  b->h1 i1->h1 i2->h1 i3->h1 i4->h1
##  -1.65   7.13   7.40  -1.76   0.47
##  b->h2 i1->h2 i2->h2 i3->h2 i4->h2
##   0.24   0.03  -0.02   0.31   0.19
##  b->h3 i1->h3 i2->h3 i3->h3 i4->h3
##  -5.54  -1.22   4.72   1.61  10.24
##  b->h4 i1->h4 i2->h4 i3->h4 i4->h4
##  -2.48   0.09   2.97   1.52  27.35
##  b->h5 i1->h5 i2->h5 i3->h5 i4->h5
##  -5.37   2.02   5.78   5.31   0.61
##  b->o h1->o h2->o h3->o h4->o h5->o
##  0.73 -8.41  0.24 -8.35 22.40 -6.59
```

Prediction

```
nn_predictions <- predict(nn_model, newdata = testData, type = "class")
```

Evaluating the Model

Use the confusion matrix to evaluate model accuracy.

```
confusion_matrix_nn <- table(Predicted = nn_predictions, Actual = testData$success)
print(confusion_matrix_nn)
```

```
##             Actual
## Predicted    No Success Success
##   No Success         32      25
##   Success            41     121
```

```
accuracy_nn <- sum(diag(confusion_matrix_nn)) / sum(confusion_matrix_nn)
print(paste("Accuracy: ", round(accuracy_nn * 100, 4), "%"))
```

```
## [1] "Accuracy:  69.863 %"
```

Classifying with Gradient Boosting

Gradient boosting combines multiple weak learners (decision trees) to create a strong predictive model.

Fit the Model

We will use a bernoulli distribution since we are working with binary classification.

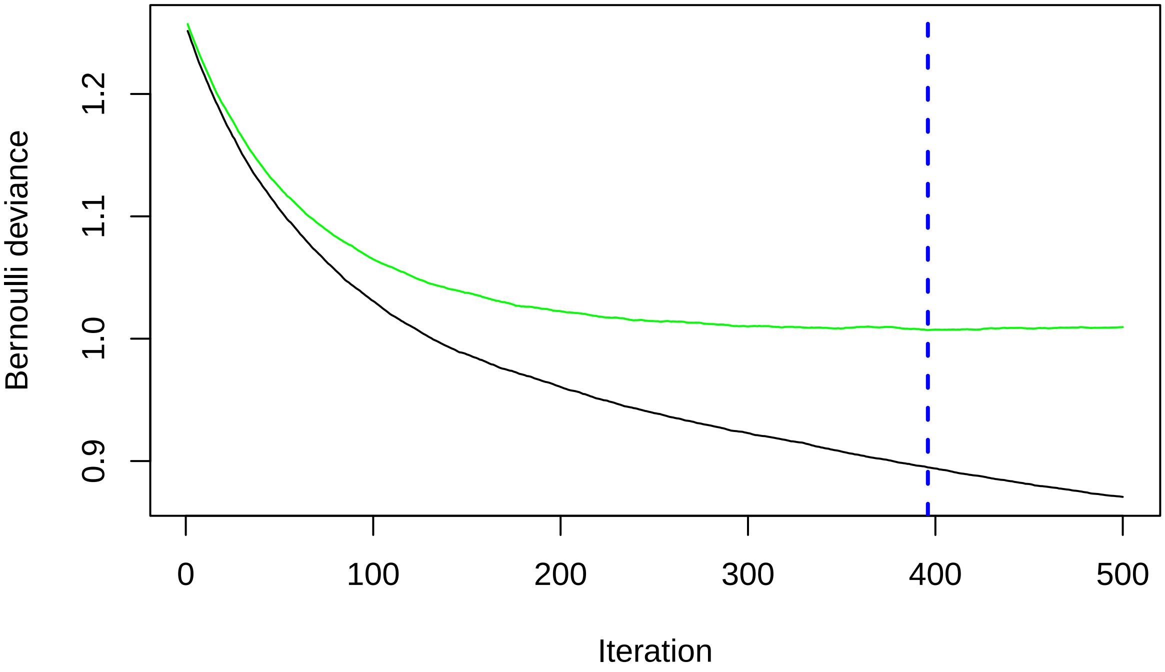
```
training$success <- ifelse(training$success == "Success", 1, 0)
```

```
set.seed(123)
gbm_model <- gbm(success ~ budget + release_year + runtime + popularity,
                 data = training,
                 distribution = "bernoulli",
                 n.trees = 500,
                 interaction.depth = 3,
                 shrinkage = 0.01,
                 cv.folds = 5)
```

Prediction

We will find the best number of decision trees to use for the probabilities using cross validation.

```
best_iter <- gbm.perf(gbm_model, method = "cv")
```



```
gbm_probabilities <- predict(gbm_model, newdata = testing, n.trees = best_iter, type = "response")
gbm_predictions <- ifelse(gbm_probabilities > 0.5, "Success", "No Success")
```

Evaluating the Model

Use the confusion matrix to evaluate the model accuracy.

```
confusion_matrix_gbm <- table(Predicted = gbm_predictions, Actual = testing$success)
print(confusion_matrix_gbm)
```

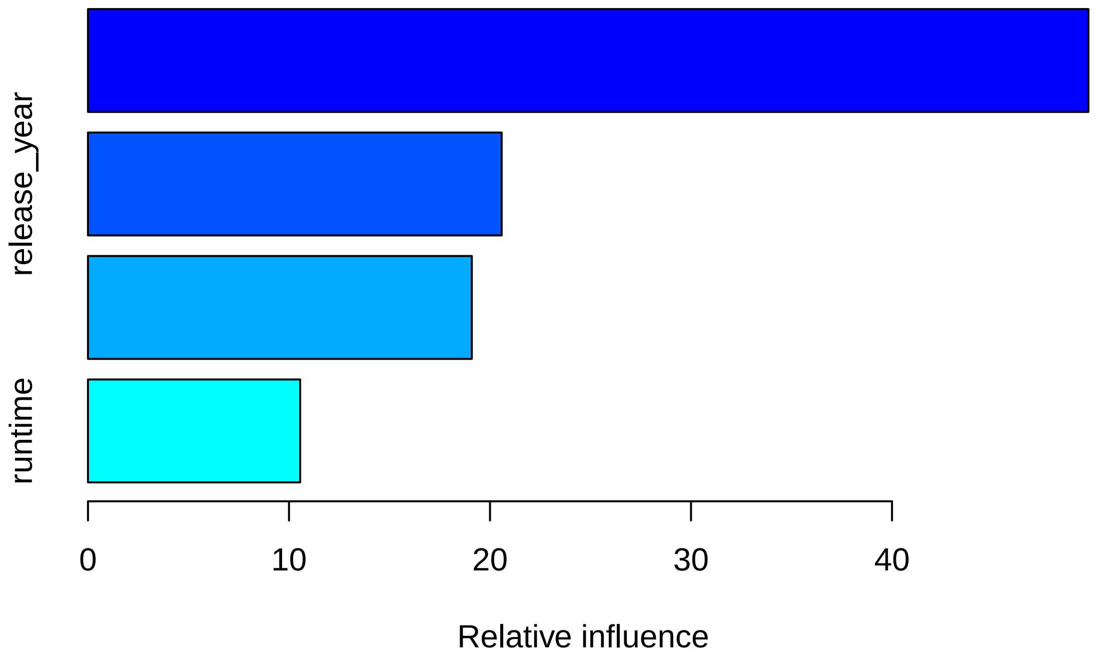
```
##              Actual
## Predicted    No Success Success
##   No Success         54      45
##   Success            99     241
```

```
accuracy_gbm <- sum(diag(confusion_matrix_gbm)) / sum(confusion_matrix_gbm)
print(paste("Accuracy: ", round(accuracy_gbm * 100, 4), "%"))
```

```
## [1] "Accuracy:  67.1982 %"
```

Feature Importance

```
importance <- summary(gbm_model)
```



```
print(importance)
```

```
##                       var  rel.inf
## popularity     popularity 49.77012
## release_year release_year 20.57941
## budget             budget 19.09468
## runtime           runtime 10.55579
```

We can see that this model predicts popularity to have the most relative influence, followed by release year, then budget, than runtime. This is different from the other models as the others predict budget as the second most influential variable. **Prediction** using Logistic regression answers the question, "Can we predict success?"

Interpretation using LDA highlights "Why are some movies predicted as successful or unsuccessful?" by examining variable relationships and decision boundaries.

Feature Selection and Comparison of Predictor Sets

Feature Importance Analysis

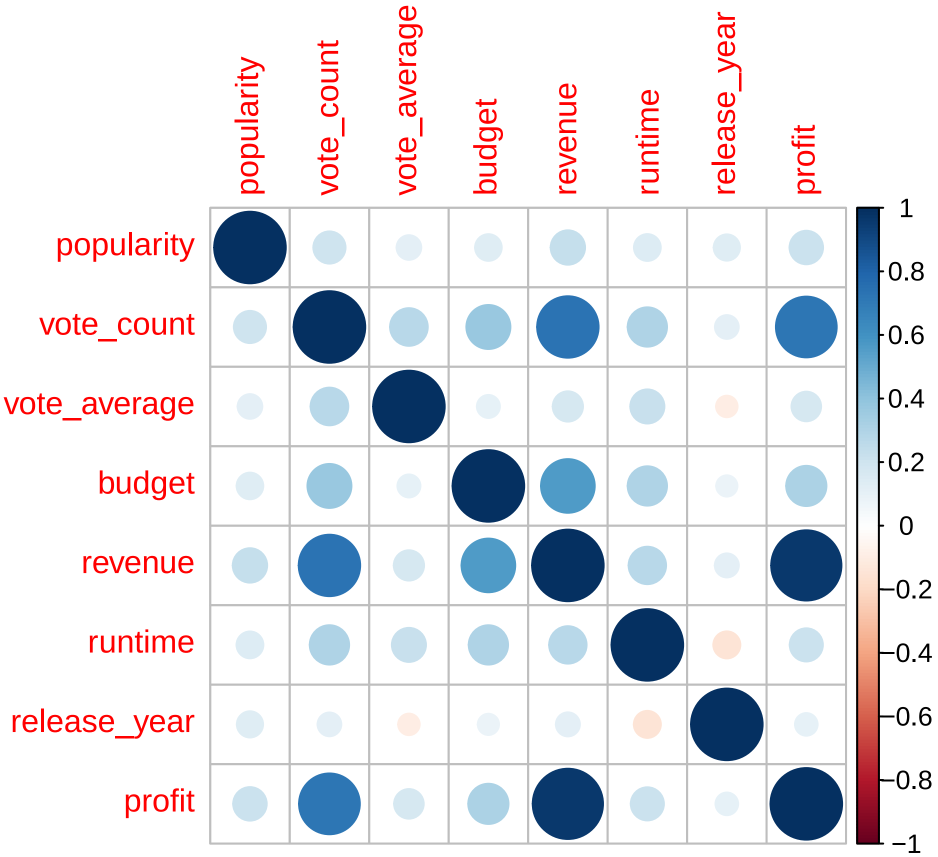
Correlation Analysis for Continuous Variables

We will analyze the correlation between predictors and the target variable, success. We will identify multicollinearity among predictors to avoid redudancy. We will do so by looking at a correlation matrix for numeric predictors.

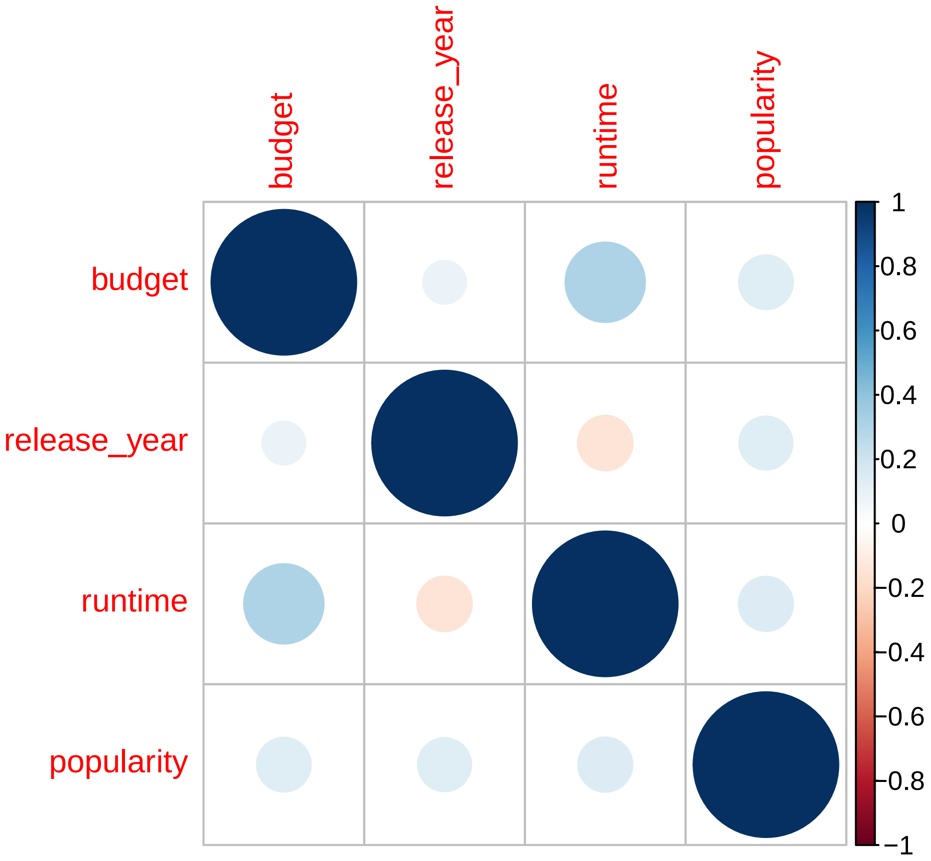
```
numeric_vars <- df_for_class[, sapply(df_for_class, is.numeric)]
correlation_matrix <- cor(numeric_vars)
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 4.3.3
## corrplot 0.94 loaded
```

```
corrplot(correlation_matrix, method = "circle")
```



```
selected_vars <- df_for_class[, c("budget", "release_year", "runtime", "popularity")]

correlation_matrix <- cor(selected_vars)

library(corrplot)
corrplot(correlation_matrix, method = "circle")
```

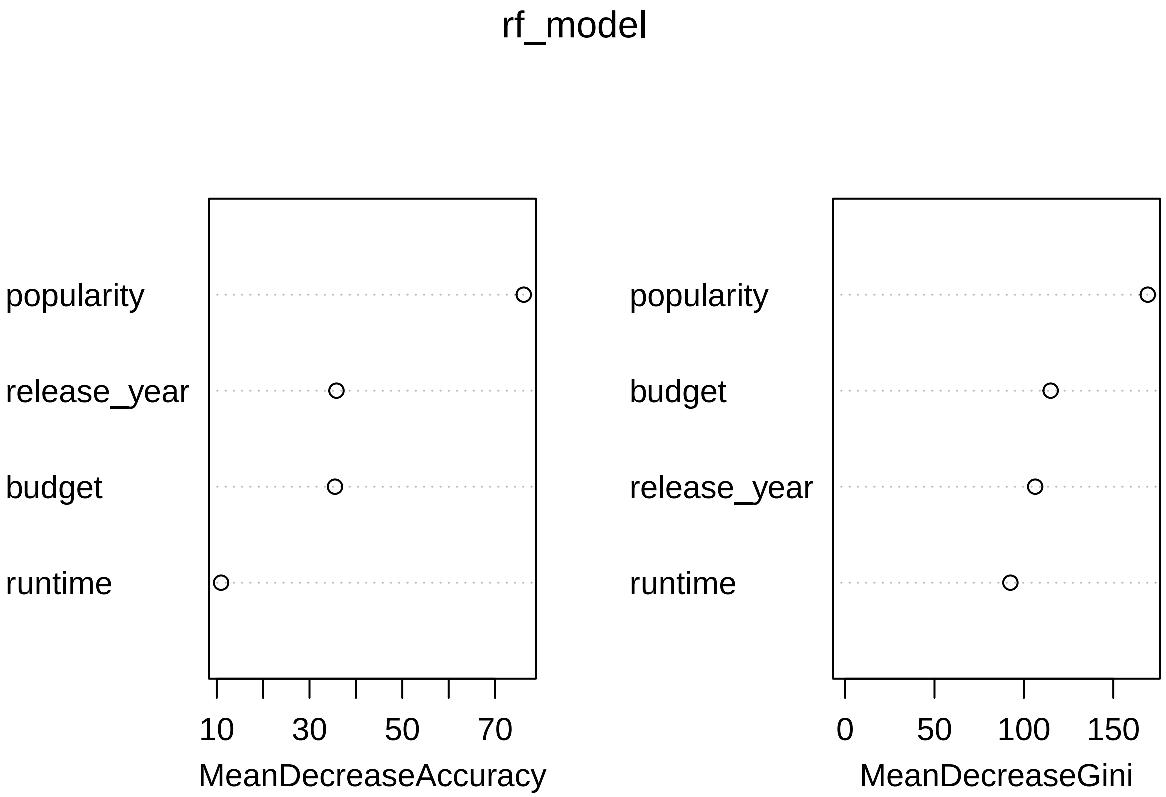


Checking to make sure there is no multicollinearity present for the variables we chose to predict. We can see that there is no multicollinearity present as the correlations between the variables we chose are small.

Variable Importance from Random Forest

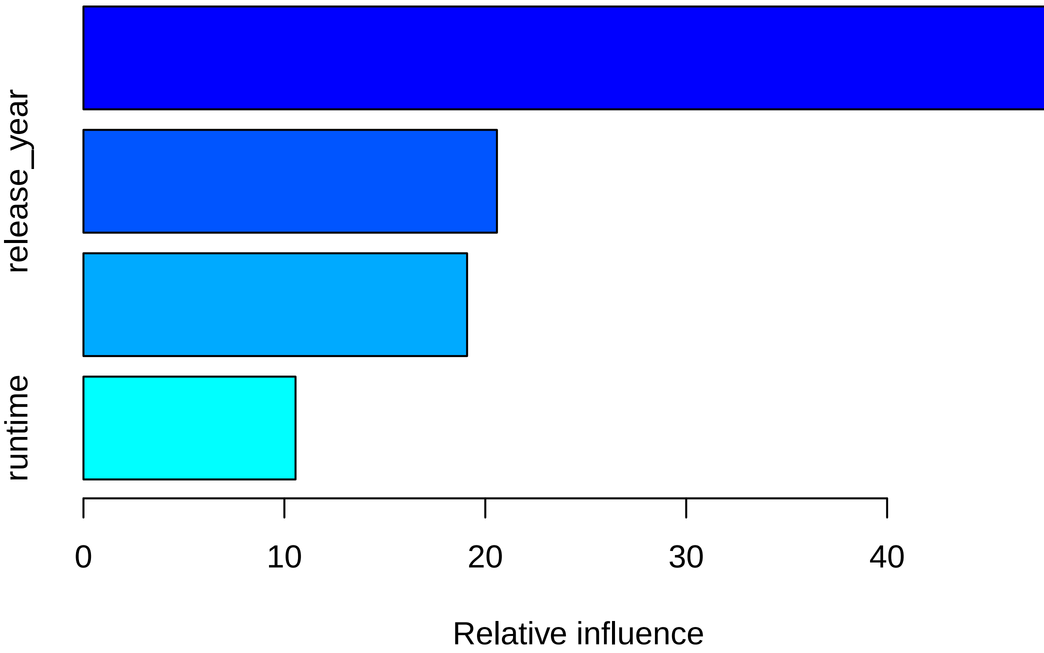
Random Forest provides a direct measure of feature importance.

```r
rf_model <- randomForest(success ~ budget + release_year + runtime + popularity, data = df_for_class, i
varImpPlot(rf_model)
```

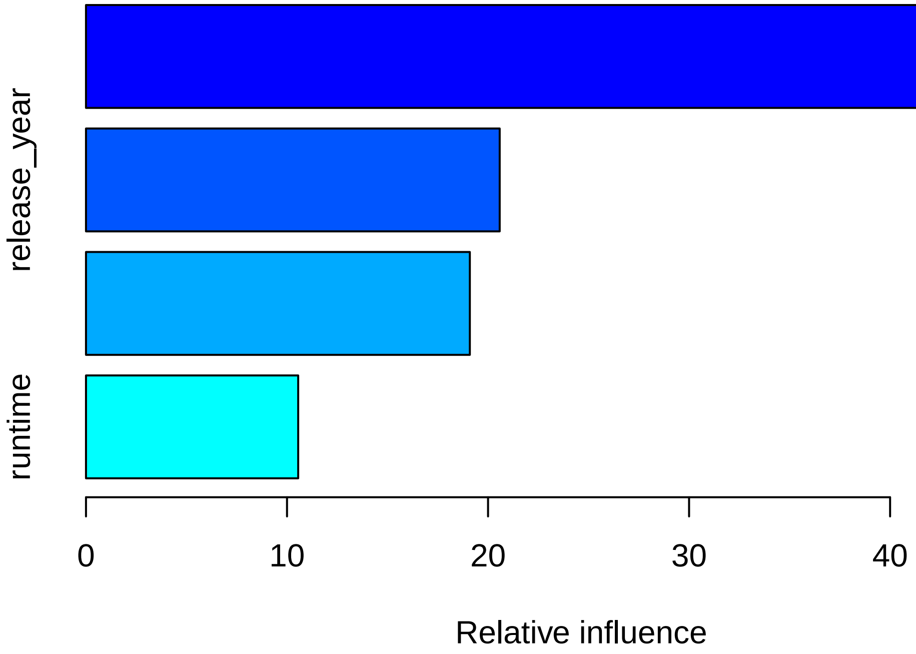


We already saw above when we did the random forest model that random forest predicts popularity to be the most influential predictor on success. However when we do random forest on the data set and not the training the second most influential variable changes. For MeanDecreaseAccuracy (which shows how a feature effects the overall prediction accuracy), it shows release_year next, followed by budget then runtime. For MeanDecreaseGini (which shows how a feature influences the splitting criteria) shows budget next, followed by release year and then runtime. ### Gradient Boosting Feature Importance and Partial Dependence

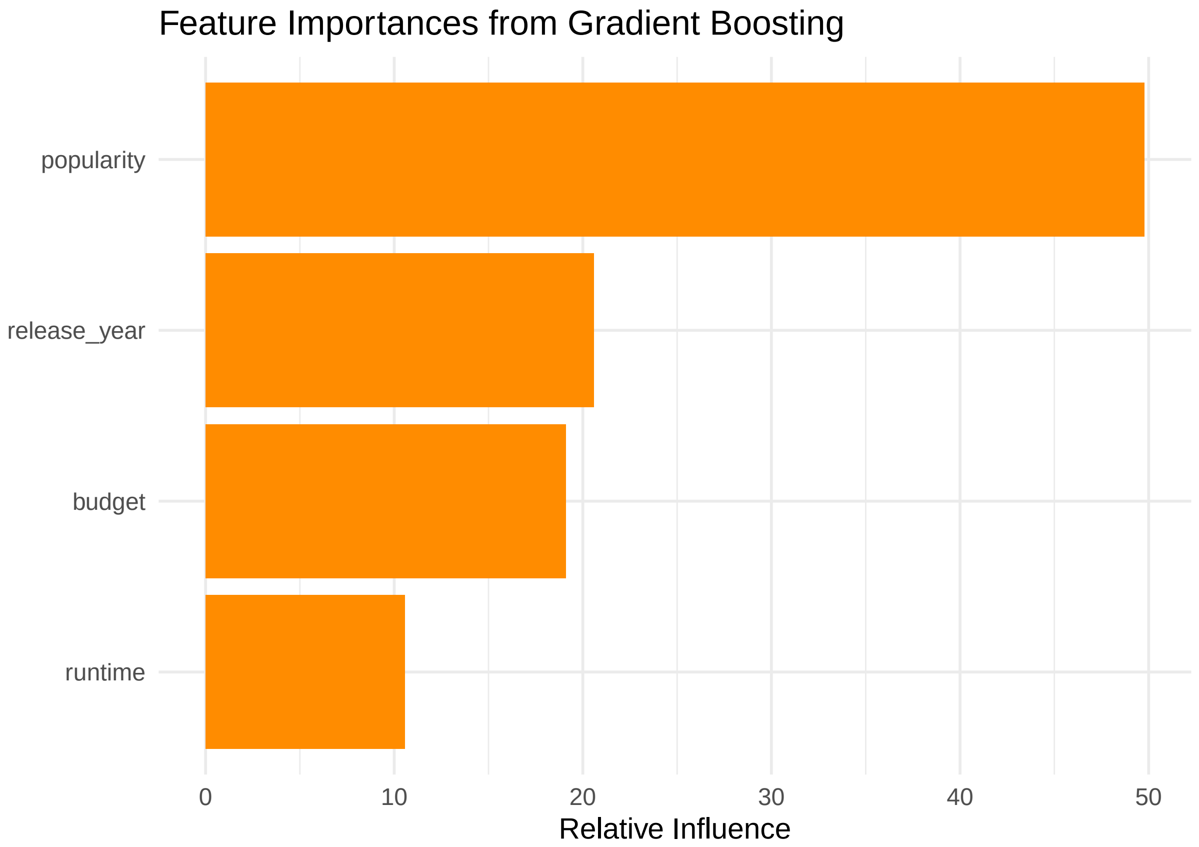
```r
importance_df_gbm <- data.frame(
  Feature = summary(gbm_model)$var,
  Importance = summary(gbm_model)$rel.inf
)
```



Feature Importance and Plot



```r
ggplot(importance_df_gbm, aes(x = reorder(Feature, Importance), y = Importance)) +
  geom_bar(stat = "identity", fill = "darkorange") +
  coord_flip() +
  ggtitle("Feature Importances from Gradient Boosting") +
  xlab("") +
  ylab("Relative Influence") +
  theme_minimal()
```



Shows popularity, then release year, then budget, then runtime is the order of relative influence of predictor variables to the overall success.

Stepwise Selection

We can use stepwise regression to identify the most relevant features for logistic regression.

```
full_model <- glm(success ~ budget + release_year + runtime + popularity, data = df_for_class, family =
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
step_model <- stepAIC(full_model, direction = "both")
```

```
## Start:  AIC=1313.79
## success ~ budget + release_year + runtime + popularity
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##                Df Deviance    AIC
## - budget        1   1303.8 1311.8
## <none>              1303.8 1313.8
## - runtime       1   1306.9 1314.9
## - release_year  1   1338.3 1346.3
## - popularity    1   1348.3 1356.3
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##
## Step:  AIC=1311.8
## success ~ release_year + runtime + popularity

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##                Df Deviance    AIC
## <none>              1303.8 1311.8
## - runtime       1   1307.0 1313.0
## + budget        1   1303.8 1313.8
## - release_year  1   1338.5 1344.5
## - popularity    1   1350.1 1356.1
```

```r
summary(step_model)
```

```
##
## Call:
## glm(formula = success ~ release_year + runtime + popularity,
##     family = binomial, data = df_for_class)
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  57.087853  10.267083   5.560 2.69e-08 ***
## release_year -0.028542   0.005102  -5.595 2.21e-08 ***
## runtime       0.004466   0.002492   1.792   0.0731 .
## popularity    0.017716   0.003308   5.355 8.54e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1396.4  on 1097  degrees of freedom
## Residual deviance: 1303.8  on 1094  degrees of freedom
## AIC: 1311.8
##
## Number of Fisher Scoring iterations: 6
```

Release_year and popularity have strong effects on predicting the success of a movie. As release_year increases, success decreases, while higher popularity increases success. Runtime is somewhat important, but its effect is weaker compared to the other variables. Initially, the model included budget, release_year, runtime, and popularity. After stepwise selection, the final model excluded budget and only included release_year, runtime, and popularity. You can see this from the change in AIC values during the stepwise process. The AIC value decreased from 1313.79 to 1311.8 after the removal of budget, indicating a slightly better model fit when excluding this variable.

SHAP Values for Model Interpretability

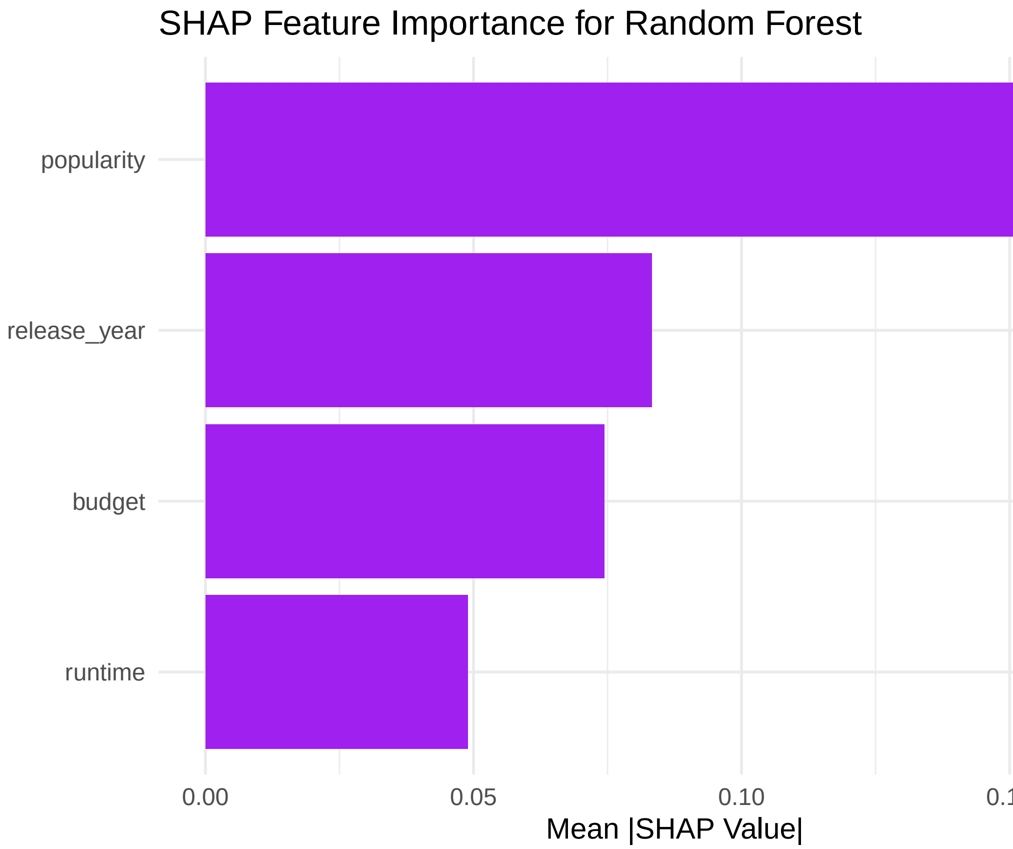
```r
predict_function <- function(object, newdata) {
  predict(object, newdata = newdata, type = "prob")[, "Success"]
}

X <- horror[, c("budget", "release_year", "runtime", "popularity")]
y <- horror$success
```

SHAP Analysis with Random Forest

```r
predict_function <- function(object, newdata) {
  predict(object, newdata = newdata, type = "prob")[, "Success"]
}

set.seed(123)
shap_values <- fastshap::explain(
  object = rf_model,
  X = df_for_class[, c("budget", "release_year", "runtime", "popularity")],
  pred_wrapper = predict_function,
  nsim = 50,
  adjust = TRUE
)

mean_abs_shap <- colMeans(abs(shap_values))
shap_importance <- data.frame(
  Feature = names(mean_abs_shap),
  MeanAbsShap = mean_abs_shap
)
```

Compute SHAP Values + Mean Absolute SHAP Values

```r
ggplot(shap_importance, aes(x = reorder(Feature, MeanAbsShap), y = MeanAbsShap)) +
  geom_bar(stat = "identity", fill = "purple") +
  coord_flip() +
  ggtitle("SHAP Feature Importance for Random Forest") +
  xlab("") +
  ylab("Mean |SHAP Value|") +
  theme_minimal()
```



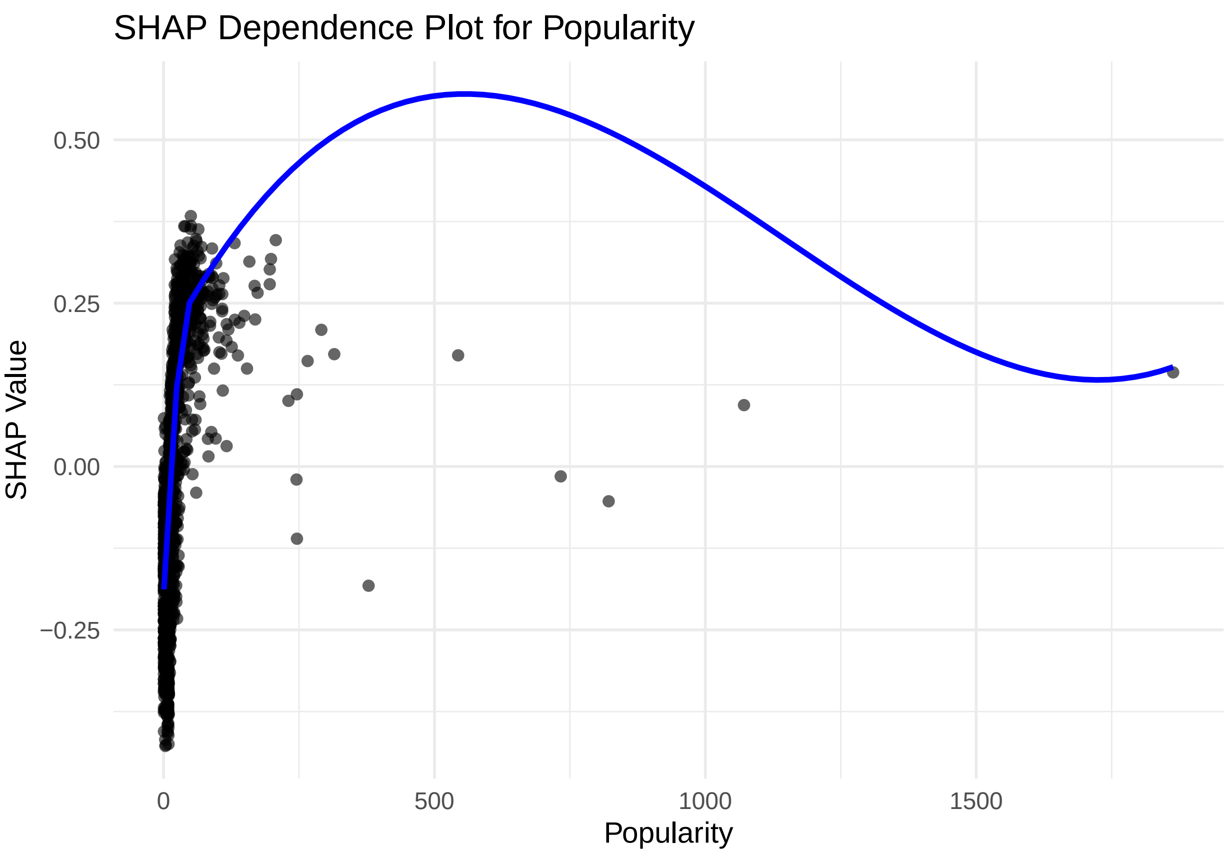
SHAP Feature Importance Plot

Again, this predicts the same as the other models with order of importance being popualrity, release_year, budget, runtime.

SHAP Dependence Plot Now we will plot a SHAP dependence plot for each variable to see the complete view of the model's decision-making process.

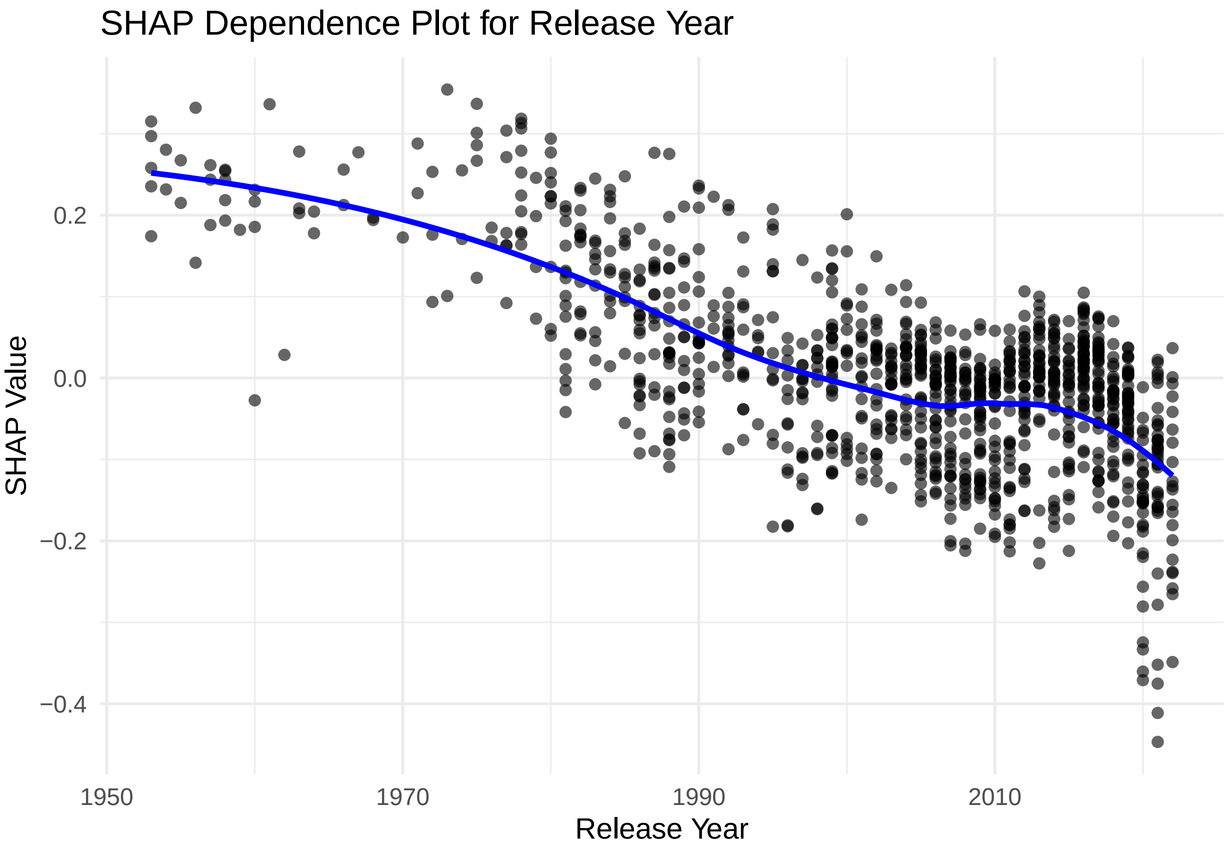
```r
shap_values_pop <- shap_values[, "popularity"]

ggplot(data = data.frame(
  SHAP_value = shap_values_pop,
  Feature_value = df_for_class$popularity
), aes(x = Feature_value, y = SHAP_value)) +
  geom_point(alpha = 0.6) +
  geom_smooth(method = "loess", se = FALSE, color = "blue") +
  ggtitle("SHAP Dependence Plot for Popularity") +
  xlab("Popularity") +
  ylab("SHAP Value") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



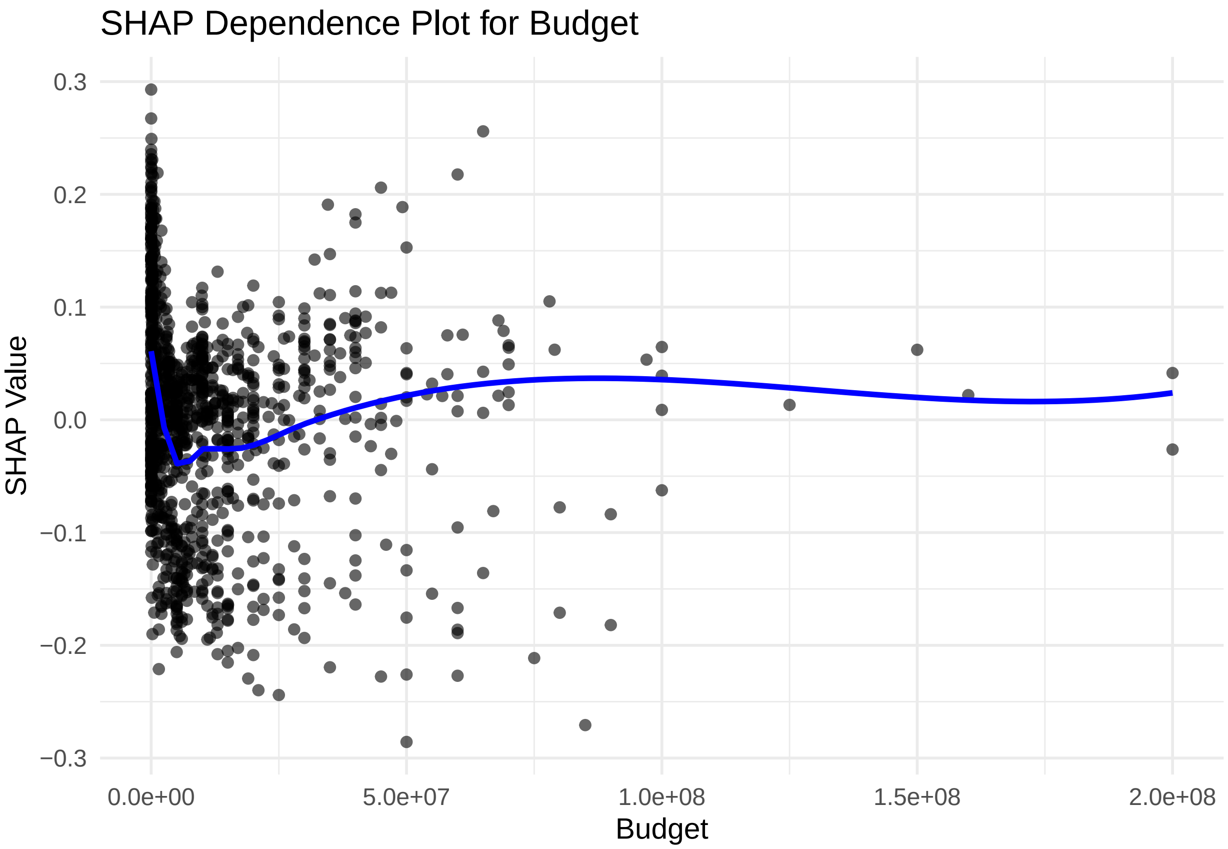
```
shap_values_yr <- shap_values[, "release_year"]

ggplot(data = data.frame(
  SHAP_value = shap_values_yr,
  Feature_value = df_for_class$release_year
), aes(x = Feature_value, y = SHAP_value)) +
  geom_point(alpha = 0.6) +
  geom_smooth(method = "loess", se = FALSE, color = "blue") +
  ggtitle("SHAP Dependence Plot for Release Year") +
  xlab("Release Year") +
  ylab("SHAP Value") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



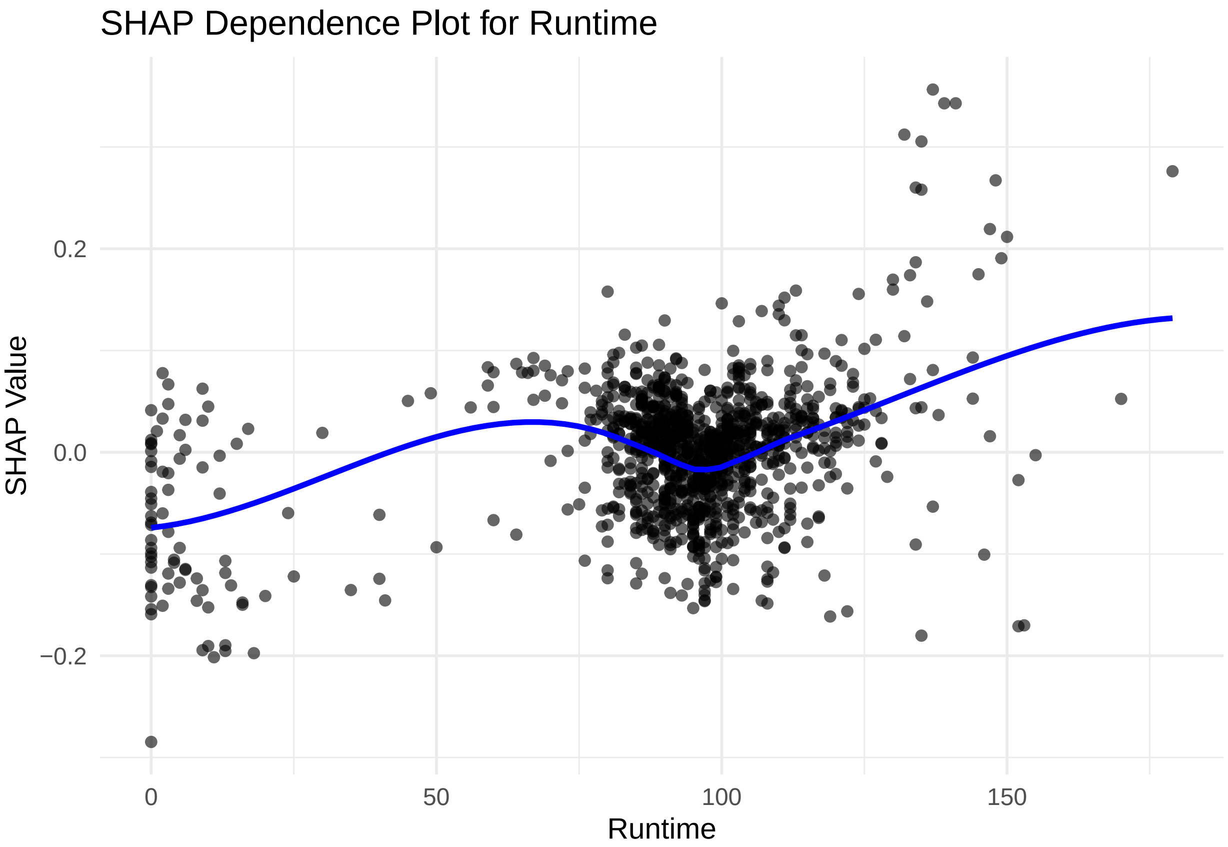
```
shap_values_budget <- shap_values[, "budget"]

ggplot(data = data.frame(
  SHAP_value = shap_values_budget,
  Feature_value = df_for_class$budget  # Original feature values for 'budget'
), aes(x = Feature_value, y = SHAP_value)) +
  geom_point(alpha = 0.6) +
  geom_smooth(method = "loess", se = FALSE, color = "blue") +
  ggtitle("SHAP Dependence Plot for Budget") +
  xlab("Budget") +
  ylab("SHAP Value") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



```r
shap_values_runtime <- shap_values[, "runtime"]

ggplot(data = data.frame(
  SHAP_value = shap_values_runtime,
  Feature_value = df_for_class$runtime
), aes(x = Feature_value, y = SHAP_value)) +
  geom_point(alpha = 0.6) +
  geom_smooth(method = "loess", se = FALSE, color = "blue") +
  ggtitle("SHAP Dependence Plot for Runtime") +
  xlab("Runtime") +
  ylab("SHAP Value") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



```
selected_features_df <- numeric_vars[, c("budget", "release_year", "runtime", "popularity")]

ctrl <- rfeControl(functions = rfFuncs, method = "cv", number = 5)

rfe_result <- rfe(selected_features_df, numeric_vars$success, sizes = c(1:ncol(selected_features_df)), 

print(rfe_result)

selected_features <- rfe_result$optVariables
print(selected_features)
```

RFE for Feature Selection

Multiple Regression with t-values for Variable Importance

```
summary(lg_model)
```

```
##
## Call:
## glm(formula = success ~ budget + release_year + runtime + popularity,
##     family = "binomial", data = training_lg)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.35118    0.50679   2.666  0.00767 **
## budget       -0.98439    1.00381  -0.981  0.32676
## release_year -1.97016    0.47477  -4.150 3.33e-05 ***
## runtime       0.05776    0.62504   0.092  0.92637
## popularity   89.83537   13.20727   6.802 1.03e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 827.89  on 658  degrees of freedom
## Residual deviance: 720.31  on 654  degrees of freedom
## AIC: 730.31
##
## Number of Fisher Scoring iterations: 6
```

We can use Pr|z| to find statistically significant features. Since release year and popularity are the variables with p values less than 0.05, we can say these are the variables that are statistically significant at predicting success.

Feature Selection with all variables in the dataset

```
numeric_vars <- df_for_class[, sapply(df_for_class, is.numeric)]
numeric_vars$success <- df_for_class$success
lg_model2 <- glm(success ~ ., data = numeric_vars, family = binomial)
```

Z-scores for Most Significant Variables

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(lg_model2)
```

```
##
## Call:
## glm(formula = success ~ ., family = binomial, data = numeric_vars)
##
## Coefficients: (1 not defined because of singularities)
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -15.096659  69.385319  -0.218    0.828
## popularity    -0.128380   0.288182  -0.445    0.656
## vote_count     0.068838   0.067987   1.013    0.311
## vote_average  -0.002380   0.074487  -0.032    0.975
## budget        -0.033929   0.007084  -4.789 1.67e-06 ***
## revenue        0.033701   0.007040   4.787 1.69e-06 ***
## runtime        0.007372   0.009173   0.804    0.422
## release_year   0.006950   0.034448   0.202    0.840
## profit               NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1396.395  on 1097  degrees of freedom
## Residual deviance:   44.941  on 1090  degrees of freedom
## AIC: 60.941
##
```

```
## Number of Fisher Scoring iterations: 25
```

We can use Pr|z| to find statistically significant features. When looking at the model with every variable, the only two with p values less than 0.05 and therefore are statistically significant at predicting success are revenue and budget. However, we need to be cautious because these are correlated.

```
step_model <- step(lg_model, direction = "both", trace = 0)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(step_model)
```

```
##
## Call:
## glm(formula = success ~ release_year + popularity, family = "binomial",
##     data = training_lg)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.3528     0.3596   3.762 0.000169 ***
## release_year  -1.9757     0.4582  -4.312 1.62e-05 ***
## popularity    86.6297    11.9003   7.280 3.35e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 827.89  on 658  degrees of freedom
## Residual deviance: 721.28  on 656  degrees of freedom
## AIC: 727.28
##
## Number of Fisher Scoring iterations: 6
```

After using the STEP model, it shows that release_year and popularity are the 2 features that were selected.

```r
ctrl <- rfeControl(functions = rfFuncs, method = "cv", number = 10)

rfe_result <- rfe(numeric_vars[, -which(names(numeric_vars) == "success")], numeric_vars$success, sizes

print(rfe_result)
```

```
##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (10 fold)
##
## Resampling performance over subset size:
##
##  Variables Accuracy Kappa AccuracySD KappaSD Selected
##          0        1     1          0       0        *
##          1        1     1          0       0
##          2        1     1          0       0
##          3        1     1          0       0
##          4        1     1          0       0
##          5        1     1          0       0
##          6        1     1          0       0
##          7        1     1          0       0
##          8        1     1          0       0
##
## The top 0 variables (out of 0):
##    profit
```

```r
selected_features <- rfe_result$optVariables
print(selected_features)
```

```
## [1] "profit"
```

This selects profit, however this is directly correlated with success so we need to be weary.

Comparing Predictor Sets

Base Set of Predictors

We will use all available predictors: budget, release_year, runtime, and popularity.

```r
# Fit logistic regression model
base_model <- glm(success ~ budget + release_year + runtime + popularity,
                  data = df_normal,
                  family = binomial)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
# Predict probabilities and classify
base_probs <- predict(base_model, type = "response")
base_preds <- ifelse(base_probs > 0.5, 1, 0)

# Calculate accuracy
base_accuracy <- mean(base_preds == df_normal$success)
cat("Base Model Accuracy: ", base_accuracy, "\n")
```

```
## Base Model Accuracy:  0
```

Reduced Set of Predictors

We will now use only the most important predictors identifies through feature selection **(ADD WHEN FOUND ABOVE).**

```r
#EXAMPLE BUT CHANGE WHEN FIND PREDICTORS TO USE
reduced_model <- glm(success ~ budget + popularity, data = df_normal, family = binomial)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
reduced_probs <- predict(reduced_model, type = "response")
reduced_preds <- ifelse(reduced_probs > 0.5, 1, 0)
reduced_accuracy <- mean(reduced_preds == df_normal$success)
cat("Reduced Model Accuracy: ", reduced_accuracy, "\n")
```

```
## Reduced Model Accuracy:  0
```

Comparing Models with Different Predictor Sets

```r
table(df_for_class$success)
```

```
##
## No Success    Success
##        365        733
```

```r
# Remove rows with missing values
df_for_class <- na.omit(df_for_class)

# Load necessary libraries
library(randomForest)
library(caret)
library(ROCR)

# Define the different predictor sets
predictor_set_1 <- c("budget", "release_year", "runtime")
predictor_set_2 <- c("budget", "release_year", "popularity")
predictor_set_3 <- c("budget", "runtime", "popularity")
predictor_set_4 <- c("budget", "release_year", "runtime", "popularity")

# Define a function to train Random Forest and return performance metrics
train_rf_model <- function(predictors, data) {
  # Train Random Forest model
  model <- randomForest(success ~ ., data = data[, c(predictors, "success")], ntree = 500)

  # Get predicted probabilities for the test data
  prob <- predict(model, type = "prob")[,2]

  # Calculate AUC
  pred <- prediction(prob, data$success)
  perf <- performance(pred, measure = "auc")
  auc <- perf@y.values[[1]]

  # Return AUC
  return(auc)
}

# Define a function to train Multiple Linear Regression and return performance metrics
```

```
train_lm_model <- function(predictors, data) {
  # Train Linear Model
  model <- lm(success ~ ., data = data[, c(predictors, "success")])

  # Get predicted probabilities
  prob <- predict(model, type = "response")

  # Convert probabilities to class labels (Success = 1, No Success = 0)
  pred_labels <- ifelse(prob > 0.5, 1, 0)

  # Calculate Accuracy
  accuracy <- mean(pred_labels == data$success)

  # Return Accuracy
  return(accuracy)
}

# Train and evaluate models with different predictor sets for Random Forest
rf_auc_1 <- train_rf_model(predictor_set_1, df_for_class)
rf_auc_2 <- train_rf_model(predictor_set_2, df_for_class)
rf_auc_3 <- train_rf_model(predictor_set_3, df_for_class)
rf_auc_4 <- train_rf_model(predictor_set_4, df_for_class)

# Train and evaluate models with different predictor sets for Multiple Linear Regression
lm_accuracy_1 <- train_lm_model(predictor_set_1, df_for_class)
```

```
## Warning in model.response(mf, "numeric"): using type = "numeric" with a factor
## response will be ignored

## Warning in Ops.factor(y, z$residuals): '-' not meaningful for factors
```

```
lm_accuracy_2 <- train_lm_model(predictor_set_2, df_for_class)
```

```
## Warning in model.response(mf, "numeric"): using type = "numeric" with a factor
## response will be ignored

## Warning in model.response(mf, "numeric"): '-' not meaningful for factors
```

```
lm_accuracy_3 <- train_lm_model(predictor_set_3, df_for_class)
```

```
## Warning in model.response(mf, "numeric"): using type = "numeric" with a factor
## response will be ignored

## Warning in model.response(mf, "numeric"): '-' not meaningful for factors
```

```
lm_accuracy_4 <- train_lm_model(predictor_set_4, df_for_class)
```

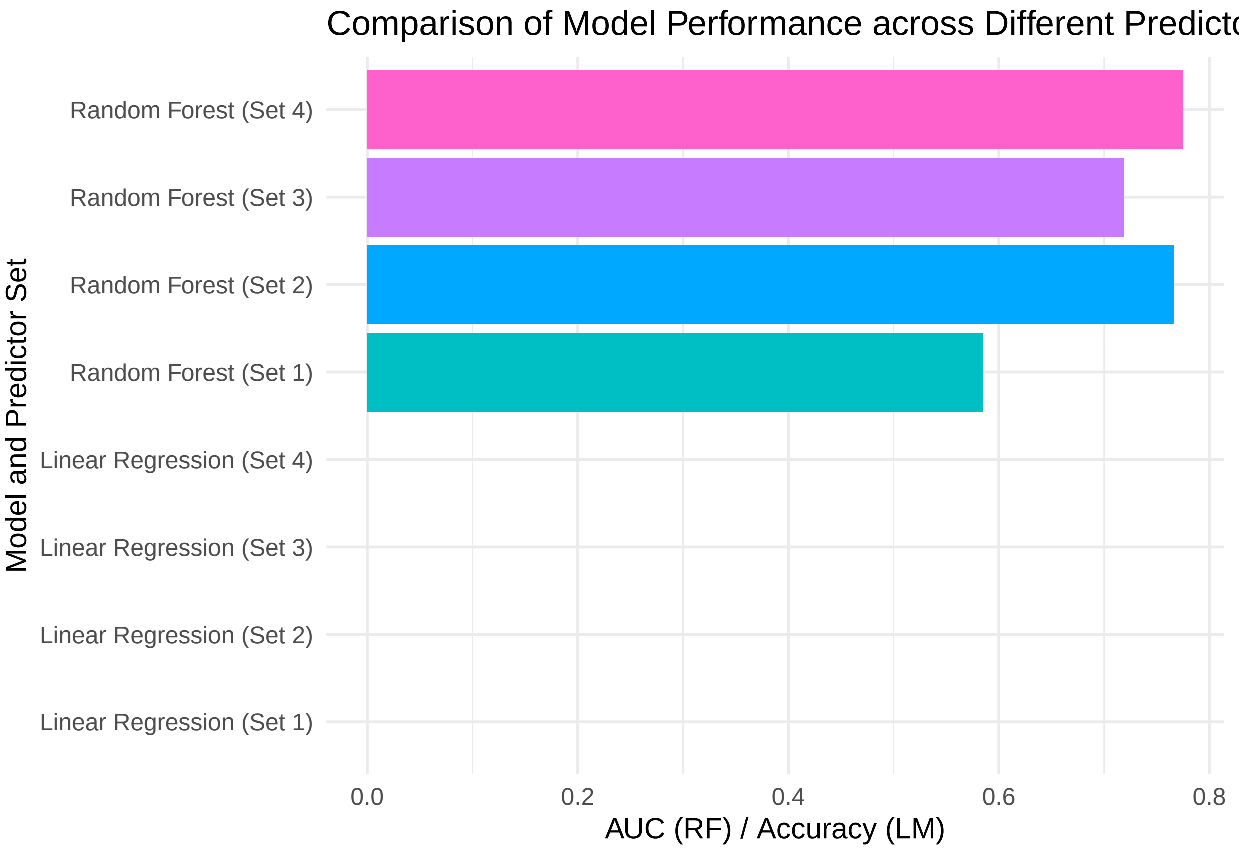
```
## Warning in model.response(mf, "numeric"): using type = "numeric" with a factor
## response will be ignored

## Warning in model.response(mf, "numeric"): '-' not meaningful for factors
```

```
# Create a summary of model performance
performance_comparison <- data.frame(
  Model = c("Random Forest (Set 1)", "Random Forest (Set 2)", "Random Forest (Set 3)", "Random Forest (
            "Linear Regression (Set 1)", "Linear Regression (Set 2)", "Linear Regression (Set 3)", "Lin
  AUC_or_Accuracy = c(rf_auc_1, rf_auc_2, rf_auc_3, rf_auc_4,
                      lm_accuracy_1, lm_accuracy_2, lm_accuracy_3, lm_accuracy_4)
)

# Print performance comparison
print(performance_comparison)
```

```
##                        Model AUC_or_Accuracy
## 1     Random Forest (Set 1)       0.5850717
## 2     Random Forest (Set 2)       0.7658581
## 3     Random Forest (Set 3)       0.7185763
## 4     Random Forest (Set 4)       0.7750005
## 5 Linear Regression (Set 1)       0.0000000
## 6 Linear Regression (Set 2)       0.0000000
## 7 Linear Regression (Set 3)       0.0000000
## 8 Linear Regression (Set 4)       0.0000000
```

Plotting Performance Comparison

```
# Plot the comparison
library(ggplot2)

ggplot(performance_comparison, aes(x = Model, y = AUC_or_Accuracy, fill = Model)) +
  geom_bar(stat = "identity", show.legend = FALSE) +
  coord_flip() +
  theme_minimal() +
  ggtitle("Comparison of Model Performance across Different Predictor Sets") +
  xlab("Model and Predictor Set") +
  ylab("AUC (RF) / Accuracy (LM)")
```



Adding Interaction Terms

We can test whether interaction terms improve model performance.

```
interaction_model <- glm(success ~ budget * popularity + runtime, data = df_normal, family = binomial)
interaction_probs <- predict(interaction_model, type = "response")
interaction_preds <- ifelse(interaction_probs > 0.5, 1, 0)
interaction_accuracy <- mean(interaction_preds == df_normal$success)
cat("Interaction Model Accuracy: ", interaction_accuracy, "\n")
```

```
## Interaction Model Accuracy:  0
```

Cross-Validation to Compare Models

Use cross-validation to evaluate the generalizability of each predictor set.

```
# Base Model
base_cv <- train(success ~ budget + release_year + runtime + popularity, data = df_for_class, method =
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
print(base_cv)
```

```
## Generalized Linear Model
##
## 1098 samples
##    4 predictor
##    2 classes: 'No Success', 'Success'
##
```

```
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 878, 878, 878, 879, 879
## Resampling results:
##
##   Accuracy   Kappa
##   0.6712121  0.1082193
```

```
# Reduced Model
reduced_cv <- train(success ~ budget + popularity, data = df_for_class, method = "glm", family = binomia
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
print(reduced_cv)
```

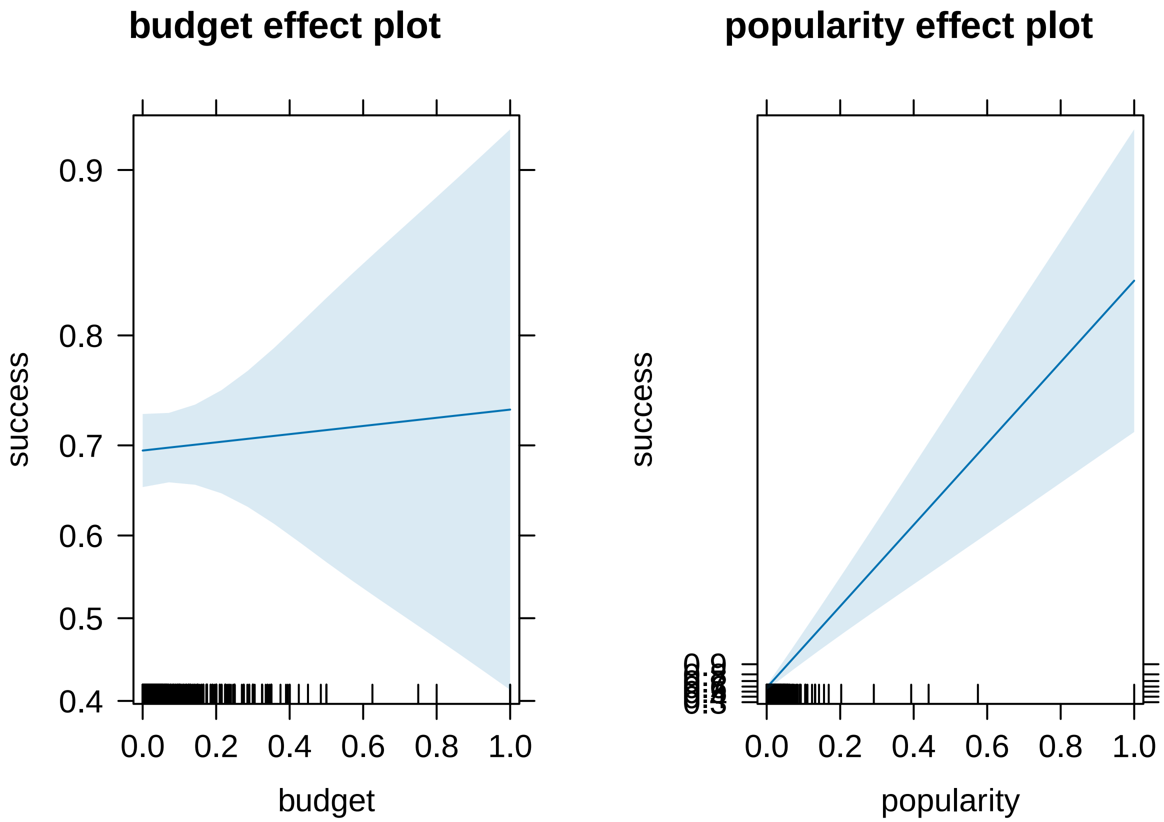
```
## Generalized Linear Model
##
## 1098 samples
##    2 predictor
##    2 classes: 'No Success', 'Success'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 879, 878, 879, 878, 878
## Resampling results:
##
##   Accuracy   Kappa
##   0.6675758  0
```

Visualize Feature Importance

Effect Plots for Logistic Regression

Visualize the effect of individual predictors on the probability of success.

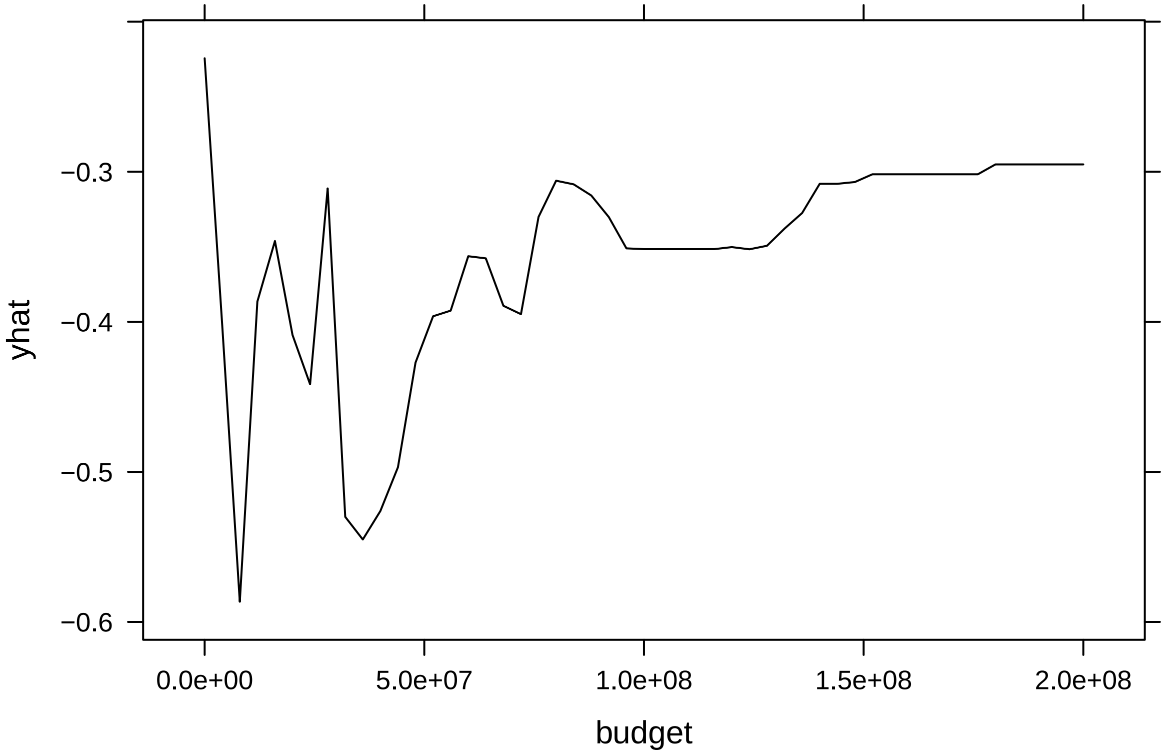
```
effect_plot <- allEffects(reduced_model)
plot(effect_plot)
```



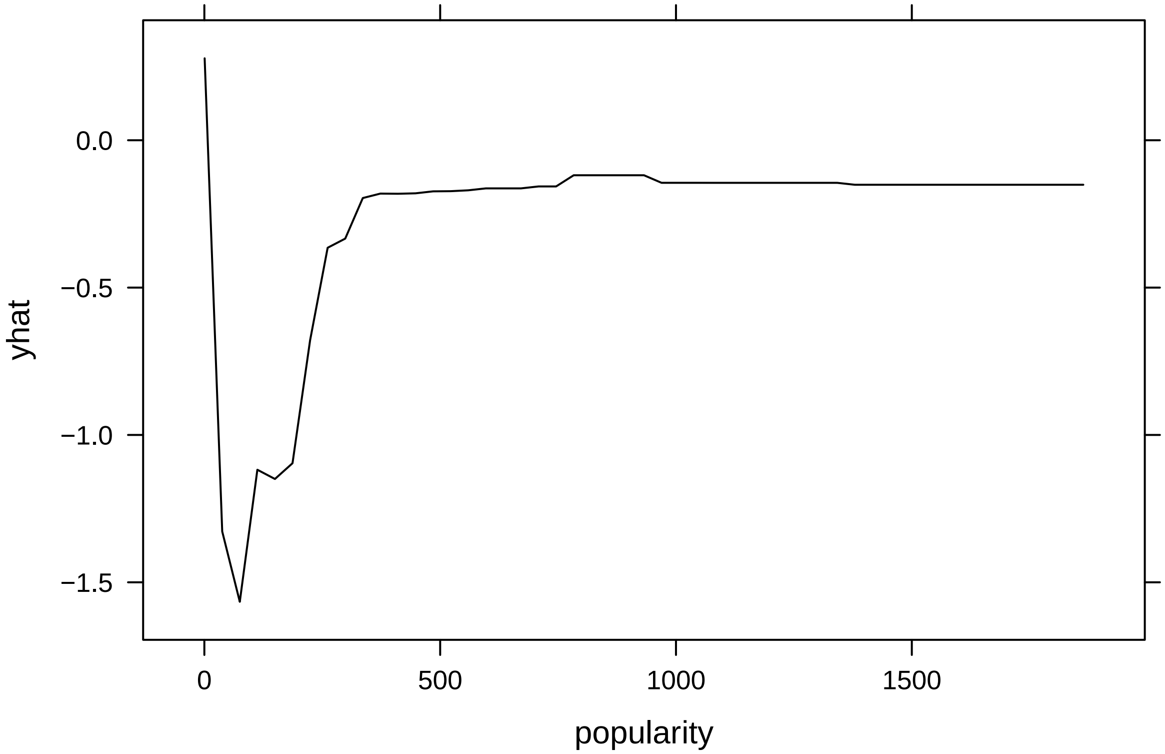
Partial Dependence Plots

Use this for tree based models like Random Forest.

```r
# Partial dependence for "budget"
pd_budget <- partial(rf_model, pred.var = "budget")
plotPartial(pd_budget)
```



```
pd_popularity <- partial(rf_model, pred.var = "popularity")
plotPartial(pd_popularity)
```


yhat
popularity