Statistical Analysis of "Hidden Gem" Score for Movies on Netflix

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```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.3     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.4     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.0
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## 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 errors
```

```
library(here)
```

```
## here() starts at /Users/zhizhiwei/Desktop/Math 208/My_Homework_208
```

```
FlixGem <- read_csv(here("/Users/zhizhiwei/Downloads/Final_Project_FlixGem.csv"))
```

```
## Rows: 9425 Columns: 29
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (19): Title, Genre, Tags, Languages, Series or Movie, Country Availabil...
## dbl   (8): Hidden Gem Score, IMDb Score, Rotten Tomatoes Score, Metacritic S...
## dttm  (2): Release Date, Netflix Release Date
##
## 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.
```

```
class(FlixGem)
```

```
## [1] "spec_tbl_df" "tbl_df"      "tbl"         "data.frame"
```

```
# subsetted and cleaned data:
FlixGem_cleaned <- FlixGem %>% filter(`Series or Movie`== "Movie") %>% drop_na()
FlixGem_cleaned
```

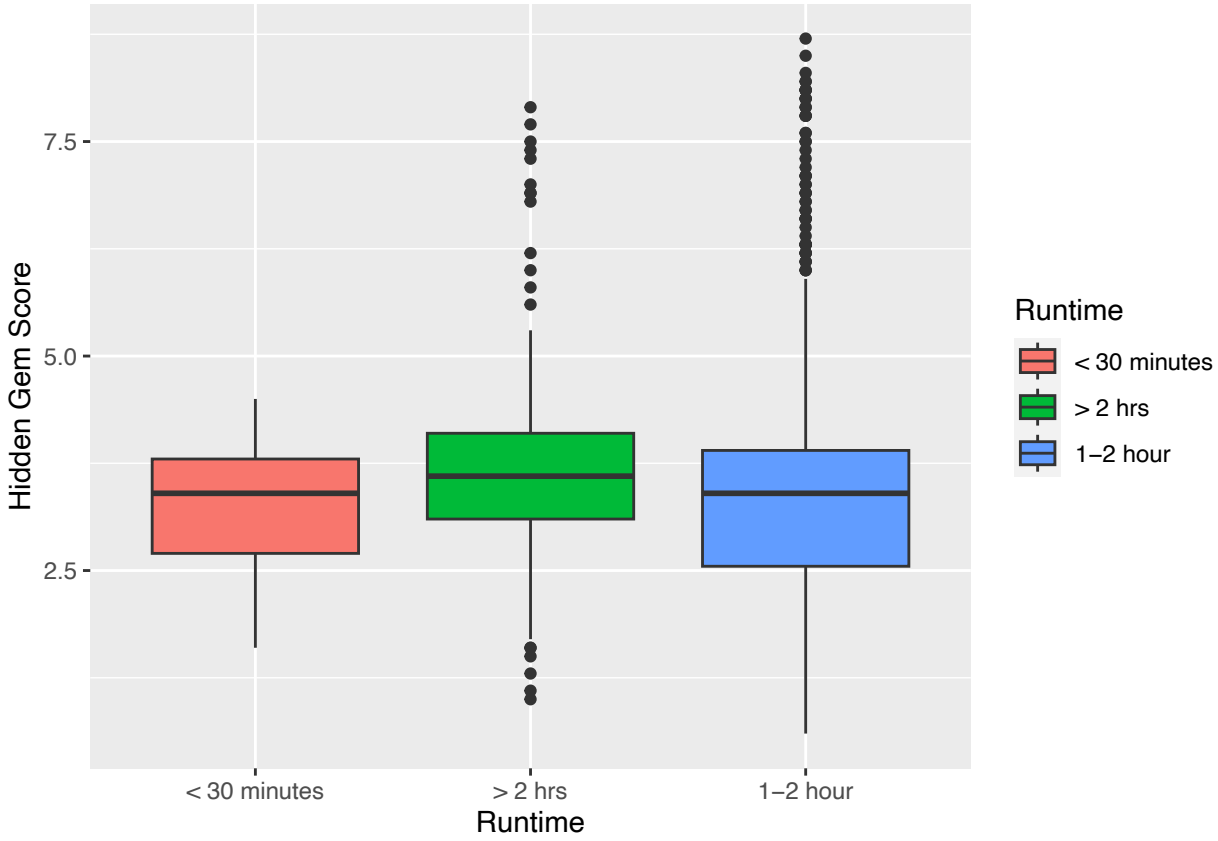
```
## # A tibble: 2,118 x 29
##    Title              Genre Tags  Languages `Series or Movie` `Hidden Gem Score`
##    <chr>              <chr> <chr> <chr>     <chr>                           <dbl>
##  1 Joker              Crim~ Dark~ English   Movie                             3.5
##  2 I                  Acti~ Dram~ English,~ Movie                             2.8
##  3 Harrys Daughters   Adve~ Dram~ English   Movie                             4.4
##  4 The Closet         Come~ Kore~ French    Movie                             3.8
##  5 Ordinary People    Drama Kore~ English   Movie                             4.2
##  6 Stand by Me        Adve~ Kore~ English   Movie                             4.1
##  7 Wonderstruck       Adve~ Chil~ English,~ Movie                             3.6
##  8 The Girl on the T~ Crim~ Boll~ English,~ Movie                             2.6
##  9 Red                Acti~ Dram~ English,~ Movie                             3.4
## 10 Burden             Drama Movi~ English   Movie                             7.8
## # i 2,108 more rows
## # i 23 more variables: `Country Availability` <chr>, Runtime <chr>,
## #   Director <chr>, Writer <chr>, Actors <chr>, `View Rating` <chr>,
## #   `IMDb Score` <dbl>, `Rotten Tomatoes Score` <dbl>,
## #   `Metacritic Score` <dbl>, `Awards Received` <dbl>,
## #   `Awards Nominated For` <dbl>, Boxoffice <dbl>, `Release Date` <dttm>,
## #   `Netflix Release Date` <dttm>, `Production House` <chr>, ...
```

Task 1

(a)

Hidden Gem Score vs. Runtime:

```
ggplot(FlixGem_cleaned, aes(x = Runtime, y = `Hidden Gem Score`, group = Runtime,
    fill = Runtime)) + geom_boxplot() + labs(x = "Runtime", y = "Hidden Gem Score")
```



We can see from the boxplot that the Hidden Gem Score mean of movies of different Runtime are very close, but runtime of >2 hours tend to have a higher score of 75% quartile, while runtime of less than 30 minutes tend to have a lower one. Also the outliers of 1-2 hours movies tend to lie in the range of higher scores. Thus we can conclude that Hidden Gem Scores associates with Runtime.

Hidden Gem Score vs. languages:

Step1: Re-coding 'Languages'

```
FlixGem_cleaned %>% pull(Languages) %>% unique(.) %>% sort(.)
```

```
FlixGem_cleaned %>% group_by(Languages) %>% summarize(count=n()) %>% arrange(desc(count))
```

```
FlixGem_lang_main <- FlixGem_cleaned %>%
    mutate(Languages_main = word(FlixGem_cleaned$Languages, 1)) %>%
    mutate(Languages_main_alt = recode(Languages_main, `English,` = "English", `French,` = "French",
        `Spanish,` = "Spanish", `Korean,` = "Korean", `Mandarin,` = "Mandarin", `Italian,` = "Italian",
        `Cantonese,` = "Cantonese", `German,` = "German", `Japanese,` = "Japanese",
        `Hindi,` = "Hindi", `Danish,` = "Danish", `Norwegian,` = "Norwegian", `Swedish,` = "Swedish",
        `Czech,` = "Czech", `Polish,` = "Polish", `Russian,` = "Russian", `Zulu,` = "Zulu",
        `Arabic,` = "Arabic", `Chinese,` = "Mandarin", `Dari,` = "Dari", `Filipino,` = "Filipino",
        `Greek,` = "Greek", `Hungarian,` = "Hungarian", `Indonesian,` = "Indonesian",
        `Neapolitan,` = "Neapolitan", `None,` = "None", `Persian,` = "Persian", `Portuguese,` = "Portug
        `Romany,` = "Romany", `Tamil,` = "Tamil", `Thai,` = "Thai", `Tswana,` = "Tswana",
```

```
        `Yiddish,` = "Yiddish"))
FlixGem_lang_main %>%
    group_by(Languages_main_alt) %>%
    summarize(count = n()) %>%
    arrange(desc(count))
```

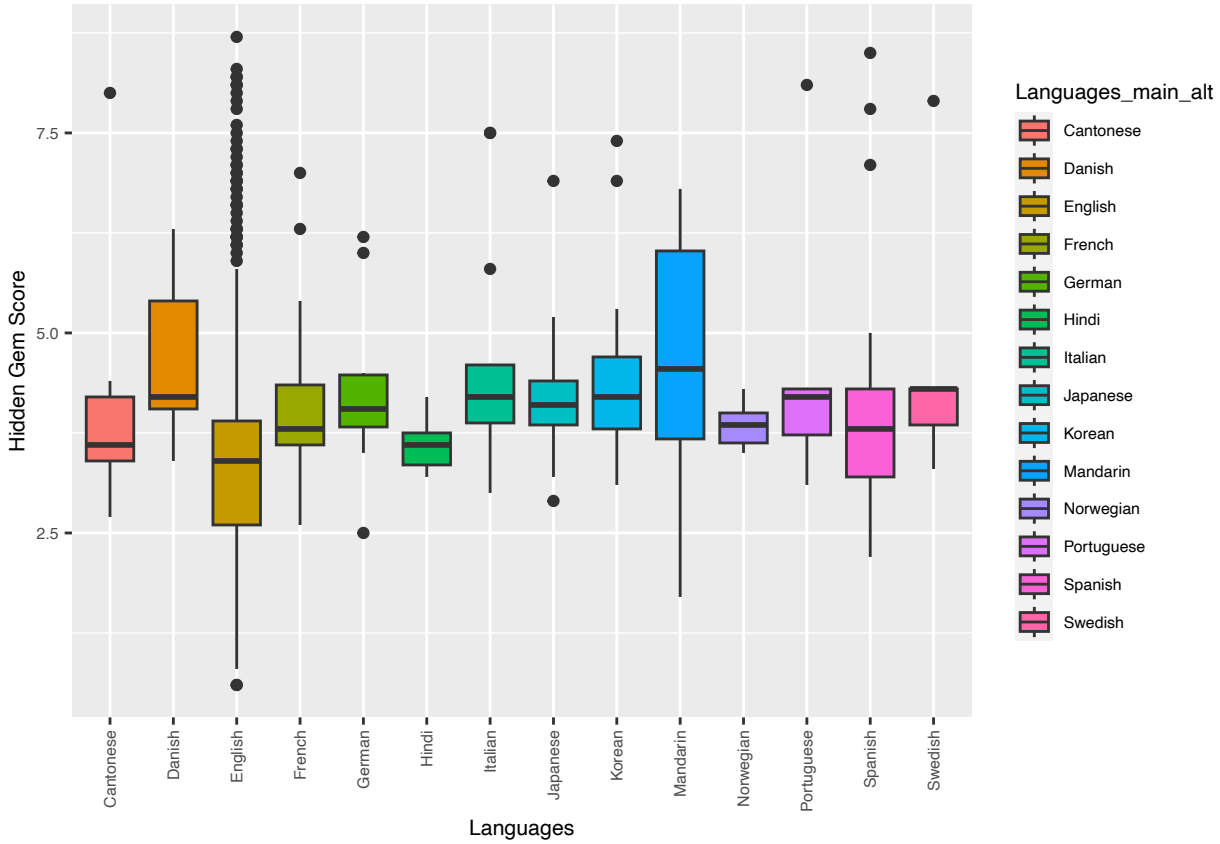
```
## # A tibble: 36 x 2
##    Languages_main_alt count
##    <chr>              <int>
##  1 English             1891
##  2 French                34
##  3 Spanish               29
##  4 Japanese              27
##  5 Mandarin              20
##  6 Korean                17
##  7 German                14
##  8 Italian               14
##  9 Cantonese              9
## 10 Hindi                  7
## # i 26 more rows
```

```
# Filter out Languages with counts > 5
FlixGem_lang_main_filter <- FlixGem_lang_main %>%
    filter(Languages_main_alt %in% c("English", "French", "Spanish", "Japanese",
        "Mandarin", "Korean", "German", "Italian", "Cantonese", "Hindi", "Swedish",
        "Danish", "Norwegian", "Portuguese"))
FlixGem_lang_main_filter %>%
    group_by(Languages_main_alt) %>%
    summarize(count = n()) %>%
    arrange(desc(count))
```

```
## # A tibble: 14 x 2
##    Languages_main_alt count
##    <chr>              <int>
##  1 English             1891
##  2 French                34
##  3 Spanish               29
##  4 Japanese              27
##  5 Mandarin              20
##  6 Korean                17
##  7 German                14
##  8 Italian               14
##  9 Cantonese              9
## 10 Hindi                  7
## 11 Swedish                7
## 12 Danish                 6
## 13 Norwegian              6
## 14 Portuguese             6
```

Step2: Plotting 'Hidden Gem Score vs. languages'

```
ggplot(FlixGem_lang_main_filter, aes(x = Languages_main_alt, y = `Hidden Gem Score`,
    group = Languages_main_alt, fill = Languages_main_alt)) + geom_boxplot() + labs(x = "Languages",
    y = "Hidden Gem Score") + theme(legend.key.size = unit(0.5, "cm"), axis.text.x = element_text(angle
    vjust = 0.5, hjust = 1), text = element_text(size = 8))
```

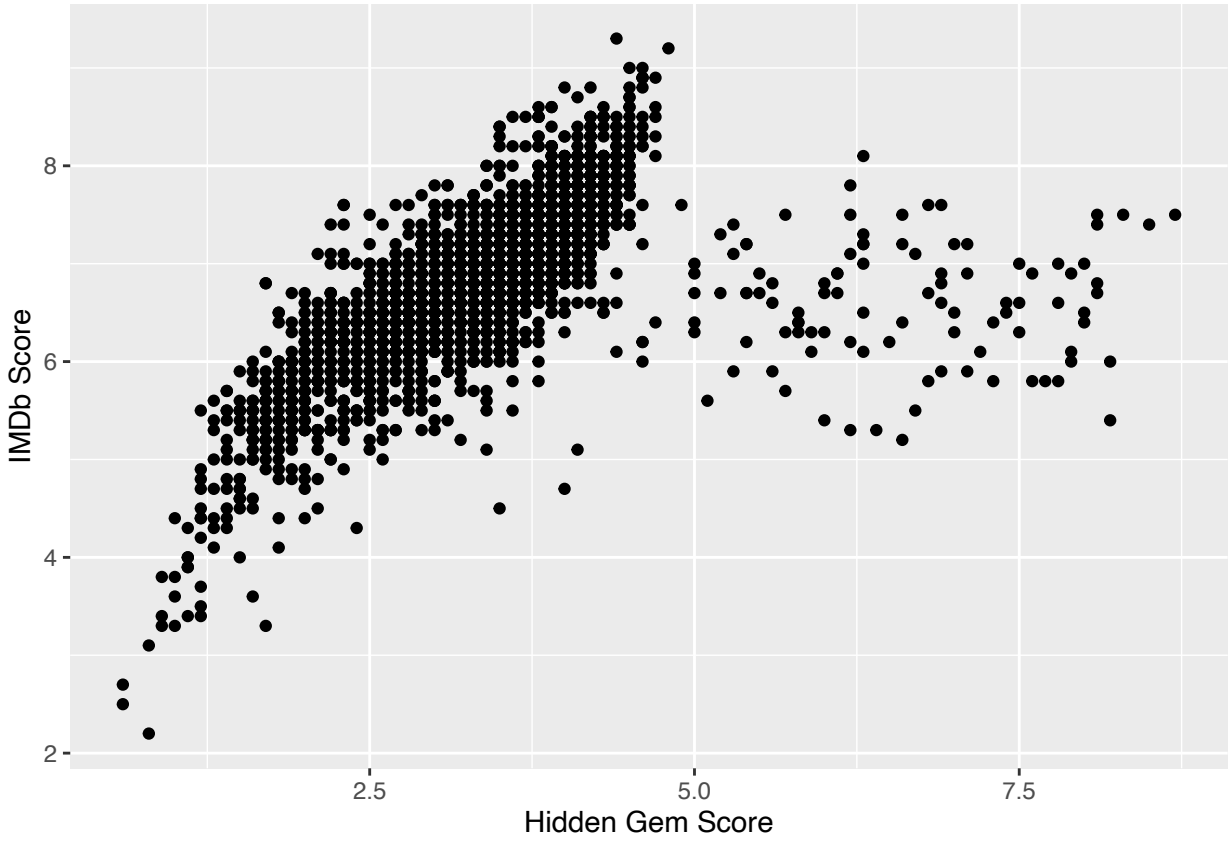


Moreover, the Hidden Gem Score seems not to have association with the language of movies. We can see from the boxplots that the mean, 25th quartile and 75th quartile range of movies of each languages are very similar, except for English and Mandarin. But these two languages' score varies widely because they have much more content and market compared to other languages. So the nature of these outliers is due to those movies' quality, not the factor of language at surface. Movies of large numbers all have different quality themselves, while audience who understand this kind of language in different market have various comments depending on cultural backgrounds etc. Thus, we can conclude that the Hidden Gem Score does not have association with the language.

(b)

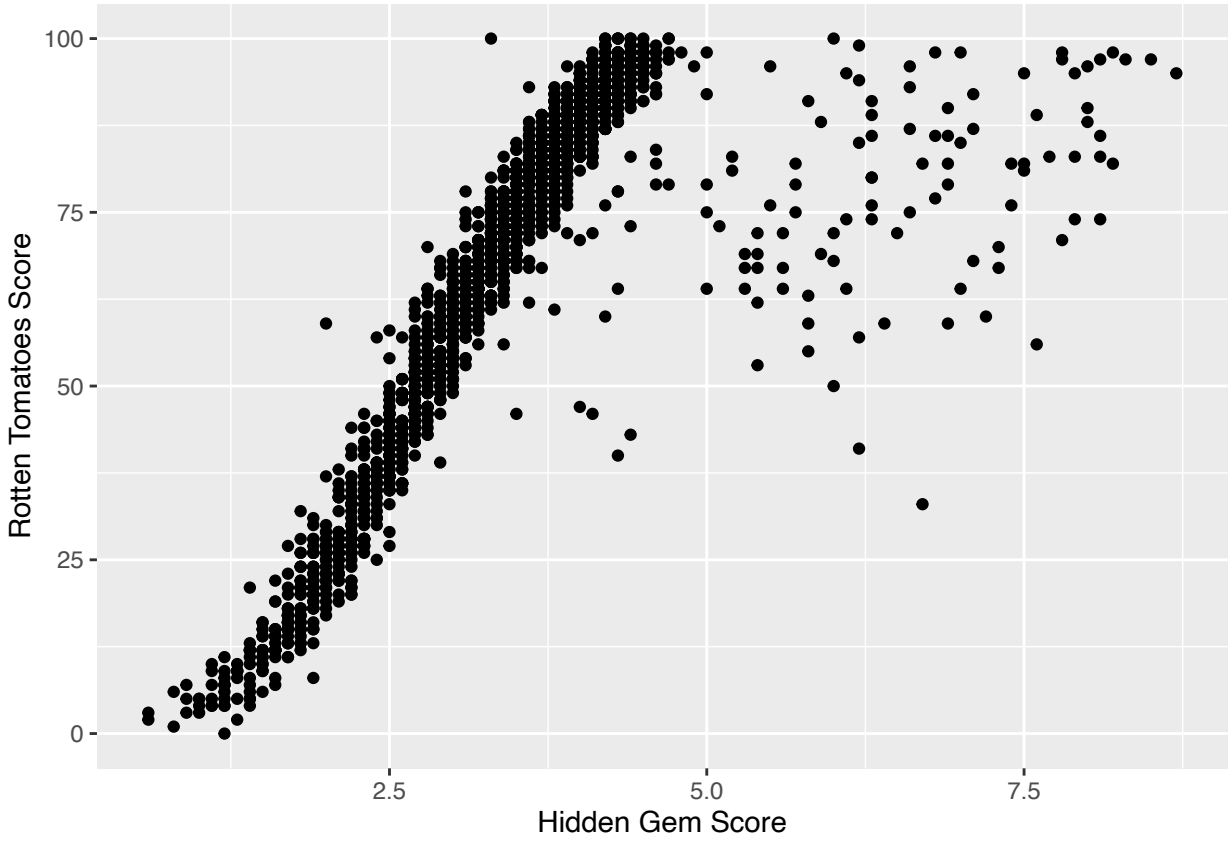
Hidden Gem Scores vs. IMDb

```
ggplot(FlixGem_cleaned, aes(x = `Hidden Gem Score`, y = `IMDb Score`)) + geom_point() +
    labs(x = "Hidden Gem Score", y = "IMDb Score")
```



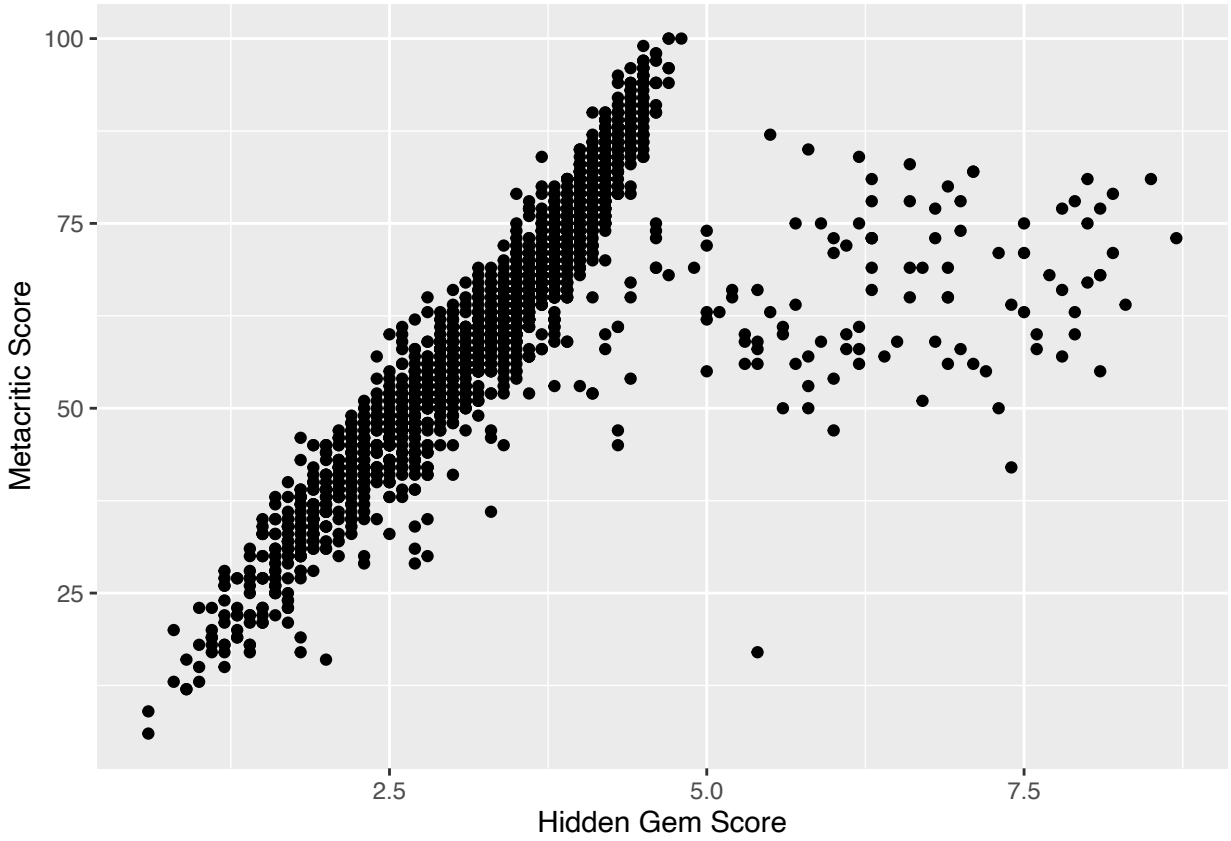
Hidden Gem Scores vs. Rotten Tomatoes Score

```
ggplot(FlixGem_cleaned, aes(x = `Hidden Gem Score`, y = `Rotten Tomatoes Score`)) +
    geom_point() + labs(x = "Hidden Gem Score", y = "Rotten Tomatoes Score")
```



Hidden Gem Scores vs. Metacritic Score

```
ggplot(FlixGem_cleaned, aes(x = `Hidden Gem Score`, y = `Metacritic Score`)) + geom_point() +
    labs(x = "Hidden Gem Score", y = "Metacritic Score")
```



The three reviews strongly correlate to the Hidden Gem Score from the three plots. We can see that the dots all form a linear relationship between each review and the Hidden Gem Score, indicating that as the Hidden Gem Score increases, the review increases along with it. By nature, they all reflect the general quality of a movie and they make relatively fair comments. The quality of a movie is consistent.

(c)

```
library(lubridate)
```

```
Release_Date_year <- rep(0, length(FlixGem_cleaned$`Release Date`))

for (i in seq_along(FlixGem_cleaned$`Release Date`)) {
    Release_Date_year[i] = year(as.POSIXlt(FlixGem_cleaned$`Release Date`[i], format = "%Y-%m-%d"))
}

FlixGem_cleaned <- FlixGem_cleaned %>%
    mutate(Release_Date_year = Release_Date_year)
```

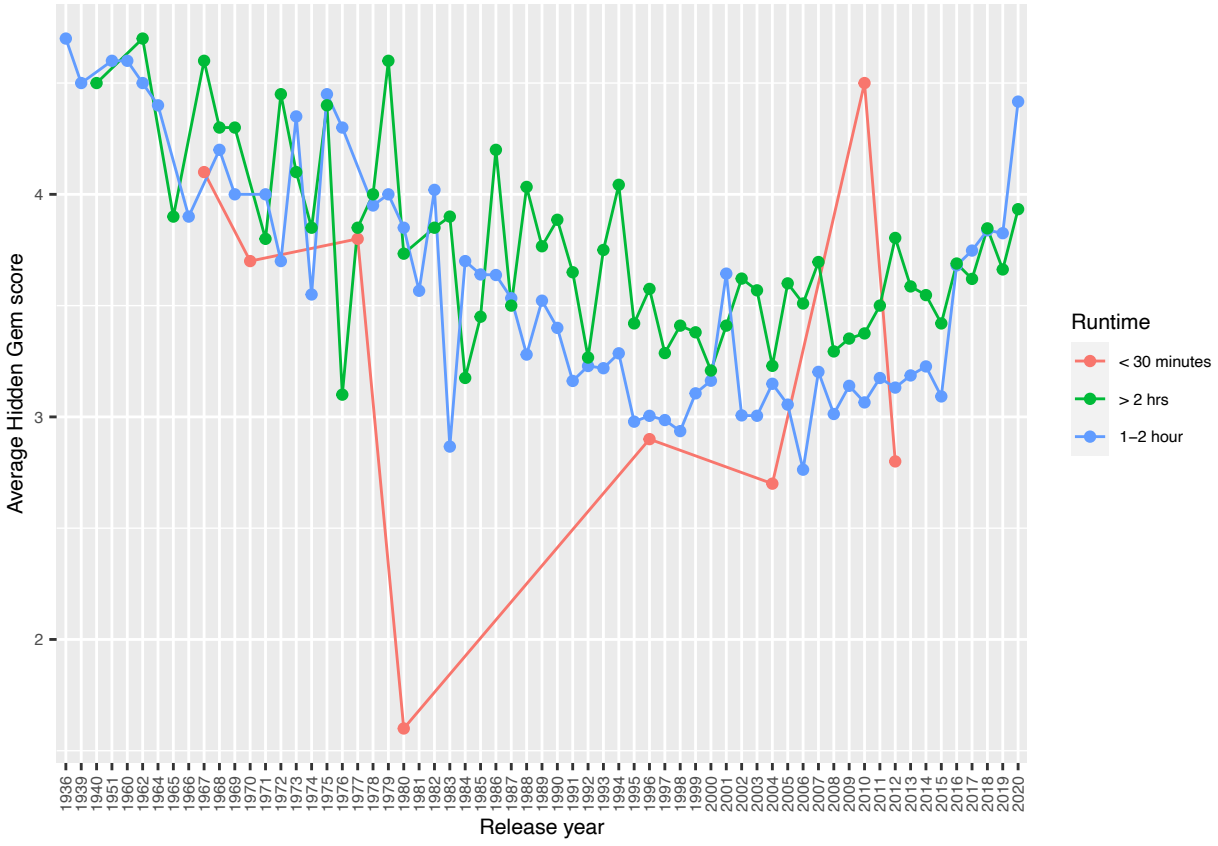
```
Avg_HG_by_year_runtime <- FlixGem_cleaned %>%
    group_by(Runtime, Release_Date_year) %>%
    summarise(Avg_HG_score = mean(`Hidden Gem Score`))
```

```
## `summarise()` has grouped output by 'Runtime'. You can override using the
## `.groups` argument.
```

```
Avg_HG_by_year_runtime
```

```
## # A tibble: 121 x 3
## # Groups:   Runtime [3]
##    Runtime  Release_Date_year Avg_HG_score
##    <chr>                <dbl>        <dbl>
##  1 1-2 hour              1936          4.7
##  2 1-2 hour              1939          4.5
##  3 1-2 hour              1951          4.6
##  4 1-2 hour              1960          4.6
##  5 1-2 hour              1962          4.5
##  6 1-2 hour              1964          4.4
##  7 1-2 hour              1966          3.9
##  8 1-2 hour              1968          4.2
##  9 1-2 hour              1969          4
## 10 1-2 hour              1971          4
## # i 111 more rows
```

```
ggplot(Avg_HG_by_year_runtime, aes(x = factor(Release_Date_year), y = Avg_HG_score,
    group = factor(Runtime), col = factor(Runtime))) + geom_line() + geom_point() +
    labs(x = "Release year", y = "Average Hidden Gem score", col = "Runtime") + theme(legend.key.size =
    "cm"), axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1), text = element_text(size = 8)
```



From the plots we can see that the average Hidden Gem Score of movies of 1-2 hours and >2 hours keep changing on a smaller range, while that of movies of <30 minutes changes dramatically especially during 1977-1997 (although it might be resulted from the lack of data). Movie >2 hours's average Score generally

remain as a leading one in a long term. Since 2015, people seem to prefer longer movies. Longer movies' Score are increasing and 1-2 hours movies' Score increase faster than that of >2 hours movies. Thus it seems like people are more accepting to longer movies.

```
tinytex::install_tinytex()
library(rsample)
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(rpart)
library(rpart.plot)
library(Metrics)

FlixGem<-read.csv("/Users/samanthazhang/Final_Project_FlixGem.csv",header=TRUE)
```

```
FlixGem_cleaned <- FlixGem[!(FlixGem$Series.or.Movie=="Series"),]
FlixGem_cleaned <- FlixGem_cleaned %>% na.omit(FlixGem_cleaned)
```

```
set.seed(123)
FlixGem_Movie_Selected <- FlixGem_cleaned %>% select(Hidden.Gem.Score, Languages,Runtime,IMDb.Score,Rot
flix_split <- initial_split(FlixGem_Movie_Selected,prop = .8)
flix_train <- training(flix_split)
flix_test <- testing(flix_split)
```

I divided the data set into 80% vs 20% for training data and testing data respectively.

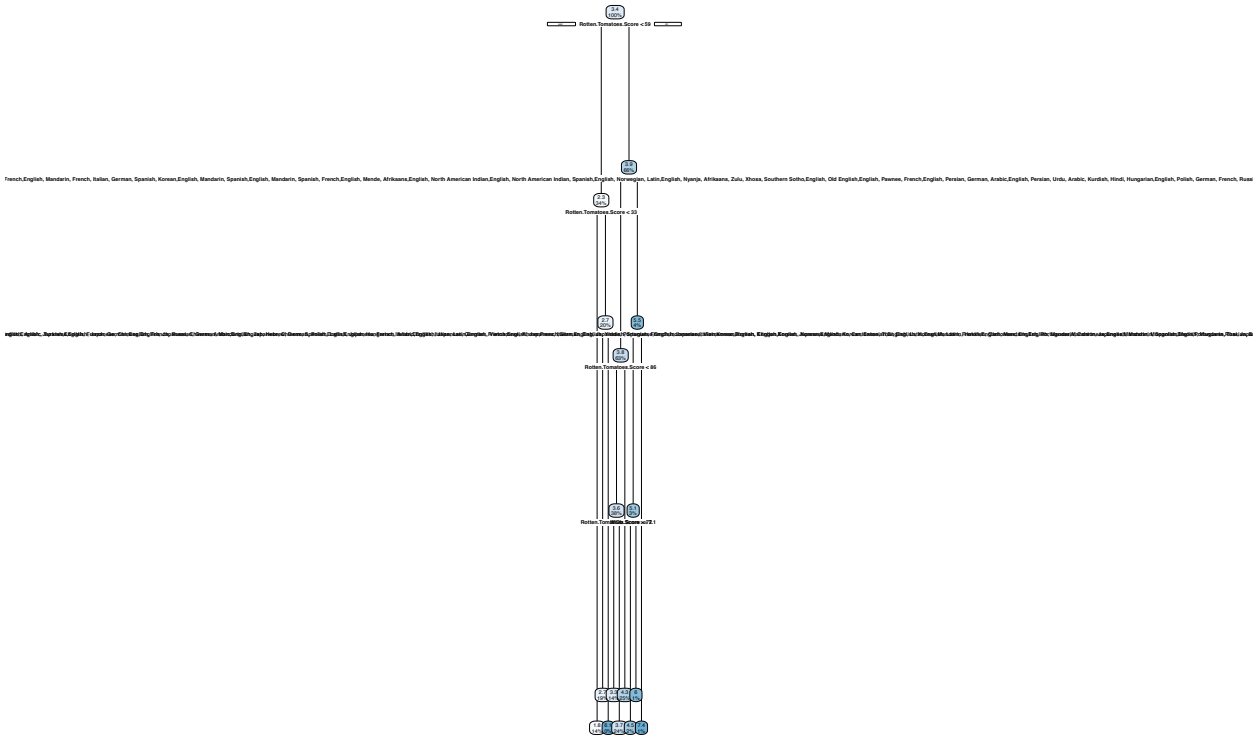
```
Gem_Score_Tree_1 <-rpart(
  formula = Hidden.Gem.Score ~.,
  data = FlixGem_Movie_Selected,
  method = "anova",
)

Gem_Score_Tree_1
```

```
## n= 2118
##
## node), split, n, deviance, yval
##       * denotes terminal node
##
##  1) root 2118 2548.053000 3.396412
##    2) Rotten.Tomatoes.Score< 58.5 716  314.626400 2.347765
##      4) Rotten.Tomatoes.Score< 32.5 299   40.345620 1.809030 *
##      5) Rotten.Tomatoes.Score>=32.5 417  125.276500 2.734053
##       10) Languages=Cantonese, Mandarin,English,English, Aboriginal, French, Portuguese,English, Afri
##       11) Languages=English, Catalan, Spanish,English, Hindi, Urdu,German,Italian, French, English,Ko
##    3) Rotten.Tomatoes.Score>=58.5 1402 1043.968000 3.931954
##      6) Languages=American Sign Language, English,Arabic,Cantonese,Cantonese, English,Cantonese, Engl
##       12) Rotten.Tomatoes.Score< 85.5 800  304.839700 3.569375
##         24) Rotten.Tomatoes.Score< 71.5 292  113.280000 3.300000 *
##         25) Rotten.Tomatoes.Score>=71.5 508  158.192200 3.724213 *
##       13) Rotten.Tomatoes.Score>=85.5 525  238.012400 4.256190 *
##      7) Languages=Arabic, English,Cantonese, English, Hokkien, Mandarin,Czech, English, German, Russi
##       14) Languages=Czech, German, English, Slovak,Danish,Danish, English,Dutch,English, Arabic, Turk
##         28) IMDb.Score>=7.05 39   20.055900 4.543590 *
##         29) IMDb.Score< 7.05 26   43.766540 6.011538 *
##       15) Languages=Arabic, English,Cantonese, English, Hokkien, Mandarin,Czech, English, German, Rus
```

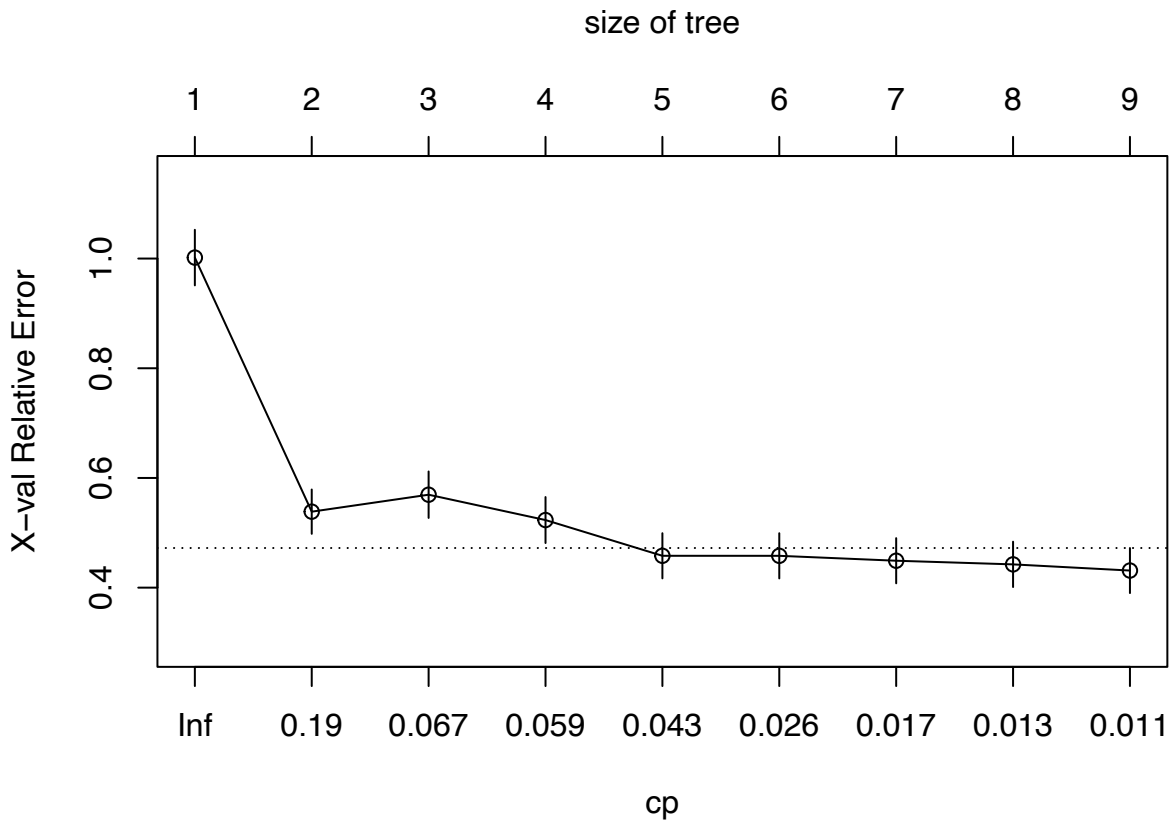
Look for the 4th branch in Gem_Score_Tree_1, you can see that 299 observations and the SSE in this region is 40.345620. Their average Hidden Gem Scores are 1.809030. The largest reduction in SSE initially is Rotten Tomatoes Score with scores under 32.5.

```
rpart.plot(Gem_Score_Tree_1)
```

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```




```
plotcp(Gem_Score_Tree_1)
```



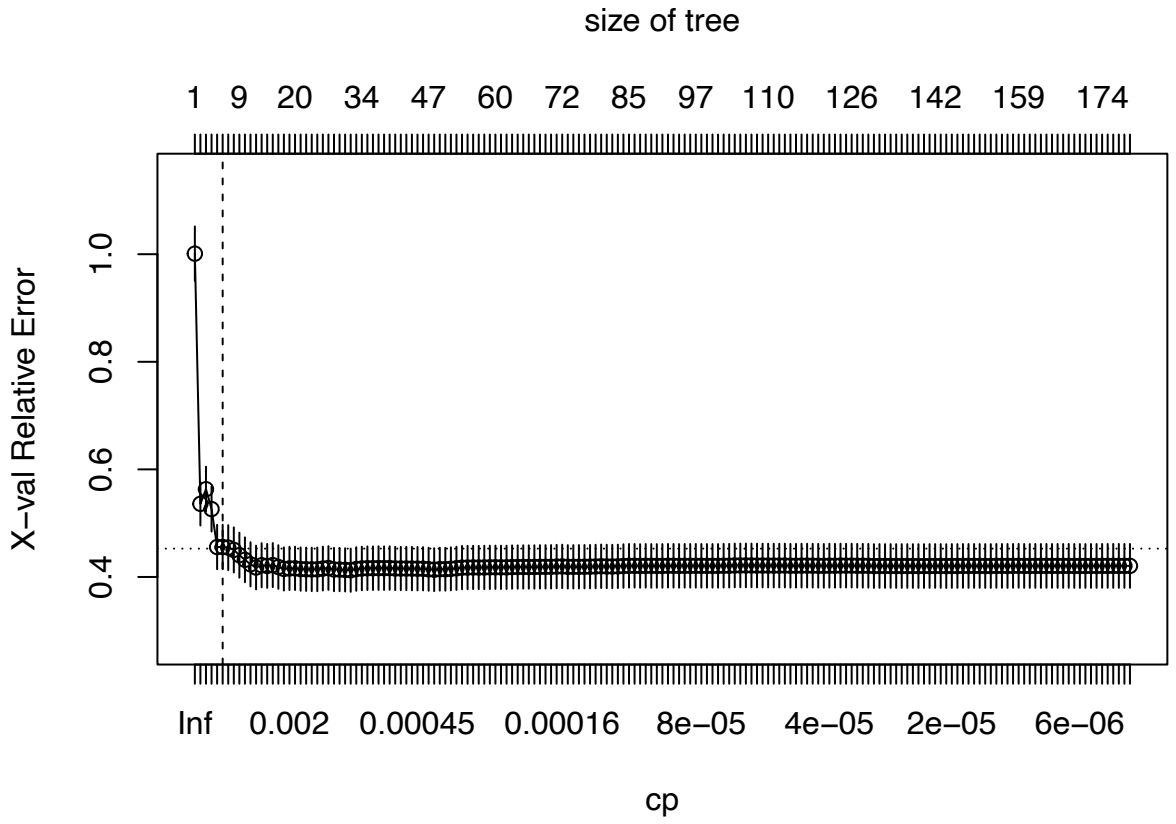

```
Gem_Score_Tree_1$cptable
```

```
##           CP nsplit rel error    xerror       xstd
## 1 0.46681054      0 1.0000000 1.0017931 0.05067076
## 2 0.07745208      1 0.5331895 0.5385332 0.04042646
## 3 0.05868203      2 0.4557374 0.5694724 0.04236183
## 4 0.05847774      3 0.3970554 0.5232722 0.04192998
## 5 0.03219573      4 0.3385776 0.4580775 0.04120398
## 6 0.02092520      5 0.3063819 0.4580370 0.04125149
## 7 0.01319283      6 0.2854567 0.4490885 0.04117956
## 8 0.01309530      7 0.2722639 0.4424352 0.04136893
## 9 0.01000000      8 0.2591686 0.4311886 0.04110606
```

After 6 terminal nodes in the plot 1 of cross-validation error results, there are diminishing returns in error reduction as the tree grows deeper. We also achieve minimal expected error by looking at the cross-validation error of 0.4311886.

```
Gem_Score_Tree_2 <-rpart(
  formula = Hidden.Gem.Score ~.,
  data = FlixGem_Movie_Selected,
  method = "anova",
  control = list(cp=0,xval = 10)

)
```

```
plotcp(Gem_Score_Tree_2)
abline(v=6, lty = "dashed")
```



After 6 terminal nodes in the plot 2 with no penalty results in a fully grown tree, we also seeing diminishing returns in error reduction as the tree grows.

```
pred <- predict(Gem_Score_Tree_1,  testdata = flix_test)
actual <-flix_test$Hidden.Gem.Score
rmse(actual,pred)
```

```
## Warning in actual - predicted: longer object length is not a multiple of shorter
## object length
```

```
## [1] 1.462105
```

Rotten Tomatoes Score is the most important feature for predicting the Hidden Gem Score. There has the largest reduction in SSE with Rotten Tomatoes Score scores under 32.5. They have almost half the average Hidden Gem scores.We can see that after 6 terminal nodes both in the plot 1 and the plot 2 of cross-validation error results, there are diminishing returns in error reduction. We achieve minimal expected error by performing this prediction. On average, our predicted HiddenGem Scores is about 1.462105 off from the actual Hidden Gem Scores. Our prediction works well.

```r
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.3     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.4     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.0
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## 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 errors
```

```r
library(here)
```

```
## here() starts at /Users/zhizhiwei/Desktop/Math 208/My_Homework_208
```

```r
FlixGem <- read_csv(here("/Users/zhizhiwei/Downloads/Final_Project_FlixGem.csv"))
```

```
## Rows: 9425 Columns: 29
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (19): Title, Genre, Tags, Languages, Series or Movie, Country Availabil...
## dbl   (8): Hidden Gem Score, IMDb Score, Rotten Tomatoes Score, Metacritic S...
## dttm  (2): Release Date, Netflix Release Date
##
## 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.
```

Task 3:

Clean data again (only drop NAs for directors, Hidden gem score and title):

```r
FlixGem_cleaned_task3 <- FlixGem %>%
    filter(`Series or Movie` == "Movie") %>%
    drop_na(Director, `Hidden Gem Score`, Title)
```

Select Directors, Movie title and HG-score out:

```
FlixGem_cleaned_HG <- FlixGem_cleaned_task3 %>%
    group_by(Director, Title) %>%
    select(Director, Title, `Hidden Gem Score`) %>%
    arrange(Director)
```

Split a list for each director:

```
FlixGem_cleaned_HG_split <- with(FlixGem_cleaned_HG, split(FlixGem_cleaned_HG,Director))
```

```
length(FlixGem_cleaned_HG_split)
```

```
## [1] 4097
```

Function that takes in a director's list and return his/her HG-H index:

```
calculate_HG_H_for_sapply <- function(each_director_list){
    H <- 0
    for(i in seq_along(each_director_list$`Hidden Gem Score`)){
      if(each_director_list$`Hidden Gem Score`[i]>=i){
        H<-H+1
      }
    }
    return(H)
}
```

Apply the function to the splitted list and returns the vector containing HG-H scores for all directors:

```
HG_H_index_vec <-sapply(FlixGem_cleaned_HG_split, calculate_HG_H_for_sapply)
```

Convert the vector to a tibble:

```
all_HG_H_index <-as.tibble(HG_H_index_vec)
```

```
## Warning: `as.tibble()` was deprecated in tibble 2.0.0.
## i Please use `as_tibble()` instead.
## i The signature and semantics have changed, see `?as_tibble`.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

Combine the Director names and their HG-H scores into one tibble:

```
Director_name_tibble <- FlixGem_cleaned_HG[,1] %>% unique(.)

combined_name_H_index <- bind_cols(Director_name_tibble, all_HG_H_index)
```

Find the top 10 directors according to their HG-H index:

```
top_10 <- combined_name_H_index %>% arrange(desc(value)) %>% head(10)
colnames(top_10) <- c("Director","HG-H-index")
top_10
```

```
## # A tibble: 10 x 2
## # Groups:   Director [10]
##    Director                                  `HG-H-index`
##    <chr>                                            <dbl>
##  1 Chan-wook Park                                       8
##  2 Rebecca Johnson                                      8
##  3 Sara Dosa, Barbara Kopple                            8
##  4 Uli Edel                                             8
##  5 Darren Lynn Bousman                                  7
##  6 Jayaprakash Radhakrishnan                            7
##  7 Je-gu Yun                                            7
##  8 Jirí Havelka                                         7
##  9 Jon Garaño, Aitor Arregi, Jose Mari Goenaga          7
## 10 Lars Kraume                                          7
```