Data 501 Fall 2021: Semester End Project

Amit Kumar Srivastava, Priyanka Lalge, Shruti Shukla, Srujan Kumar Nunna

Due Date = 12/17/2021

Introduction

As part of the MSDA Data 501 final project, our group decided to research on the following questions.

- Is an Oscar winning actor or actress in the cast associated with the IMDB rating of the movie?
- Is there a difference in mean audience scores between genres?
- Which variables are associated with, and hence can be used to predict, the Rating of a movie on IMDB?

Team Work

First, we started working on the research questions individually, later discussed and picked the best amongst these questions. After this, we decided that each member of the group shall try to come up with the prediction model individually in order to get familiar with all the related concepts. All of us came up with possible solutions for the research questions and then collaborated and enhanced our works to get the best possible solution.

Loading required libraries...

```
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(dplyr)
library(car)
```

```
## Loading required package: carData

##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:dplyr':
##
##     recode

## The following object is masked from 'package:purrr':
##
##     some
```

```
library(ggcorrplot)
```

```
## Warning: package 'ggcorrplot' was built under R version 4.1.3
```

```
library(GGally)
```

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

```
library(car)
library(MASS)
```

```
##
## Attaching package: 'MASS'

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

Exploratory data analysis

We load the data from the url provided. Once the data is loaded we took a glance on the summary and structure of the dataset.

```
load(url("http://people.math.binghamton.edu/qiao/data501/data/movies.RData"))
head(movies)
```

```
## # A tibble: 6 x 32
##   title title_type genre runtime mpaa_rating studio thtr_rel_year thtr_rel_month
##   <chr> <fct>      <fct>   <dbl> <fct>       <fct>          <dbl>          <dbl>
## 1 Fill~ Feature F~ Drama      80 R           Indom~          2013              4
## 2 The ~ Feature F~ Drama     101 PG-13       Warne~          2001              3
## 3 Wait~ Feature F~ Come~      84 R           Sony ~          1996              8
## 4 The ~ Feature F~ Drama     139 PG          Colum~          1993             10
## 5 Male~ Feature F~ Horr~      90 R           Ancho~          2004              9
## 6 Old ~ Documenta~ Docu~      78 Unrated     Shcal~          2009              1
## # ... with 24 more variables: thtr_rel_day <dbl>, dvd_rel_year <dbl>,
## #   dvd_rel_month <dbl>, dvd_rel_day <dbl>, imdb_rating <dbl>,
## #   imdb_num_votes <int>, critics_rating <fct>, critics_score <dbl>,
## #   audience_rating <fct>, audience_score <dbl>, best_pic_nom <fct>,
## #   best_pic_win <fct>, best_actor_win <fct>, best_actress_win <fct>,
## #   best_dir_win <fct>, top200_box <fct>, director <chr>, actor1 <chr>,
## #   actor2 <chr>, actor3 <chr>, actor4 <chr>, actor5 <chr>, imdb_url <chr>, ...
```

```
summary(movies)
```

```
##     title                    title_type                  genre        runtime
##  Length:651         Documentary : 55   Drama              :305   Min.   : 39.0
##  Class :character   Feature Film:591   Comedy             : 87   1st Qu.: 92.0
##  Mode  :character   TV Movie    :  5   Action & Adventure: 65   Median :103.0
##                                        Mystery & Suspense: 59   Mean   :105.8
##                                        Documentary        : 52   3rd Qu.:115.8
##                                        Horror             : 23   Max.   :267.0
##                                        (Other)            : 60   NA's   :1
##   mpaa_rating                                  studio    thtr_rel_year
##  G      : 19   Paramount Pictures              : 37   Min.   :1970
##  NC-17  :  2   Warner Bros. Pictures           : 30   1st Qu.:1990
##  PG     :118   Sony Pictures Home Entertainment: 27   Median :2000
##  PG-13  :133   Universal Pictures              : 23   Mean   :1998
##  R      :329   Warner Home Video               : 19   3rd Qu.:2007
##  Unrated: 50   (Other)                         :507   Max.   :2014
##                NA's                            :  8
##  thtr_rel_month   thtr_rel_day    dvd_rel_year  dvd_rel_month
##  Min.   : 1.00   Min.   : 1.00   Min.   :1991   Min.   : 1.000
##  1st Qu.: 4.00   1st Qu.: 7.00   1st Qu.:2001   1st Qu.: 3.000
##  Median : 7.00   Median :15.00   Median :2004   Median : 6.000
##  Mean   : 6.74   Mean   :14.42   Mean   :2004   Mean   : 6.333
##  3rd Qu.:10.00   3rd Qu.:21.00   3rd Qu.:2008   3rd Qu.: 9.000
##  Max.   :12.00   Max.   :31.00   Max.   :2015   Max.   :12.000
##                                  NA's   :8      NA's   :8
##   dvd_rel_day     imdb_rating    imdb_num_votes           critics_rating
##  Min.   : 1.00   Min.   :1.900   Min.   :   180   Certified Fresh:135
##  1st Qu.: 7.00   1st Qu.:5.900   1st Qu.:  4546   Fresh          :209
##  Median :15.00   Median :6.600   Median : 15116   Rotten         :307
##  Mean   :15.01   Mean   :6.493   Mean   : 57533
##  3rd Qu.:23.00   3rd Qu.:7.300   3rd Qu.: 58301
##  Max.   :31.00   Max.   :9.000   Max.   :893008
##  NA's   :8
##  critics_score    audience_rating audience_score  best_pic_nom best_pic_win
##  Min.   :  1.00   Spilled:275     Min.   :11.00   no :629      no :644
##  1st Qu.: 33.00   Upright:376     1st Qu.:46.00   yes: 22      yes:  7
##  Median : 61.00                   Median :65.00
##  Mean   : 57.69                   Mean   :62.36
##  3rd Qu.: 83.00                   3rd Qu.:80.00
##  Max.   :100.00                   Max.   :97.00
##
##  best_actor_win best_actress_win best_dir_win top200_box   director
##  no :558        no :579          no :608      no :636    Length:651
##  yes: 93        yes: 72          yes: 43      yes: 15    Class :character
##                                                         Mode  :character
##
##
##
##
##     actor1             actor2             actor3             actor4
##  Length:651         Length:651         Length:651         Length:651
##  Class :character   Class :character   Class :character   Class :character
```

```
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##     actor5            imdb_url            rt_url
##  Length:651         Length:651         Length:651
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
##
```

```
str(movies)
```

```
## tibble [651 x 32] (S3: tbl_df/tbl/data.frame)
##  $ title           : chr [1:651] "Filly Brown" "The Dish" "Waiting for Guffman" "The Age of Innocenc
##  $ title_type      : Factor w/ 3 levels "Documentary",..: 2 2 2 2 2 1 2 2 1 2 ...
##  $ genre           : Factor w/ 11 levels "Action & Adventure",..: 6 6 4 6 7 5 6 6 5 6 ...
##  $ runtime         : num [1:651] 80 101 84 139 90 78 142 93 88 119 ...
##  $ mpaa_rating     : Factor w/ 6 levels "G","NC-17","PG",..: 5 4 5 3 5 6 4 5 6 6 ...
##  $ studio          : Factor w/ 211 levels "20th Century Fox",..: 91 202 167 34 13 163 147 118 88 84
##  $ thtr_rel_year   : num [1:651] 2013 2001 1996 1993 2004 ...
##  $ thtr_rel_month  : num [1:651] 4 3 8 10 9 1 1 11 9 3 ...
##  $ thtr_rel_day    : num [1:651] 19 14 21 1 10 15 1 8 7 2 ...
##  $ dvd_rel_year    : num [1:651] 2013 2001 2001 2001 2005 ...
##  $ dvd_rel_month   : num [1:651] 7 8 8 11 4 4 2 3 1 8 ...
##  $ dvd_rel_day     : num [1:651] 30 28 21 6 19 20 18 2 21 14 ...
##  $ imdb_rating     : num [1:651] 5.5 7.3 7.6 7.2 5.1 7.8 7.2 5.5 7.5 6.6 ...
##  $ imdb_num_votes  : int [1:651] 899 12285 22381 35096 2386 333 5016 2272 880 12496 ...
##  $ critics_rating  : Factor w/ 3 levels "Certified Fresh",..: 3 1 1 1 3 2 3 3 2 1 ...
##  $ critics_score   : num [1:651] 45 96 91 80 33 91 57 17 90 83 ...
##  $ audience_rating : Factor w/ 2 levels "Spilled","Upright": 2 2 2 2 1 2 2 1 2 2 ...
##  $ audience_score  : num [1:651] 73 81 91 76 27 86 76 47 89 66 ...
##  $ best_pic_nom    : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
##  $ best_pic_win    : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
##  $ best_actor_win  : Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 1 2 1 1 ...
##  $ best_actress_win: Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
##  $ best_dir_win    : Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 1 1 1 1 ...
##  $ top200_box      : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
##  $ director        : chr [1:651] "Michael D. Olmos" "Rob Sitch" "Christopher Guest" "Martin Scorsese
##  $ actor1          : chr [1:651] "Gina Rodriguez" "Sam Neill" "Christopher Guest" "Daniel Day-Lewis"
##  $ actor2          : chr [1:651] "Jenni Rivera" "Kevin Harrington" "Catherine O'Hara" "Michelle Pfei
##  $ actor3          : chr [1:651] "Lou Diamond Phillips" "Patrick Warburton" "Parker Posey" "Winona Ry
##  $ actor4          : chr [1:651] "Emilio Rivera" "Tom Long" "Eugene Levy" "Richard E. Grant" ...
##  $ actor5          : chr [1:651] "Joseph Julian Soria" "Genevieve Mooy" "Bob Balaban" "Alec McCowen"
##  $ imdb_url        : chr [1:651] "http://www.imdb.com/title/tt1869425/" "http://www.imdb.com/title/t
##  $ rt_url          : chr [1:651] "//www.rottentomatoes.com/m/filly_brown_2012/" "//www.rottentomatoes
```

Preprocessing

The columns are segregated into two lists - `cat_var` containing the categorical variables and `cont_vars` with the continuous variables. Factor is applied to the categorical variables in the `movies` dataset.

`title`, `actor1`, `actor2`, `actor3`, `actor4`, `actor5`, `imdb_url`, `rt_url` columns are not considered at all as these variables doesn't have much significance as per our research orientation. Further `director` and `studio` are also removed as the structure contains 200+ levels in the structure.

`thtr_rel_year`, `thtr_rel_day`, `dvd_rel_year`, `dvd_rel_day` is the list of variables that are not considered as we assumed it would be better to deal with the months rather than year and days.

Lastly, the rows with `NA` values are removed from the dataset.

```
names(movies)
```

```
##  [1] "title"            "title_type"       "genre"            "runtime"
##  [5] "mpaa_rating"      "studio"           "thtr_rel_year"    "thtr_rel_month"
##  [9] "thtr_rel_day"     "dvd_rel_year"     "dvd_rel_month"    "dvd_rel_day"
## [13] "imdb_rating"      "imdb_num_votes"   "critics_rating"   "critics_score"
## [17] "audience_rating"  "audience_score"   "best_pic_nom"     "best_pic_win"
## [21] "best_actor_win"   "best_actress_win" "best_dir_win"     "top200_box"
## [25] "director"         "actor1"           "actor2"           "actor3"
## [29] "actor4"           "actor5"           "imdb_url"         "rt_url"
```

```
movies1 <- subset(movies, select = -c(title, studio, thtr_rel_year, thtr_rel_day, dvd_rel_year, dvd_rel

summary(movies1)
```

```
##         title_type                  genre        runtime       mpaa_rating
##  Documentary : 55   Drama              :305   Min.   : 39.0   G      : 19
##  Feature Film:591   Comedy             : 87   1st Qu.: 92.0   NC-17  :  2
##  TV Movie    :  5   Action & Adventure: 65   Median :103.0   PG     :118
##                     Mystery & Suspense: 59   Mean   :105.8   PG-13  :133
##                     Documentary        : 52   3rd Qu.:115.8   R      :329
##                     Horror             : 23   Max.   :267.0   Unrated: 50
##                     (Other)            : 60   NA's   :1
##  thtr_rel_month  dvd_rel_month     imdb_rating    imdb_num_votes
##  Min.   : 1.00   Min.   : 1.000   Min.   :1.900   Min.   :   180
##  1st Qu.: 4.00   1st Qu.: 3.000   1st Qu.:5.900   1st Qu.:  4546
##  Median : 7.00   Median : 6.000   Median :6.600   Median : 15116
##  Mean   : 6.74   Mean   : 6.333   Mean   :6.493   Mean   : 57533
##  3rd Qu.:10.00   3rd Qu.: 9.000   3rd Qu.:7.300   3rd Qu.: 58301
##  Max.   :12.00   Max.   :12.000   Max.   :9.000   Max.   :893008
##                  NA's   :8
##          critics_rating critics_score    audience_rating audience_score
##  Certified Fresh:135    Min.   :  1.00   Spilled:275     Min.   :11.00
##  Fresh          :209    1st Qu.: 33.00   Upright:376     1st Qu.:46.00
##  Rotten         :307    Median : 61.00                   Median :65.00
##                         Mean   : 57.69                   Mean   :62.36
##                         3rd Qu.: 83.00                   3rd Qu.:80.00
##                         Max.   :100.00                   Max.   :97.00
##
##  best_pic_nom best_pic_win best_actor_win best_actress_win best_dir_win
```

```
##  no :629      no :644      no :558        no :579          no :608
##  yes: 22      yes:  7      yes: 93        yes: 72          yes: 43
##
##
##
##
##
##  top200_box
##  no :636
##  yes: 15
##
##
##
##
##
```

```
movies2 <- movies1 %>% filter(!is.na(runtime), !is.na(dvd_rel_month))
summary(movies2)
```

```
##         title_type                  genre        runtime        mpaa_rating
##  Documentary : 52   Drama              :303   Min.   : 39.00   G      : 18
##  Feature Film:585   Comedy             : 87   1st Qu.: 92.25   NC-17  :  2
##  TV Movie    :  5   Action & Adventure: 63   Median :103.00   PG     :115
##                     Mystery & Suspense: 59   Mean   :105.93   PG-13  :132
##                     Documentary        : 49   3rd Qu.:116.00   R      :327
##                     Horror             : 23   Max.   :267.00   Unrated: 48
##                     (Other)            : 58
##  thtr_rel_month   dvd_rel_month     imdb_rating  imdb_num_votes
##  Min.   : 1.000   Min.   : 1.000   Min.   :1.9   Min.   :   180
##  1st Qu.: 4.000   1st Qu.: 3.000   1st Qu.:5.9   1st Qu.:  4830
##  Median : 7.000   Median : 6.000   Median :6.6   Median : 15508
##  Mean   : 6.737   Mean   : 6.341   Mean   :6.5   Mean   : 58296
##  3rd Qu.:10.000   3rd Qu.: 9.000   3rd Qu.:7.3   3rd Qu.: 59034
##  Max.   :12.000   Max.   :12.000   Max.   :9.0   Max.   :893008
##
##          critics_rating critics_score    audience_rating audience_score
##  Certified Fresh:135    Min.   :  1.00   Spilled:271     Min.   :11.00
##  Fresh          :206    1st Qu.: 33.00   Upright:371     1st Qu.:46.00
##  Rotten         :301    Median : 61.50                   Median :65.00
##                         Mean   : 57.84                   Mean   :62.44
##                         3rd Qu.: 83.00                   3rd Qu.:80.00
##                         Max.   :100.00                   Max.   :97.00
##
##  best_pic_nom best_pic_win best_actor_win best_actress_win best_dir_win
##  no :620      no :635      no :549        no :570          no :599
##  yes: 22      yes:  7      yes: 93        yes: 72          yes: 43
##
##
##
##
##
##  top200_box
##  no :627
##  yes: 15
```

```
##
##
##
##
##
```

```
cat_vars <- c("title_type", "genre", "mpaa_rating", "critics_rating", "audience_rating", "best_pic_nom"

cont_vars <- c("runtime", "imdb_rating", "imdb_num_votes", "critics_score", "audience_score")

movies2[cat_vars] = lapply(movies2[cat_vars], factor)
```

Now, we start with the exploration of the data. First of all we explore the continuous variables. Here we observed the descriptive summary of the variables as well as the correlation among the variables.

```
summary(movies2[cont_vars])
```

```
##     runtime        imdb_rating  imdb_num_votes   critics_score
##  Min.   : 39.00   Min.   :1.9   Min.   :   180   Min.   :  1.00
##  1st Qu.: 92.25   1st Qu.:5.9   1st Qu.:  4830   1st Qu.: 33.00
##  Median :103.00   Median :6.6   Median : 15508   Median : 61.50
##  Mean   :105.93   Mean   :6.5   Mean   : 58296   Mean   : 57.84
##  3rd Qu.:116.00   3rd Qu.:7.3   3rd Qu.: 59034   3rd Qu.: 83.00
##  Max.   :267.00   Max.   :9.0   Max.   :893008   Max.   :100.00
##  audience_score
##  Min.   :11.00
##  1st Qu.:46.00
##  Median :65.00
##  Mean   :62.44
##  3rd Qu.:80.00
##  Max.   :97.00
```

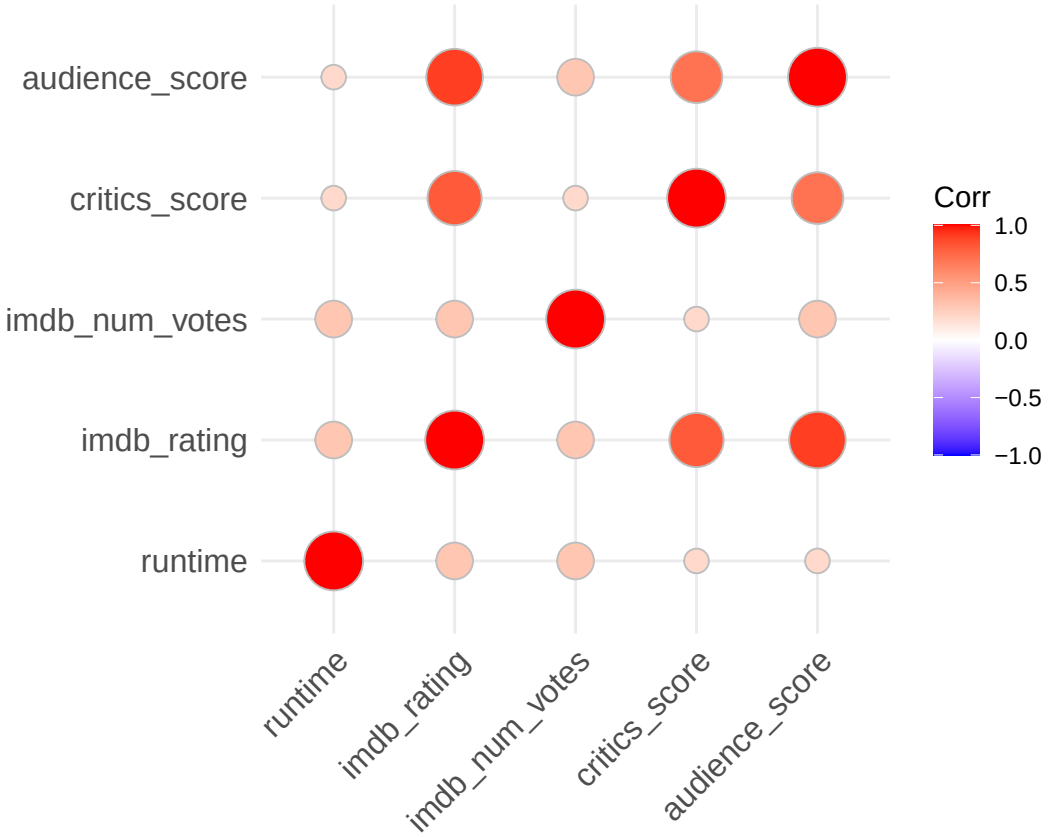
```
corr <- round(cor(movies2[cont_vars]), 1)
head(corr)
```

```
##                runtime imdb_rating imdb_num_votes critics_score audience_score
## runtime            1.0         0.3            0.3           0.2            0.2
## imdb_rating        0.3         1.0            0.3           0.8            0.9
## imdb_num_votes     0.3         0.3            1.0           0.2            0.3
## critics_score      0.2         0.8            0.2           1.0            0.7
## audience_score     0.2         0.9            0.3           0.7            1.0
```

As per the correlation matrix, we could observe a correlation between `imdb_rating`, `critics_score` and `audience_score`. The variable `runtime` is not correlated significantly.

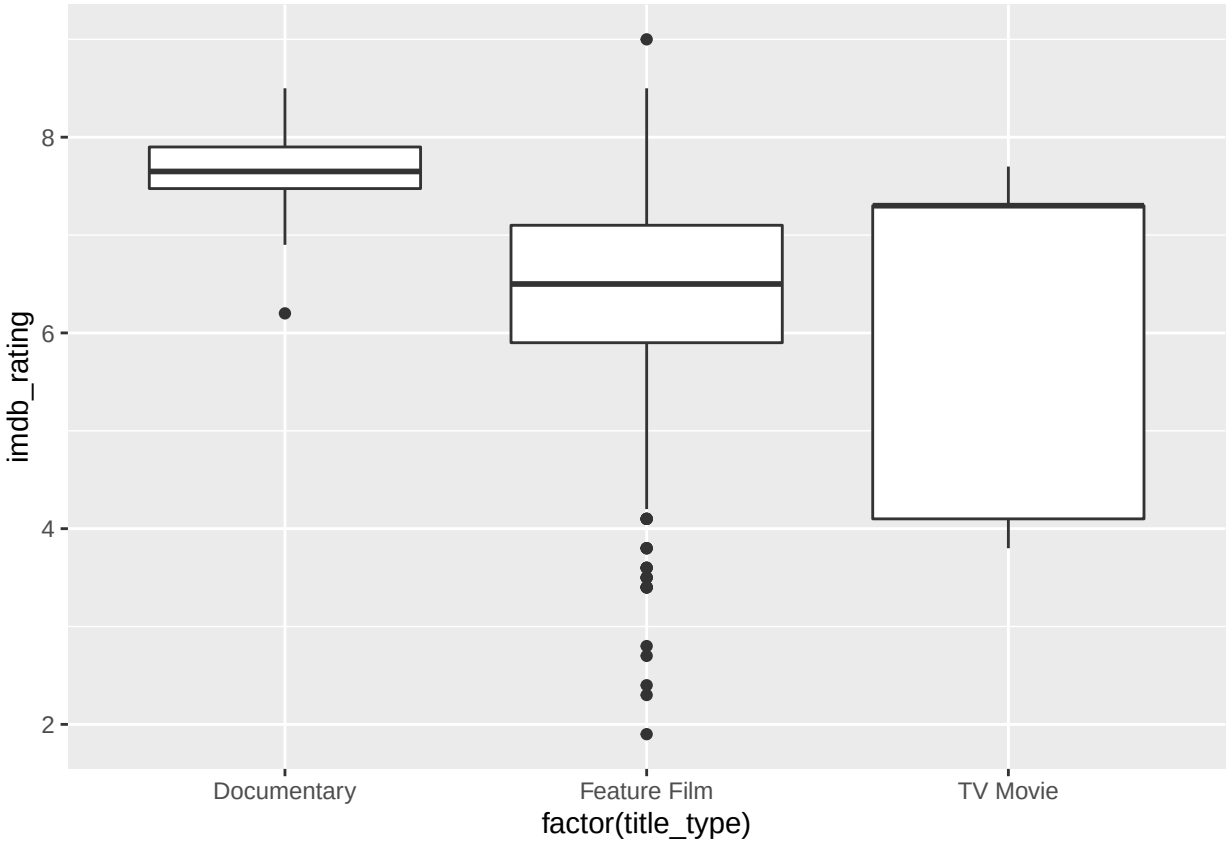
```
# Visualize the correlation matrix
# --------------------------------
# method = "square" (default)
ggcorrplot(corr, method = "circle")
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```

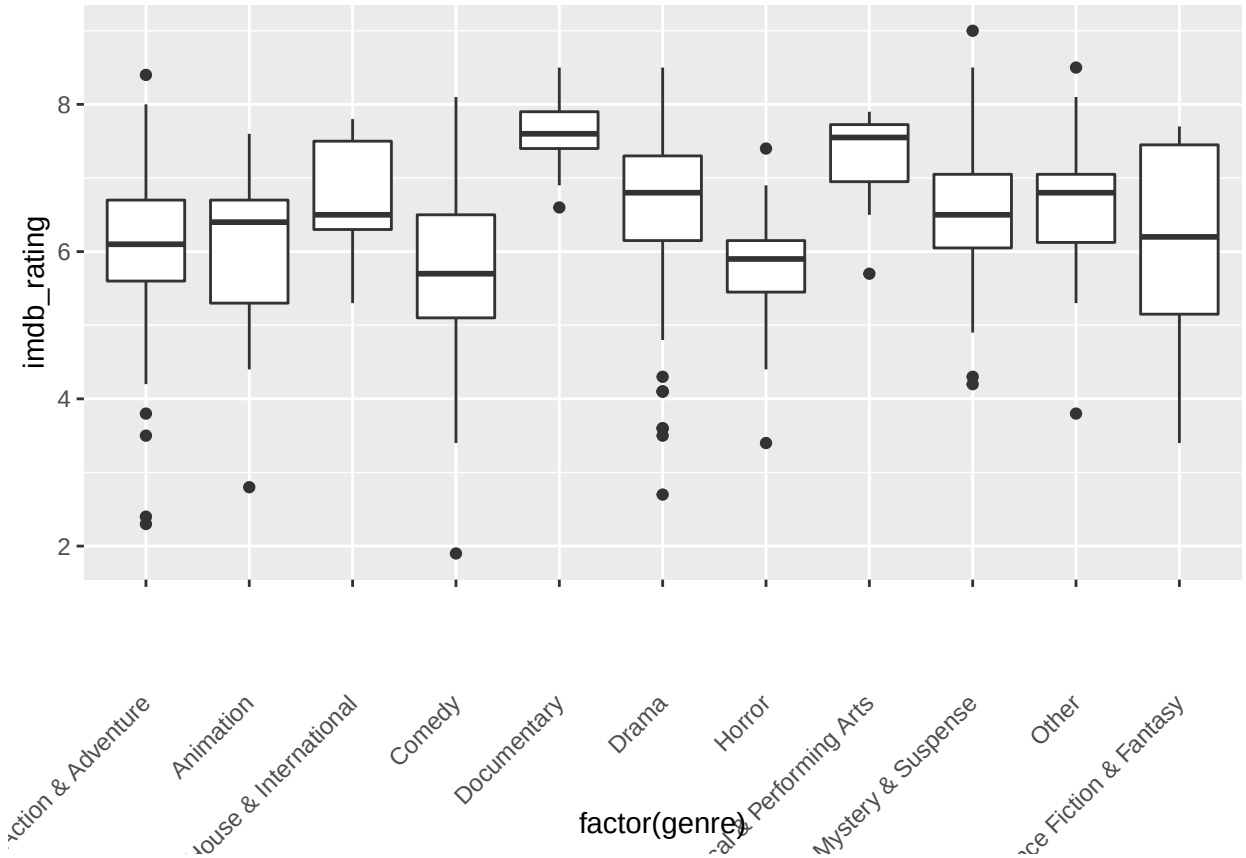


After the observation of the continuous variables, we proceed towards the categorical variables. As the main question revolves around the `imdb_rating`, all the categorical variables are plotted against `imdb_rating`.

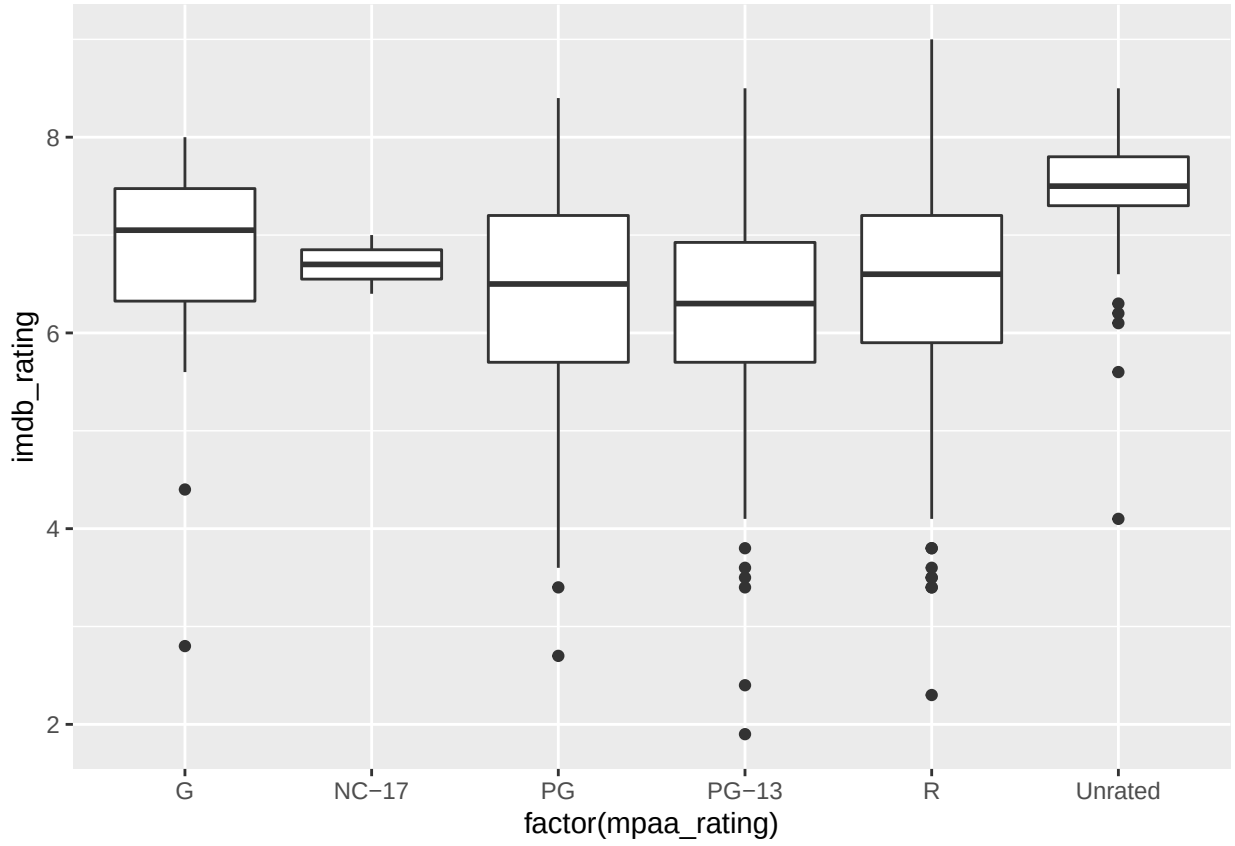
```
ggplot(movies2, aes(x = factor(title_type), y = imdb_rating)) + geom_boxplot()
```



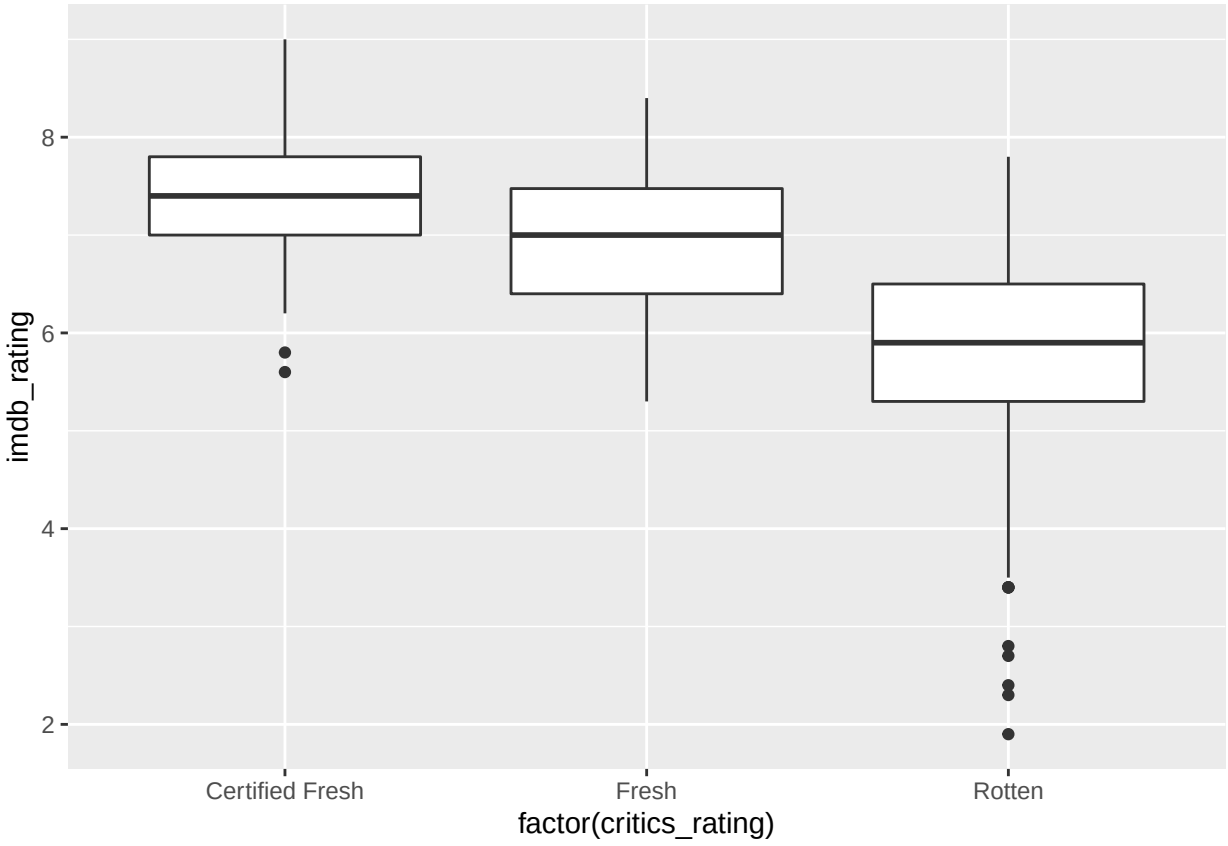

```
ggplot(movies2, aes(x = factor(genre), y = imdb_rating)) + geom_boxplot() + theme(axis.text.x = element_
```



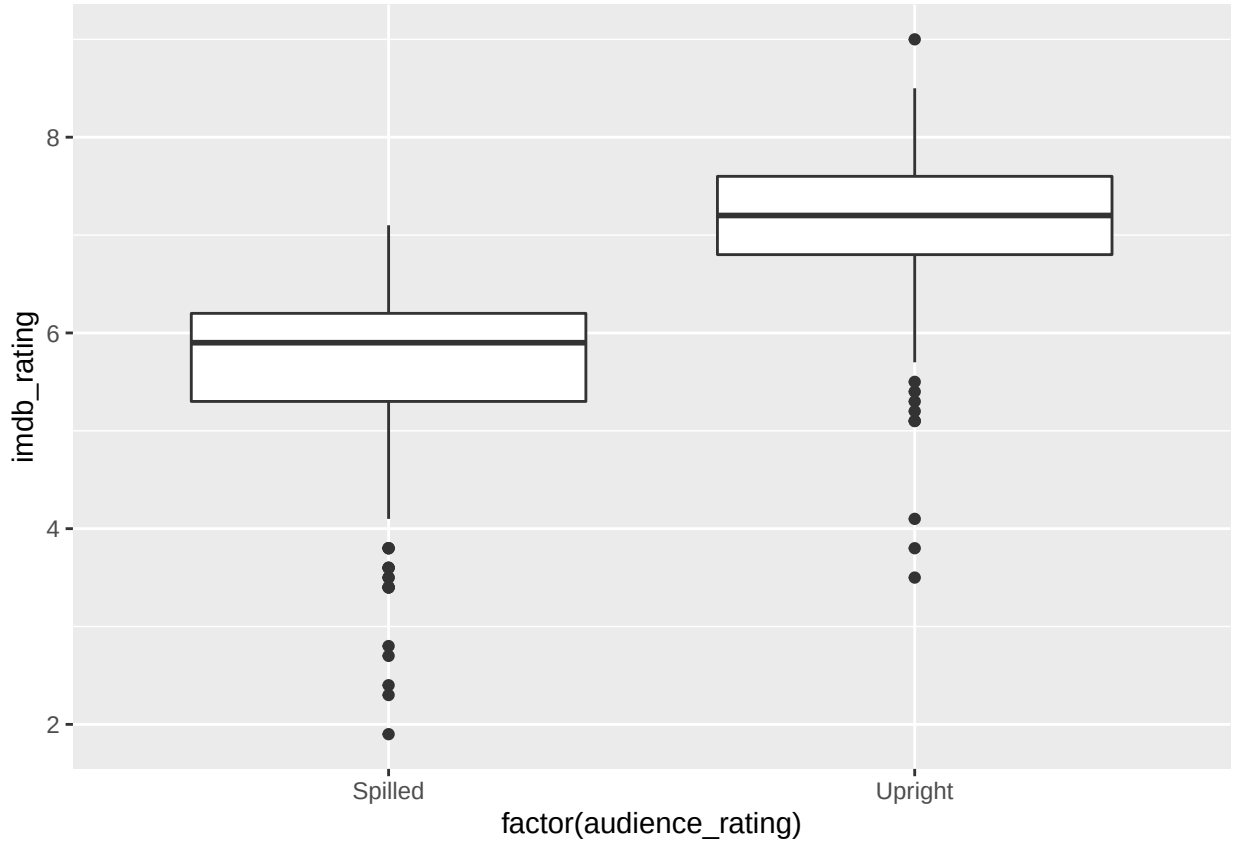

```
ggplot(movies2, aes(x = factor(mpaa_rating), y = imdb_rating)) + geom_boxplot()
```



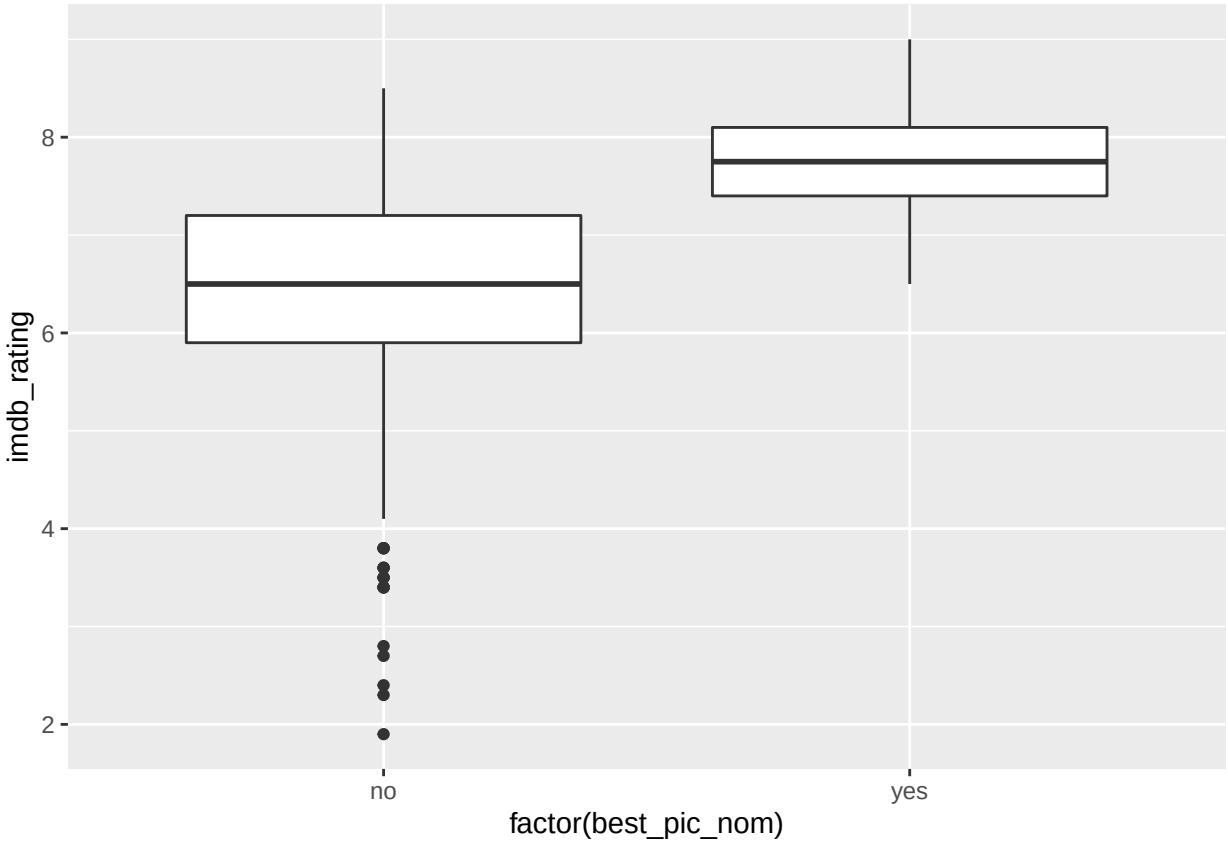

```
ggplot(movies2, aes(x = factor(critics_rating), y = imdb_rating)) + geom_boxplot()
```



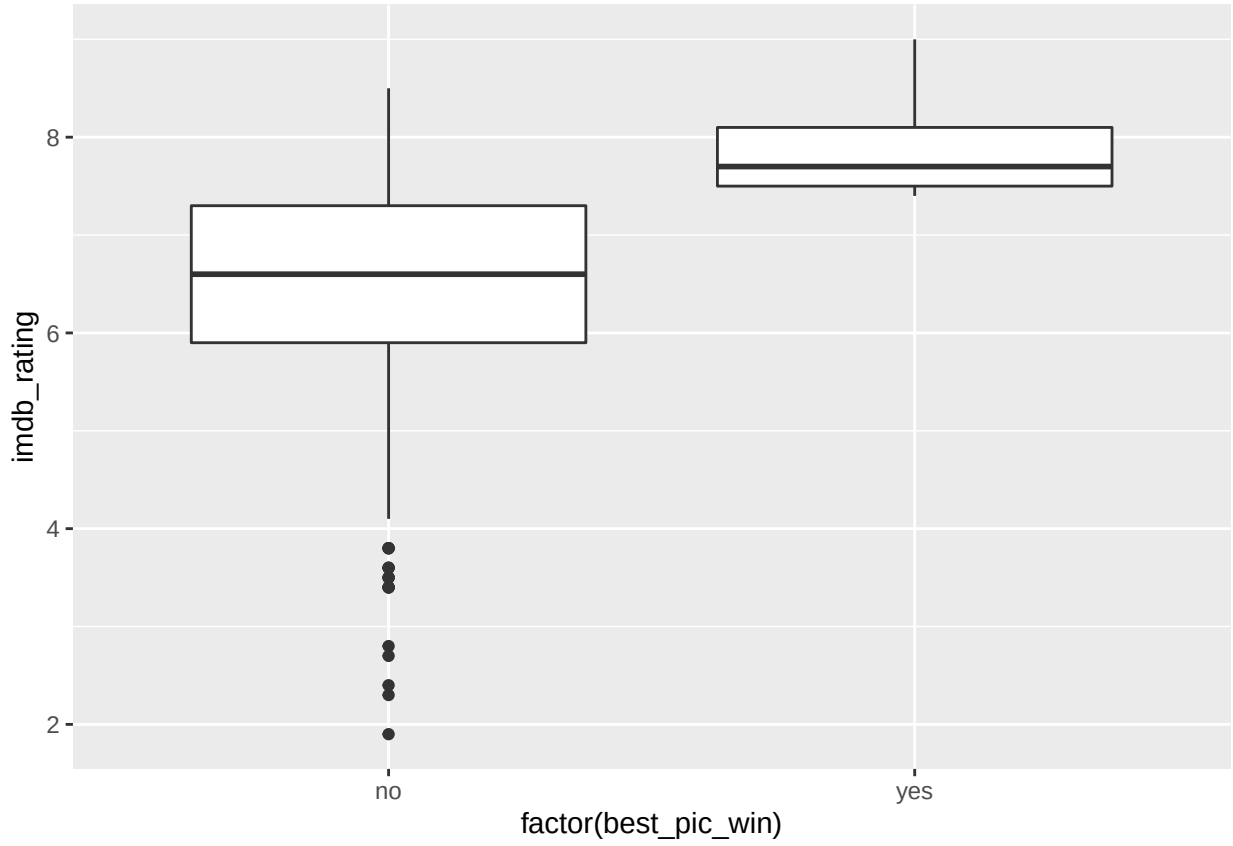

```
ggplot(movies2, aes(x = factor(audience_rating), y = imdb_rating)) + geom_boxplot()
```



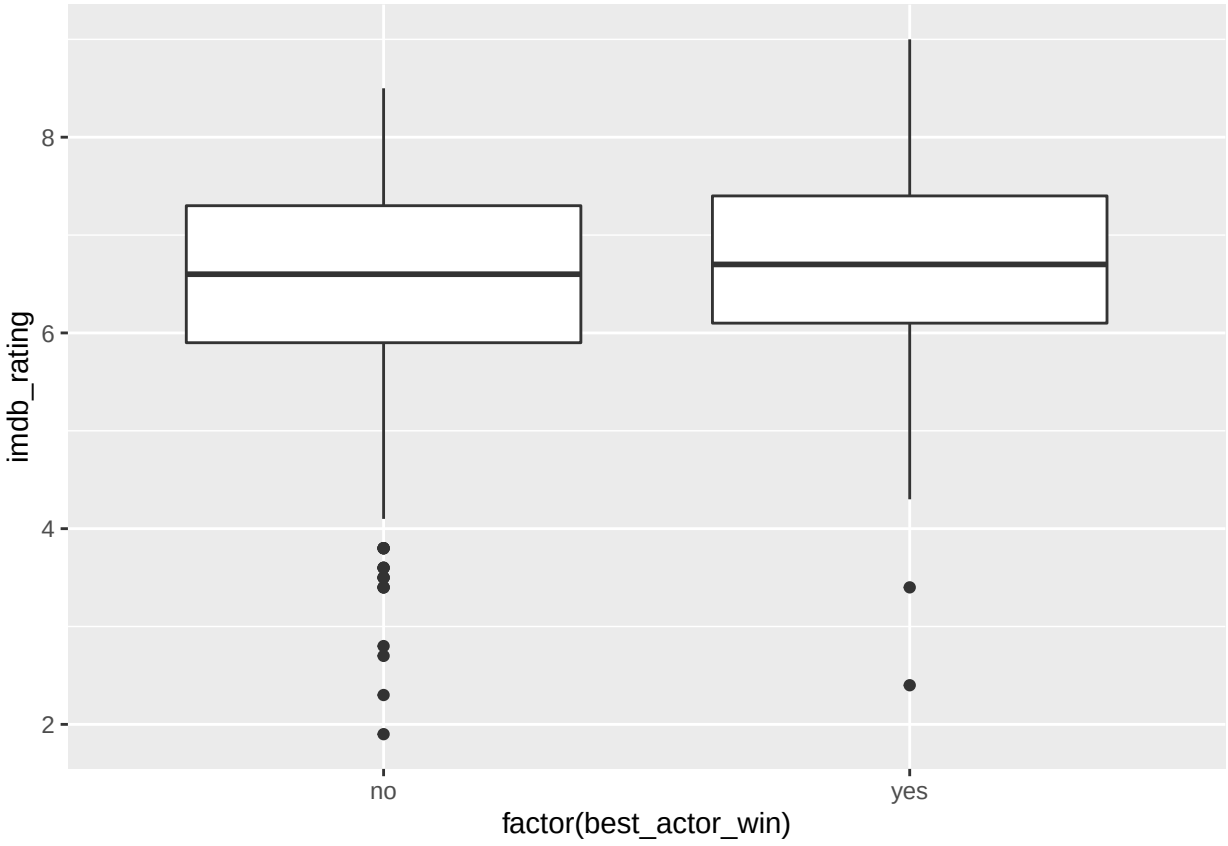

```
ggplot(movies2, aes(x = factor(best_pic_nom), y = imdb_rating)) + geom_boxplot()
```



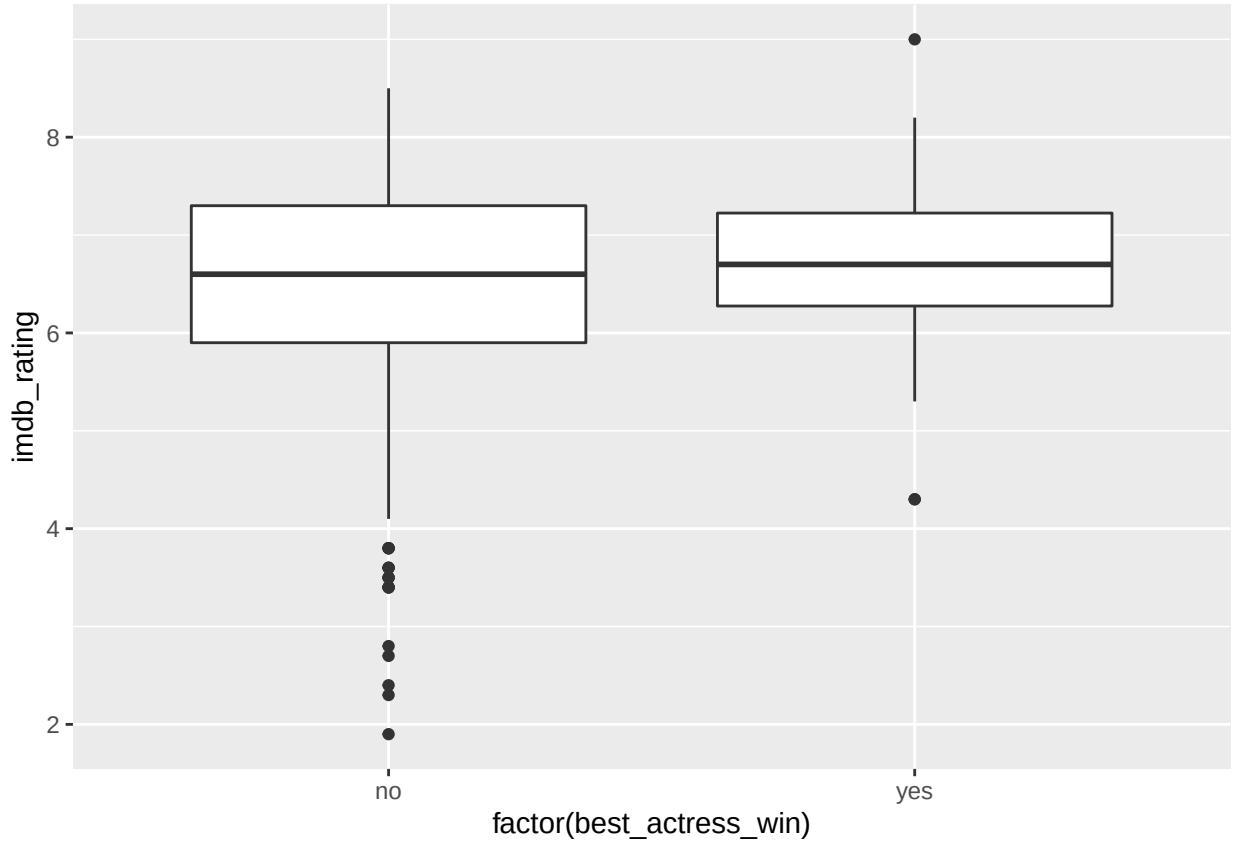

```
ggplot(movies2, aes(x = factor(best_pic_win), y = imdb_rating)) + geom_boxplot()
```



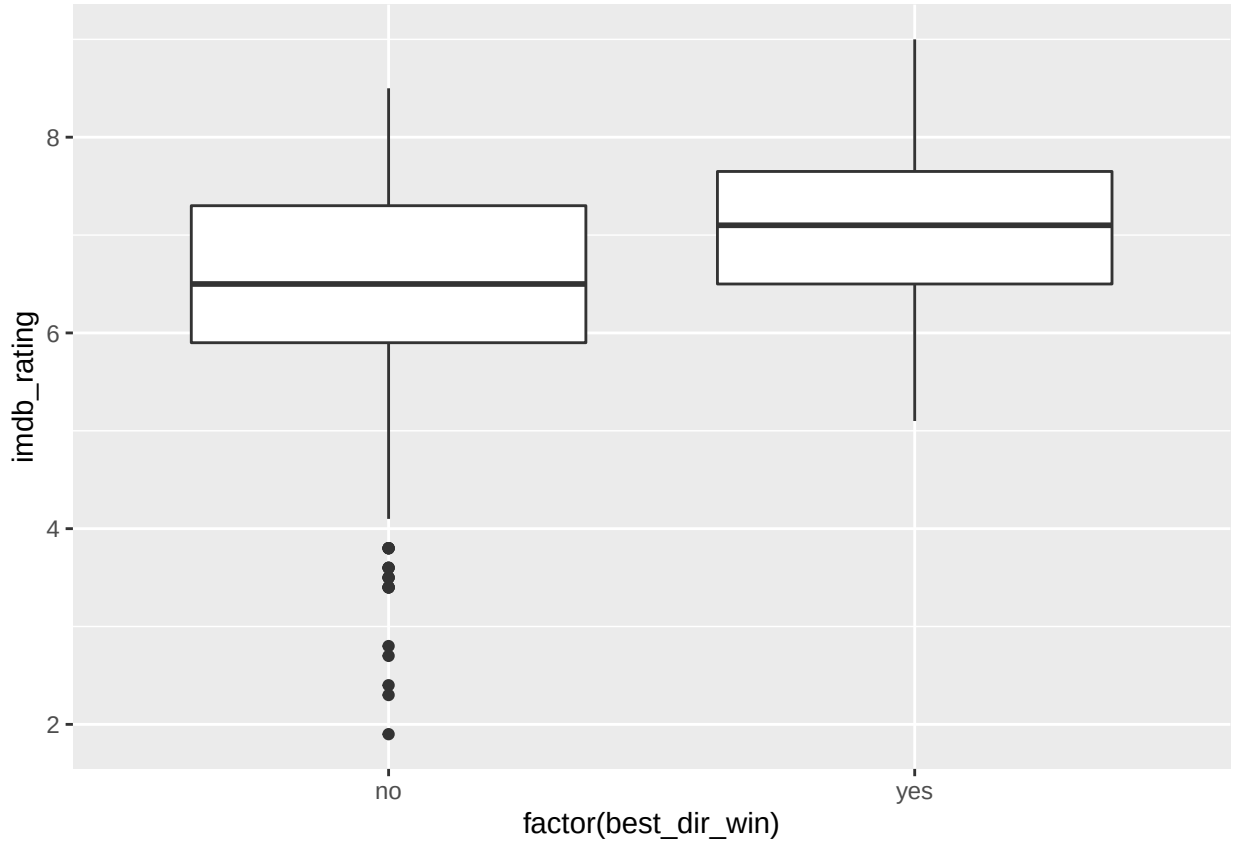

```
ggplot(movies2, aes(x = factor(best_actor_win), y = imdb_rating)) + geom_boxplot()
```



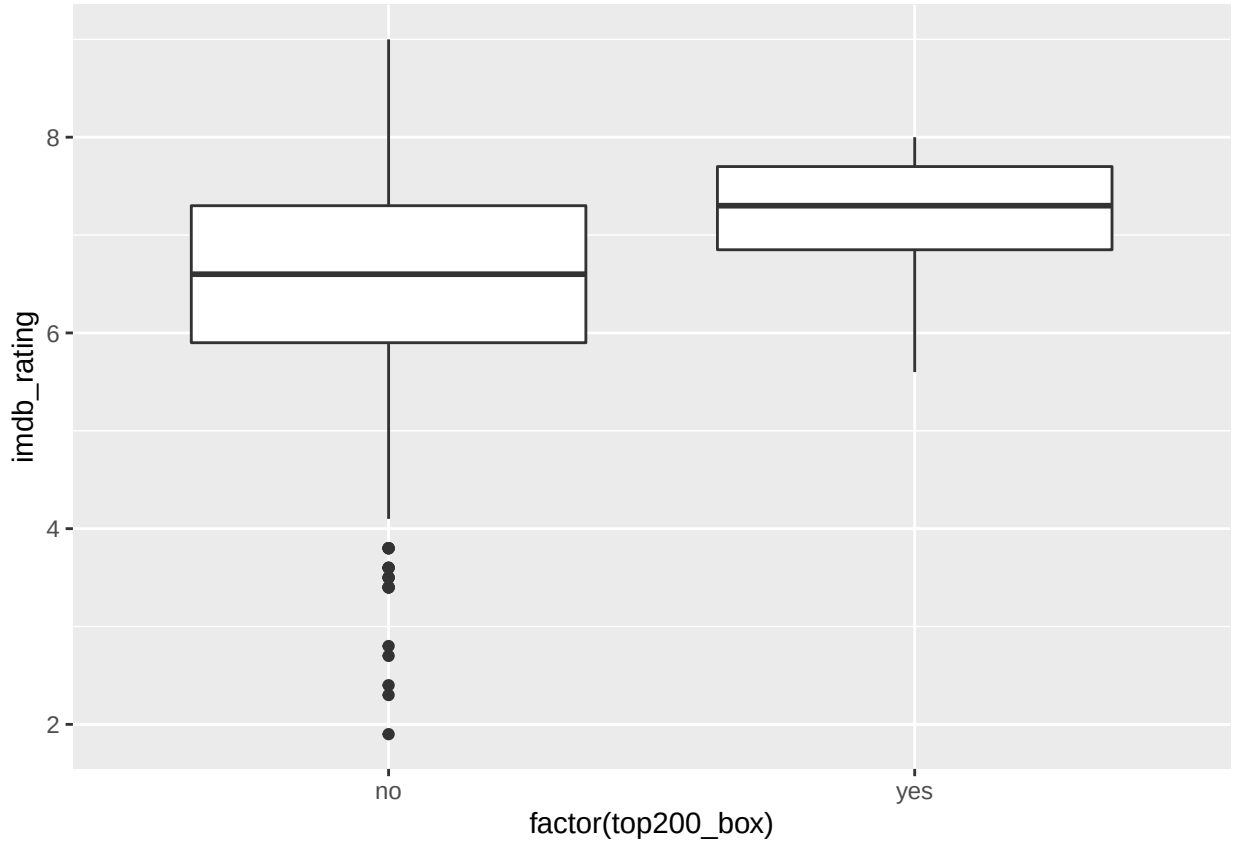

```
ggplot(movies2, aes(x = factor(best_actress_win), y = imdb_rating)) + geom_boxplot()
```



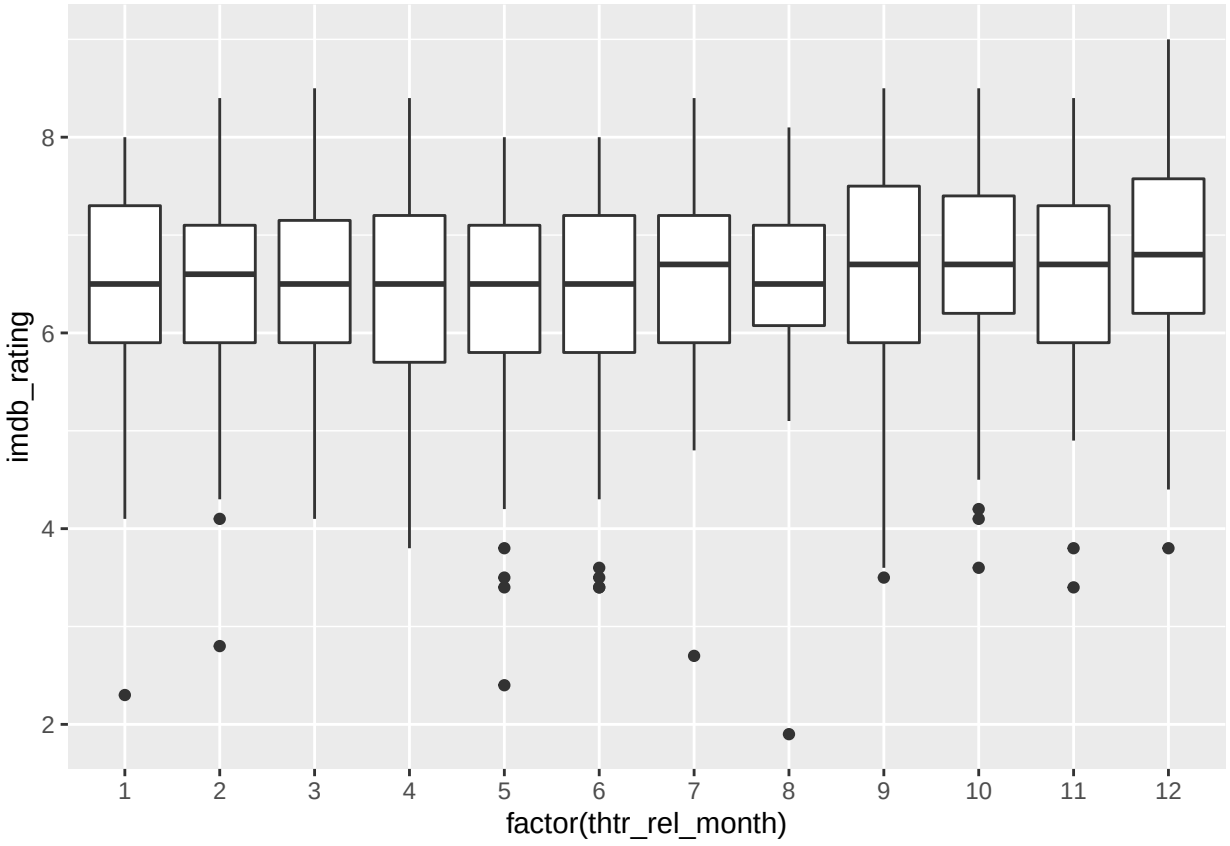

```
ggplot(movies2, aes(x = factor(best_dir_win), y = imdb_rating)) + geom_boxplot()
```



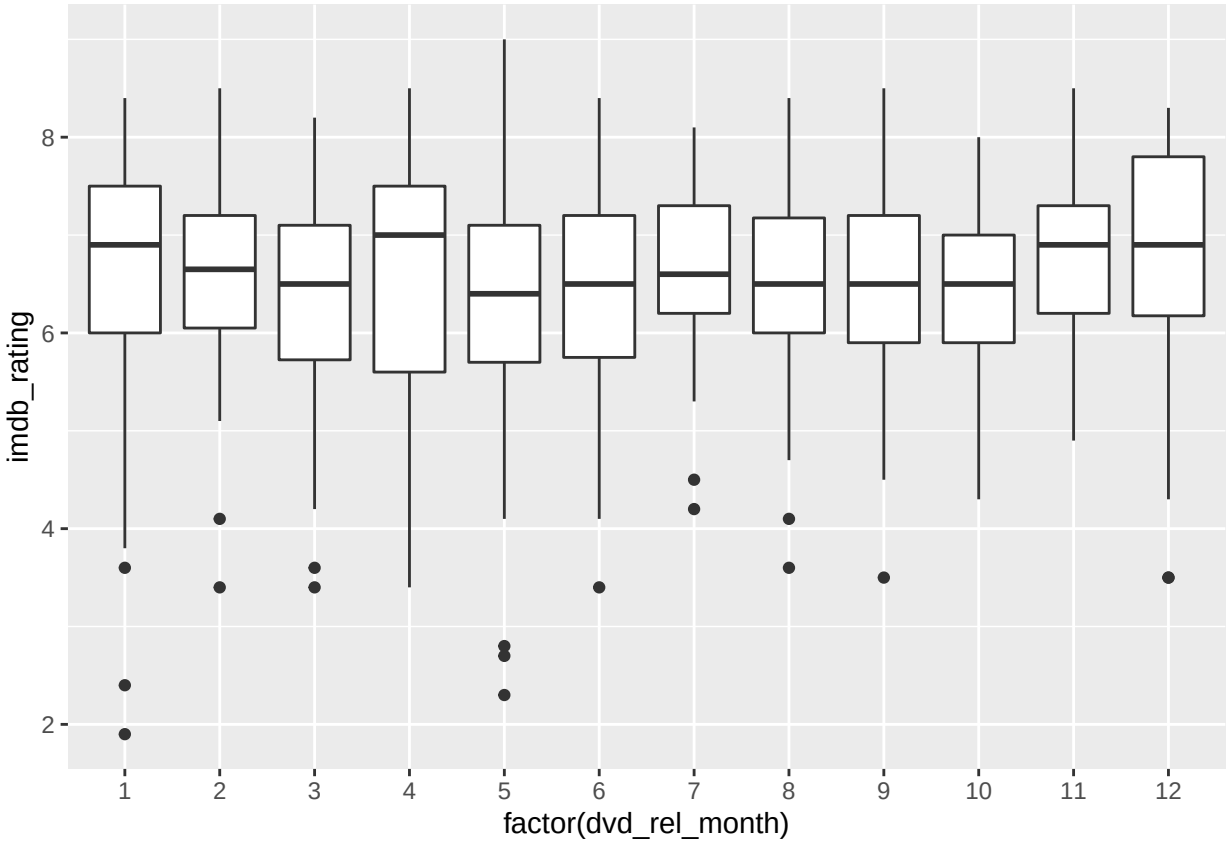

```
ggplot(movies2, aes(x = factor(top200_box), y = imdb_rating)) + geom_boxplot()
```




```
ggplot(movies2, aes(x = factor(thtr_rel_month), y = imdb_rating)) + geom_boxplot()
```




```
ggplot(movies2, aes(x = factor(dvd_rel_month), y = imdb_rating)) + geom_boxplot()
```


imdb_rating
8
6
4
2
1
2
3
4
5
6
7
8
9
10
11
12
factor(dvd_rel_month)

Inference

The purpose of this section is to use the statistical inference tool of t-test and check the first question of our research, i.e.,

- Is an Oscar winning actor or actress in the cast associated with the IMDB rating of the movie?

To answer the question, first of all, we split the dataset into two subsets. One of the subset contains the movies that casted either a best winning actor or actress. The second set contains the movies that did not cast an oscar winning actor/actress.

```
movies_oscar_cast = movies2[(movies2$best_actor_win=='yes' | movies2$best_actress_win ==  'yes'),]
movies_without_oscar_cast = movies2[(movies2$best_actor_win=='no' & movies2$best_actress_win =='no'),]
head(movies_oscar_cast)
```

```
## # A tibble: 6 x 18
##   title_type   genre runtime mpaa_rating thtr_rel_month dvd_rel_month imdb_rating
##   <fct>        <fct>   <dbl> <fct>       <fct>          <fct>                <dbl>
## 1 Feature Film Drama     139 PG          10             11                     7.2
## 2 Feature Film Drama      93 R           11             3                      5.5
## 3 Feature Film Acti~     127 PG          6              5                      6.8
## 4 Feature Film Come~     110 R           1              7                      7.6
## 5 Feature Film Drama      96 R           8              12                     7
## 6 Feature Film Drama     124 R           6              6                      7
## # ... with 11 more variables: imdb_num_votes <int>, critics_rating <fct>,
## #   critics_score <dbl>, audience_rating <fct>, audience_score <dbl>,
## #   best_pic_nom <fct>, best_pic_win <fct>, best_actor_win <fct>,
## #   best_actress_win <fct>, best_dir_win <fct>, top200_box <fct>
```

Once the data is split, we come up with our null and alternate hypothesis and perform the two-sample t-test.

H_0: There is no difference in imdb rating for movies casted by oscar won actor/actress H_a: There is a difference in imdb rating for movies casted by oscar won actor/actress

Note: Here we assumed variance to be equal in order to simplify our research.

```
t.test(movies_oscar_cast$imdb_rating, movies_without_oscar_cast$imdb_rating , alt = "two.sided", conf =
```

```
##
##  Two Sample t-test
##
## data:  movies_oscar_cast$imdb_rating and movies_without_oscar_cast$imdb_rating
## t = 1.7087, df = 640, p-value = 0.08798
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.02581435  0.37187138
## sample estimates:
## mean of x mean of y
##  6.633793  6.460765
```

Since the p-value $\not< \alpha = 0.05$, hence we fail to reject the H_0. It implies that there is no difference in imdb rating for movies casted by oscar won actor/actress.

Modeling

We shall proceed to split the data into two subsets for modeling purpose - train dataset with 70% rows and test dataset with 30% rows of the `movies2` dataset. Further, we shall take the help of the model selection techniques to consider the adequate predictor variables. In addition, we will validate the MSE for various models and select the one with the least MSE.

```
set.seed(1234)
index = sample(c(rep(TRUE,450), rep(FALSE,192)))
mov_train = movies2[index, ]
mov_test = movies2[!index, ]

dim(mov_train)
```

```
## [1] 450  18
```

```
dim(mov_test)
```

```
## [1] 192  18
```

With the split of dataset in place, we will start with question 2 and also with the model selection process.

Now, to answer the 2nd question of our project, we shall perform one way anova test using either the pairwise t-test for the `genre` categorical variable or `TukeyHSD`. We proceed with the `TukeyHSD` below.

Since our anova is significant (p-value= $2e-16 < \alpha = 0.05$) hence we performed `TukeyHSD` which gives the pairwise comparison of means. From the results of the graph we have found that Documentary-Action & Adventure, Drama-Action & Adventure, Musical & Performing Arts-Action & Adventure, Documentary-Comedy, Drama-Comedy, Musical & Performing Arts-Comedy, Drama-Documentary, Horror-Documentary, Mystery & Suspense-Documentary, Other-Documentary, Horror-Drama, Musical & Performing Arts-Horror, Mystery & Suspense-Musical & Performing Arts these pairs are significant and their mean difference would not be zero.

```
mov.aov = aov(audience_score ~ genre , data = mov_train)
summary(mov.aov)
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## genre         10  37865    3787   12.24 <2e-16 ***
## Residuals   439 135855     309
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
TukeyHSD(mov.aov)
```

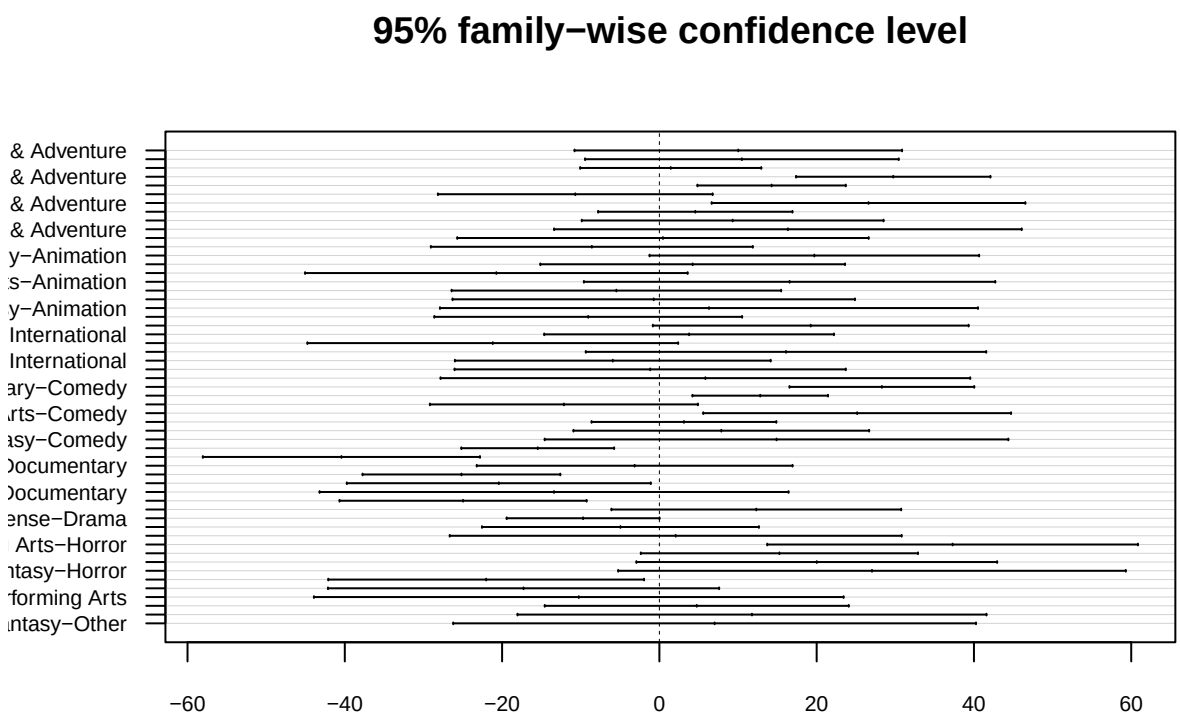
```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = audience_score ~ genre, data = mov_train)
##
## $genre
##                                                      diff         lwr
## Animation-Action & Adventure                   10.0353535 -10.7892843
```

```
## Art House & International-Action & Adventure         10.4909091  -9.4505833
## Comedy-Action & Adventure                             1.4454545 -10.0677715
## Documentary-Action & Adventure                       29.7372506  17.3812388
## Drama-Action & Adventure                             14.2686342   4.8347696
## Horror-Action & Adventure                           -10.6948052 -28.1615010
## Musical & Performing Arts-Action & Adventure         26.5909091   6.6494167
## Mystery & Suspense-Action & Adventure                 4.5665188  -7.7894929
## Other-Action & Adventure                              9.3181818  -9.8705282
## Science Fiction & Fantasy-Action & Adventure         16.3409091 -13.3861126
## Art House & International-Animation                   0.4555556 -25.6987180
## Comedy-Animation                                     -8.5898990 -29.0578563
## Documentary-Animation                                19.7018970  -1.2517168
## Drama-Animation                                       4.2332807 -15.1414634
## Horror-Animation                                    -20.7301587 -45.0502814
## Musical & Performing Arts-Animation                  16.5555556  -9.5987180
## Mystery & Suspense-Animation                         -5.4688347 -26.4224485
## Other-Animation                                      -0.7171717 -26.3021184
## Science Fiction & Fantasy-Animation                   6.3055556 -27.9008580
## Comedy-Art House & International                     -9.0454545 -28.6141759
## Documentary-Art House & International                19.2463415  -0.8298013
## Drama-Art House & International                       3.7777251 -14.6444975
## Horror-Art House & International                    -21.1857143 -44.7540393
## Musical & Performing Arts-Art House & International  16.1000000  -9.3567005
## Mystery & Suspense-Art House & International         -5.9243902 -26.0005330
## Other-Art House & International                      -1.1727273 -26.0441381
## Science Fiction & Fantasy-Art House & International   5.8500000 -27.8260494
## Documentary-Comedy                                   28.2917960  16.5468923
## Drama-Comedy                                         12.8231797   4.2052020
## Horror-Comedy                                       -12.1402597 -29.1801306
## Musical & Performing Arts-Comedy                     25.1454545   5.5767332
## Mystery & Suspense-Comedy                             3.1210643  -8.6238394
## Other-Comedy                                          7.8727273 -10.9282921
## Science Fiction & Fantasy-Comedy                     14.8954545 -14.5828011
## Drama-Documentary                                   -15.4686163 -25.1838719
## Horror-Documentary                                  -40.4320557 -58.0523239
## Musical & Performing Arts-Documentary                -3.1463415 -23.2224842
## Mystery & Suspense-Documentary                      -25.1707317 -37.7429000
## Other-Documentary                                   -20.4190687 -39.7476740
## Science Fiction & Fantasy-Documentary               -13.3963415 -43.2138566
## Horror-Drama                                        -24.9634394 -40.6733289
## Musical & Performing Arts-Drama                      12.3222749  -6.0999477
## Mystery & Suspense-Drama                             -9.7021154 -19.4173709
## Other-Drama                                          -4.9504524 -22.5550472
## Science Fiction & Fantasy-Drama                       2.0722749 -26.6576918
## Musical & Performing Arts-Horror                     37.2857143  13.7173893
## Mystery & Suspense-Horror                            15.2613240  -2.3589442
## Other-Horror                                         20.0129870  -2.9219082
## Science Fiction & Fantasy-Horror                     27.0357143  -5.2365439
## Mystery & Suspense-Musical & Performing Arts        -22.0243902 -42.1005330
## Other-Musical & Performing Arts                     -17.2727273 -42.1441381
## Science Fiction & Fantasy-Musical & Performing Arts -10.2500000 -43.9260494
## Other-Mystery & Suspense                              4.7516630 -14.5769423
## Science Fiction & Fantasy-Mystery & Suspense         11.7743902 -18.0431249
## Science Fiction & Fantasy-Other                       7.0227273 -26.2130934
```

```
##                                                        upr     p adj
## Animation-Action & Adventure                      30.85999139 0.8982375
## Art House & International-Action & Adventure      30.43240150 0.8339212
## Comedy-Action & Adventure                         12.95868056 0.9999988
## Documentary-Action & Adventure                    42.09326229 0.0000000
## Drama-Action & Adventure                          23.70249884 0.0000736
## Horror-Action & Adventure                          6.77189060 0.6621600
## Musical & Performing Arts-Action & Adventure      46.53240150 0.0009942
## Mystery & Suspense-Action & Adventure             16.92253058 0.9827584
## Other-Action & Adventure                          28.50689184 0.8935579
## Science Fiction & Fantasy-Action & Adventure      46.06793083 0.7922139
## Art House & International-Animation               26.60982910 1.0000000
## Comedy-Animation                                  11.87805836 0.9575830
## Documentary-Animation                             40.65551081 0.0868992
## Drama-Animation                                   23.60802472 0.9997842
## Horror-Animation                                   3.58996395 0.1780939
## Musical & Performing Arts-Animation               42.70982910 0.6150129
## Mystery & Suspense-Animation                      15.48477911 0.9989613
## Other-Animation                                   24.86777498 1.0000000
## Science Fiction & Fantasy-Animation               40.51196908 0.9999546
## Comedy-Art House & International                  10.52326682 0.9208281
## Documentary-Art House & International             39.32248424 0.0736899
## Drama-Art House & International                   22.19994769 0.9998788
## Horror-Art House & International                   2.38261075 0.1236044
## Musical & Performing Arts-Art House & International  41.55670054 0.6162797
## Mystery & Suspense-Art House & International      14.15175253 0.9970638
## Other-Art House & International                   23.69868352 1.0000000
## Science Fiction & Fantasy-Art House & International  39.52604941 0.9999739
## Documentary-Comedy                                40.03669968 0.0000000
## Drama-Comedy                                      21.44115728 0.0001071
## Horror-Comedy                                      4.89961111 0.4320268
## Musical & Performing Arts-Comedy                  44.71417591 0.0019023
## Mystery & Suspense-Comedy                         14.86596798 0.9987871
## Other-Comedy                                      26.67374662 0.9582176
## Science Fiction & Fantasy-Comedy                  44.37371022 0.8664846
## Drama-Documentary                                 -5.75336076 0.0000209
## Horror-Documentary                               -22.81178755 0.0000000
## Musical & Performing Arts-Documentary             16.92980131 0.9999901
## Mystery & Suspense-Documentary                   -12.59856343 0.0000000
## Other-Documentary                                 -1.09046347 0.0283571
## Science Fiction & Fantasy-Documentary             16.42117370 0.9337288
## Horror-Drama                                      -9.25354993 0.0000220
## Musical & Performing Arts-Drama                   30.74449746 0.5316015
## Mystery & Suspense-Drama                           0.01314022 0.0506577
## Other-Drama                                       12.65414239 0.9980375
## Science Fiction & Fantasy-Drama                   30.80224158 1.0000000
## Musical & Performing Arts-Horror                  60.85403932 0.0000246
## Mystery & Suspense-Horror                         32.88159224 0.1604488
## Other-Horror                                      42.94788220 0.1525896
## Science Fiction & Fantasy-Horror                  59.30797244 0.1983985
## Mystery & Suspense-Musical & Performing Arts      -1.94824747 0.0183687
## Other-Musical & Performing Arts                    7.59868352 0.4725291
## Science Fiction & Fantasy-Musical & Performing Arts  23.42604941 0.9962125
## Other-Mystery & Suspense                          24.08026823 0.9993832
```

```
## Science Fiction & Fantasy-Mystery & Suspense          41.59190541 0.9721543
## Science Fiction & Fantasy-Other                       40.25854796 0.9998407
```

```
plot(TukeyHSD(mov.aov), las=1, cex.axis=0.7)
```




```
# pairwise.t.test(mov_train$audience_score, mov_train$genre, p.adjust.method = "bonferroni")
```

Now, let us proceed with the modeling.

```
full <- lm(imdb_rating ~ ., data = mov_train)
null <- lm(imdb_rating ~ 1, data = mov_train)
```

```
X <- model.matrix(full)[,-1]

# both BIC models with forward/backward steps
both_BIC = step(null, list(lower = ~ 1, upper = formula(full)), trace = F,
direction = 'both', k = log(nrow(X)))

both_backward_BIC = step(full, list( upper = null), trace = F,
direction = 'both', k = log(nrow(X)))

# both BIC models with forward/backward steps
both_AIC = step(null, list(lower = ~ 1, upper = formula(full)), trace = F,
direction = 'both', k = 2)
```

```
both_backward_AIC = step(full, list( upper = null), trace = F,
direction = 'both', k = 2)
```

```
MSE.BIC.forward = mean((predict(both_BIC, mov_test) - mov_test$imdb_rating)^2)
MSE.BIC.backward = mean((predict(both_backward_BIC, mov_test) - mov_test$imdb_rating)^2)

MSE.AIC.forward = mean((predict(both_AIC, mov_test) - mov_test$imdb_rating)^2)
MSE.AIC.backward = mean((predict(both_backward_AIC, mov_test) - mov_test$imdb_rating)^2)

data.frame(MSE.BIC.forward, MSE.BIC.backward, MSE.AIC.forward, MSE.AIC.backward)
```

```
##   MSE.BIC.forward MSE.BIC.backward MSE.AIC.forward MSE.AIC.backward
## 1       0.1846557        0.1786505       0.1765288        0.1765288
```

```
formula(both_BIC) # imdb_num_votes, critics_rating
```

```
## imdb_rating ~ audience_score + critics_score + runtime + audience_rating
```

```
formula(both_backward_BIC)
```

```
## imdb_rating ~ runtime + imdb_num_votes + critics_rating + critics_score +
##     audience_rating + audience_score
```

```
formula(both_AIC)
```

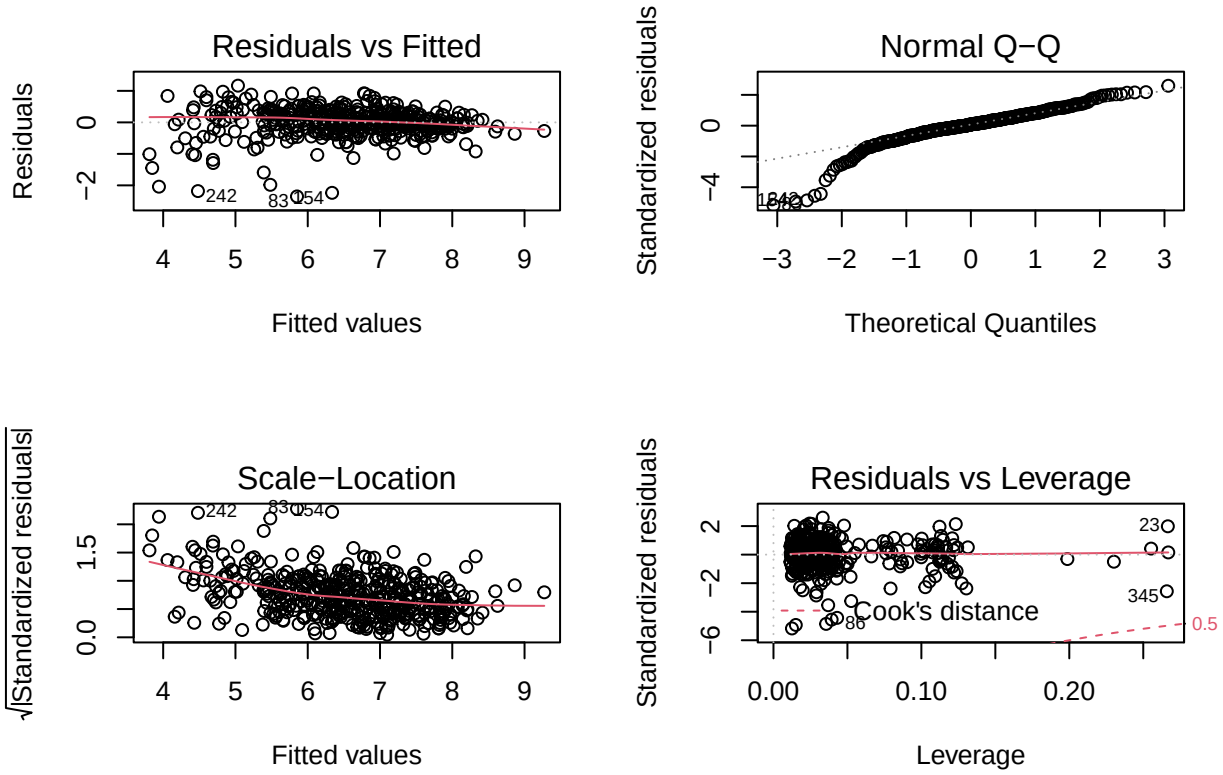
```
## imdb_rating ~ audience_score + critics_score + genre + imdb_num_votes +
##     audience_rating + critics_rating + runtime
```

```
formula(both_backward_AIC)
```

```
## imdb_rating ~ genre + runtime + imdb_num_votes + critics_rating +
##     critics_score + audience_rating + audience_score
```

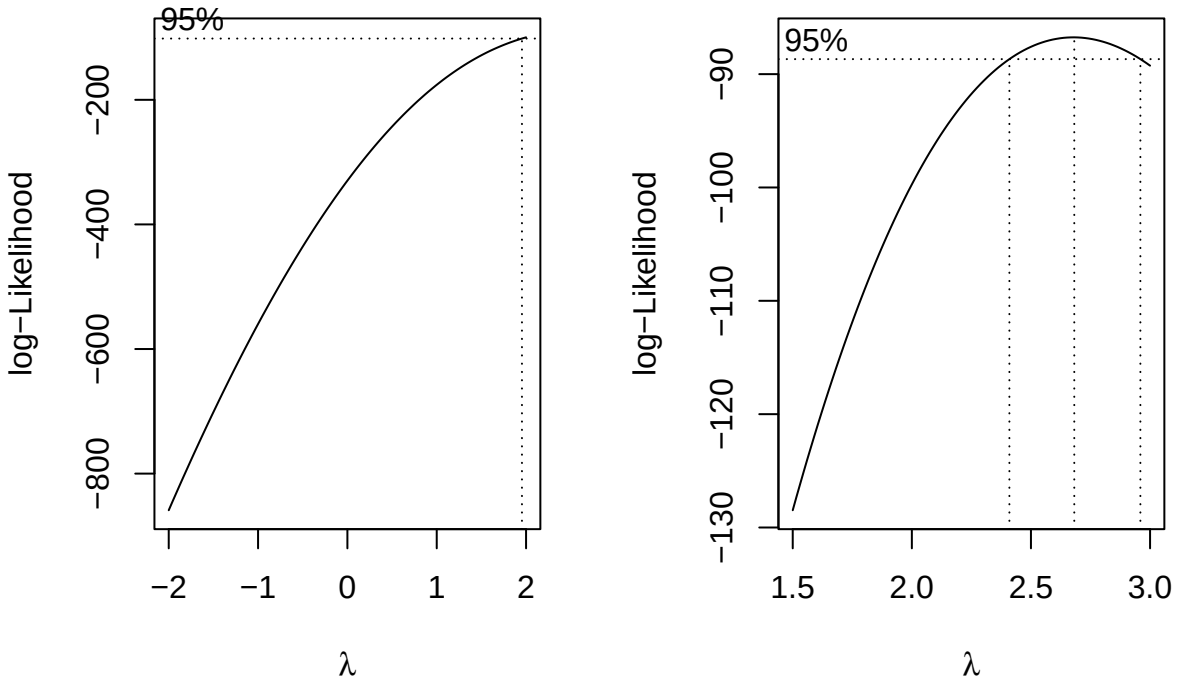
We select the `both_AIC` model with least MSE. Now, we shall proceed to diagnose the model to improve it. From the diagnostic plots, we could observe that linearity assumption of the model doesn't hold and a possible heteroscedasticity is observed.

```
par(mfrow = c(2,2))
plot(both_AIC)
```



Let us apply the transformation to remove heteroscedasticity and linearize the model.

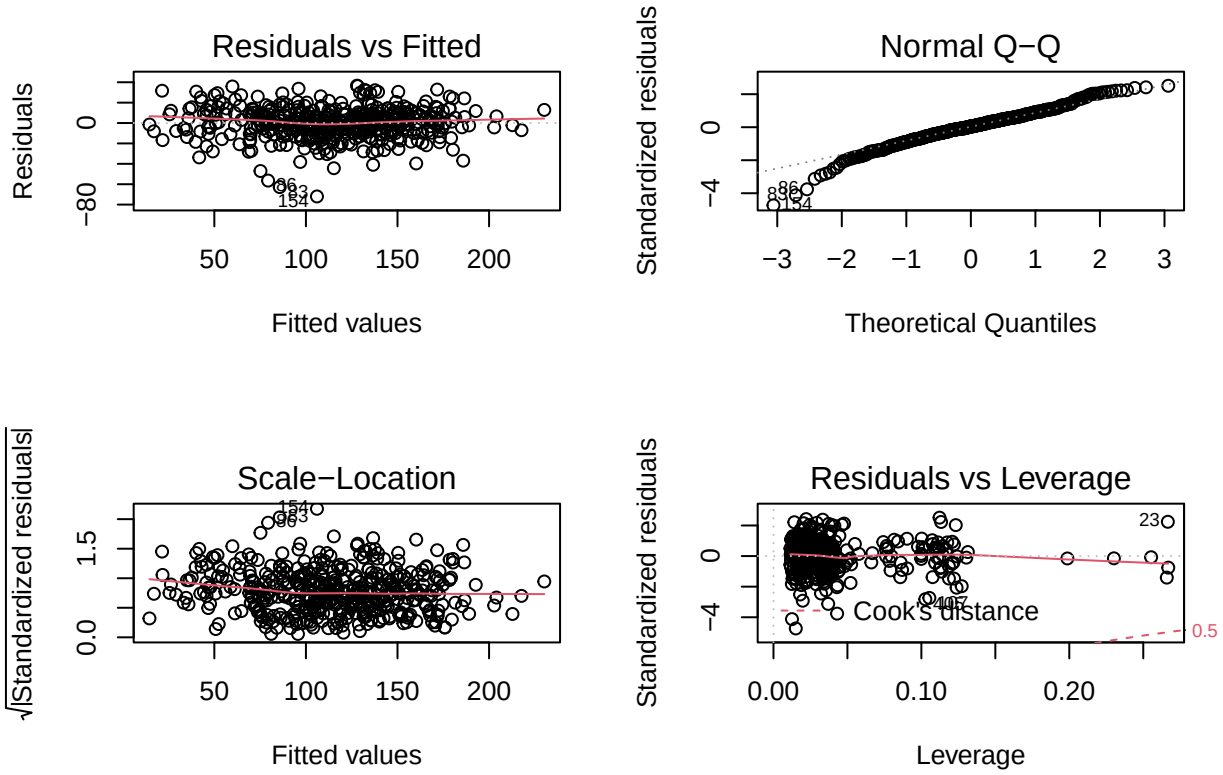
```
par(mfrow = c(1,2))
boxcox(both_AIC, plotit=T)
boxcox(both_AIC, plotit=T, lambda=seq(1.5,3,by=0.05))
```



As per boxcox plot, we shall consider a transformation of 10/4 (= 2.5) for the response variable.

```
# transformed model
mod1 <- lm(imdb_rating ^ 2.5 ~ audience_score + critics_score + genre + imdb_num_votes +
    audience_rating + critics_rating + runtime, data = mov_train)

#Diagnostic Plots
par(mfrow = c(2,2))
plot(mod1)
```



Let us now check for collinearity. As per below, here we observe that, VIF < 10 & $\kappa_p < 15$. Hence, collinearity is ok.

```
# VIF
car::vif(mod1)
```

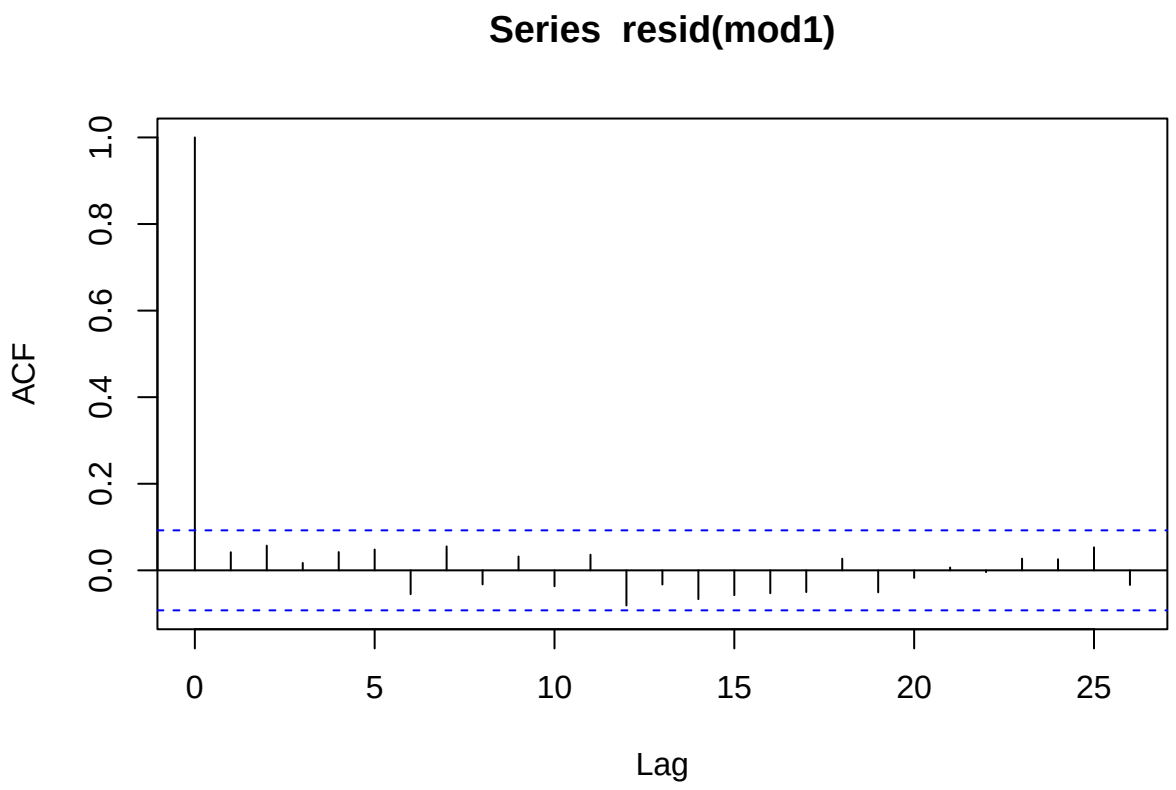
```
##                     GVIF Df GVIF^(1/(2*Df))
## audience_score  5.895377  1        2.428040
## critics_score   6.117419  1        2.473342
## genre           1.820407 10        1.030406
## imdb_num_votes  1.615459  1        1.271007
## audience_rating 4.148237  1        2.036722
## critics_rating  5.393049  2        1.523907
## runtime         1.339764  1        1.157482
```

```
# condition index
X = model.matrix(mod1)[,-1]
R = cor(X)
ev = eigen(R)$val
sqrt(ev[1]*ev^(-1))
```

```
##  [1] 1.000000 1.450132 1.663677 1.714164 1.858079 1.880353 1.882544 1.893225
##  [9] 1.904681 1.974370 1.998278 2.334482 2.688485 3.223667 5.295403 5.507654
## [17] 6.975310
```

Let us check for autocorrelation even though we could skip it. From the graph, we could see that no correlation exists.

```
acf(resid(mod1))
```



Now, our modelling step is complete.

Prediction

First, let us test the prediction with one of the existing row in the `mov_test` dataset. In this case, let us consider the movie `Locke`. The dataframe is created with the values relevant to `Locke` movie.

```
new_df = data.frame(audience_score = 71 ,
critics_score = 91,
genre  = 'Mystery & Suspense',
imdb_num_votes  = 82851,
audience_rating  = 'Upright',
critics_rating  = 'Certified Fresh',
runtime  = 85)
```

Based on the prediction, we could observe that the fitted value is `7.121779` which is ~ equal to the original value of `7.1`. Hence we can say that the model prediction is working properly.

```
predict(mod1 , newdata = new_df, interval = 'prediction')^(1/2.5)
```

```
##        fit      lwr      upr
## 1 7.121779 6.422304 7.730952
```

Now let us predict for a movie not from the datasets. In this case, let us consider the movie `Dune`. The dataframe is created with the values relevant to `Dune` movie.

```
new_df1 = data.frame(audience_score = 90,
critics_score = 83,
genre  = 'Science Fiction & Fantasy',
imdb_num_votes  = 390470,
audience_rating  = 'Upright',
critics_rating  = 'Certified Fresh',
runtime  = 155)
```

Based on the prediction, we could observe that the fitted value is `7.9` which is very close to the original value of `8.2`. Hence we can say that the model prediction is working properly.

```
predict(mod1 , newdata = new_df1, interval = 'prediction')^(1/2.5)
```

```
##        fit      lwr      upr
## 1 7.921116 7.273341 8.497836
```

Now let us predict for a movie not from the datasets. In this case, let us consider the movie `RUN`. The dataframe is created with the values relevant to `RUN` movie.

```
new_df2 = data.frame(audience_score = 74,
critics_score = 88,
genre  = 'Mystery & Suspense',
imdb_num_votes  = 62456,
audience_rating  = 'Upright',
critics_rating  = 'Certified Fresh',
runtime  = 90)
```

Based on the prediction, we could observe that the fitted value is `7.1` which is very close to the original value of `6.7`. Hence we can say that the model prediction is working properly.

```
predict(mod1 , newdata = new_df2, interval = 'prediction')^(1/2.5)
```

```
##        fit      lwr      upr
## 1 7.170732 6.480396 7.773505
```

Conclusion

While researching on the topics mentioned in the report, first we found many insignificant variables which were removed from the dataset in the pre-processing step. We have also removed the rows having 'NA' values. For the first research question, we used two sample t-test and determined that there is no association between Oscar winning actor or actress with the IMDB rating of the movies.

For the second research question we have performed TukeyHSD test which suggests that there is a difference between mean audience score between genres. We have found few such pairs in the results.

For the third research question we found that audience_score, critics_score, genre, imdb_num_votes, audience_rating, critics_rating and runtime are associated and can be used to predict the rating of a movie on IMBD. We have used `both_AIC` model with least MSE. We have tested our model on the given dataset values as well as with the values apart from the given dataset and we obtain a good accuracy which falls within the 95% confidence interval.

For the model built, we didn't consider the interaction terms as well as different model approaches like lasso and ridge regression. In the future studies, these could be considered while model building and see if there is an improvement in prediction.

One of the shortcomings of the dataset is that the data available is related to the movies of USA and hence for the movies outside of the USA, there could be possible bias if this model is used.
