Visualizations

```
library("tidyverse")
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.4     v dplyr   1.0.7
## v tidyr   1.1.4     v stringr 1.4.0
## v readr   2.0.2     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library("readr")
library("stringr")
library("dplyr")
library("ggplot2")
```

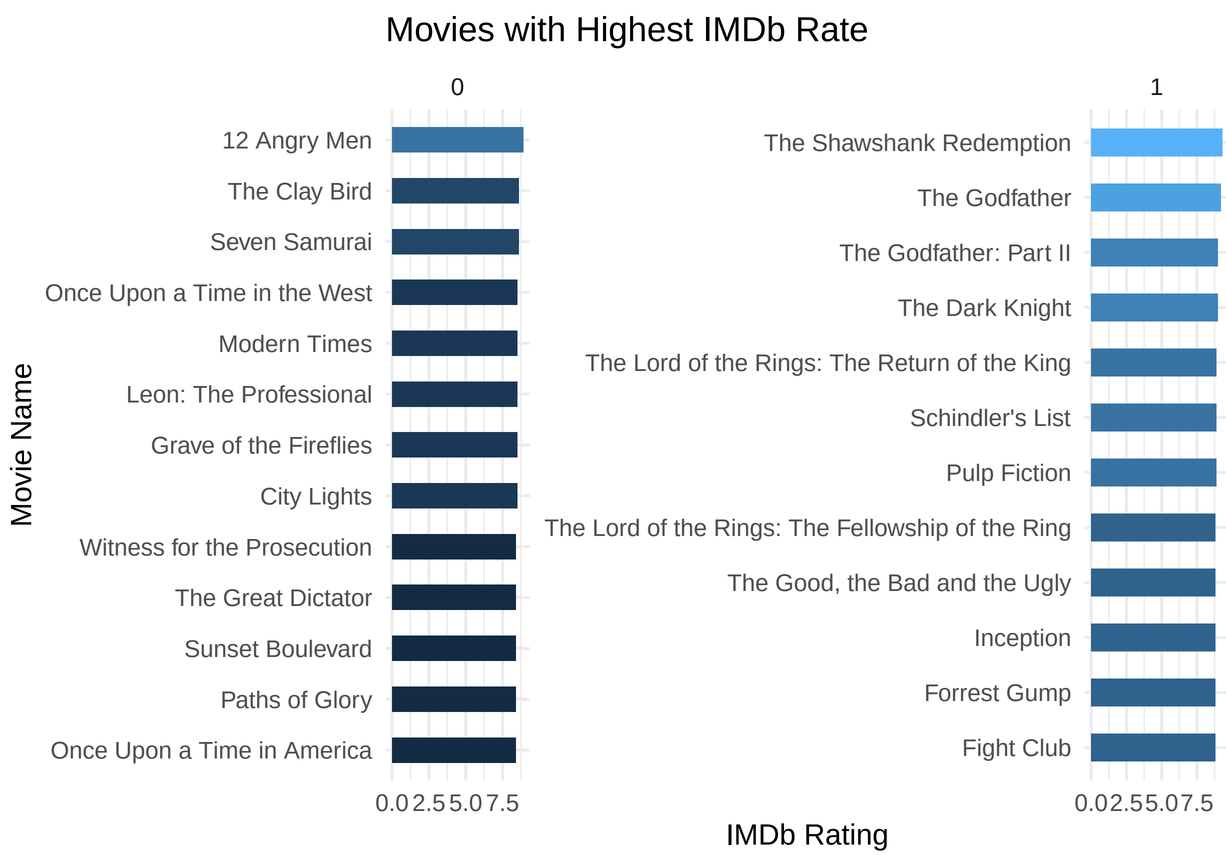
```
# Importing the tidy data file
setwd(getwd())
Cleaned_data <- as_tibble(read_csv("cleaned_merged.csv"))
```

```
## Rows: 8992 Columns: 147

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr   (7): genres, imdb_id, production_countries, original_language, title, ...
## dbl (139): popularity, runtime, vote_count, year, budget, worlwide_gross_inc...
## lgl   (1): adult

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
# The top 20 Miovies with High IMDb Scores, For hit and not
# hit movies
top_imdb_movie <- Cleaned_data %>%
    group_by(`hit/not`) %>%
    top_n(10, wt = weighted_average_vote) %>%
    summarise(title, weighted_average_vote, `hit/not`) %>%
    arrange(desc(weighted_average_vote))
```

```
## `summarise()` has grouped output by 'hit/not'. You can override using the `.groups` argument.
```

```r
top_imdb_movie %>%
    ggplot(aes(x = reorder(title, weighted_average_vote), y = weighted_average_vote,
        fill = weighted_average_vote)) + geom_col(width = 0.5,
    show.legend = FALSE) + facet_wrap(~`hit/not`, scales = "free") +
    coord_flip() + labs(x = "Movie Name", y = "IMDb Rating",
    title = "Movies with Highest IMDb Rate") + theme_minimal()
```

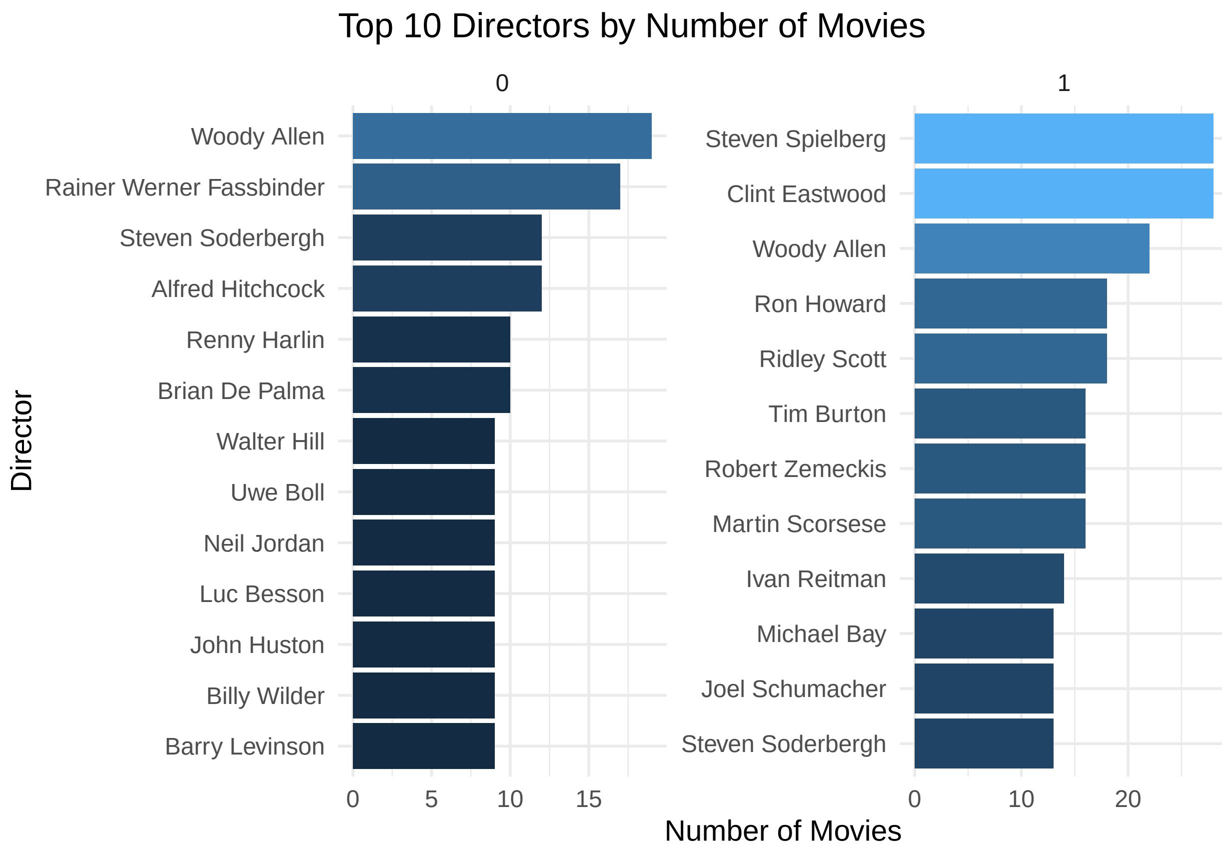



```r
# From the above Figure we can see that the hit movies
# (hit/not=1), have demonstrated higher IMDb numbers in
# compared with the non-hit
```

```r
# Top 10 directors for hit and not hit movies

top_directors <- Cleaned_data %>%
    group_by(`hit/not`) %>%
    count(director, sort = TRUE) %>%
    top_n(10) %>%
    ggplot(aes(x = reorder(director, n), y = n, fill = n)) +
    geom_col(show.legend = FALSE) + facet_wrap(~`hit/not`, scales = "free") +
    labs(x = "Director", y = "Number of Movies", title = "Top 10 Directors by Number of Movies") +
    coord_flip() + theme_minimal()
```

```
## Selecting by n
```

```r
top_directors
```

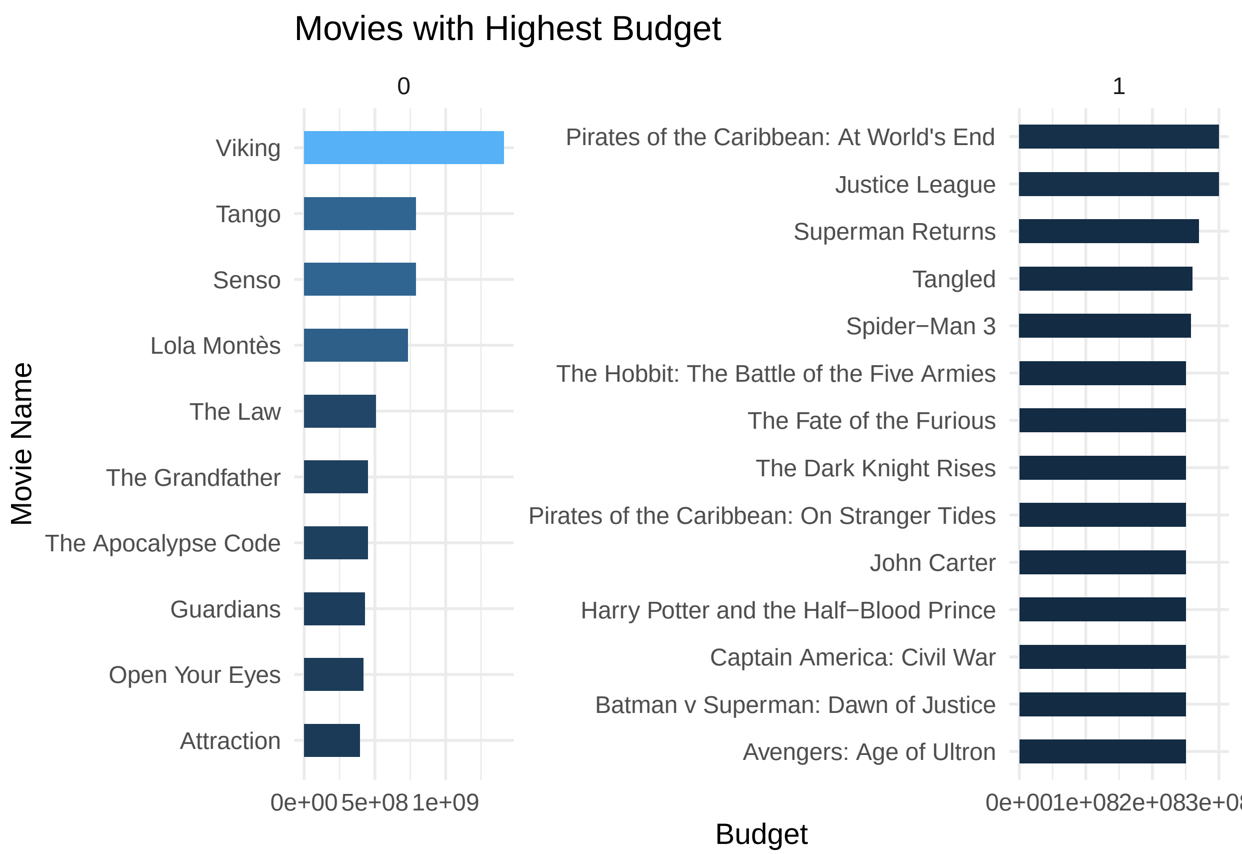



```r
# Here we see that for hit movies the number of movies the
# director has produced is more
```

```r
# Movies with Highest budget faceted by hit or not hit

highest_budgets <- Cleaned_data %>%
    group_by(`hit/not`) %>%
    top_n(10, wt = budget) %>%
    summarise(title, budget, `hit/not`) %>%
    arrange(desc(budget))
```

```
## `summarise()` has grouped output by 'hit/not'. You can override using the `.groups` argument.
```

```r
highest_budgets %>%
    ggplot(aes(x = reorder(title, budget), y = budget, fill = budget)) +
    geom_col(width = 0.5, show.legend = FALSE) + facet_wrap(~`hit/not`,
    scales = "free") + coord_flip() + labs(x = "Movie Name",
    y = "Budget", title = "Movies with Highest Budget") + theme_minimal()
```

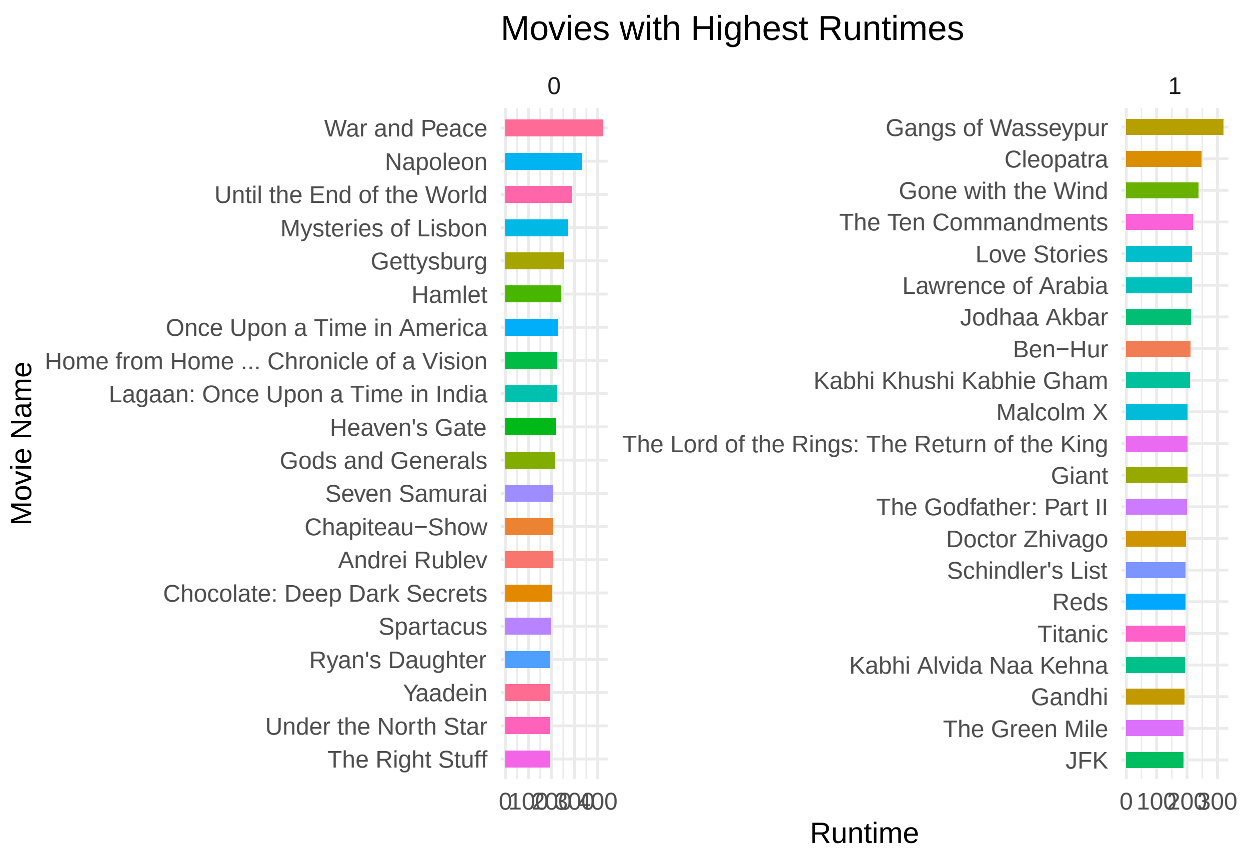



```
# For some reason we can see that non hit movies have
# higher movie budgets
```

```
# Movies with highest runtimes in terms of hit and non hit
highest_runtimes <- Cleaned_data %>%
    group_by(`hit/not`) %>%
    top_n(20, wt = runtime) %>%
    summarise(title, runtime, `hit/not`) %>%
    arrange(desc(runtime))
```

```
## `summarise()` has grouped output by 'hit/not'. You can override using the `.groups` argument.
```

```
highest_runtimes %>%
    ggplot(aes(x = reorder(title, runtime), y = runtime, fill = title)) +
    geom_col(width = 0.5, show.legend = FALSE) + facet_wrap(~`hit/not`,
    scales = "free") + coord_flip() + labs(x = "Movie Name",
    y = "Runtime", title = "Movies with Highest Runtimes") +
    theme_minimal()
```

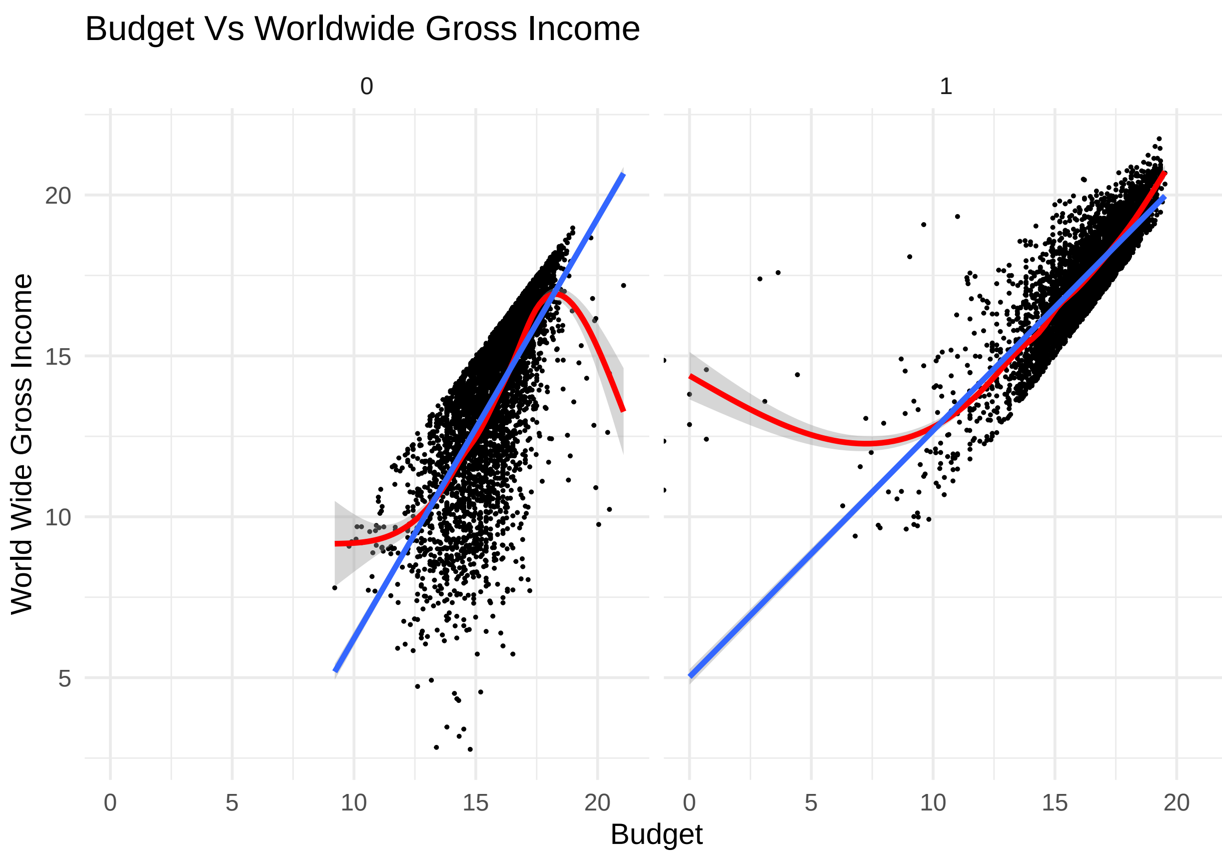



```
# We can see that the movie with the highest runtime was a
# nonhit movie.The rest of the movies weather it was a hit
# or not demonstrated an average runtime no more that 200.
```

```
# Scatter plot to see if there is any relationship between
# budget and worldwide gross income faceted by hit or not
# hit movie
budget_grossincome <- ggplot(data = Cleaned_data, mapping = aes(x = log(budget),
    y = log(worlwide_gross_income))) + geom_point(size = 0.2) +
    labs(x = "Budget", y = "World Wide Gross Income", title = "Budget Vs Worldwide Gross Income") +
    facet_wrap(~`hit/not`) + geom_smooth(color = "red") + geom_smooth(method = lm) +
    theme_minimal()

budget_grossincome
```

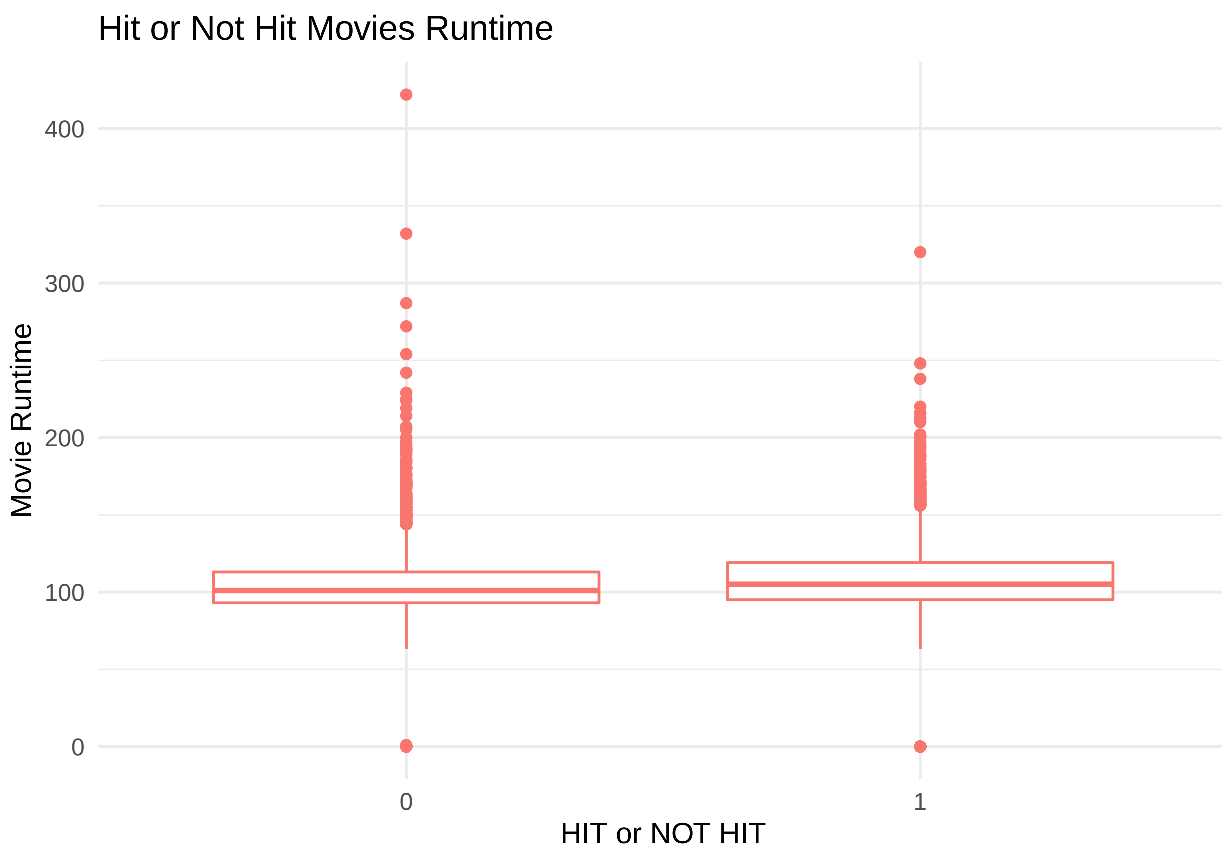
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

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




```
# From the above we can see that for both hit or not heat
# there is a positive relationship between budget and world
# wide gross income
```

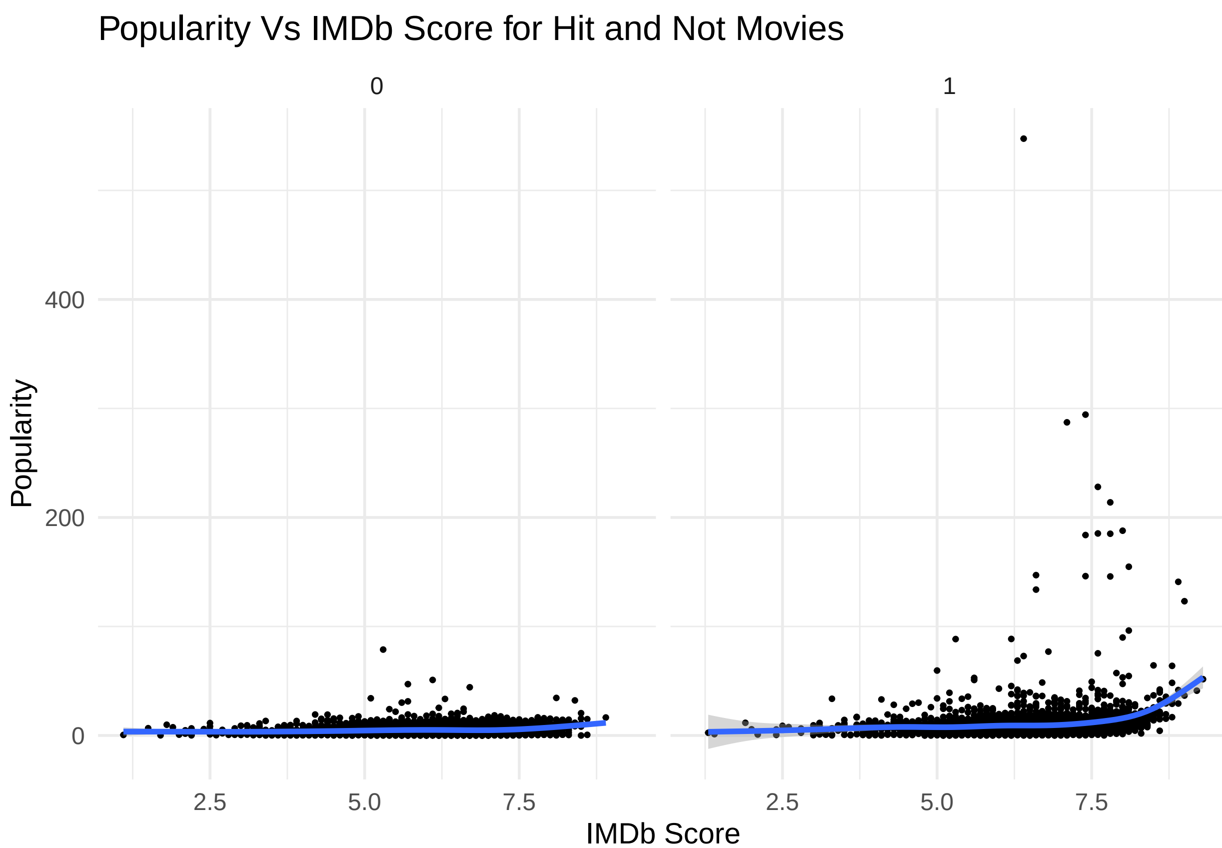
```
# runtime vs hit not hit boxplot
run_time_budget <- ggplot(data = Cleaned_data, mapping = aes(y = runtime,
    color = "`hit/not")) + geom_boxplot(aes(x = as.character(`hit/not`)),
    show.legend = "False") + labs(y = "Movie Runtime", x = "HIT or NOT HIT",
    title = "Hit or Not Hit Movies Runtime") + theme_minimal()
run_time_budget
```




```
# From the boxplot we can see that that most nonhit movies
# have demonstrated an average run time about 100 and for
# hit movies the average run time was a bit higher, both
# demonstrated right skewed model.
```

```
# IMDb Score and popularity #weird
Vote_average_popularity <- ggplot(data = Cleaned_data, mapping = aes(x = weighted_average_vote,
    y = popularity)) + geom_point(size = 0.5) + facet_wrap(~`hit/not`) +
    labs(x = "IMDb Score", y = "Popularity", title = "Popularity Vs IMDb Score for Hit and Not Movies")
    geom_smooth() + theme_minimal()
Vote_average_popularity
```

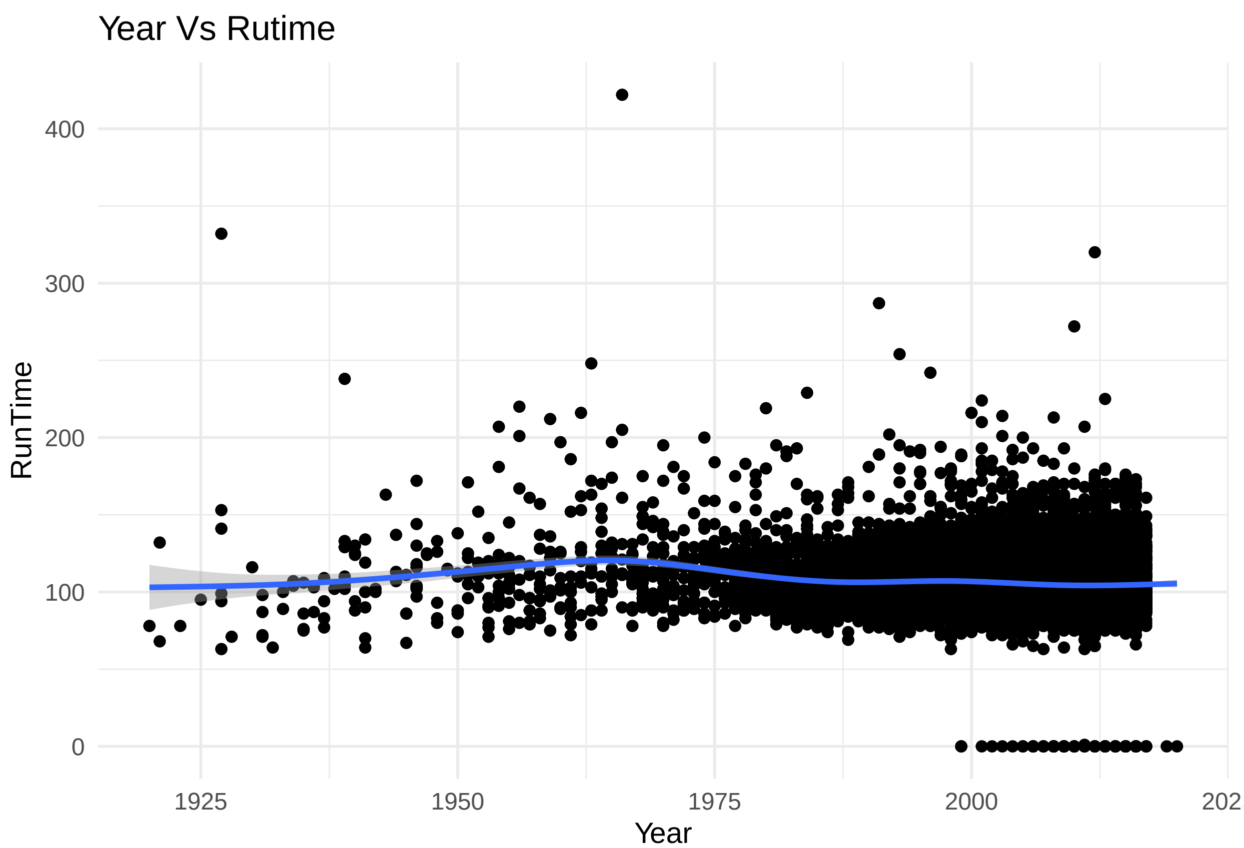
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```




```
# For both hit and non nit movies it showed a weird
# correlation between population and IMDb Score, where the
# popularity was relatively low, but it demonstrated a
# higher value for hit movies with higher
```

```
# runtimevs released year
runtime_vs_release_year <- ggplot(data = Cleaned_data, mapping = aes(x = year,
    y = runtime)) + geom_point() + labs(x = "Year", y = "RunTime",
    title = "Year Vs Rutime") + geom_smooth() + theme_minimal()

runtime_vs_release_year
```

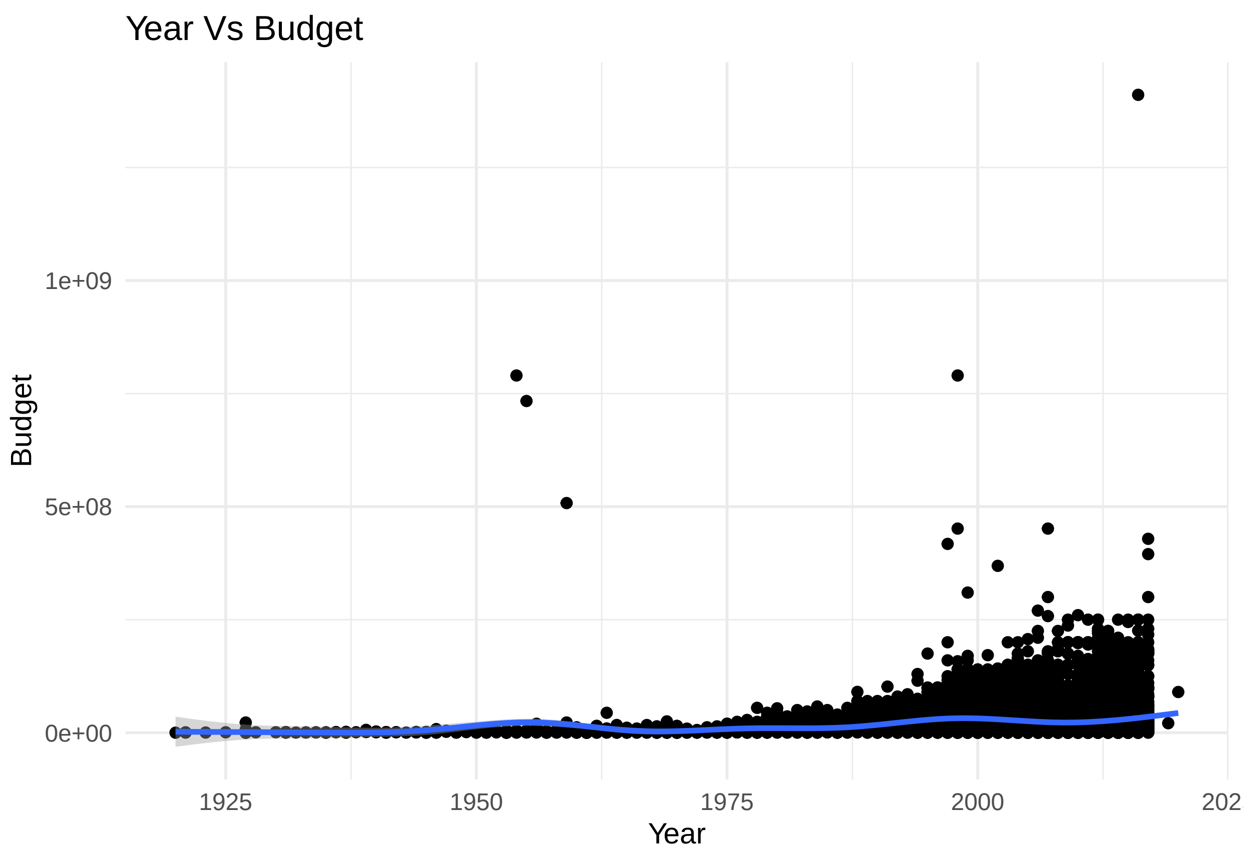
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```




```
# We can see as the years increase we see higher runtimes
```

```
# budgetvs release year
budget_vs_release_year <- ggplot(data = Cleaned_data, mapping = aes(x = year,
    y = budget)) + geom_point() + labs(x = "Year", y = "Budget",
    title = "Year Vs Budget") + geom_smooth() + theme_minimal()

budget_vs_release_year
```

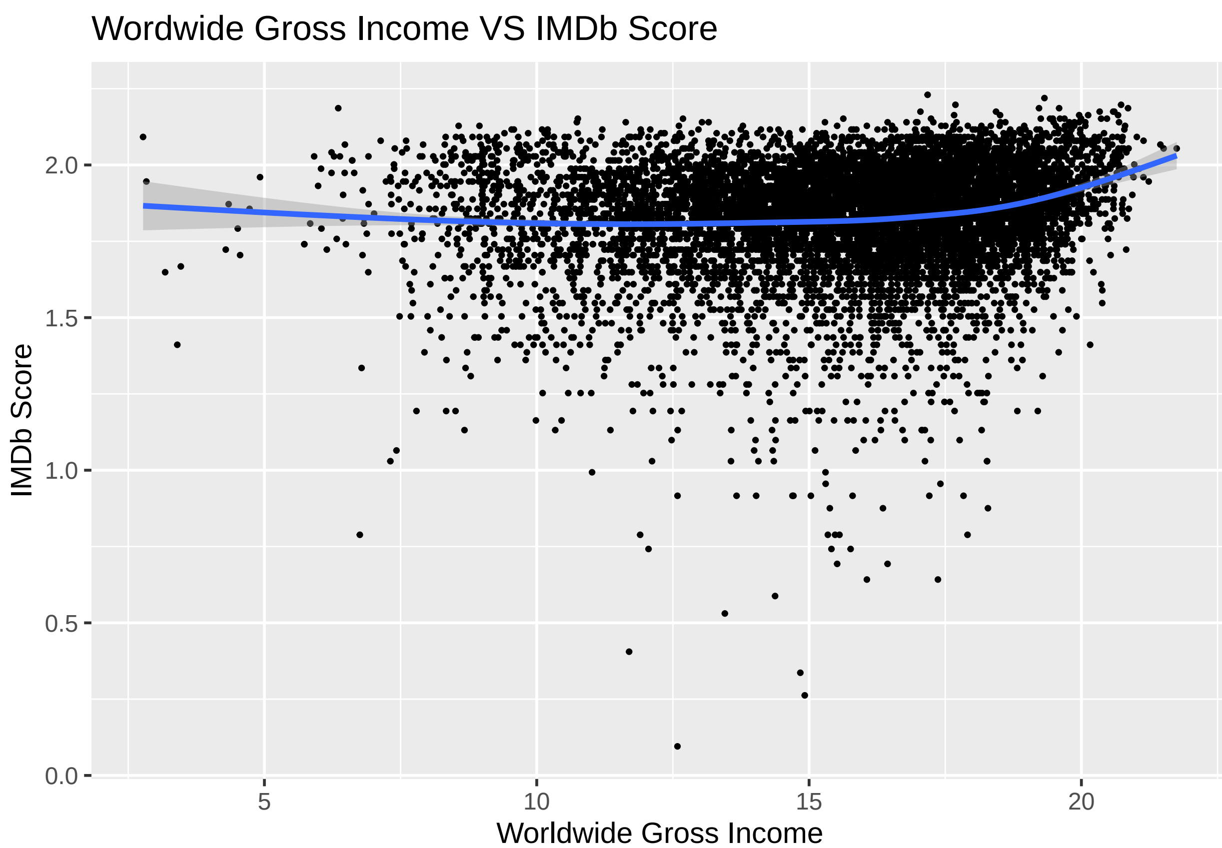
```
## 'geom_smooth()' using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



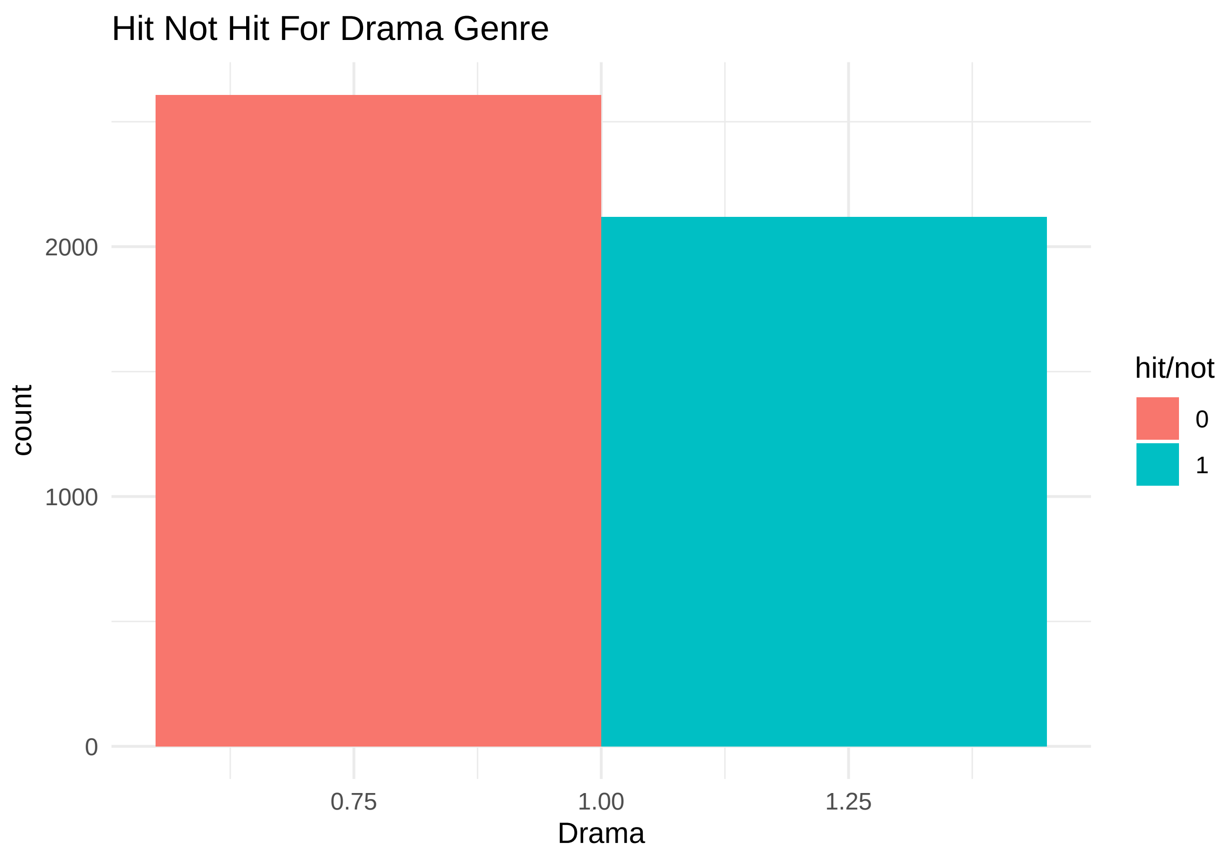

```
# we also see that as the years increase the budget
# increases
```

```
# IMDB Score vs world_wide income
world_vote <- ggplot(data = Cleaned_data, mapping = aes(x = log(worlwide_gross_income),
    y = log(weighted_average_vote))) + geom_point(size = 0.5) +
    labs(x = "Worldwide Gross Income", y = "IMDb Score", title = "Wordwide Gross Income VS IMDb Score")
    geom_smooth()

world_vote
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

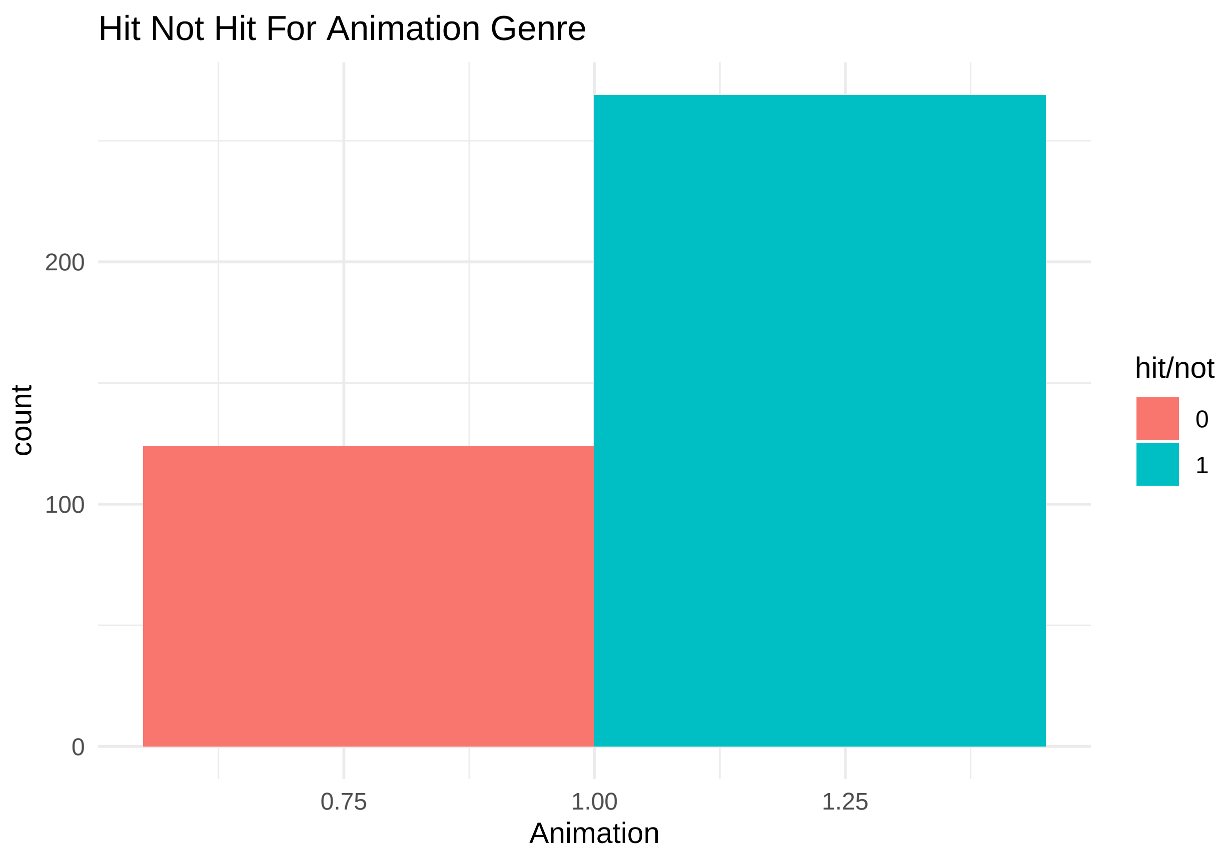



```r
# hit not hit agisnt drama
Drama_hit_not <- Cleaned_data %>%
    filter(Drama == 1) %>%
    ggplot(aes(x = Drama, fill = as.factor(`hit/not`))) + geom_bar(position = "dodge") +
    scale_fill_discrete(name = "hit/not") + labs(title = "Hit Not Hit For Drama Genre") +
    theme_minimal()

Drama_hit_not
```

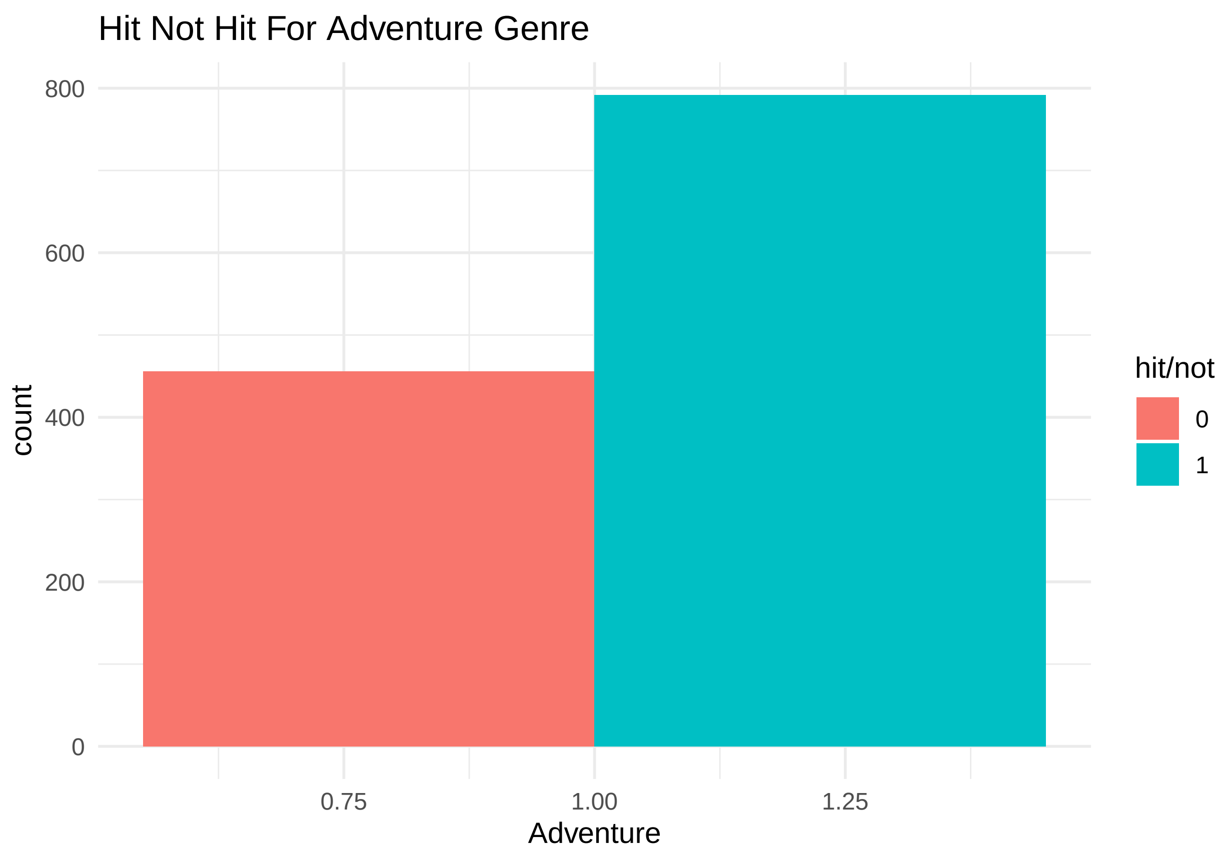



```
# we can see for Drama (genre) that movies that were not
# hit were more in the drama genre
```

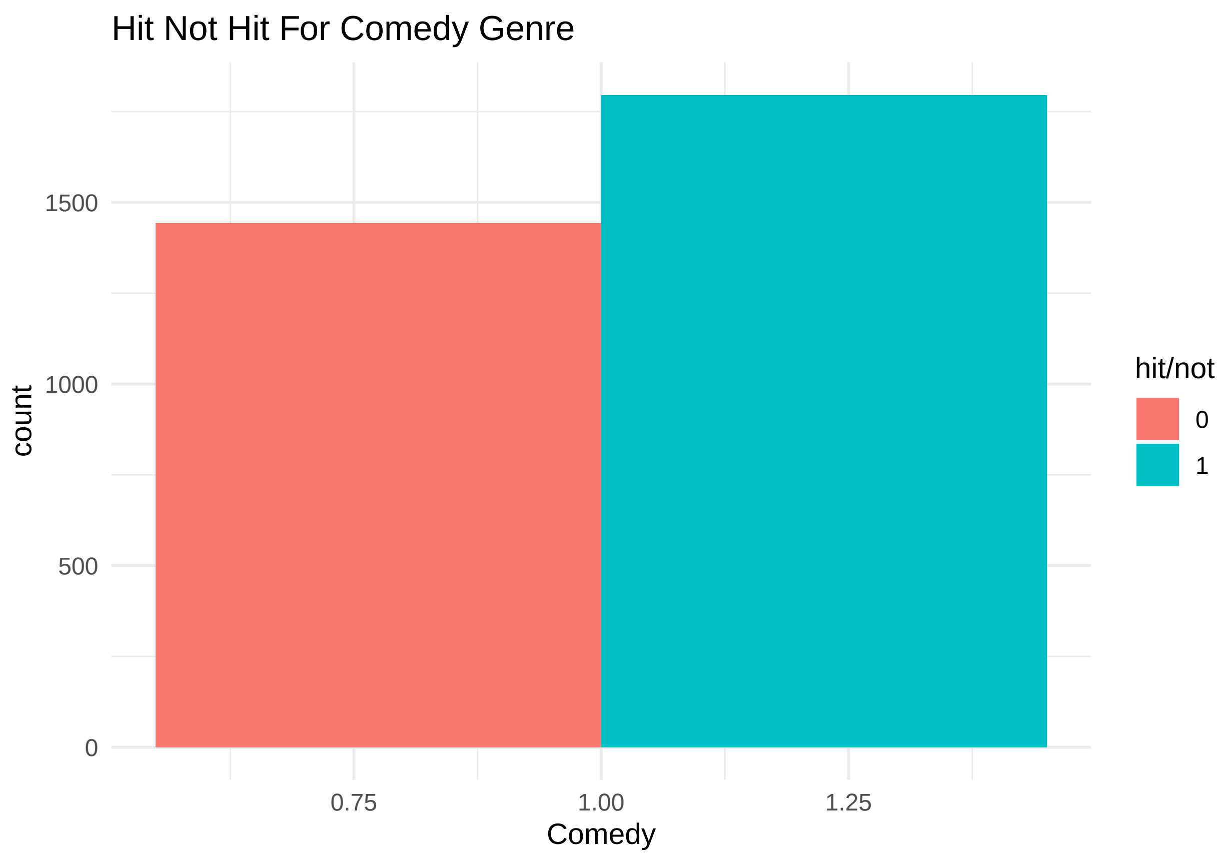
```
Animation_hit_not <- Cleaned_data %>%
    filter(Animation == 1) %>%
    ggplot(aes(x = Animation, fill = as.factor(`hit/not`))) +
    geom_bar(position = "dodge") + scale_fill_discrete(name = "hit/not") +
    labs(title = "Hit Not Hit For Animation Genre") + theme_minimal()

Animation_hit_not
```



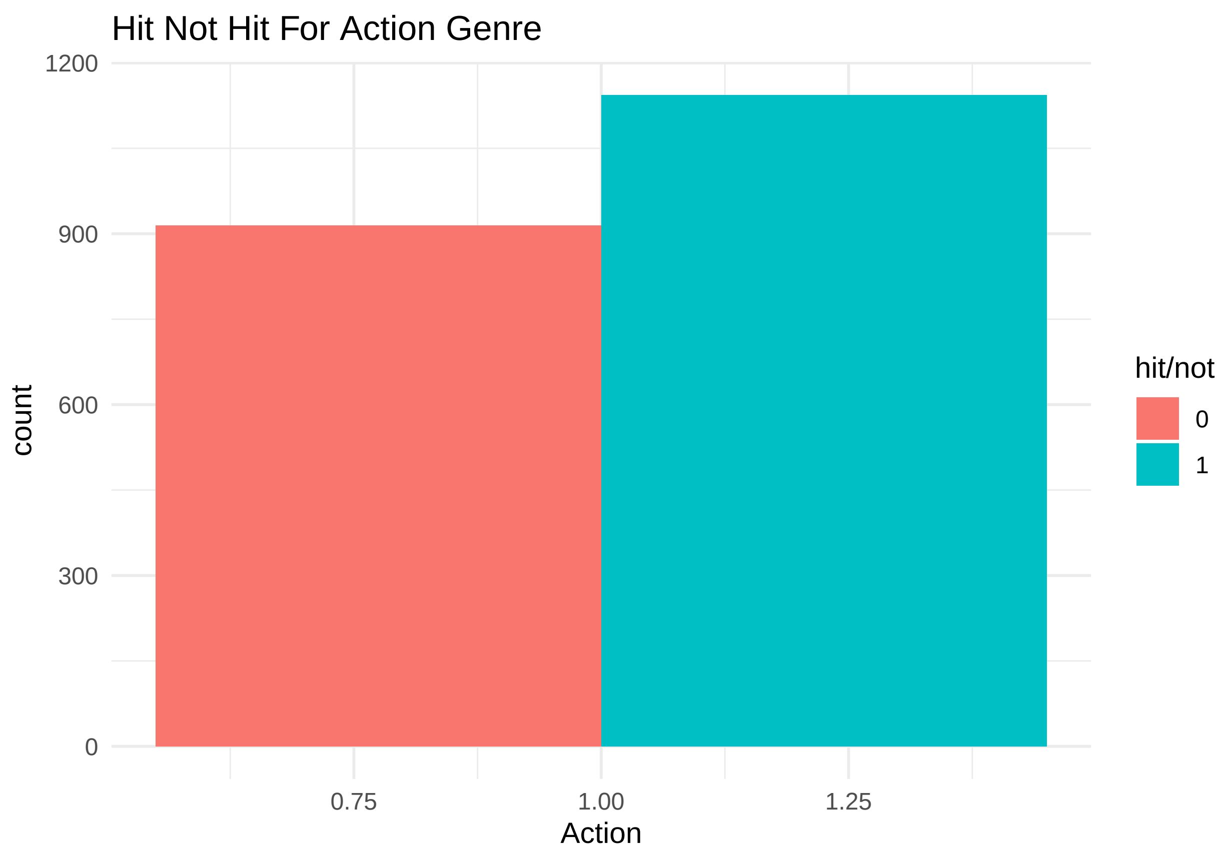

```
# hot not hit for Adventure
Adventure_hit_not <- Cleaned_data %>%
    filter(Adventure == 1) %>%
    ggplot(aes(x = Adventure, fill = as.factor(`hit/not`))) +
    geom_bar(position = "dodge") + scale_fill_discrete(name = "hit/not") +
    labs(title = "Hit Not Hit For Adventure Genre") + theme_minimal()

Adventure_hit_not
```



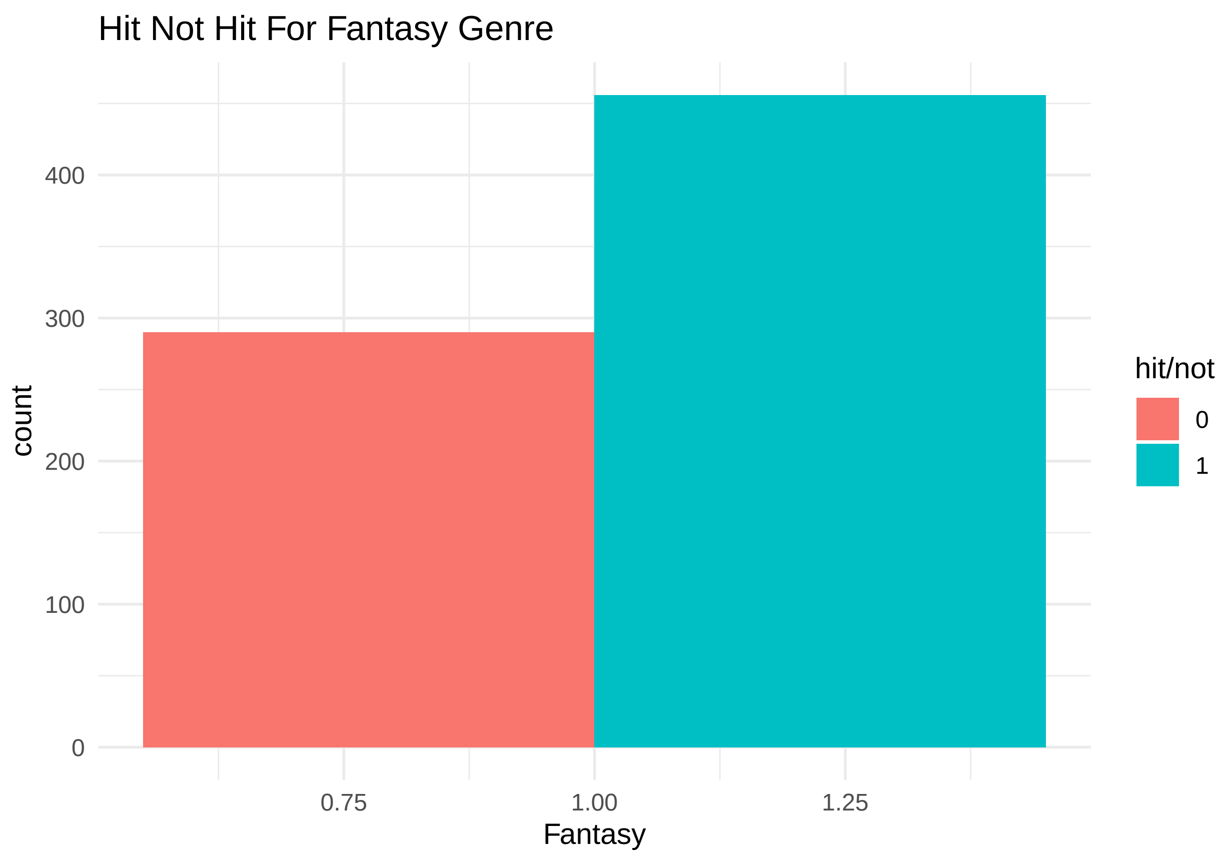

```r
Comedy_hit_not <- Cleaned_data %>%
    filter(Comedy == 1) %>%
    ggplot(aes(x = Comedy, fill = as.factor(`hit/not`))) + geom_bar(position = "dodge") +
    scale_fill_discrete(name = "hit/not") + labs(title = "Hit Not Hit For Comedy Genre") +
    theme_minimal()
Comedy_hit_not
```



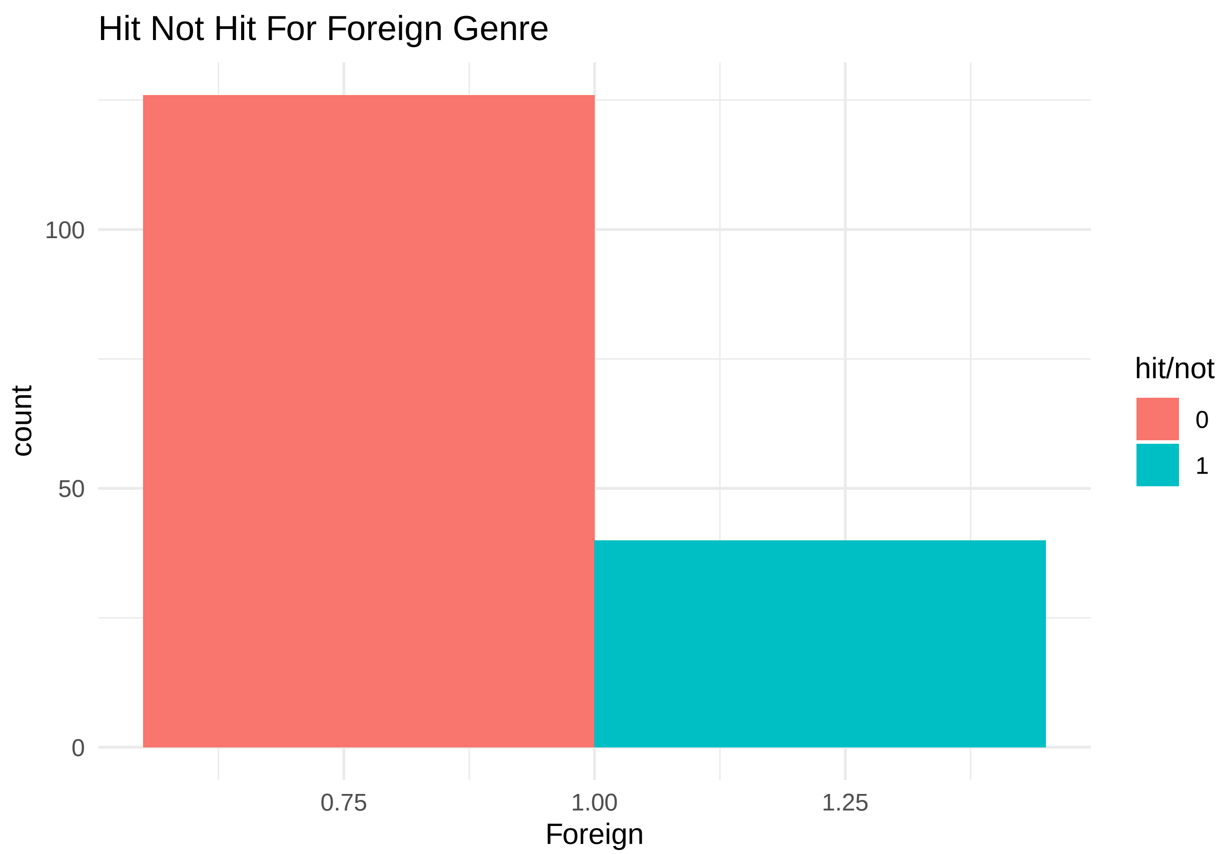

```
Action_hit_not <- Cleaned_data %>%
    filter(Action == 1) %>%
    ggplot(aes(x = Action, fill = as.factor(`hit/not`))) + geom_bar(position = "dodge") +
    scale_fill_discrete(name = "hit/not") + labs(title = "Hit Not Hit For Action Genre") +
    theme_minimal()

Action_hit_not
```



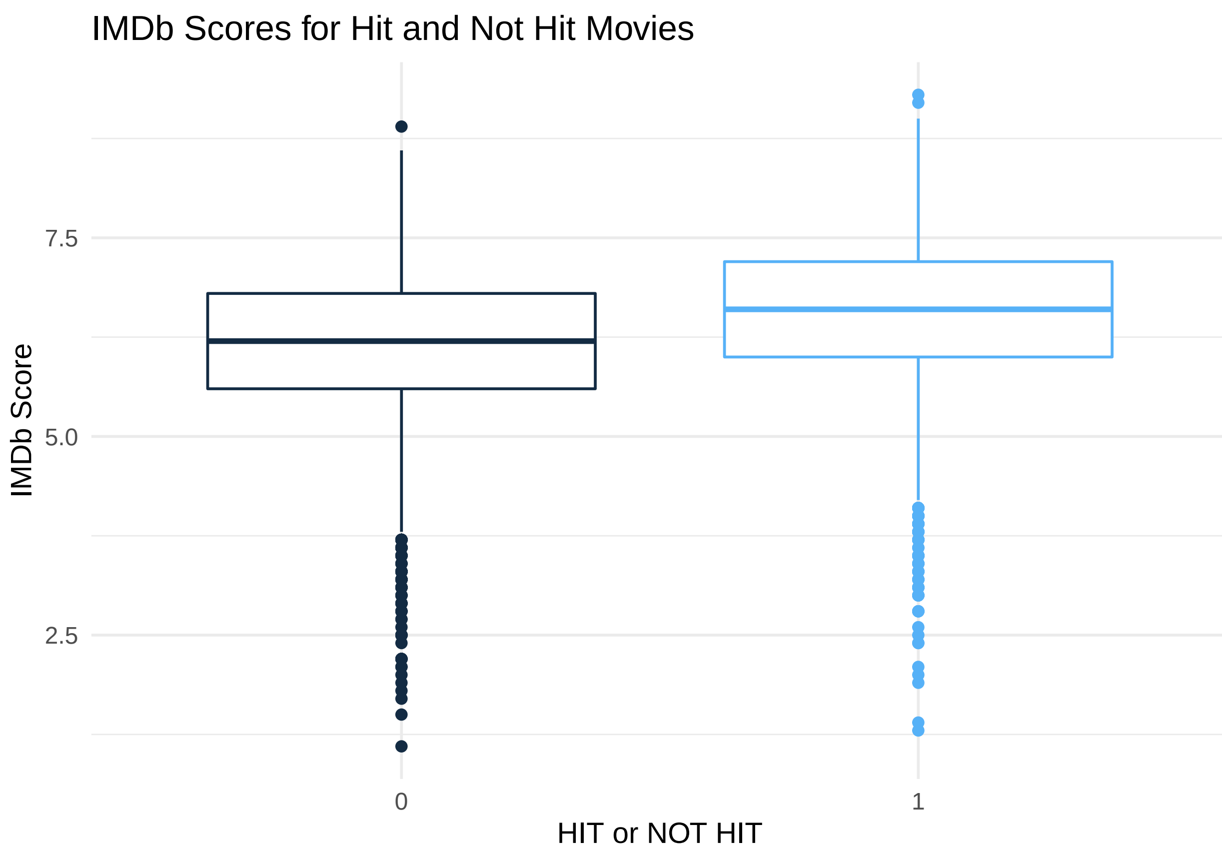

```
Fantasy_hit_not <- Cleaned_data %>%
    filter(Fantasy == 1) %>%
    ggplot(aes(x = Fantasy, fill = as.factor(`hit/not`))) + geom_bar(position = "dodge") +
    scale_fill_discrete(name = "hit/not") + labs(title = "Hit Not Hit For Fantasy Genre") +
    theme_minimal()

Fantasy_hit_not
```




```
Foreign_hit_not <- Cleaned_data %>%
    filter(Foreign == 1) %>%
    ggplot(aes(x = Foreign, fill = as.factor(`hit/not`))) + geom_bar(position = "dodge") +
    scale_fill_discrete(name = "hit/not") + labs(title = "Hit Not Hit For Foreign Genre") +
    theme_minimal()

Foreign_hit_not
```

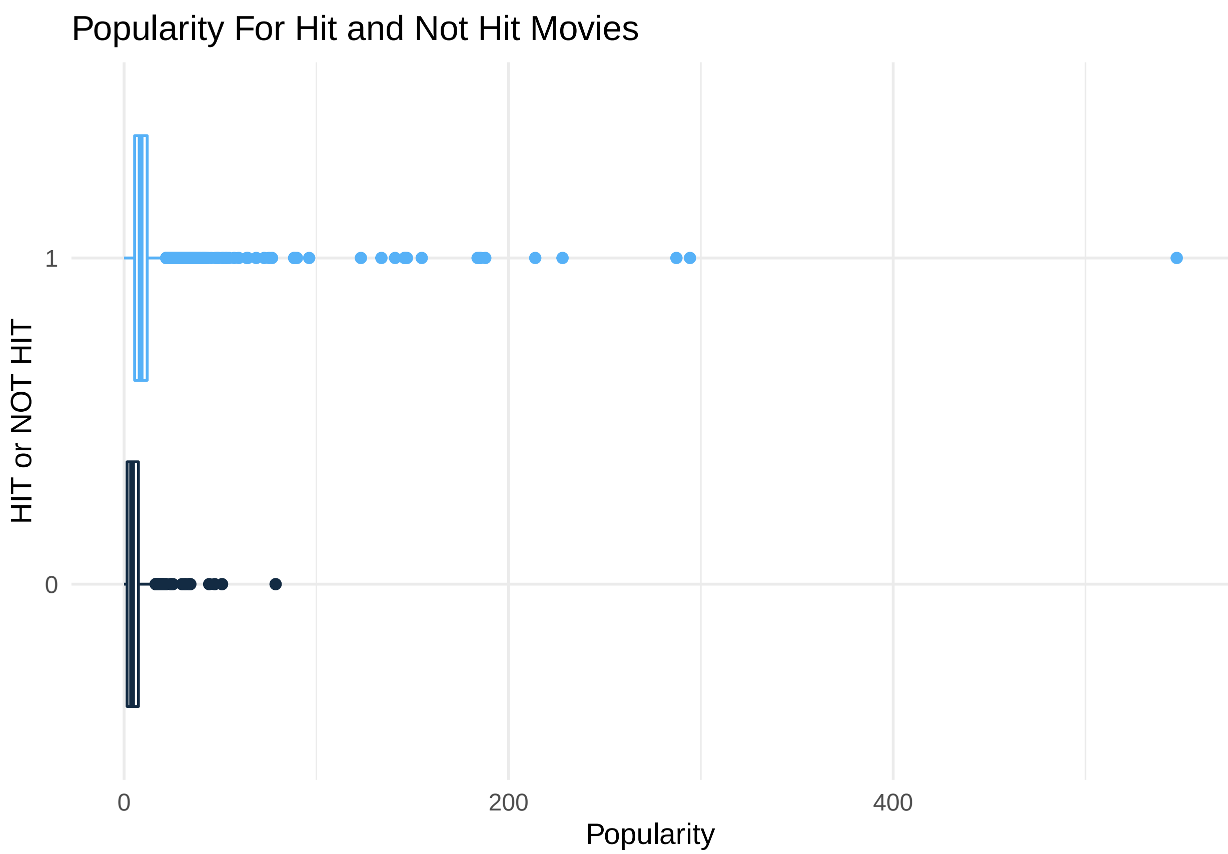



```r
Cleaned_data <- Cleaned_data %>%
    mutate(ratio = ifelse(budget == 0, 0, as.numeric(worlwide_gross_income)/as.numeric(budget)))


# hit not hit with IMDb Score
vote_hit_not <- ggplot(data = Cleaned_data, mapping = aes(y = weighted_average_vote)) +
    geom_boxplot(aes(x = as.character(`hit/not`), color = `hit/not`),
        show.legend = FALSE) + labs(y = "IMDb Score", x = "HIT or NOT HIT",
    title = "IMDb Scores for Hit and Not Hit Movies") + theme_minimal()
vote_hit_not
```

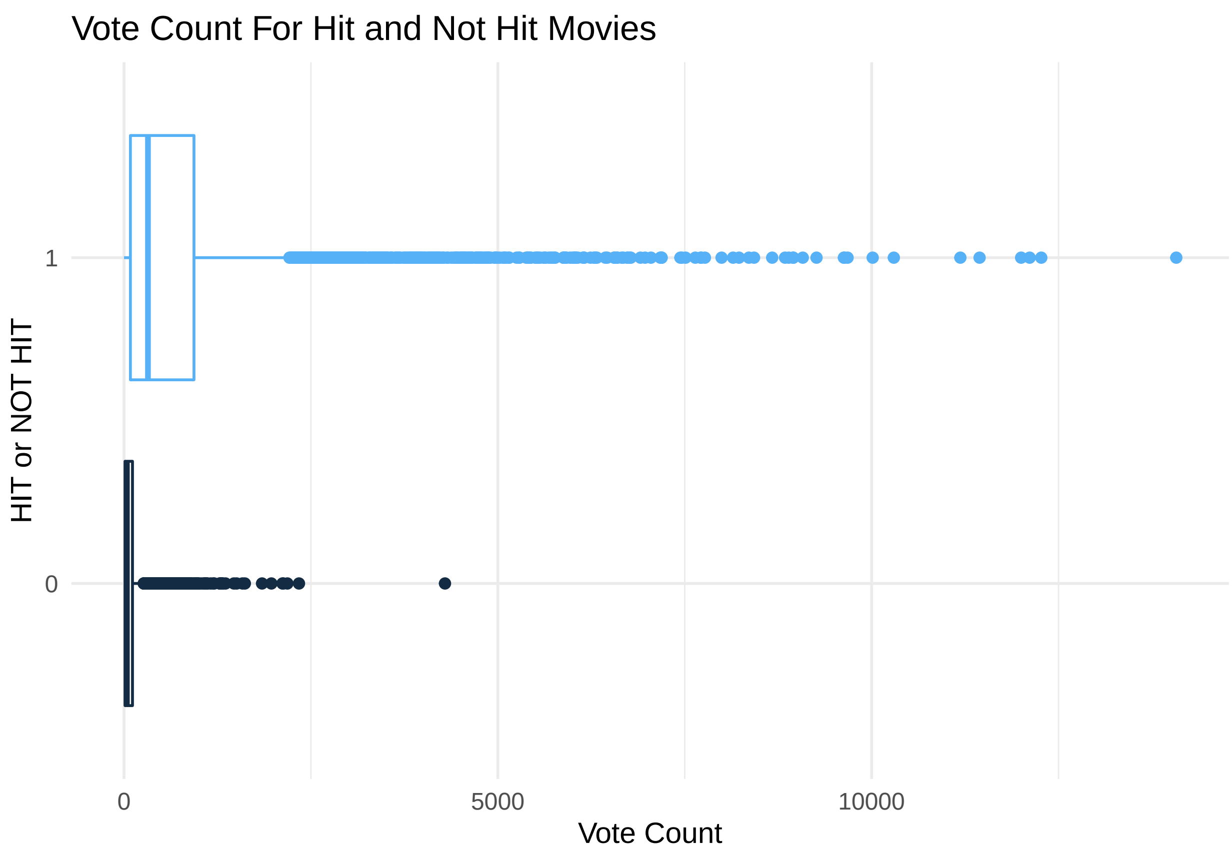



```
# we can see that hit movies have higher imdb scores
```

```
# hit not hit with popularity
popularity_hit_not <- ggplot(data = Cleaned_data, mapping = aes(x = popularity)) +
    geom_boxplot(aes(y = as.character(`hit/not`), color = `hit/not`),
        show.legend = FALSE) + labs(x = "Popularity", y = "HIT or NOT HIT",
    title = "Popularity For Hit and Not Hit Movies") + theme_minimal()

popularity_hit_not
```




```r
Votecount_hit_not <- ggplot(data = Cleaned_data, mapping = aes(x = vote_count)) +
    geom_boxplot(aes(y = as.character(`hit/not`), color = `hit/not`),
        show.legend = FALSE) + labs(x = "Vote Count", y = "HIT or NOT HIT",
    title = "Vote Count For Hit and Not Hit Movies") + theme_minimal()


Votecount_hit_not
```


Vote Count For Hit and Not Hit Movies
HIT or NOT HIT
1
0
0
5000
10000
Vote Count