Exploring the TMDB movie database by R

Let's load the packages we need to use.

```
library(tidyverse) # Multiple packages
library(ggthemes) # Visualization themes
library(gridExtra) # Grids for visualizations
library(lubridate) # Working with dates
```

Importing the dataset.

```
setwd("C:\\Users\\USA\\Desktop\\Movie")
train_data <- read_csv('train.csv')
test_data <- read_csv('test.csv')
```

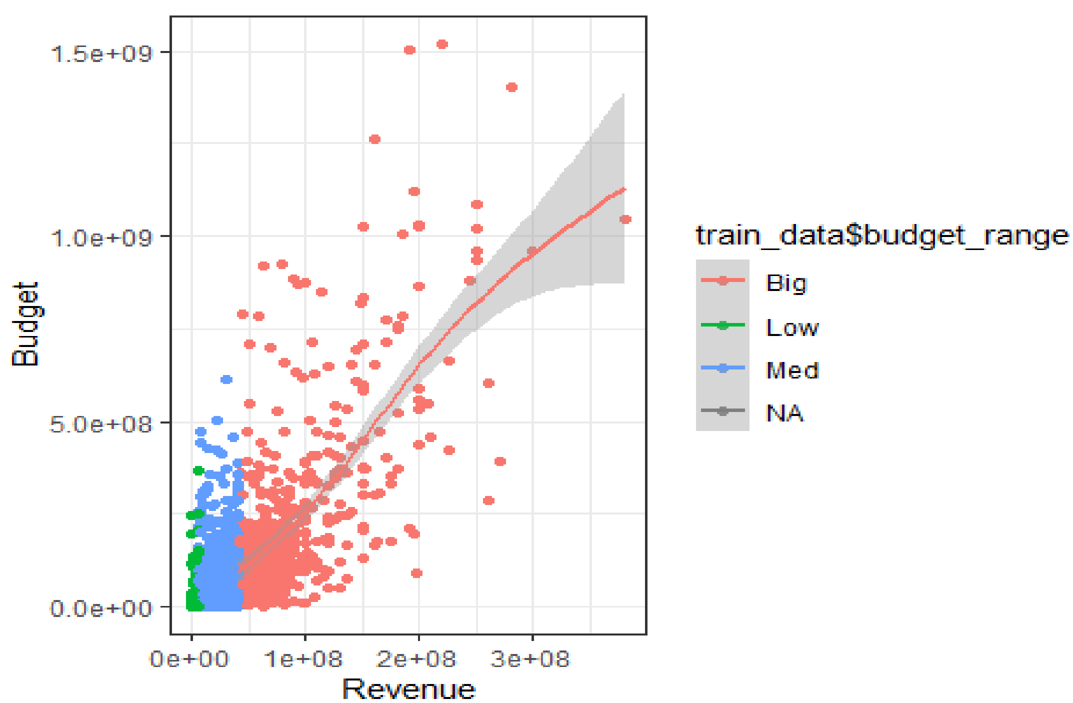
Let's investigate missing values and condition the data set little bit to carry out our further analysis.

```
train_data <- train_data %>% mutate(budget = replace(budget, budget == '0', N
A))
train_data$homepage[!is.na(train_data$homepage)] <- "YES"
train_data$homepage[is.na(train_data$homepage)] <- "NO"
imdb <- str_replace(train_data$imdb_id, "tt", '')
train_data["imdb_id"] <- imdb
train_data$release_date <- parse_date_time2(train_data$release_date, "mdy",cu
toff_2000 = 20)
train_data <- train_data %>% separate(release_date, c("Year", "Month", "Day")
)
sum(is.na(train_data$runtime))

## [1] 2

which(is.na(train_data$runtime))

## [1] 1336 2303

train_data <- train_data %>% drop_na(runtime)
train_data$tagline[!is.na(train_data$tagline)] <- "Yes"
train_data$tagline[is.na(train_data$tagline)] <- "NO"
train_data$collection_name <- str_extract(train_data$belongs_to_collection,pa
```

```
ttern = "(?<=name\\'\\:\\s{1}\\').+(?=\\'\\,\\s{1}\\'poster)")
train_data$Franchise[!is.na(train_data$collection_name)] <- "YES"
train_data$Franchise[is.na(train_data$collection_name)] <- "No"
train_data$prod_country <- str_extract(string = train_data$production_countri
es, pattern = "[:upper:]+")
genres_matching_point <- "Comedy|Horror|Action|Drama|Documentary|Science Fict
ion|Crime|Fantasy|Thriller|Animation|Adventure|Mystery|War|Romance|Music|
Family|Western|History|TV Movie|Foreign"
train_data$main_genre <- str_extract(train_data$genres, genres_matching_point
)
train_data$budget_range[train_data$budget <= 5.10e+06] <- "Low"
train_data$budget_range[train_data$budget > 5.10e+06 & train_data$budget <= 4
.00e+07 ] <- "Med"
train_data$budget_range[train_data$budget > 4.00e+07] <- "Big"
```

Let’s start to explore the data and relations between our variable and find some important features of our dataset. Shall We?

```
train_data$budget_range <- as.factor(train_data$budget_range)
ggplot(train_data, aes(train_data$budget, train_data$revenue, color = train_d
ata$budget_range)) + geom_point() + geom_smooth() + theme_bw()+xlab("Revenue"
)+ylab("Budget")
```



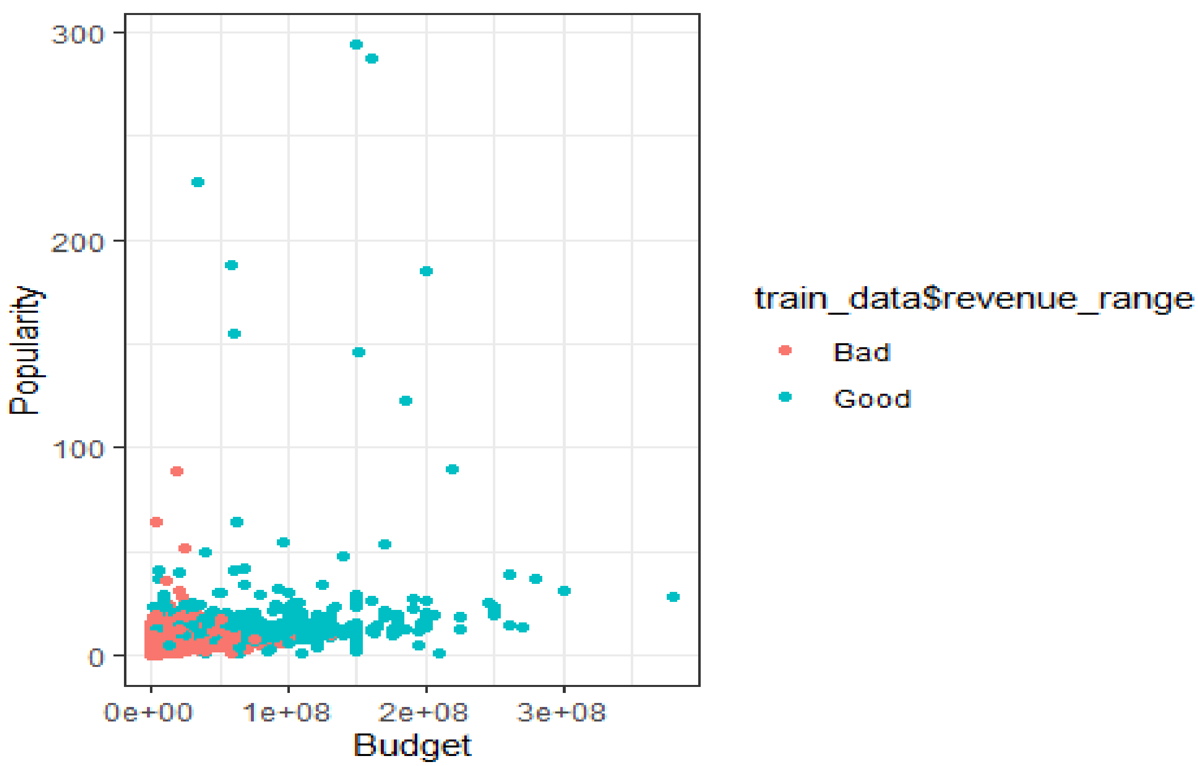
There are very few Low budget movies, most of them are medium or high budget movies. Budget seems very related with revenue. More budget seems to earn more.

```r
train_data$revenue_range[train_data$revenue <= 6.677e+07] <- "Bad"
train_data$revenue_range[train_data$revenue > 6.677e+07] <- "Good"
table(train_data$budget_range, train_data$revenue_range)
```

```
##        Bad Good
##    Big 106  396
##    Low 523   24
##    Med 818  320
```

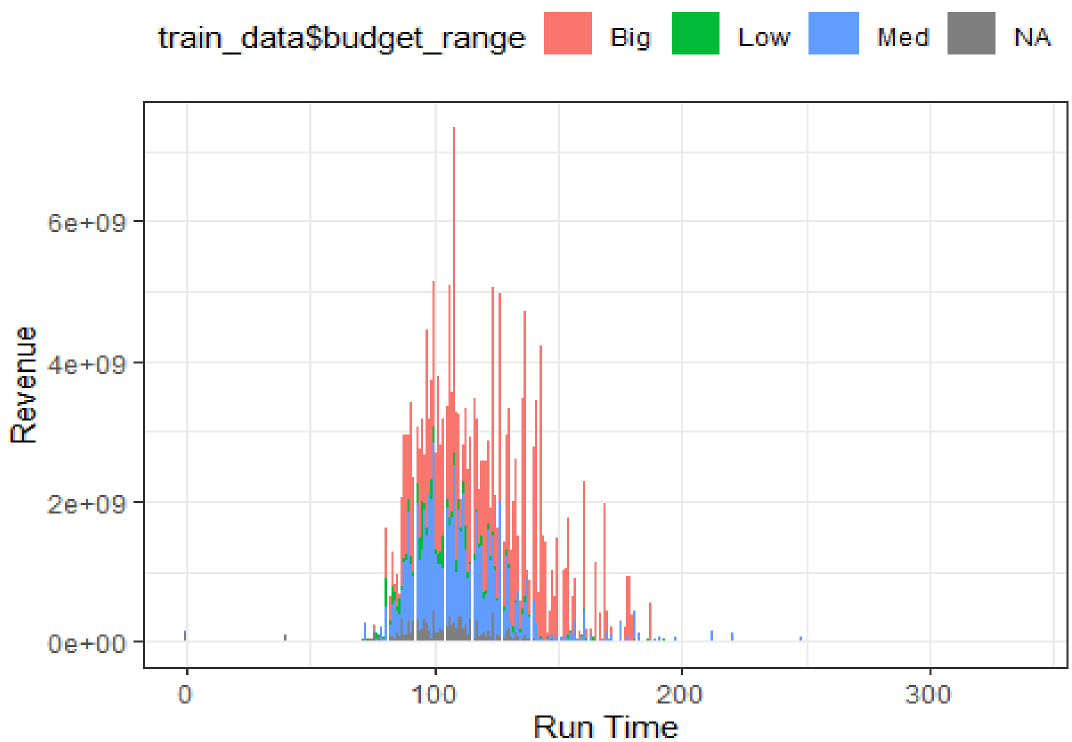
Observations: 1. Out of every 5 Big Budget, 4 will do good. 2. Only 4% Low buget can make the cut-off 3. 30% medium budget movie earning good 4. Money Brings Money

```r
ggplot(train_data, aes(train_data$budget, train_data$popularity, color = trai
n_data$revenue_range)) + geom_point()+theme_bw()+xlab("Budget")+ylab("Popular
ity")
```



Popularity also has a positive correlation with budget as expected but not as much as revenue. There is a sweet spot where low budget movie seems to have good revenue and good popularity: These movies will be interesting to study. Maybe some other time.

```
ggplot(train_data, aes(train_data$runtime, train_data$revenue, fill = train_d
ata$budget_range)) + geom_col()+xlab("Run Time")+ylab("Revenue")+theme_bw()+t
heme(legend.position = "top")
```



Observations: 1. Runtime is important, people tend to spend money on movies ranging from 90 min - 145 min. 2. Big budgets and medium budgets movie are clearly aware of this fact. 3. This surely says something about our attention span.

```
Median_budget <- train_data %>% group_by(train_data$budget_range) %>% summari
se(median_revenue=median(revenue))
Median_revenue <- train_data %>% group_by(train_data$budget_range) %>% summar
ise(median_budget=median(budget))
Median <- merge(Median_revenue, Median_budget, by = "train_data$budget_range"
)

train_data %>% filter(budget_range == "Big") %>% arrange(desc(revenue)) %>% s
elect(title, revenue) %>% head(10)



#Top 10 Big Budgets titles based on Revenue

## # A tibble: 10 x 2
##    title                                             revenue
##    <chr>                                               <dbl>
##  1 The Avengers                                   1519557910
```

```
##  2 Furious 7                                  1506249360
##  3 Avengers: Age of Ultron                    1405403694
##  4 Beauty and the Beast                       1262886337
##  5 Transformers: Dark of the Moon             1123746996
##  6 The Dark Knight Rises                      1084939099
##  7 Pirates of the Caribbean: On Stranger Tides 1045713802
##  8 Finding Dory                               1028570889
##  9 Alice in Wonderland                        1025491110
## 10 Zootopia                                   1023784195
```

```r
train_data %>% filter(budget_range == "Med") %>% arrange(desc(revenue)) %>% s
elect(title, revenue) %>% head(10)

#Top 10 Medium Budget titles based on Revenue
```

```
## # A tibble: 10 x 2
##    title                        revenue
##    <chr>                          <dbl>
##  1 The Passion of the Christ 611899420
##  2 Ghost                     505000000
##  3 Jaws                      470654000
##  4 The Hangover              459270619
##  5 The Exorcist              441306145
##  6 The Intouchables          426480871
##  7 Dances with Wolves        424208848
##  8 The Bodyguard             411006740
##  9 Monster Hunt              385284817
## 10 Toy Story                 373554033
```

```r
train_data %>% filter(budget_range == "Low") %>% arrange(desc(revenue)) %>% s
elect(title, revenue) %>% head(10)

#Top 10 Low Budgets based on Revenue
```

```
## # A tibble: 10 x 2
##    title                       revenue
##    <chr>                         <dbl>
##  1 My Big Fat Greek Wedding 368744044
##  2 Get Out                  252434250
##  3 The Blair Witch Project  248000000
##  4 Paranormal Activity 3    205703818
##  5 Paranormal Activity      193355800
##  6 Lights Out               148868835
##  7 Paranormal Activity 4    142817992
##  8 Animal House             141000000
##  9 Love Story               136400000
## 10 Porky's                  125728258
```

Observations:

The top 10 movies by earning for low budget criteria seems very interesting: 6 of them horror, 4 of them commedy.

If you get less money in the movie business, either bring good wit or crazy vison to scare people off. Franchise movies dominate big budget genre.

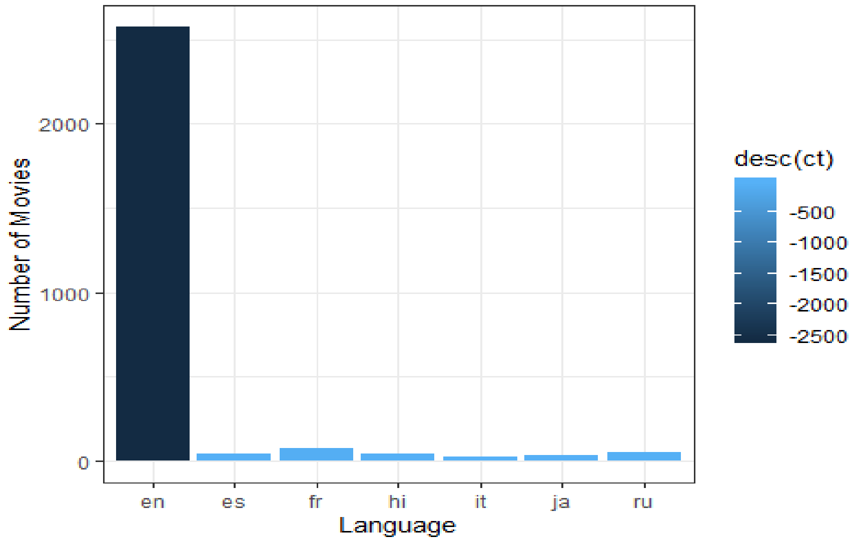
It Seems like medium budget movie can hold more creativity and experiments.

```
train_data %>% filter(budget_range == "Big") %>% arrange(desc(revenue)) %>% s
elect(title, revenue) %>% tail(10)

#Top 10 Big Budget yet Fails:

## # A tibble: 10 x 2
##    title                         revenue
##    <chr>                           <dbl>
##  1 Stay                          8342132
##  2 Gigli                         7266209
##  3 1492: Conquest of Paradise    7191399
##  4 The Adventures of Pluto Nash 7103973
##  5 The Big Bounce                6808550
##  6 A Sound of Thunder            5989640
##  7 Heaven's Gate                 3484331
##  8 Child 44                      3324330
##  9 Shadow Conspiracy             2154540
## 10 Lolita                        1060056
```

I do keep myself informed with movies at least with thee big hits: Never heard about any of these movies: seems well justified to me.

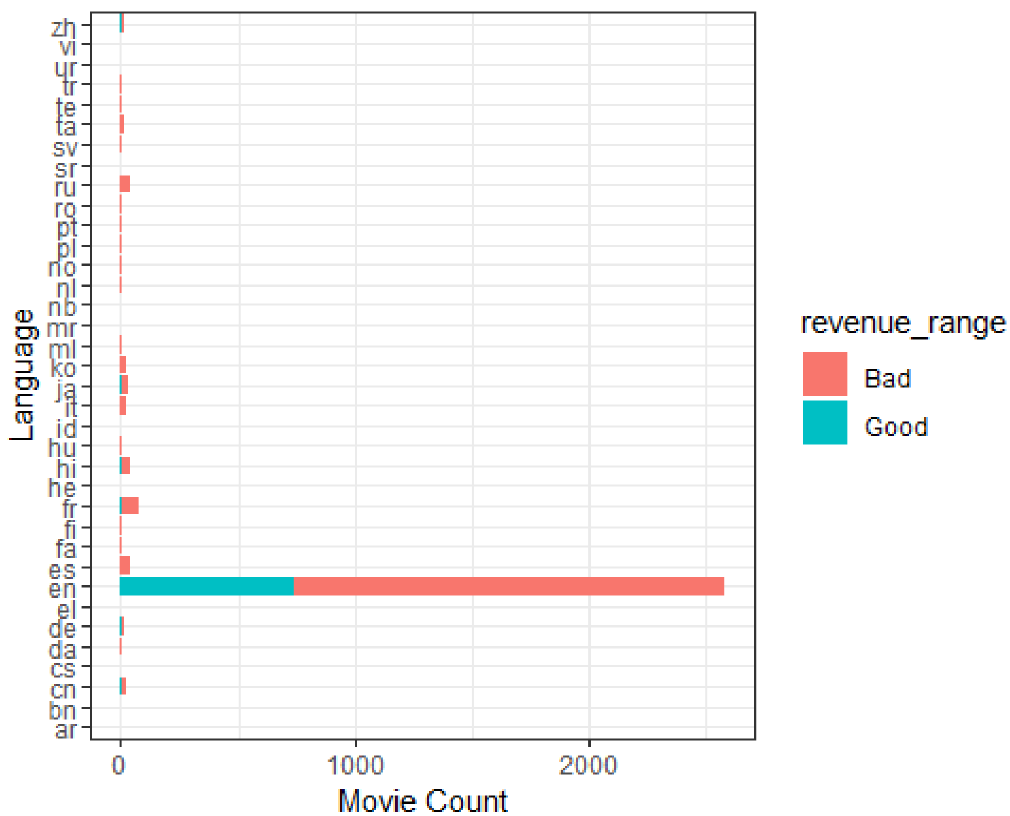
Moving on.

```
language_number <- train_data %>% group_by(original_language) %>% summarise(c
t = n()) %>% arrange(desc(ct)) %>% head(7)
language_number$original_language <- as.factor(language_number$original_langu
age)
ggplot(language_number, aes(language_number$original_language, language_numbe
r$ct, fill = desc(ct))) + geom_col() + xlab("Language") + ylab("Number of Mov
ies")+theme_bw()
```



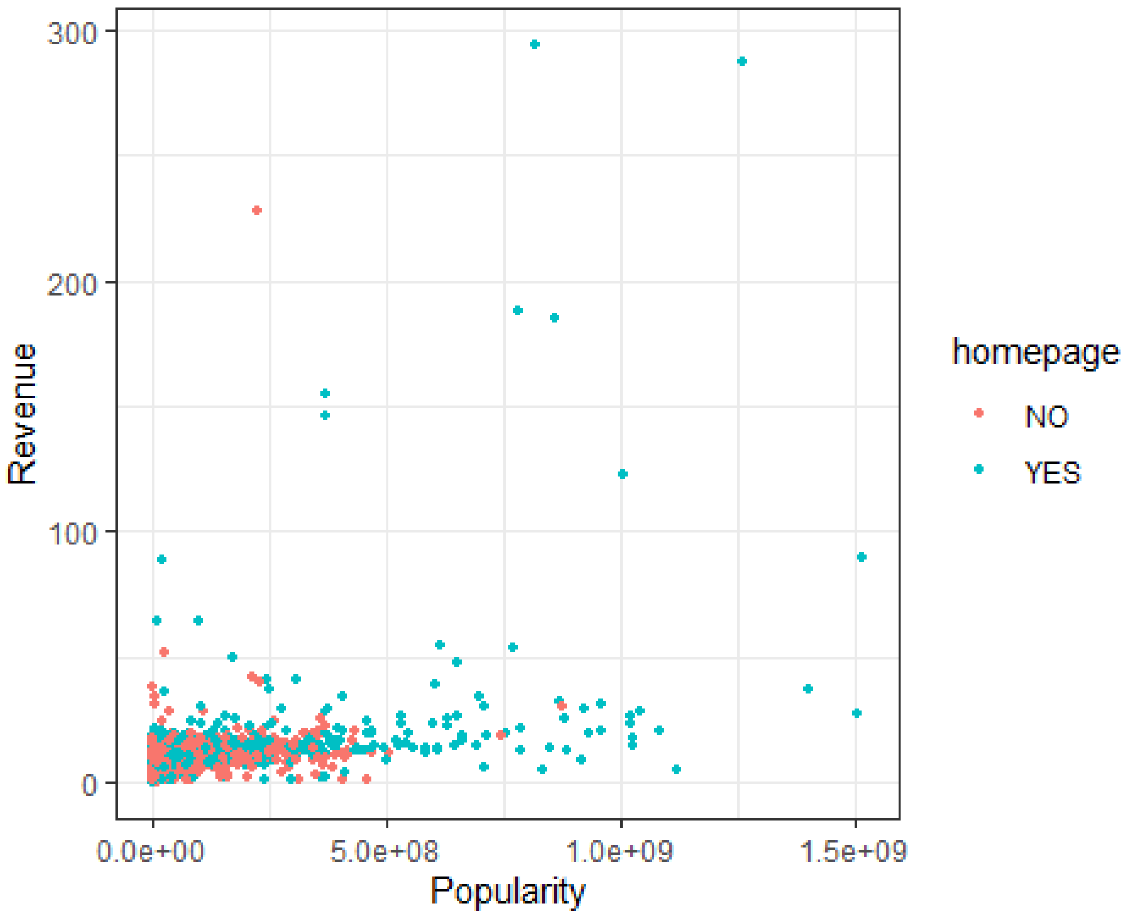
No wonder, there will be monopoly of english language. Other signifacnt languages are french, russian, hindi, spanish and italian.

```
ggplot(train_data, aes(original_language, fill = revenue_range)) + geom_bar()
+ coord_flip()+xlab("Language") + ylab("Movie Count")+theme_bw()+theme(plot.m
argin = margin(.01,.01,.01,.01, "cm"))
```



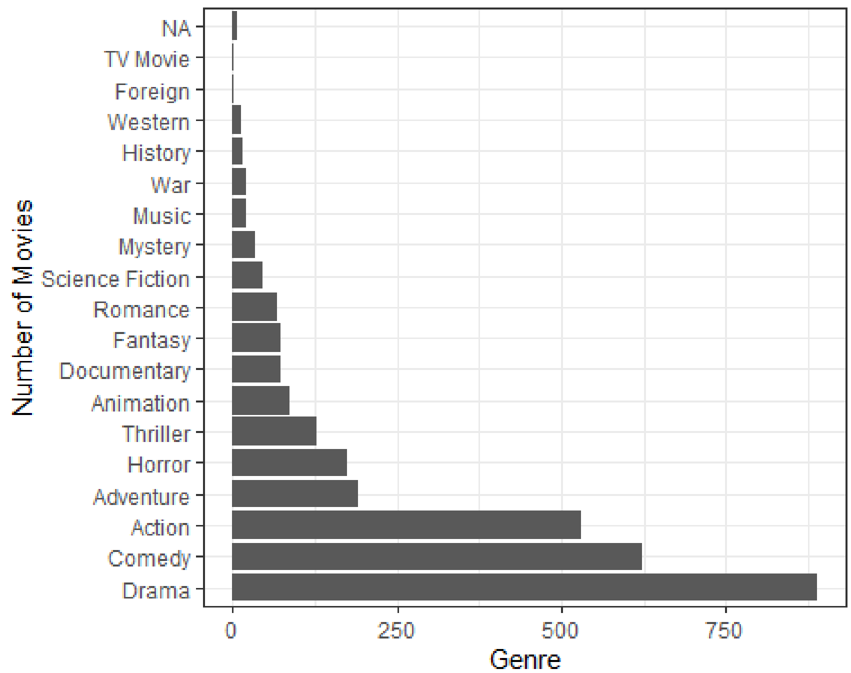
By global standard, other languages other than english are not successful that much except few languages like japanese, hindi, french, tr, zh. Russian language film seems to suffer a lot; Giant land with small population effect, I guess.

```
ggplot(train_data, aes(revenue, popularity, color = homepage)) + geom_point(s
ize = 1.2)+theme_bw()+xlab("Popularity")+ ylab("Revenue")
```

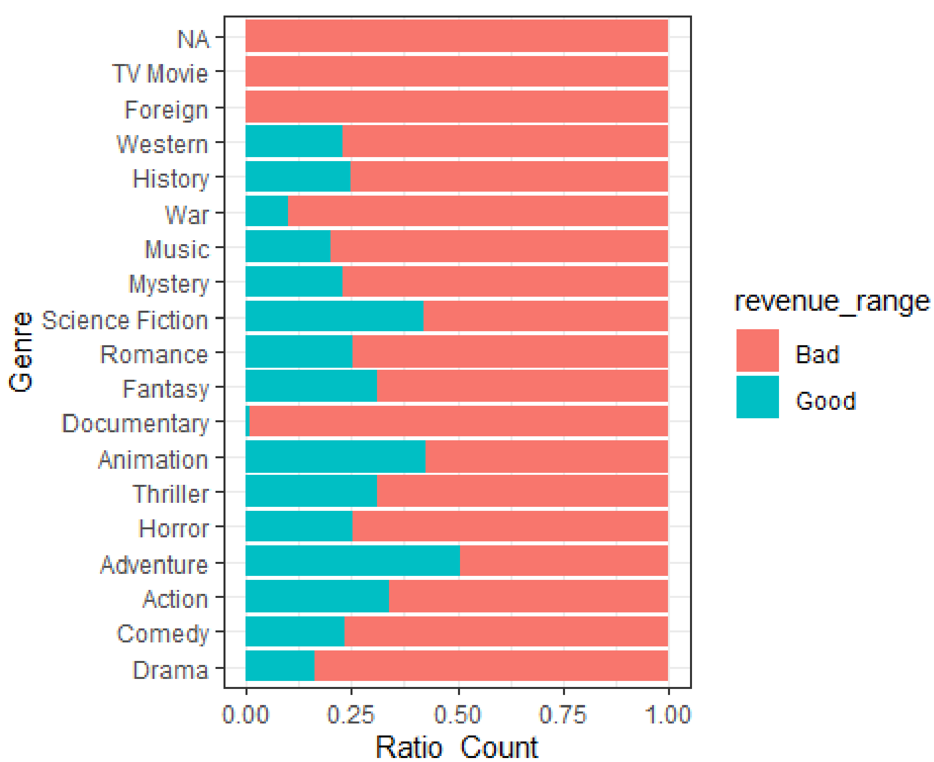


The graph might be misleading: seems like having homepage have clear effect on being the movie popular and successful. Most of the successful or popular movies are high budget movies: thereby can afford to build or care about having a homepage. Domain Knowledge!!

```
ggplot(train_data, aes(fct_infreq(train_data$main_genre))) + geom_bar(na.rm=
TRUE) + coord_flip() + ylab("Genre")+xlab("Number of Movies")+theme_bw()
```

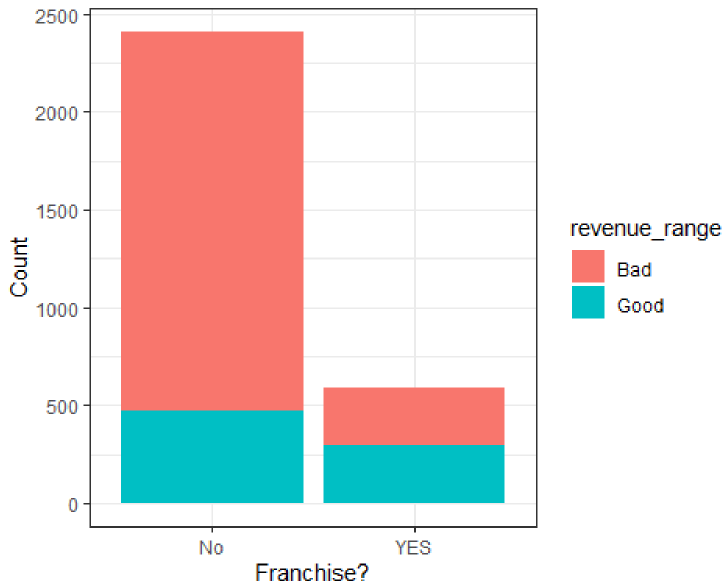



```
ggplot(train_data, aes(fct_infreq(train_data$main_genre),  fill = revenue_range)) + geom_bar(position = "fill") + coord_flip()+ xlab("Genre")+ylab("Ratio_Count")+theme_bw()
```



Drama, comedy, action overwhelms other genres. But Revenue wise Adventure, Science fictions & animation beats everybody. Hollywood stands high in every category.

```
ggplot(train_data, aes(Franchise, fill = revenue_range)) + geom_bar()+xlab("F
ranchise?")+ylab("Count")+theme_bw()
```



This is one interesting plot, looks like probability of being a winner is much higher for a franchise movie.