632 Project

```
library(tidyverse)
library(dplyr)
library(stringr)
library(randomForest)
library(vip)
library(rpart)
library(rpart.plot)
library(caret)
library(tidytext)
library(tidyr)
library(MASS)
library(car)
```

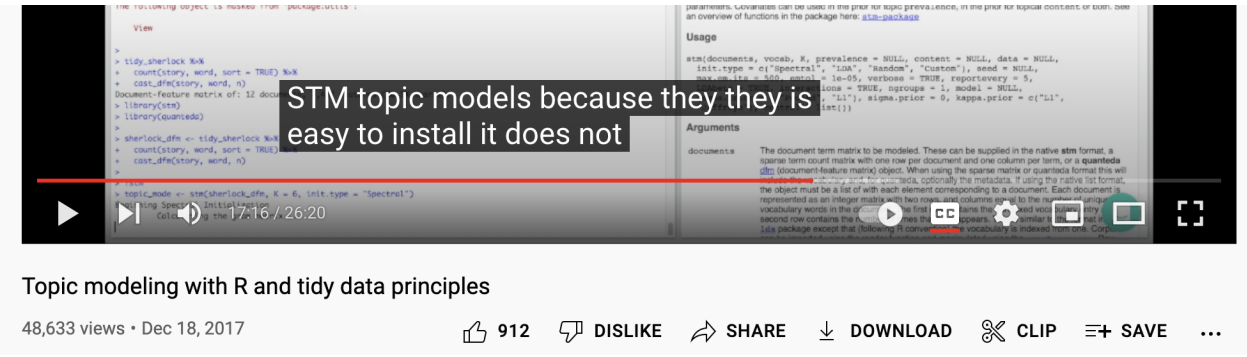
Research Data

The dataset contains **2515 unique videos** and their **subtitles** from over **91 different YouTubers**, ranging from all different kinds of categories.

```
df_raw <- read.csv("data.csv")
head(df_raw)
```

```
##            Id              Channel       Subscribers
## 1 FozCkl1xj-w            JRE Clips 6.28M subscribers
## 2 RN8yoi-e2yc     Mythical Kitchen  1.9M subscribers
## 3 IugcIAAZJ2M             Munchies 4.59M subscribers
## 4 JiEO6F8i0eU Parks and Recreation  282K subscribers
## 5 1T4XMNN4bNM               Vsauce 17.4M subscribers
## 6 0ZWGeidvrJw           Doctor Who 1.59M subscribers
##                                                                    Title CC
## 1                        Former CIA Agent Breaks Down Jeffrey Epstein Case  0
## 2 $420 Pizza Hut Stuffed Crust Pizza | Fancy Fast Food | Mythical Kitchen  1
## 3                    The Iconic $1 Pizza Slice of NYC | Street Food Icons  0
## 4                  Ron Swanson: The Papa of Pawnee | Parks and Recreation  0
## 5                               What's The Most Dangerous Place on Earth?  1
## 6     The Doctor Defeats the Abzorbaloff | Love and Monsters | Doctor Who  1
##                                        URL    Released      Views
## 1 https://www.youtube.com/watch?v=FozCkl1xj-w 2 years ago 7.9M views
## 2 https://www.youtube.com/watch?v=RN8yoi-e2yc             2.7M views
## 3 https://www.youtube.com/watch?v=IugcIAAZJ2M 2 years ago  11M views
## 4 https://www.youtube.com/watch?v=JiEO6F8i0eU 3 years ago 2.3M views
## 5 https://www.youtube.com/watch?v=1T4XMNN4bNM 9 years ago  21M views
## 6 https://www.youtube.com/watch?v=0ZWGeidvrJw 7 years ago 8.5M views
##               Category
## 1                 Blog
```

```
## 2                  Food
## 3                  Food
## 4 Entertainment,Comedy
## 5               Science
## 6         Entertainment
##
## 1
## 2 - Oh, that's dirty.\n- Wow! - Whoa.\n- You're a dirty girl. (upbeat music) - Hey man. - What'd you
## 3
## 4
## 5
## 6
##   Length
## 1  13:32
## 2  24:26
## 3   7:51
## 4  10:06
## 5   9:29
## 6   4:20
```



Research Goal

Do a sentiment analysis on the subtitles and find the best multiple linear regression model to predict the number of views using Subscribers, CC, Released, Category, Sentiment and Length.

Tasks

1. Data Cleaning.
2. Conduct a sentiment analysis on the subtitles.
3. Try various statistical models like linear regression, decision tree and random forest.
4. Compare these models in terms of prediction performation and interpretability.

Data Cleaning

```
df_raw %>% dplyr::select(URL, Channel, Views, Subscribers, Released, Length) %>% head(10)
```

```
##                                          URL              Channel      Views
## 1  https://www.youtube.com/watch?v=FozCkl1xj-w            JRE Clips 7.9M views
## 2  https://www.youtube.com/watch?v=RN8yoi-e2yc     Mythical Kitchen 2.7M views
## 3  https://www.youtube.com/watch?v=IugcIAAZJ2M             Munchies  11M views
## 4  https://www.youtube.com/watch?v=JiEO6F8i0eU Parks and Recreation 2.3M views
## 5  https://www.youtube.com/watch?v=1T4XMNN4bNM               Vsauce  21M views
## 6  https://www.youtube.com/watch?v=0ZWGeidvrJw           Doctor Who 8.5M views
## 7  https://www.youtube.com/watch?v=YiEj9mrqTN0                 A&E  14M views
## 8  https://www.youtube.com/watch?v=PZFLM2DVQHs          EpicNameBro 502K views
## 9  https://www.youtube.com/watch?v=CoDpjqZpAh0         Insider News 583K views
## 10 https://www.youtube.com/watch?v=VT128ElBWkM       Incognito Mode 2.2M views
##          Subscribers     Released Length
## 1  6.28M subscribers  2 years ago  13:32
## 2   1.9M subscribers               24:26
## 3  4.59M subscribers  2 years ago   7:51
## 4   282K subscribers  3 years ago  10:06
## 5  17.4M subscribers  9 years ago   9:29
## 6  1.59M subscribers  7 years ago   4:20
## 7  7.93M subscribers  2 years ago  20:54
## 8   389K subscribers  6 years ago  33:13
## 9   216K subscribers 6 months ago   7:17
## 10 1.62M subscribers  4 years ago   4:20
```

Looking at the data, we notice several problems in the data, like:

1. Views: The Views variable is in string format and the units are different, like “10K views”, “10M views”. We prefer it to be in number and in the same unit in order to conduct statistical analysis.
2. Subscribers: The same problems as Views. The Subscribers variable is like “10K subscribers”, “10M subscribers”.
3. Length: The video length is in string format, like “12:00”, “1:12:00”. We need it to be in number and in the same unit.
4. Released: The Released variable is in string format, like “2 years age”, “10 month ago”. We need it to be in number and in the same unit.

Therefore, we need to do data cleaning first.

```
# Unify units and convert string to number, like: 10K views -> 10, 10M views -> 10000
cleanViews <- function(str) {
  str <- str_remove(str, " views")
  last <- str_sub(str, -1)
  views <- str %>% str_remove(last) %>% as.numeric()
  if (last == "M") return(1000*views)
  else return(views)
}

# Unify units and convert string to number, like: 10K subscribers -> 10, 10M subscribers -> 10000
cleanSubscribers <- function(str) {
  str <- str_remove(str, " subscribers")
```

```
  last <- str_sub(str, -1)
  views <- str %>% str_remove(last) %>% as.numeric()
  if (last == "M") return(1000*views)
  else return(views)
}

# Convert time in string format to number of minutes, like: 12:00 -> 12, 1:12:00 -> 72
cleanLength <- function(str) {
  list <- str_split(str, ":")
  len <- length(list[[1]])
  if (len == 3) {
     h <- as.numeric(list[[1]][1])
     m <- as.numeric(list[[1]][2])
     return((m + 1) + 60*h)
  } else {
     m <- as.numeric(list[[1]][1])
     return(m+1)
  }
}

# Convert time to number of months ago, like: 1 years ago -> 12, 10 months ago to 10
cleanReleased <- function(str) {
  str <- str_remove(str, "Streamed ")
  list <- str_split(str, " ")
  if (list[[1]][2] == "years") return(as.numeric(list[[1]][1])*12)
  else return(as.numeric(list[[1]][1]))
}

# Remove NAs
df <- df_raw %>%
  na.omit() %>%
  filter(
    Released != "",
    Title != "",
    Transcript != ""
  )

# Clean the data
df <- df %>% mutate(
  Views = map_dbl(Views, cleanViews),
  Subscribers = map_dbl(Subscribers, cleanSubscribers),
  Length = map_dbl(Length, cleanLength),
  Released = map_dbl(Released, cleanReleased)
)

df %>% dplyr::select(URL, Channel, Views, Subscribers, Released, Length) %>% head(10)

# Save for future use
write_csv(df, "cleaned_data.csv")
```

After cleaning, Views, Subscribers, Released and Length are numbers, while Views, Subscribers are in K and Released and Length are in minute.

Data Discovery / Diagnostics for Linear Regression

```
df <- read_csv("cleaned_data.csv")
```

```
## Rows: 2098 Columns: 11

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (6): Id, Channel, Title, URL, Category, Transcript
## dbl (5): Subscribers, CC, Released, Views, Length

##
## 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.
```

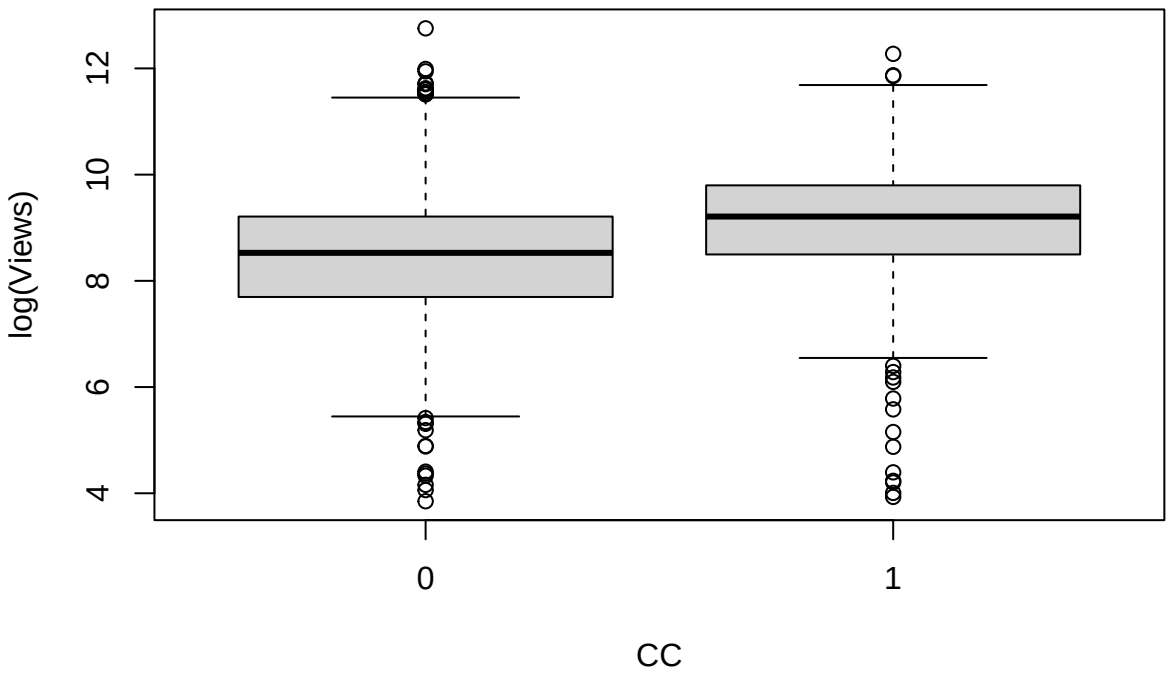
```
df$CC <- as.factor(df$CC)
df$Category <- as.factor(df$Category)
df$Subscribers <- as.numeric(df$Subscribers)

head(df)
```

```
## # A tibble: 6 x 11
##   Id    Channel Subscribers Title CC    URL   Released Views Category Transcript
##   <chr> <chr>         <dbl> <chr> <fct> <chr>    <dbl> <dbl> <fct>    <chr>
## 1 FozC~ JRE Cl~        6280 Form~ 0     http~       24  7900 Blog     "the Joe ~
## 2 Iugc~ Munchi~        4590 The ~ 0     http~       24 11000 Food     "if you w~
## 3 JiEO~ Parks ~         282 Ron ~ 0     http~       36  2300 Enterta~ "April wh~
## 4 1T4X~ Vsauce        17400 What~ 1     http~      108 21000 Science  "Hey, Vsa~
## 5 OZWG~ Doctor~        1590 The ~ 1     http~       84  8500 Enterta~ "Oh, what~
## 6 YiEj~ A&E            7930 Live~ 1     http~       24 14000 News     "[music p~
## # ... with 1 more variable: Length <dbl>
```

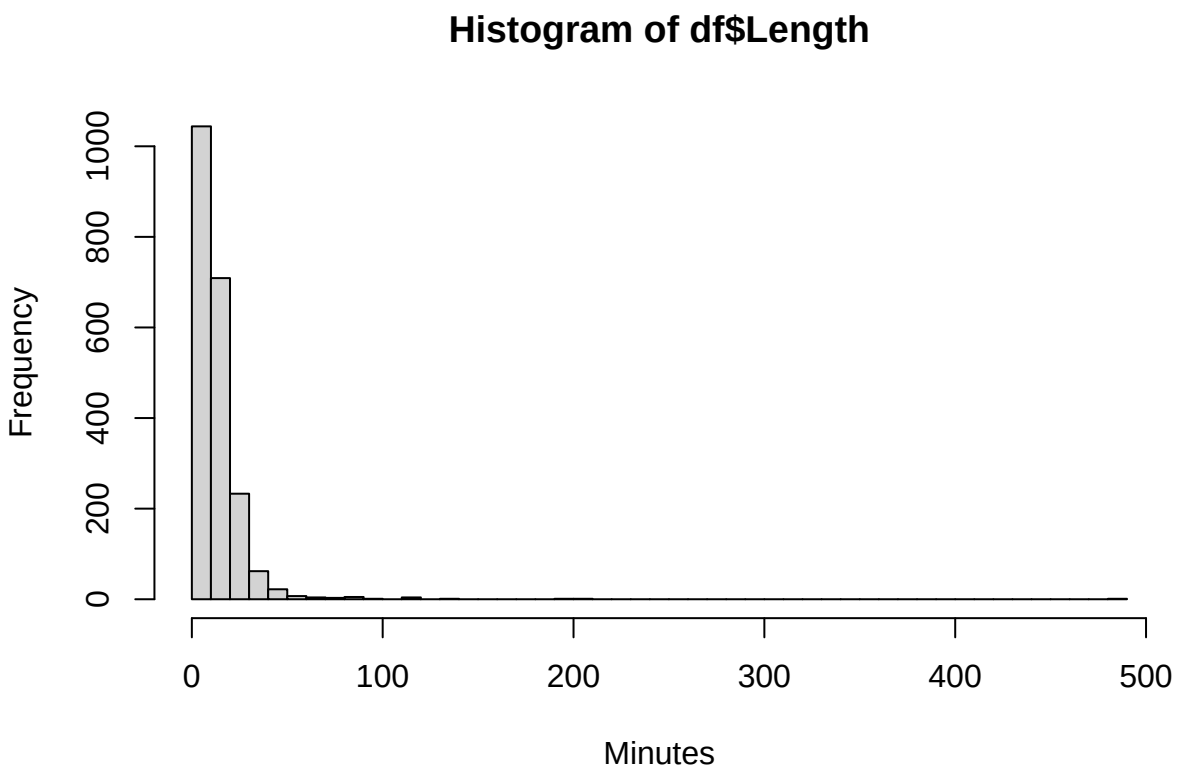
```
table(df$CC)
```

```
##
##    0    1
## 1094 1004
```

```
boxplot(log(Views) ~ CC, data = df)
```




```
hist(df$Length, xlab = "Minutes", breaks = 50)
```



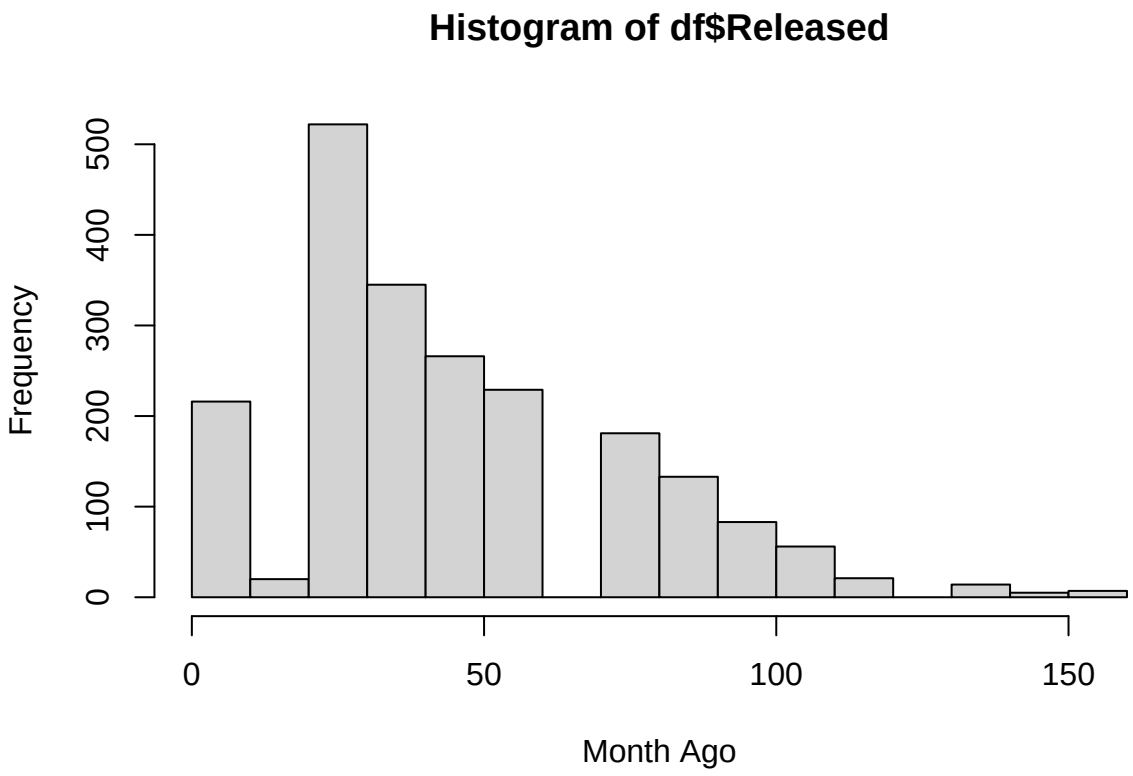

```
summary(df$Length)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    6.00   11.00   13.55   17.00  486.00
```

```
summary(df$Released)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    2.00   24.00   36.00   46.46   60.00  156.00
```

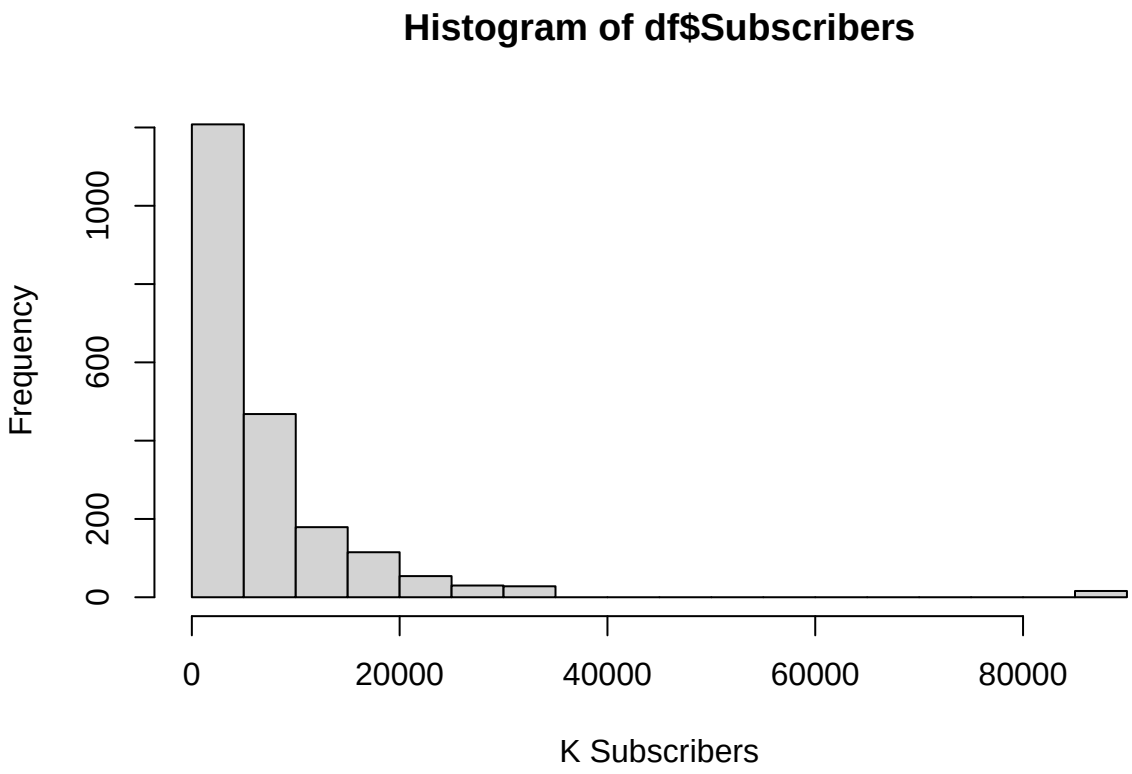
```
hist(df$Released, xlab = "Month Ago")
```



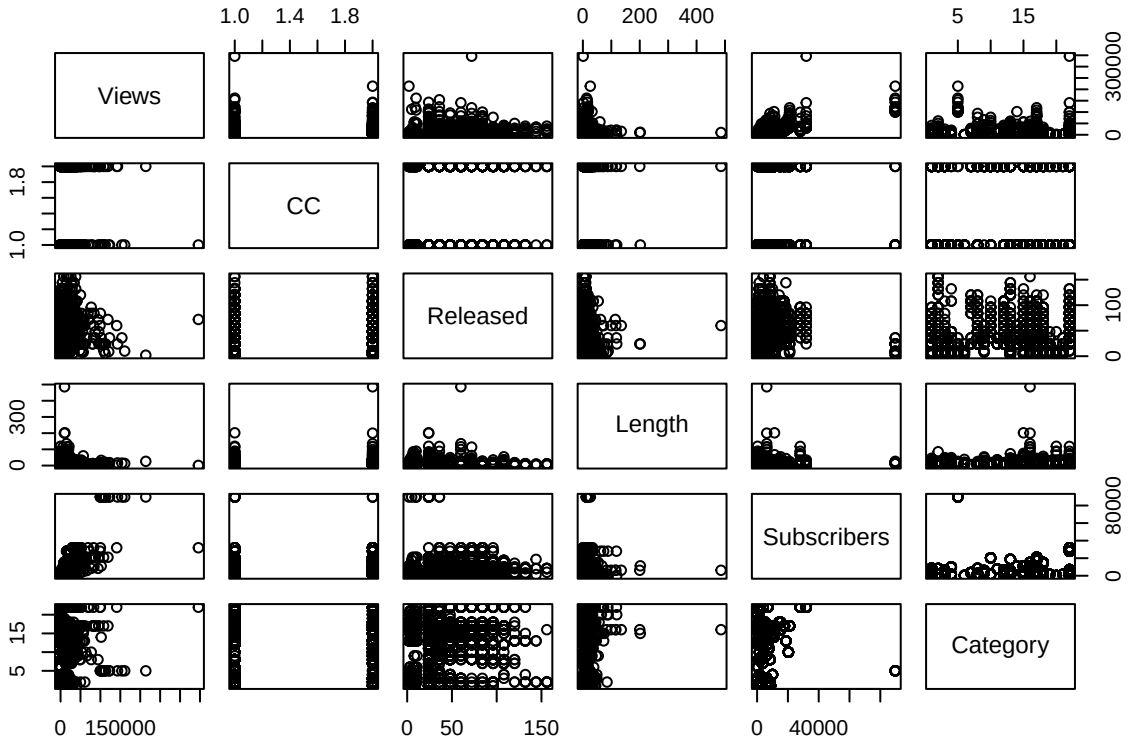

```
summary(df$Subscribers)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     179    1730    4010    6871    8240   89700
```

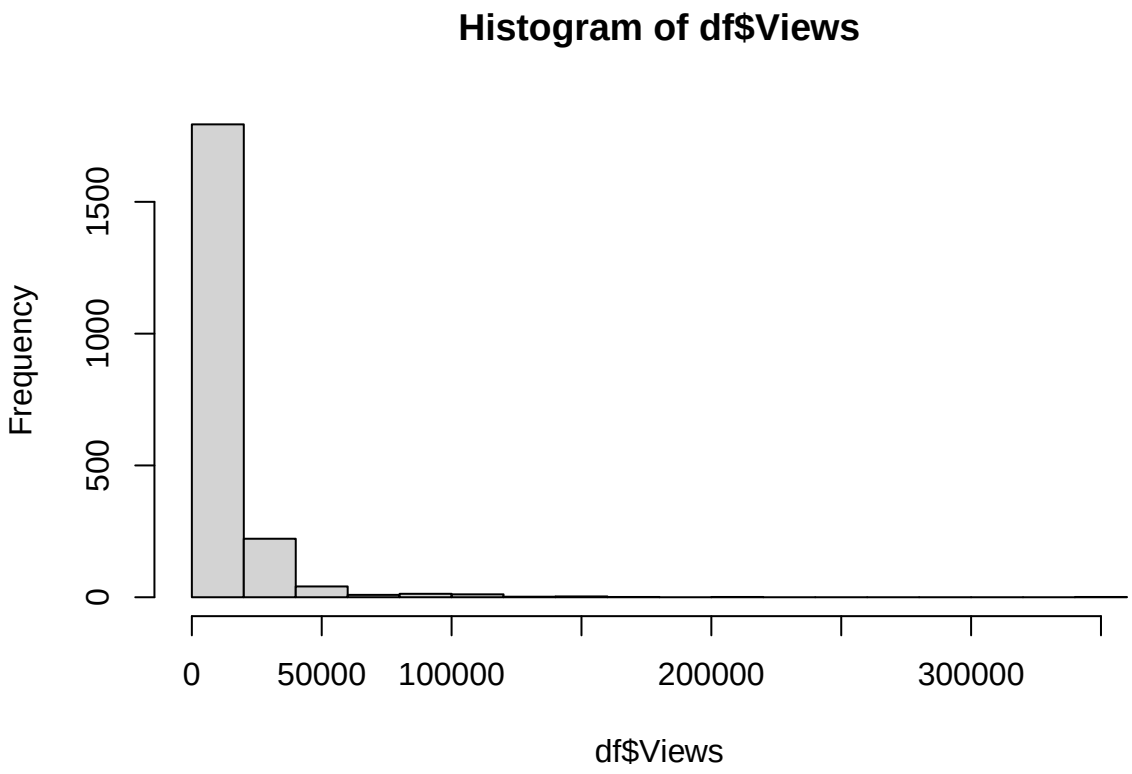
```
hist(df$Subscribers, xlab = "K Subscribers")
```




```
pairs(Views ~ CC + Released + Length + Subscribers + Category, data=df)
```




```
hist(df$Views)
```



From the diagnostics, Views, Subscribers, Released and Length need log transformation.

Sentiment Analysis / Text mining

TODO by Xinyi

```
df_script <- df %>%
  dplyr::select(Id, Title, Transcript)
head(df_script)
```

```
## # A tibble: 6 x 3
##   Id          Title                          Transcript
##   <chr>       <chr>                          <chr>
## 1 FozCkl1xj-w Former CIA Agent Breaks Down~ "the Joe Rogan experience well how ~
## 2 IugcIAAZJ2M The Iconic $1 Pizza Slice of~ "if you want good pizza come to st ~
## 3 JiEO6F8i0eU Ron Swanson: The Papa of Paw~ "April where have you been over two~
## 4 1T4XMNN4bNM What's The Most Dangerous Pl~ "Hey, Vsauce. Michael here. 93% of ~
## 5 0ZWGeidvrJw The Doctor Defeats the Abzor~ "Oh, what's the matter?\nHave you g~
## 6 YiEj9mrqTN0 Live PD: Most Viewed Moments~ "[music playing] We'll be on Lavern~
```

```
# just use this code to watch the video to check the transcript
df %>%
  filter(Title == "Former CIA Agent Breaks Down Jeffrey Epstein Case")
```

```
data("stop_words")
custom_stop_words <- rbind(stop_words, c("_", "custom"))
```

```
#bigram
 bigrams_separated <- df_script %>%
  group_by(Id) %>%
  # unnest Transcript in bigram format
  unnest_tokens(bigram, Transcript, token = "ngrams", n = 2) %>%
  separate(bigram, c("word1", "word2"), sep = " ") %>% # separate bigram
  filter(!word1 %in% custom_stop_words$word) %>% # filter out all the stop words
  filter(!word2 %in% custom_stop_words$word)

bigrams_united <- bigrams_separated %>%
  unite(bigram, word1, word2, sep = " ")  # unite words back together
```

```
head(bigrams_separated)
```

```
# Using bigrams to provide context in sentiment analysis
# not in presentation!!
negation_words <- c("not", "no", "never", "without")

bigrams_separated %>%
  filter(word1 %in% negation_words) %>%
  inner_join(get_sentiments("afinn"), by = c(word2 = "word")) %>%
  count(word1, word2, value, sort = TRUE)
```

```
df_word <- df %>%
  group_by(Id) %>%
  unnest_tokens(word, Transcript) %>%
  anti_join(custom_stop_words) %>%
  count(word, sort = TRUE) %>%
  mutate(total = sum(n)) %>%
  ungroup()
```

```
## Joining, by = "word"
```

```
  #inner_join(get_sentiments("afinn")) #%>%
  #summarise(sentiment = sum(value))
  #mutate(total = sum(word)) %>%
  #mutate(perc = round(n/total, 2))

head(df_word)
```

```
## # A tibble: 6 x 4
##   Id          word          n total
##   <chr>       <chr>     <int> <int>
## 1 prd2RfhF1tM president   566 19722
## 2 prd2RfhF1tM trump       345 19722
## 3 FPs_lU01KoI president   275  9702
## 4 prd2RfhF1tM people      259 19722
## 5 fTgm36y884c cheese      197  2817
## 6 FPs_lU01KoI complaint   187  9702
```

```
df_title_word <- df %>%
  group_by(Id) %>%
  unnest_tokens(word, Title) %>%
  anti_join(custom_stop_words) %>%
  count(word, sort = TRUE) %>%
  mutate(total = sum(n)) %>%
  ungroup()
```

```
## Joining, by = "word"
```

```
  #inner_join(get_sentiments("afinn")) #%>%
  #summarise(sentiment = sum(value))
  #mutate(total = sum(word)) %>%
  #mutate(perc = round(n/total, 2))

head(df_title_word)
```

```
## # A tibble: 6 x 4
##   Id          word       n total
##   <chr>       <chr>  <int> <int>
## 1 DLjJwW1lFxI doctor     4     8
## 2 s5GfhGFVCFE 20         4     7
## 3 0e71KWwE5Fk doctor     3    10
## 4 GLSPub4ydiM core       3     7
## 5 uB_p1Pyv1ps paul       3    11
## 6 ZgyU0LyWZ9M con        3     9
```

Below codes:

use tf-idf to find the importance of a word in the transcript, then times it to a word's afinn score, and sum up all the words' socre to a video afinn_score.

Will use "afinn_score" to represent the sentiment score in the regression modeling!

Transcript sentiment

```
df_afinn <- df_word %>%
  left_join(get_sentiments("afinn")) %>%
  #mutate(afinn_score = sum(value)) %>%
  #mutate(perc = round(n/total, 2)) %>%
  group_by(Id) %>%
  bind_tf_idf(word, Id, n) %>%
  mutate(value = ifelse(is.na(value), 0, value)) %>%
  mutate(afinn_score = sum(value*tf_idf)) %>%
  ungroup()
```

```
## Joining, by = "word"
```

```
  #filter(Title == "2018 Jeep Trackhawk Review - The SUV That's Quicker Than a Supercar")

head(df_afinn)
```

```
## # A tibble: 6 x 9
##   Id          word          n total value     tf   idf  tf_idf afinn_score
##   <chr>       <chr>     <int> <int> <dbl>  <dbl> <dbl>   <dbl>       <dbl>
## 1 prd2RfhF1tM president   566 19722     0 0.0287 3.03  0.0871       0.146
## 2 prd2RfhF1tM trump       345 19722     0 0.0175 3.74  0.0654       0.146
## 3 FPs_lU01KoI president   275  9702     0 0.0283 3.03  0.0860       0.0362
## 4 prd2RfhF1tM people      259 19722     0 0.0131 0.386 0.00507      0.146
## 5 fTgm36y884c cheese      197  2817     0 0.0699 2.49  0.174        0.167
## 6 FPs_lU01KoI complaint   187  9702     0 0.0193 4.39  0.0846       0.0362
```

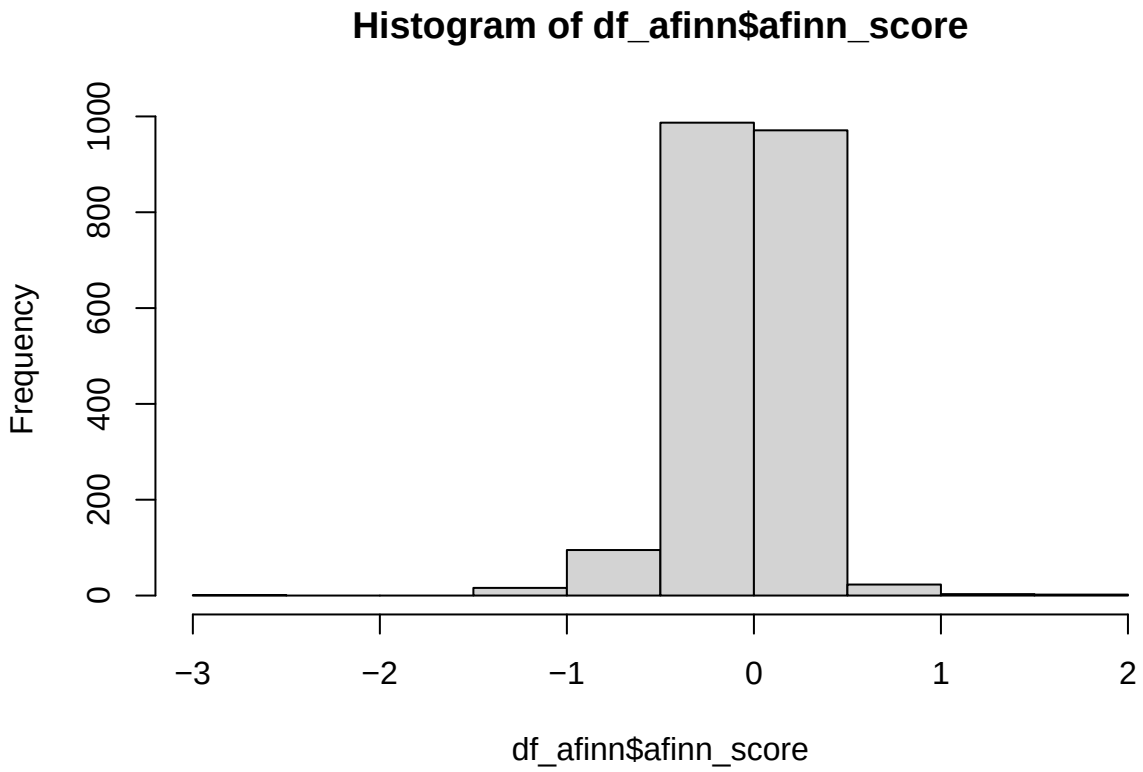
```
df_afinn <- df_afinn %>%
  dplyr::select(Id, afinn_score) %>%
  unique() %>%
  ungroup()

df_afinn
```

```
## # A tibble: 2,098 x 2
##    Id          afinn_score
##    <chr>             <dbl>
##  1 prd2RfhF1tM     0.146
##  2 FPs_lU01KoI     0.0362
##  3 fTgm36y884c     0.167
##  4 qWAagS_MANg     0.0225
##  5 YeFzkC2awTM    -0.00155
##  6 p3qvj9hO_Bo     0.0548
##  7 fbjYkPKRm-8     0.0285
##  8 ZRuSS0iiFyo    -0.285
##  9 hc3TEaT3WHA     0.0613
## 10 4VTOplLl2BM     0.155
## # ... with 2,088 more rows
```

```
summary(df_afinn$afinn_score)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -2.68050 -0.17631 -0.01230 -0.04816  0.10676  1.72980
```

```
hist(df_afinn$afinn_score)
```



Title sentiment

```
df_title_afinn <- df_title_word %>%
  left_join(get_sentiments("afinn")) %>%
  #mutate(afinn_score = sum(value)) %>%
  #mutate(perc = round(n/total, 2)) %>%
  group_by(Id) %>%
  bind_tf_idf(word, Id, n) %>%
  mutate(value = ifelse(is.na(value), 0, value)) %>%
  mutate(afinn_title_score = sum(value*tf_idf)) %>%
  ungroup()
```

```
## Joining, by = "word"
```

```
  #filter(Title == "2018 Jeep Trackhawk Review - The SUV That's Quicker Than a Supercar")

head(df_title_afinn)
```

```
## # A tibble: 6 x 9
```

```
##   Id          word       n total value    tf   idf tf_idf afinn_title_score
##   <chr>       <chr>  <int> <int> <dbl> <dbl> <dbl>  <dbl>              <dbl>
## 1 DLjJwW1lFxI doctor     4     8     0 0.5    4.39   2.19               0
## 2 s5GfhGFVCFE 20         4     7     0 0.571  5.70   3.26               0
## 3 0e71KWwE5Fk doctor     3    10     0 0.3    4.39   1.32               0
## 4 GLSPub4ydiM core       3     7     0 0.429  6.55   2.81               0
## 5 uB_p1Pyv1ps paul       3    11     0 0.273  5.01   1.37              -1.39
## 6 ZgyU0LyWZ9M con        3     9     0 0.333  6.95   2.32               0
```

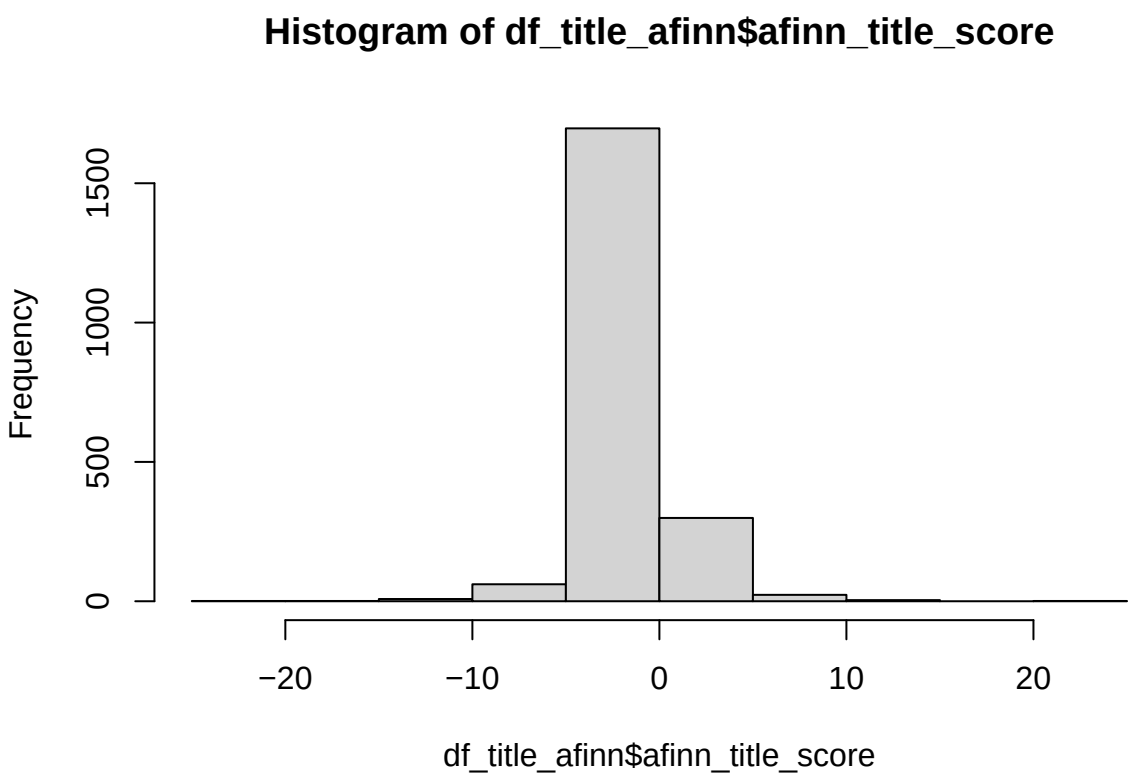
```
df_title_afinn <- df_title_afinn %>% dplyr::select(Id, afinn_title_score) %>%
  unique() %>%
  ungroup()

head(df_title_afinn)
```

```
## # A tibble: 6 x 2
##   Id          afinn_title_score
##   <chr>                   <dbl>
## 1 DLjJwW1lFxI              0
## 2 s5GfhGFVCFE              0
## 3 0e71KWwE5Fk              0
## 4 GLSPub4ydiM              0
## 5 uB_p1Pyv1ps             -1.39
## 6 ZgyU0LyWZ9M              0
```

```
summary(df_title_afinn$afinn_title_score)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -20.8625   0.0000   0.0000  -0.2664   0.0000  22.9419
```

```
hist(df_title_afinn$afinn_title_score)
```




```
df1 <- df %>%
  left_join(df_afinn) %>%
  left_join(df_title_afinn) %>%
  mutate(
    afinn_title_score = ifelse(is.na(afinn_title_score), 0, afinn_title_score)
  ) %>%
  unique()
```

```
## Joining, by = "Id"
## Joining, by = "Id"
```

```
head(df1)
```

```
## # A tibble: 6 x 13
##   Id    Channel Subscribers Title CC    URL   Released Views Category Transcript
##   <chr> <chr>         <dbl> <chr> <fct> <chr>    <dbl> <dbl> <fct>    <chr>
## 1 FozC~ JRE Cl~        6280 Form~ 0     http~       24  7900 Blog     "the Joe ~
## 2 Iugc~ Munchi~        4590 The ~ 0     http~       24 11000 Food     "if you w~
## 3 JiEO~ Parks ~         282 Ron ~ 0     http~       36  2300 Enterta~ "April wh~
## 4 1T4X~ Vsauce        17400 What~ 1     http~      108 21000 Science  "Hey, Vsa~
## 5 0ZWG~ Doctor~        1590 The ~ 1     http~       84  8500 Enterta~ "Oh, what~
## 6 YiEj~ A&E            7930 Live~ 1     http~       24 14000 News     "[music p~
## # ... with 3 more variables: Length <dbl>, afinn_score <dbl>,
## #   afinn_title_score <dbl>
```

```r
# Save for future use
write_csv(df1, "cleaned_data_with_sentiment.csv")
```

Preparation for Cross-Validation

Randomly split the data set in a 70% training and 30% test set. Make sure to use set.seed() so that your results are reproducible

```r
df1 <- read_csv("cleaned_data_with_sentiment.csv")
```

```
## Rows: 2098 Columns: 13
```

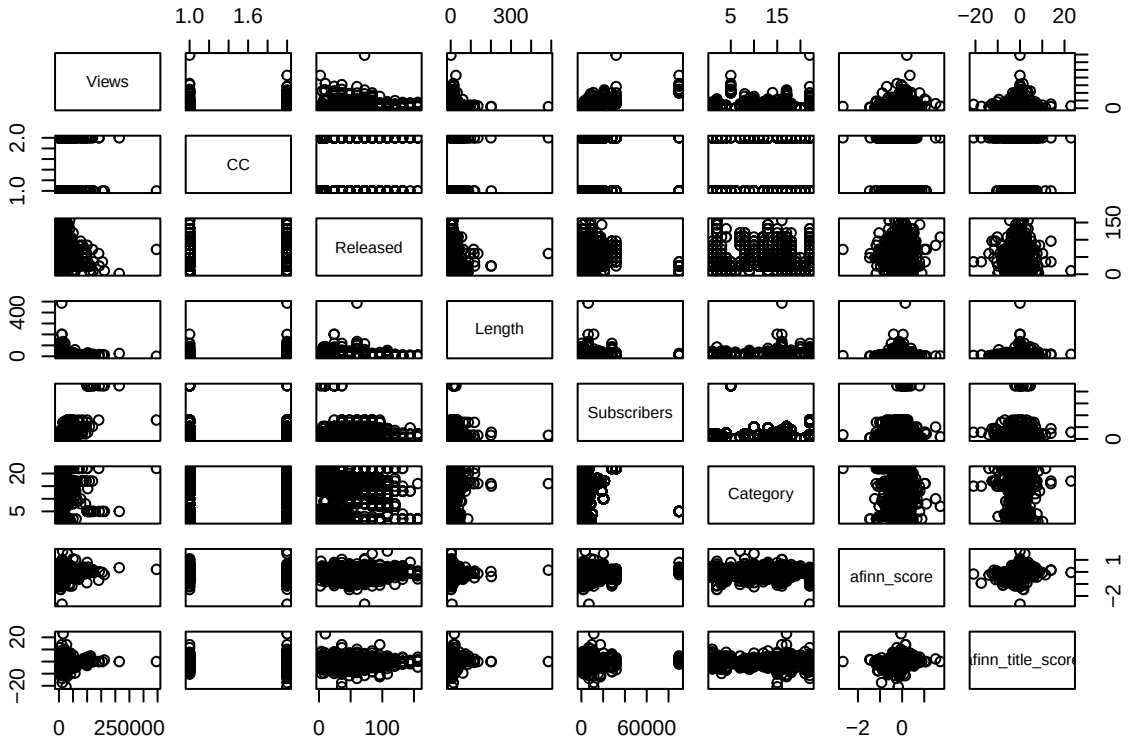
```
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (6): Id, Channel, Title, URL, Category, Transcript
## dbl (7): Subscribers, CC, Released, Views, Length, afinn_score, afinn_title_...
```

```
##
## 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.
```

```r
df1$CC <- as.factor(df1$CC)
df1$Category <- as.factor(df1$Category)
df1$Subscribers <- as.numeric(df1$Subscribers)

set.seed(652)
n <- nrow(df1)
train_index <- sample(1:n, round(0.7*n))
df_train <- df1[train_index,]
df_test <- df1[-train_index,]

# function to compute RMSE
RMSE <- function(y, y_hat) {
  sqrt(mean((y - y_hat)^2))
}
```

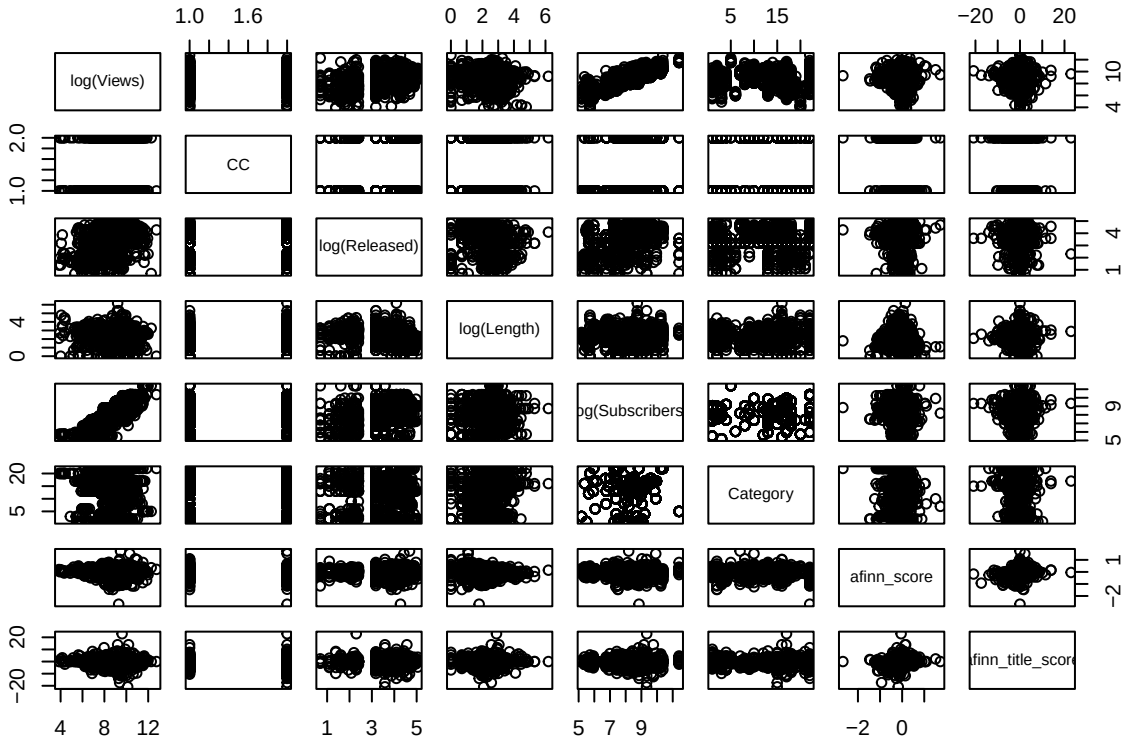
Linear Regression

```r
# original response and predictors
pairs(Views ~ CC + Released +
        Length + Subscribers + Category +
        afinn_score + afinn_title_score,
      data=df1)
```



From the plot above, we didn't see any obvious strong correlation between the predictors.

```
# log reponse and other predictors that are right skewed
pairs(log(Views) ~ CC + log(Released) +
        log(Length) + log(Subscribers) + Category +
        afinn_score + afinn_title_score,
      data=df1)
```



From the plot above, we didn't see any obvious strong correlation between the predictors.

```
round(cor(df1[, c(3,7,11,12,13)]), 2)
```

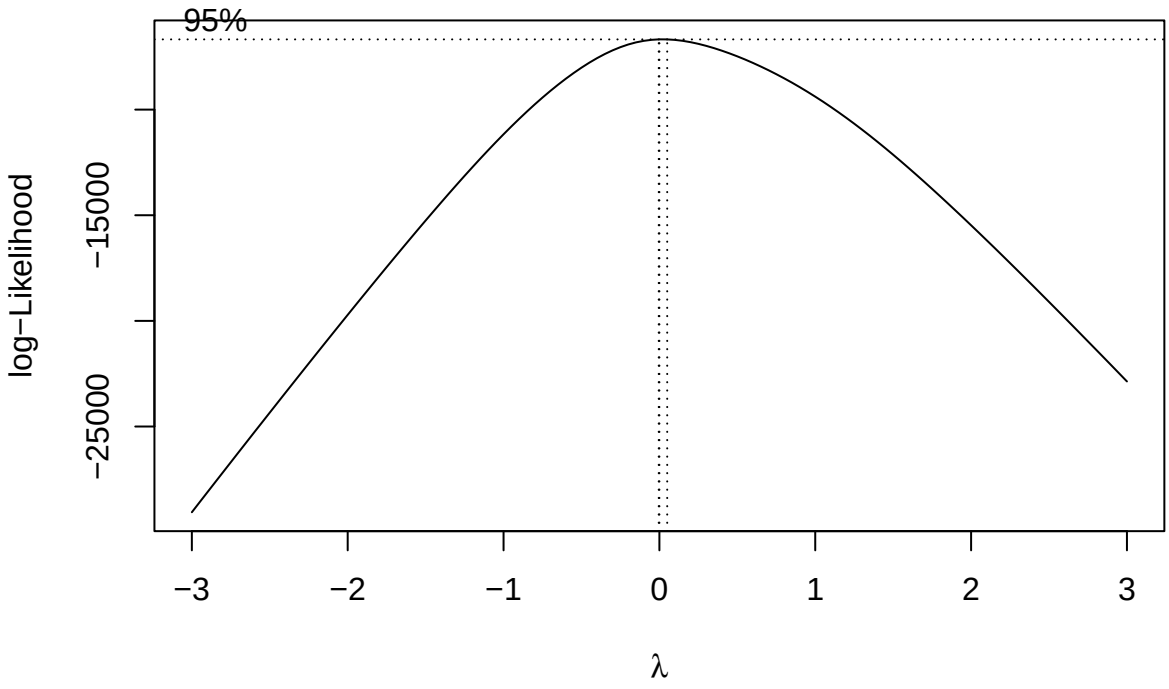
```
##                   Subscribers Released Length afinn_score afinn_title_score
## Subscribers              1.00     0.09   0.02       -0.02              0.01
## Released                 0.09     1.00  -0.18       -0.05              0.03
## Length                   0.02    -0.18   1.00        0.03              0.03
## afinn_score             -0.02    -0.05   0.03        1.00              0.22
## afinn_title_score        0.01     0.03   0.03        0.22              1.00
```

The correlation table also indicates this.

```
plot(log(Views)~ afinn_score, data = df1)
```

```
plot(log(Views)~ afinn_title_score, data = df1)
```

```
boxcox(Views ~ CC + log(Released) + log(Length) + log(Subscribers) + Category + afinn_score + afinn_tit
       data=df1,
       lambda = seq(-3, 3, by = 0.05))
```




```
summary(powerTransform(Views ~
                         CC + log(Released) + log(Length) +
                         log(Subscribers) + Category + afinn_score + afinn_title_score,
                       data=df1))
```

```
## bcPower Transformation to Normality
##    Est Power Rounded Pwr Wald Lwr Bnd Wald Upr Bnd
## Y1     0.021        0.02        7e-04       0.0412
##
## Likelihood ratio test that transformation parameter is equal to 0
##  (log transformation)
##                            LRT df     pval
## LR test, lambda = (0) 4.15773  1 0.041445
##
## Likelihood ratio test that no transformation is needed
##                             LRT df       pval
## LR test, lambda = (1) 5428.034  1 < 2.22e-16
```

```
lm_full <- lm(Views ~ CC + Released + Length + Subscribers + Category + afinn_score+ afinn_title_score,
summary(lm_full)
```

```
##
## Call:
## lm(formula = Views ~ CC + Released + Length + Subscribers + Category +
##     afinn_score + afinn_title_score, data = df1)
```

```
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -25663  -4088   -883   1907 299360
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   5.013e+02  1.034e+03   0.485 0.627801
## CC1                           5.904e+02  5.813e+02   1.016 0.309909
## Released                      1.656e+00  9.779e+00   0.169 0.865512
## Length                       -2.443e+01  1.587e+01  -1.539 0.123935
## Subscribers                   1.489e+00  4.445e-02  33.487  < 2e-16 ***
## CategoryAutomobile,Comedy     5.772e+03  1.647e+03   3.504 0.000468 ***
## CategoryBlog                 -8.700e+02  1.362e+03  -0.639 0.522927
## CategoryBlog,Comedy          -2.030e+03  1.975e+03  -1.028 0.304224
## CategoryBlog,Entertainment   -1.060e+04  4.895e+03  -2.165 0.030486 *
## CategoryBlog,Science         -3.780e+02  3.591e+03  -0.105 0.916190
## CategoryComedy                1.086e+04  2.341e+03   4.637 3.75e-06 ***
## CategoryComedy,Entertainment  9.045e+03  1.555e+03   5.815 7.02e-09 ***
## CategoryComedy,Informative    1.114e+04  1.946e+03   5.725 1.19e-08 ***
## CategoryEntertainment         3.926e+03  1.848e+03   2.124 0.033754 *
## CategoryEntertainment,Blog    2.765e+03  2.393e+03   1.156 0.247943
## CategoryEntertainment,Comedy  6.283e+03  1.564e+03   4.017 6.12e-05 ***
## CategoryFood                  2.560e+03  1.180e+03   2.170 0.030109 *
## CategoryFood,Entertainment    8.604e+03  2.548e+03   3.377 0.000745 ***
## CategoryInformative           2.401e+02  1.251e+03   0.192 0.847864
## CategoryNews                  1.351e+03  1.348e+03   1.002 0.316437
## CategoryScience               1.968e+03  1.181e+03   1.667 0.095759 .
## CategoryTech                 -3.942e+03  1.274e+03  -3.094 0.002001 **
## CategoryTech,Comedy          -6.025e+02  2.617e+03  -0.230 0.817916
## CategoryTech,Informative     -4.183e+02  2.813e+03  -0.149 0.881818
## CategoryTech,News            -1.998e+03  2.942e+03  -0.679 0.497212
## CategoryVideoGames           -1.694e+03  1.239e+03  -1.367 0.171766
## afinn_score                   1.187e+03  9.982e+02   1.189 0.234713
## afinn_title_score            -1.251e+02  1.167e+02  -1.073 0.283554
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11470 on 2070 degrees of freedom
## Multiple R-squared:  0.5998, Adjusted R-squared:  0.5946
## F-statistic: 114.9 on 27 and 2070 DF,  p-value: < 2.2e-16
```

```
# include all the predictors and with log transf's
lm1 <- lm(log(Views) ~ CC + log(Released) + log(Length) + log(Subscribers) + Category + afinn_score+ af
summary(lm1)
```

```
##
## Call:
## lm(formula = log(Views) ~ CC + log(Released) + log(Length) +
##     log(Subscribers) + Category + afinn_score + afinn_title_score,
##     data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -1.28291 -0.34836 -0.06359  0.29517  2.62433
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   1.994258   0.115062  17.332  < 2e-16 ***
## CC1                           0.061293   0.027270   2.248 0.024702 *
## log(Released)                 0.010325   0.016986   0.608 0.543333
## log(Length)                  -0.081625   0.016780  -4.864 1.23e-06 ***
## log(Subscribers)              0.828092   0.012171  68.038  < 2e-16 ***
## CategoryAutomobile,Comedy     0.404303   0.076396   5.292 1.34e-07 ***
## CategoryBlog                 -0.218388   0.063018  -3.465 0.000540 ***
## CategoryBlog,Comedy          -0.133908   0.091557  -1.463 0.143737
## CategoryBlog,Entertainment    0.458470   0.147371   3.111 0.001890 **
## CategoryBlog,Science         -0.626816   0.167315  -3.746 0.000184 ***
## CategoryComedy                0.950982   0.108783   8.742  < 2e-16 ***
## CategoryComedy,Entertainment  0.832074   0.072040  11.550  < 2e-16 ***
## CategoryComedy,Informative    0.785949   0.089692   8.763  < 2e-16 ***
## CategoryEntertainment         0.393832   0.085010   4.633 3.83e-06 ***
## CategoryEntertainment,Blog    0.321985   0.110675   2.909 0.003661 **
## CategoryEntertainment,Comedy  0.904802   0.072662  12.452  < 2e-16 ***
## CategoryFood                  0.295938   0.054581   5.422 6.58e-08 ***
## CategoryFood,Entertainment    0.511487   0.118622   4.312 1.69e-05 ***
## CategoryInformative           0.040345   0.057819   0.698 0.485392
## CategoryNews                  0.199804   0.062303   3.207 0.001362 **
## CategoryScience              -0.049413   0.054384  -0.909 0.363669
## CategoryTech                 -0.583077   0.058816  -9.914  < 2e-16 ***
## CategoryTech,Comedy          -0.381650   0.120859  -3.158 0.001612 **
## CategoryTech,Informative     -1.785302   0.132530 -13.471  < 2e-16 ***
## CategoryTech,News            -1.015799   0.136331  -7.451 1.35e-13 ***
## CategoryVideoGames           -0.202371   0.056352  -3.591 0.000337 ***
## afinn_score                  -0.057197   0.046152  -1.239 0.215366
## afinn_title_score            -0.006662   0.005383  -1.238 0.215996
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5293 on 2070 degrees of freedom
## Multiple R-squared:  0.8154, Adjusted R-squared:  0.813
## F-statistic: 338.7 on 27 and 2070 DF,  p-value: < 2.2e-16
```

check variance inflation factors by faraway::vif()

```
round(faraway::vif(lm_full), 2)
```

```
##                          CC1                     Released
##                         1.34                         1.30
##                       Length                   Subscribers
##                         1.08                         2.94
##    CategoryAutomobile,Comedy                  CategoryBlog
##                         1.43                         1.77
##          CategoryBlog,Comedy   CategoryBlog,Entertainment
##                         1.28                         2.89
##         CategoryBlog,Science                CategoryComedy
```

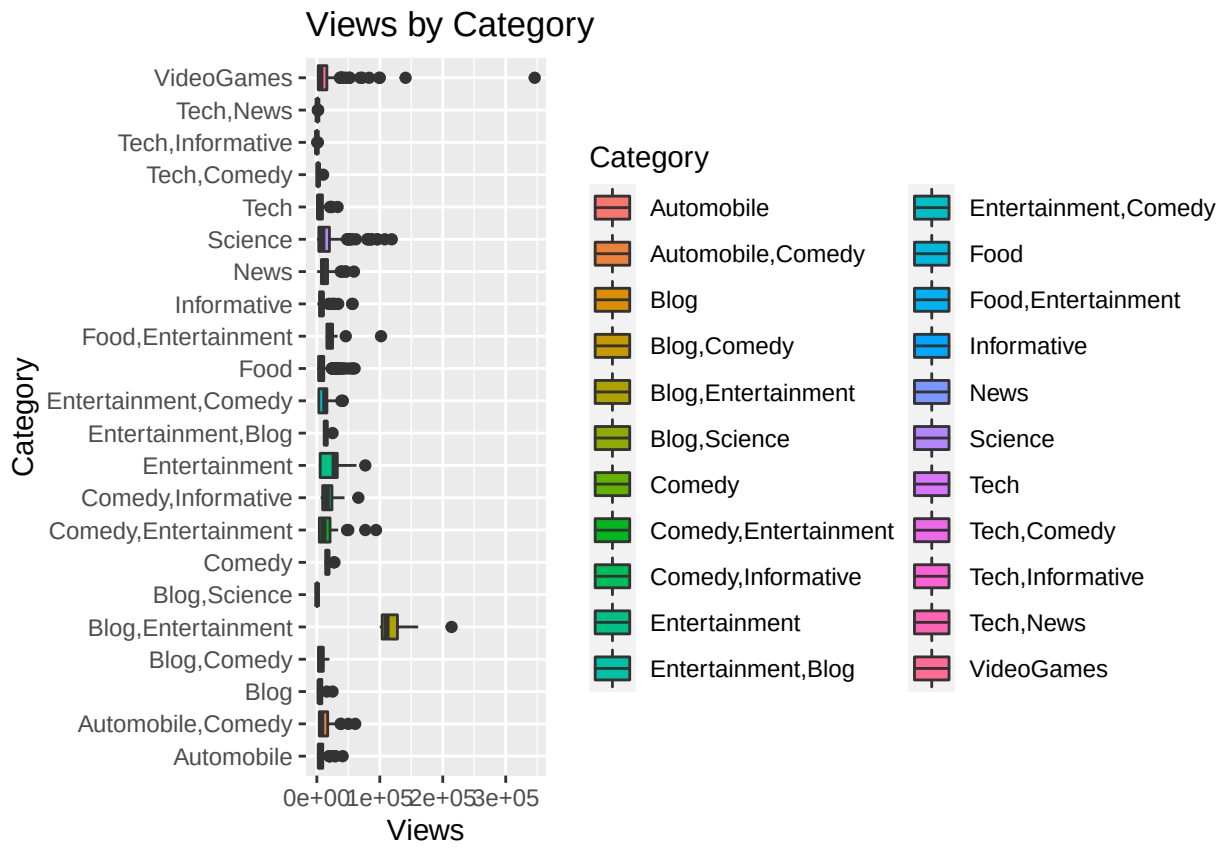
```
##                          1.07                          1.23
## CategoryComedy,Entertainment   CategoryComedy,Informative
##                          1.48                          1.38
##        CategoryEntertainment   CategoryEntertainment,Blog
##                          1.39                          1.20
## CategoryEntertainment,Comedy                CategoryFood
##                          1.50                          2.19
##   CategoryFood,Entertainment          CategoryInformative
##                          1.17                          2.08
##                 CategoryNews              CategoryScience
##                          1.83                          2.56
##                 CategoryTech          CategoryTech,Comedy
##                          1.88                          1.13
##     CategoryTech,Informative            CategoryTech,News
##                          1.13                          1.11
##           CategoryVideoGames                  afinn_score
##                          2.46                          1.23
##            afinn_title_score
##                          1.09
```

```
round(faraway::vif(lm1), 2)
```

```
##                           CC1                log(Released)
##                          1.39                          1.41
##                   log(Length)             log(Subscribers)
##                          1.25                          1.50
##    CategoryAutomobile,Comedy                 CategoryBlog
##                          1.45                          1.78
##          CategoryBlog,Comedy   CategoryBlog,Entertainment
##                          1.29                          1.23
##         CategoryBlog,Science               CategoryComedy
##                          1.09                          1.25
## CategoryComedy,Entertainment   CategoryComedy,Informative
##                          1.49                          1.37
##        CategoryEntertainment   CategoryEntertainment,Blog
##                          1.38                          1.21
## CategoryEntertainment,Comedy                CategoryFood
##                          1.52                          2.20
##   CategoryFood,Entertainment          CategoryInformative
##                          1.19                          2.08
##                 CategoryNews              CategoryScience
##                          1.83                          2.55
##                 CategoryTech          CategoryTech,Comedy
##                          1.88                          1.13
##     CategoryTech,Informative            CategoryTech,News
##                          1.18                          1.12
##           CategoryVideoGames                  afinn_score
##                          2.39                          1.24
##            afinn_title_score
##                          1.08
```

```
ggplot(df1, aes(x=Category, y=Views, fill=Category)) +
  geom_boxplot() +
```

```
  coord_flip() +
  ggtitle('Views by Category')
```




```
df1 %>%
  filter(Category == "VideoGames") %>%
  arrange(desc(Views)) %>%
  head(10)
```

```
## # A tibble: 10 x 13
##    Id          Channel  Subscribers Title  CC    URL    Released  Views Category
##    <chr>       <chr>          <dbl> <chr>  <fct> <chr>     <dbl>  <dbl> <fct>
##  1 ndsaoMFz9J4 Markipl~       31900 "MEOW" 0     https~       72 346000 VideoGa~
##  2 MujRLvZ61jE Markipl~       31900 "WOOF" 1     https~       60 141000 VideoGa~
##  3 iOztnsBPrAA Markipl~       31900 "WARN~ 1     https~       84 100000 VideoGa~
##  4 BJPc49z57bU jacksep~       28000 "ALL ~ 1     https~       60  99000 VideoGa~
##  5 I4Q3YDezqcM Markipl~       31900 "MOO"  1     https~       36  83000 VideoGa~
##  6 bqNzbkIHYF8 jacksep~       28000 "Five~ 1     https~       72  72000 VideoGa~
##  7 Zz8MCVJb0_k Markipl~       31900 "Five~ 0     https~       84  69000 VideoGa~
##  8 60wLvPWXCCc Markipl~       31900 "SCAR~ 1     https~       84  52000 VideoGa~
##  9 N9K2p54k9GA Markipl~       31900 "I'M ~ 0     https~       72  52000 VideoGa~
## 10 GlZtlTon7_I Markipl~       31900 "Five~ 1     https~       60  47000 VideoGa~
## # ... with 4 more variables: Transcript <chr>, Length <dbl>, afinn_score <dbl>,
## #   afinn_title_score <dbl>
```

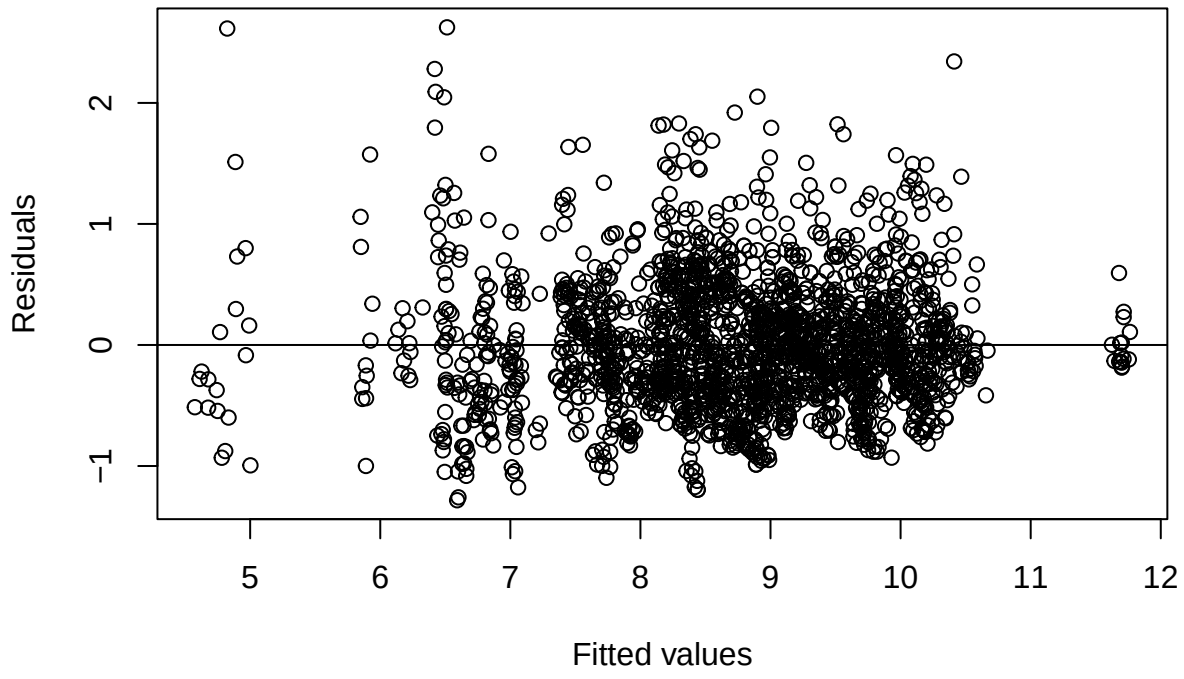
```
df1 %>%
  arrange(desc(Views)) %>%
  dplyr::select(Channel, Subscribers, Title, Views, Category)
```

```
## # A tibble: 2,098 x 5
##    Channel    Subscribers Title                                Views Category
##    <chr>            <dbl> <chr>                                <dbl> <fct>
##  1 Markiplier       31900 MEOW                                346000 VideoGames
##  2 MrBeast          89700 $456,000 Squid Game In Real Life!   214000 Blog,Enterta~
##  3 MrBeast          89700 I Spent 50 Hours Buried Alive       161000 Blog,Enterta~
##  4 MrBeast          89700 I Put 100 Million Orbeez In My F~   154000 Blog,Enterta~
##  5 MrBeast          89700 Going Through The Same Drive Thr~   143000 Blog,Enterta~
##  6 Markiplier       31900 WOOF                                141000 VideoGames
##  7 MrBeast          89700 I Went Back To 1st Grade For A D~   123000 Blog,Enterta~
##  8 MrBeast          89700 Would You Sit In Snakes For $10,~   121000 Blog,Enterta~
##  9 Mark Rober       21100 SKIN A WATERMELON party trick       119000 Science
## 10 MrBeast          89700 Surviving 24 Hours Straight In T~   113000 Blog,Enterta~
## # ... with 2,088 more rows
```

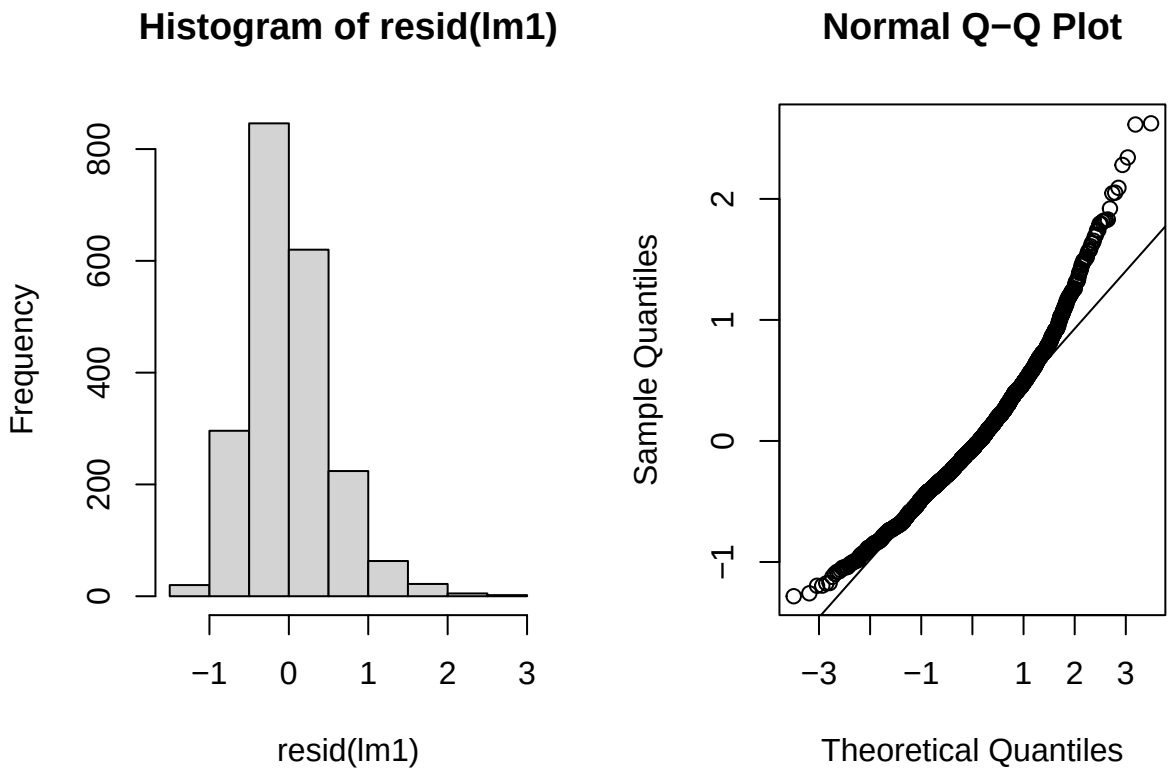
```
  head(10)
```

```
## [1] 10
```

```
plot(predict(lm1), resid(lm1), xlab = "Fitted values", ylab = "Residuals")
abline(h=0)
```



```
par(mfrow=c(1,2))
hist(resid(lm1))
qqnorm(resid(lm1))
qqline(resid(lm1))
```

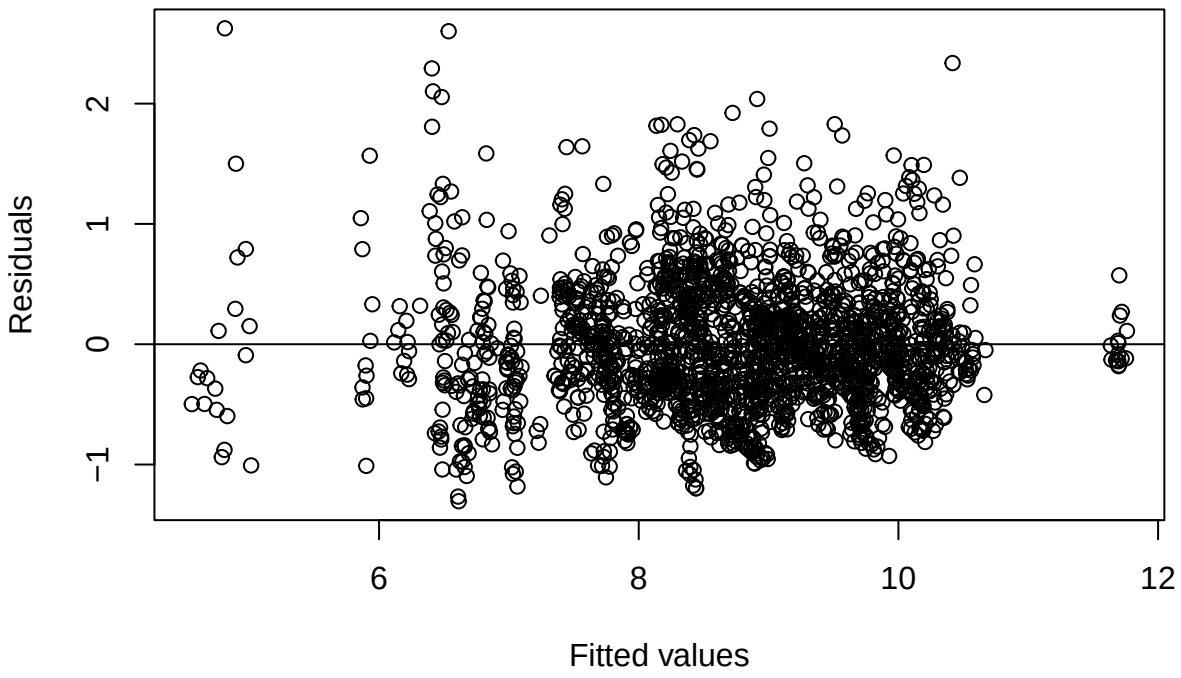



```
# remove log(Length) / Length
lm2 <- lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score + afinn_title_score
summary(lm2)
```

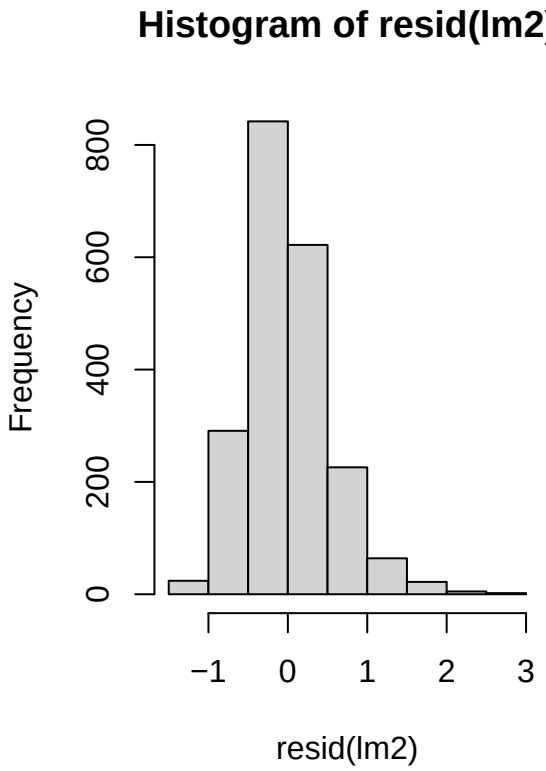
```
##
## Call:
## lm(formula = log(Views) ~ CC + log(Length) + log(Subscribers) +
##     Category + afinn_score + afinn_title_score, data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.30509 -0.34612 -0.06073  0.29173  2.62569
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    2.019276   0.107433  18.796  < 2e-16 ***
## CC1                            0.062746   0.027160   2.310 0.020974 *
## log(Length)                   -0.083559   0.016473  -5.072 4.28e-07 ***
## log(Subscribers)               0.830128   0.011700  70.953  < 2e-16 ***
## CategoryAutomobile,Comedy      0.402173   0.076304   5.271 1.50e-07 ***
```

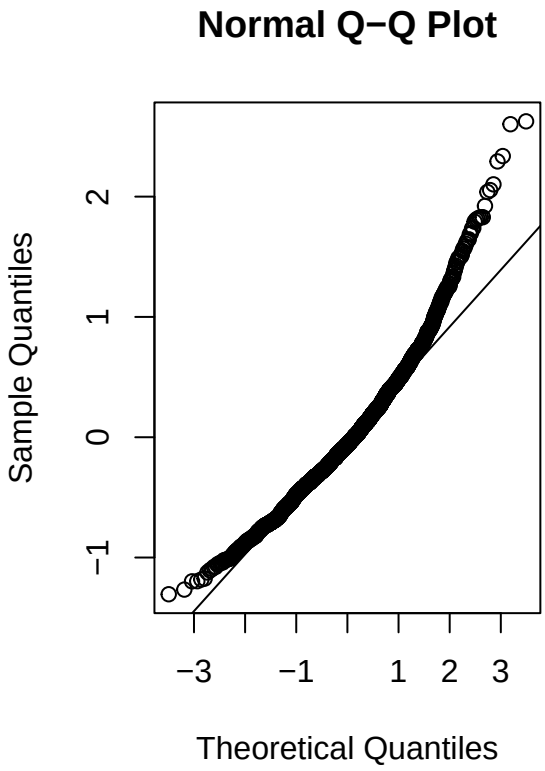
```
## CategoryBlog                 -0.221634   0.062782  -3.530 0.000424 ***
## CategoryBlog,Comedy          -0.138616   0.091215  -1.520 0.128748
## CategoryBlog,Entertainment    0.444115   0.145445   3.053 0.002291 **
## CategoryBlog,Science         -0.638321   0.166216  -3.840 0.000127 ***
## CategoryComedy                0.953490   0.108689   8.773  < 2e-16 ***
## CategoryComedy,Entertainment  0.834924   0.071877  11.616  < 2e-16 ***
## CategoryComedy,Informative    0.784121   0.089628   8.749  < 2e-16 ***
## CategoryEntertainment         0.396675   0.084868   4.674 3.14e-06 ***
## CategoryEntertainment,Blog    0.318365   0.110498   2.881 0.004003 **
## CategoryEntertainment,Comedy  0.908790   0.072354  12.560  < 2e-16 ***
## CategoryFood                  0.293166   0.054382   5.391 7.81e-08 ***
## CategoryFood,Entertainment    0.510386   0.118590   4.304 1.76e-05 ***
## CategoryInformative           0.040077   0.057809   0.693 0.488215
## CategoryNews                  0.197180   0.062144   3.173 0.001531 **
## CategoryScience              -0.050974   0.054315  -0.938 0.348107
## CategoryTech                 -0.584057   0.058785  -9.935  < 2e-16 ***
## CategoryTech,Comedy          -0.387360   0.120475  -3.215 0.001323 **
## CategoryTech,Informative     -1.796723   0.131172 -13.697  < 2e-16 ***
## CategoryTech,News            -1.025647   0.135345  -7.578 5.26e-14 ***
## CategoryVideoGames           -0.198996   0.056069  -3.549 0.000395 ***
## afinn_score                  -0.056556   0.046132  -1.226 0.220360
## afinn_title_score            -0.006585   0.005381  -1.224 0.221167
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5293 on 2071 degrees of freedom
## Multiple R-squared:  0.8154, Adjusted R-squared:  0.8131
## F-statistic: 351.8 on 26 and 2071 DF,  p-value: < 2.2e-16
```

```
plot(predict(lm2), resid(lm2), xlab = "Fitted values", ylab = "Residuals")
abline(h=0)
```




```
par(mfrow=c(1,2))
hist(resid(lm2))
qqnorm(resid(lm2))
qqline(resid(lm2))
```



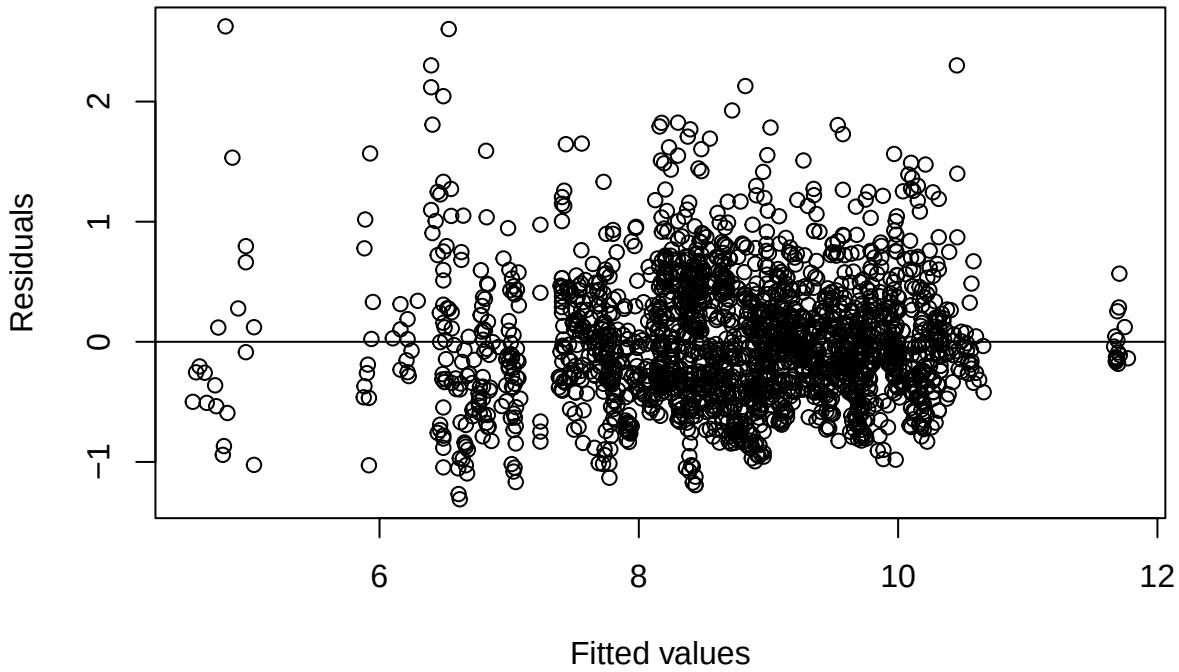



```
# remove log(Length) / Length, afinn_score and afinn_title_score
lm3 <- lm(log(Views) ~ CC  + log(Length) + log(Subscribers) + Category, data=df1)
summary(lm3)
```

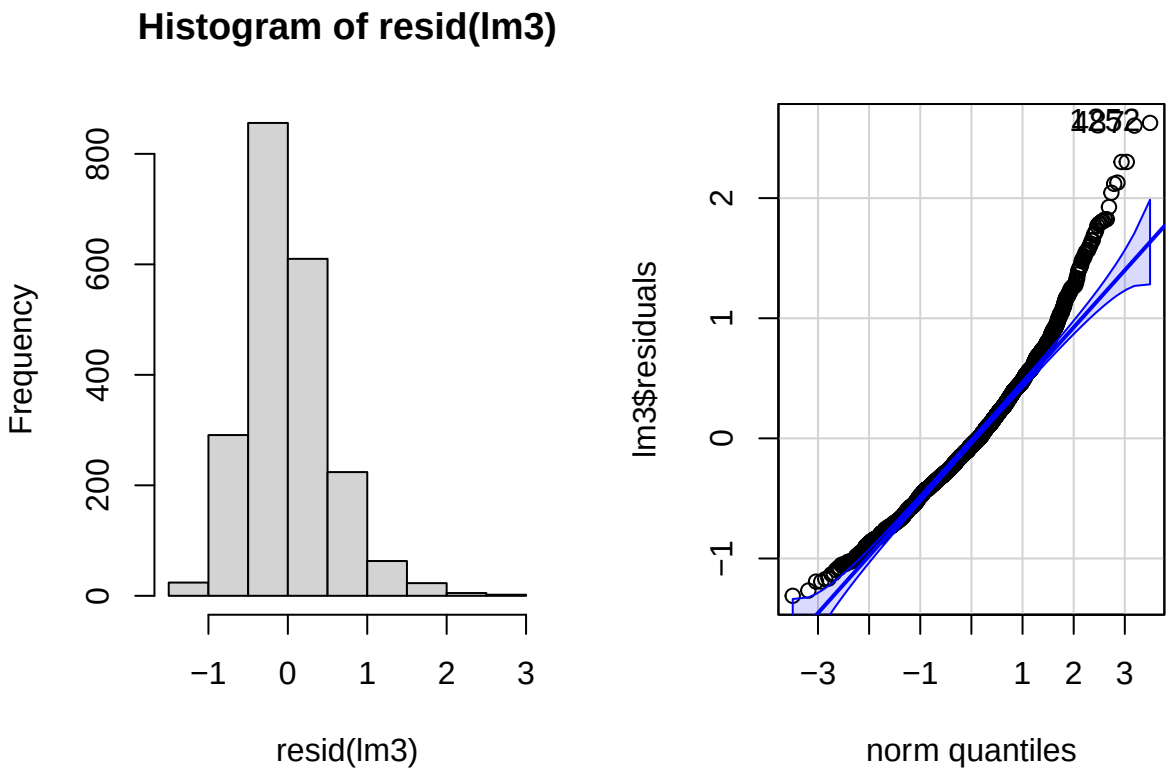
```
##
## Call:
## lm(formula = log(Views) ~ CC + log(Length) + log(Subscribers) +
##     Category, data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.31084 -0.34829 -0.06337  0.29337  2.62607
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    2.00861    0.10733  18.714  < 2e-16 ***
## CC1                            0.06272    0.02708   2.316 0.020641 *
## log(Length)                   -0.08558    0.01644  -5.207 2.11e-07 ***
## log(Subscribers)               0.83148    0.01168  71.174  < 2e-16 ***
## CategoryAutomobile,Comedy      0.40744    0.07596   5.364 9.04e-08 ***
## CategoryBlog                  -0.20643    0.06224  -3.317 0.000927 ***
## CategoryBlog,Comedy           -0.11874    0.09049  -1.312 0.189592
## CategoryBlog,Entertainment     0.43143    0.14535   2.968 0.003031 **
## CategoryBlog,Science          -0.63111    0.16624  -3.796 0.000151 ***
## CategoryComedy                 0.96028    0.10867   8.836  < 2e-16 ***
```

```
## CategoryComedy,Entertainment  0.84196    0.07180  11.726  < 2e-16 ***
## CategoryComedy,Informative    0.81443    0.08825   9.229  < 2e-16 ***
## CategoryEntertainment         0.40076    0.08487   4.722 2.49e-06 ***
## CategoryEntertainment,Blog    0.32391    0.11051   2.931 0.003414 **
## CategoryEntertainment,Comedy  0.91276    0.07222  12.639  < 2e-16 ***
## CategoryFood                  0.29325    0.05434   5.396 7.58e-08 ***
## CategoryFood,Entertainment    0.51929    0.11849   4.383 1.23e-05 ***
## CategoryInformative           0.05449    0.05729   0.951 0.341700
## CategoryNews                  0.21266    0.06159   3.453 0.000566 ***
## CategoryScience              -0.04546    0.05426  -0.838 0.402255
## CategoryTech                 -0.58282    0.05879  -9.913  < 2e-16 ***
## CategoryTech,Comedy          -0.38986    0.12048  -3.236 0.001232 **
## CategoryTech,Informative     -1.79859    0.13122 -13.707  < 2e-16 ***
## CategoryTech,News            -1.01322    0.13521  -7.494 9.85e-14 ***
## CategoryVideoGames           -0.17836    0.05463  -3.265 0.001114 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5295 on 2073 degrees of freedom
## Multiple R-squared:  0.8151, Adjusted R-squared:  0.8129
## F-statistic: 380.7 on 24 and 2073 DF,  p-value: < 2.2e-16
```

```r
plot(predict(lm3), resid(lm3), xlab = "Fitted values", ylab = "Residuals")
abline(h=0)
```



```
par(mfrow=c(1,2))
hist(resid(lm3))
qqPlot(lm3$residuals)
```




```
## [1] 1252  487
```

variable selection

```
# lm1 <- lm(log(Views) ~ CC + log(Released) + log(Length) + log(Subscribers) + Category + afinn_score+ 
lm4 <- step(lm1)
```

```
## Start:  AIC=-2641.29
## log(Views) ~ CC + log(Released) + log(Length) + log(Subscribers) + 
##     Category + afinn_score + afinn_title_score
##
##                       Df Sum of Sq     RSS      AIC
## - log(Released)        1      0.10  580.14 -2642.91
## - afinn_title_score    1      0.43  580.47 -2641.74
## - afinn_score          1      0.43  580.47 -2641.73
## <none>                              580.04 -2641.29
## - CC                   1      1.42  581.45 -2638.17
## - log(Length)          1      6.63  586.67 -2619.44
```

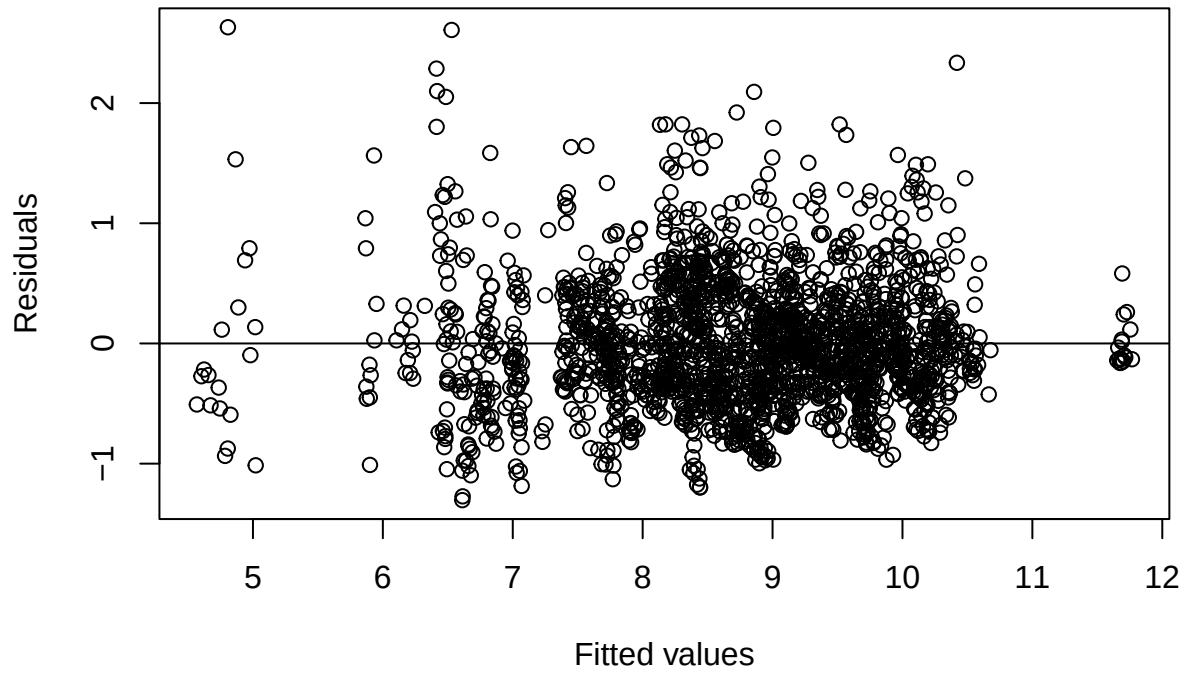
```
## - Category          21    368.50  948.54 -1651.43
## - log(Subscribers)   1   1297.14 1877.18  -179.33
##
## Step:  AIC=-2642.91
## log(Views) ~ CC + log(Length) + log(Subscribers) + Category +
##     afinn_score + afinn_title_score
##
##                     Df Sum of Sq     RSS      AIC
## - afinn_title_score  1      0.42  580.56 -2643.40
## - afinn_score        1      0.42  580.56 -2643.39
## <none>                             580.14 -2642.91
## - CC                 1      1.50  581.64 -2639.51
## - log(Length)        1      7.21  587.35 -2619.01
## - Category          21    376.47  956.61 -1635.65
## - log(Subscribers)   1   1410.26 1990.40   -58.45
##
## Step:  AIC=-2643.4
## log(Views) ~ CC + log(Length) + log(Subscribers) + Category +
##     afinn_score
##
##                   Df Sum of Sq     RSS      AIC
## <none>                          580.56 -2643.40
## - afinn_score       1      0.62  581.18 -2643.15
## - CC                1      1.40  581.96 -2640.34
## - log(Length)       1      7.25  587.81 -2619.36
## - Category         21    376.15  956.71 -1637.43
## - log(Subscribers)  1   1415.80 1996.36   -54.18
```

```
summary(lm4)
```

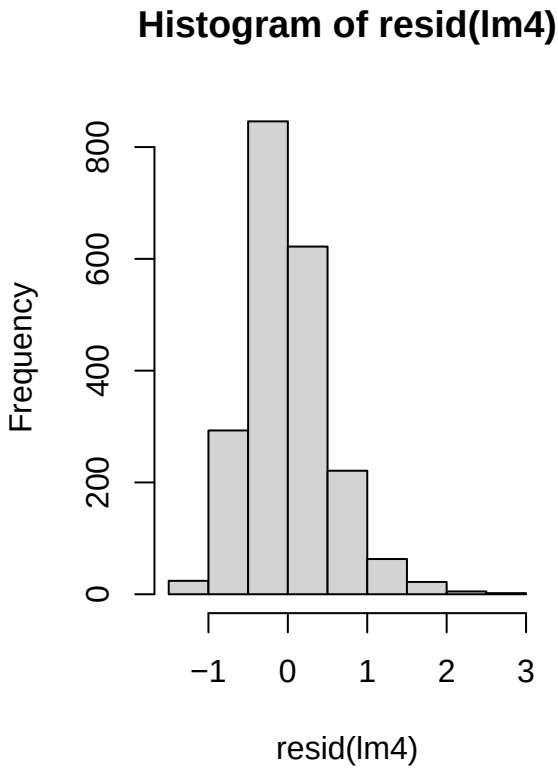
```
##
## Call:
## lm(formula = log(Views) ~ CC + log(Length) + log(Subscribers) +
##     Category + afinn_score, data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.30364 -0.34696 -0.06379  0.29275  2.63096
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    2.01453    0.10738  18.761  < 2e-16 ***
## CC1                            0.06063    0.02711   2.237 0.025411 *
## log(Length)                   -0.08380    0.01647  -5.087 3.97e-07 ***
## log(Subscribers)               0.83081    0.01169  71.084  < 2e-16 ***
## CategoryAutomobile,Comedy      0.39759    0.07622   5.216 2.01e-07 ***
## CategoryBlog                  -0.21831    0.06273  -3.480 0.000512 ***
## CategoryBlog,Comedy           -0.13598    0.09120  -1.491 0.136110
## CategoryBlog,Entertainment     0.43821    0.14538   3.014 0.002608 **
## CategoryBlog,Science          -0.63493    0.16621  -3.820 0.000137 ***
## CategoryComedy                 0.95713    0.10866   8.808  < 2e-16 ***
## CategoryComedy,Entertainment   0.83664    0.07187  11.641  < 2e-16 ***
## CategoryComedy,Informative     0.79422    0.08926   8.898  < 2e-16 ***
## CategoryEntertainment          0.39775    0.08487   4.686 2.96e-06 ***
```

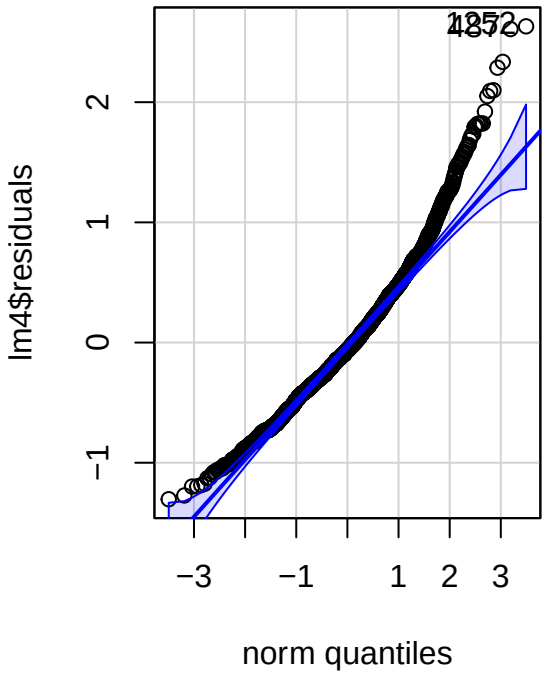
```
## CategoryEntertainment,Blog    0.32099    0.11049   2.905 0.003710 **
## CategoryEntertainment,Comedy  0.90616    0.07233  12.528  < 2e-16 ***
## CategoryFood                  0.29563    0.05435   5.439 5.98e-08 ***
## CategoryFood,Entertainment    0.51036    0.11860   4.303 1.76e-05 ***
## CategoryInformative           0.04349    0.05775   0.753 0.451476
## CategoryNews                  0.20090    0.06208   3.236 0.001230 **
## CategoryScience              -0.04915    0.05430  -0.905 0.365534
## CategoryTech                 -0.58233    0.05878  -9.908  < 2e-16 ***
## CategoryTech,Comedy          -0.38563    0.12048  -3.201 0.001391 **
## CategoryTech,Informative     -1.79659    0.13119 -13.695  < 2e-16 ***
## CategoryTech,News            -1.01754    0.13520  -7.526 7.74e-14 ***
## CategoryVideoGames           -0.19716    0.05606  -3.517 0.000446 ***
## afinn_score                  -0.06743    0.04527  -1.489 0.136523
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5293 on 2072 degrees of freedom
## Multiple R-squared:  0.8153, Adjusted R-squared:  0.813
## F-statistic: 365.8 on 25 and 2072 DF,  p-value: < 2.2e-16
```

```
plot(predict(lm4), resid(lm4), xlab = "Fitted values", ylab = "Residuals")
abline(h=0)
```




```
par(mfrow=c(1,2))
hist(resid(lm4))
qqPlot(lm4$residuals)
```






```
## [1] 1252  487
```

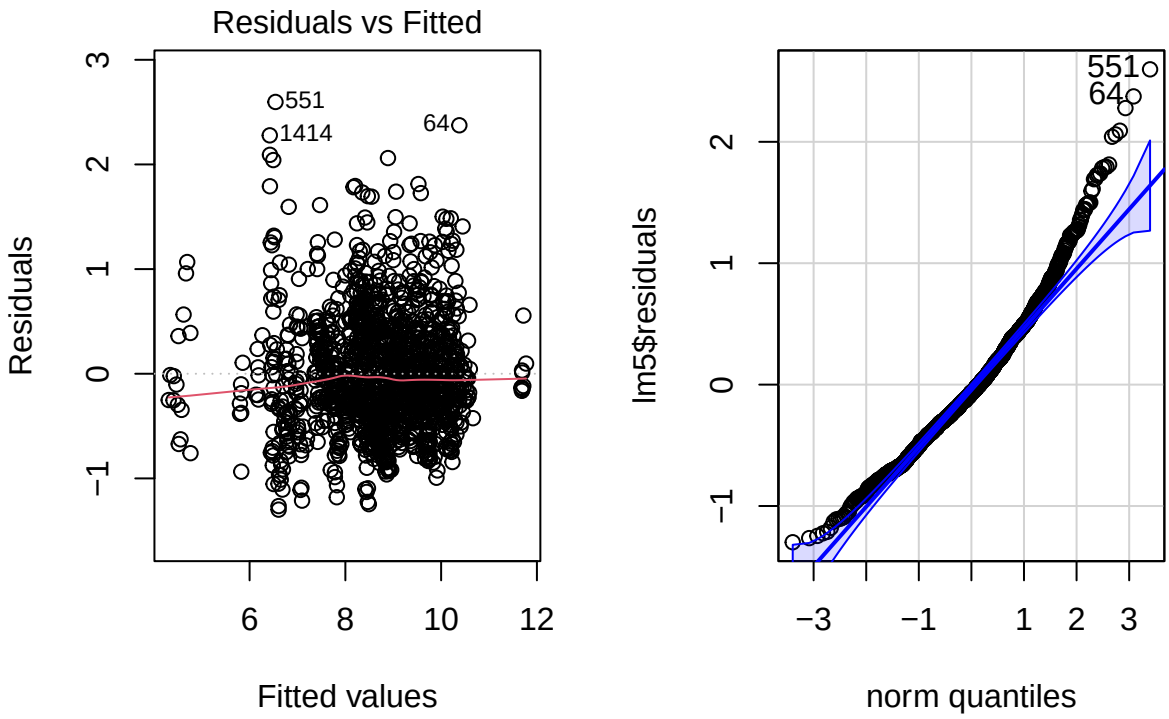
```
# fit lm4 (the final model in MLR part) to df_train:
# lm(formula = log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score, data = df1)
lm5 <- lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score, data = df_train)


# make prediction
pred1 <- predict(lm5, newdata = df_test)
pred_lm5 <- exp(pred1); length(pred_lm5)
```

```
## [1] 629
```

```
# Compute the RMSE
lm_RMSE <- RMSE(df_test$Views, pred_lm5); lm_RMSE
```

```
## [1] 7618.171
```

```
par(mfrow = c(1,2))
plot(lm5, 1)
qqPlot(lm5$residuals)
```




```
## [1] 551  64
```

Regression Tree

Fit a regression tree on the training set.

```
# Fit tree model
t1 <- rpart(Views ~ CC + Released + Category + Length + Subscribers + afinn_score + afinn_title_score,
            data = df_train,
            method = "anova")
summary(t1)
```

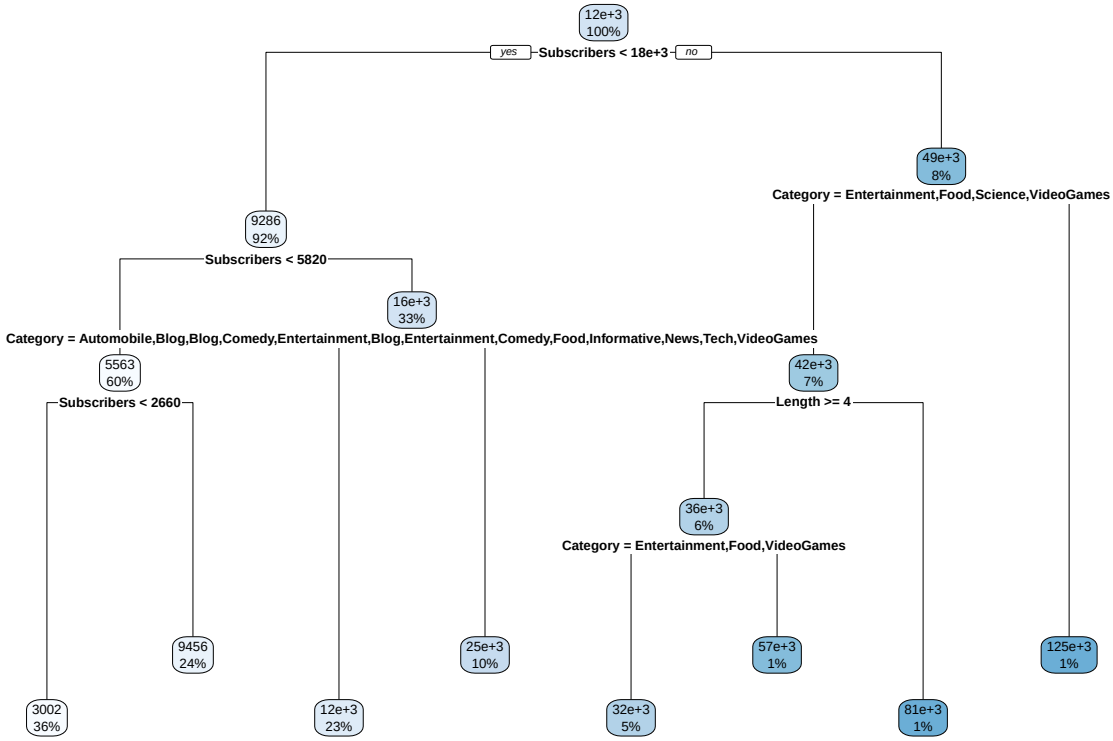
```
## Call:
## rpart(formula = Views ~ CC + Released + Category + Length + Subscribers +
##     afinn_score + afinn_title_score, data = df_train, method = "anova")
##   n= 1469
##
##           CP nsplit rel error    xerror      xstd
## 1 0.31049310      0 1.0000000 1.0015040 0.2464760
## 2 0.11052780      1 0.6895069 0.7397027 0.1912329
## 3 0.06701585      2 0.5789791 0.6522043 0.1974818
## 4 0.04473830      3 0.5119633 0.6064179 0.1936102
## 5 0.03135581      4 0.4672250 0.5810376 0.1906906
```

```
## 6 0.01707528      5 0.4358692 0.5440516 0.1895579
## 7 0.01616416      6 0.4187939 0.5403960 0.1944559
## 8 0.01000000      7 0.4026297 0.5250192 0.1942670
##
## Variable importance
## Subscribers    Category      Length    Released afinn_score
##          63          25           6           4           3
##
## Node number 1: 1469 observations,    complexity param=0.3104931
##   mean=12259.92, MSE=3.485821e+08
##   left son=2 (1358 obs) right son=3 (111 obs)
##   Primary splits:
##       Subscribers < 18200       to the left,  improve=0.310493100, (0 missing)
##       Category    splits as  LLLLRLLLLLLLLLLLLLLLL, improve=0.223444300, (0 missing)
##       CC          splits as  LR, improve=0.021839480, (0 missing)
##       Released    < 54          to the left,  improve=0.016626150, (0 missing)
##       afinn_score < -0.4679184  to the right, improve=0.005393465, (0 missing)
##   Surrogate splits:
##       Category splits as  LLLLRLLLLRLLLLLLLLLLL, agree=0.931, adj=0.09, (0 split)
##
## Node number 2: 1358 observations,    complexity param=0.06701585
##   mean=9285.58, MSE=9.976327e+07
##   left son=4 (877 obs) right son=5 (481 obs)
##   Primary splits:
##       Subscribers < 5820        to the left,  improve=0.25329930, (0 missing)
##       Category    splits as  LRLL-LRRRLRRLRLRRLLLLL, improve=0.13649260, (0 missing)
##       CC          splits as  LR, improve=0.06061949, (0 missing)
##       Released    < 17.5        to the left,  improve=0.03278464, (0 missing)
##       afinn_score < -0.3582549  to the right, improve=0.01406778, (0 missing)
##   Surrogate splits:
##       Category          splits as  LLLL-LLLLLRLLRLRLLLLLL, agree=0.706, adj=0.170, (0 split)
##       afinn_score       < -0.4130772  to the right, agree=0.653, adj=0.021, (0 split)
##       afinn_title_score < -10.00973   to the right, agree=0.651, adj=0.015, (0 split)
##       Length            < 94          to the left,  agree=0.650, adj=0.012, (0 split)
##       Released          < 138         to the left,  agree=0.649, adj=0.010, (0 split)
##
## Node number 3: 111 observations,    complexity param=0.1105278
##   mean=48648.65, MSE=1.960318e+09
##   left son=6 (102 obs) right son=7 (9 obs)
##   Primary splits:
##       Category    splits as  ----R----L--L---L----L, improve=0.26010510, (0 missing)
##       Subscribers < 60800       to the left,  improve=0.26010510, (0 missing)
##       Released    < 30          to the right, improve=0.11589390, (0 missing)
##       Length      < 3.5         to the right, improve=0.07149841, (0 missing)
##       afinn_score < -0.09233514 to the left,  improve=0.04949090, (0 missing)
##   Surrogate splits:
##       Subscribers < 60800       to the left,  agree=1.000, adj=1.000, (0 split)
##       Released    < 10.5        to the right, agree=0.937, adj=0.222, (0 split)
##
## Node number 4: 877 observations,    complexity param=0.01707528
##   mean=5562.734, MSE=3.63767e+07
##   left son=8 (529 obs) right son=9 (348 obs)
##   Primary splits:
##       Subscribers < 2660        to the left,  improve=0.27407660, (0 missing)
```

```
##       Category    splits as  LLLL-LRRRR-RR-RRLLLLLL, improve=0.16847750, (0 missing)
##       CC          splits as  LR, improve=0.04789304, (0 missing)
##       Released    < 17.5        to the left,  improve=0.03350874, (0 missing)
##       Length      < 5.5         to the right, improve=0.02945479, (0 missing)
##   Surrogate splits:
##       Category          splits as  LLLL-LRRRL-LL-RLRLLLLL, agree=0.688, adj=0.213, (0 split)
##       afinn_score       < -0.4415035  to the right, agree=0.627, adj=0.060, (0 split)
##       CC                splits as  LR, agree=0.620, adj=0.043, (0 split)
##       afinn_title_score < -3.477081   to the right, agree=0.613, adj=0.026, (0 split)
##
## Node number 5: 481 observations,    complexity param=0.03135581
##   mean=16073.39, MSE=1.439907e+08
##   left son=10 (334 obs) right son=11 (147 obs)
##   Primary splits:
##       Category    splits as  LRLL---RR-LLLRLLRL---L, improve=0.23182770, (0 missing)
##       Subscribers < 7815        to the left,  improve=0.07282145, (0 missing)
##       Released    < 66          to the left,  improve=0.06285942, (0 missing)
##       CC          splits as  LR, improve=0.02763750, (0 missing)
##       Length      < 2.5         to the right, improve=0.01042117, (0 missing)
##   Surrogate splits:
##       Subscribers < 16350       to the left,  agree=0.771, adj=0.252, (0 split)
##       Released    < 78          to the left,  agree=0.736, adj=0.136, (0 split)
##
## Node number 6: 102 observations,    complexity param=0.0447383
##   mean=41941.18, MSE=1.47584e+09
##   left son=12 (89 obs) right son=13 (13 obs)
##   Primary splits:
##       Length            < 3.5         to the right, improve=0.15218330, (0 missing)
##       Subscribers       < 29950       to the left,  improve=0.07016891, (0 missing)
##       Category          splits as  ---------L--L---R----L, improve=0.04652797, (0 missing)
##       afinn_score       < 0.2123762   to the right, improve=0.02369423, (0 missing)
##       afinn_title_score < 0.1749704   to the right, improve=0.01726483, (0 missing)
##   Surrogate splits:
##       afinn_score < -0.6155792  to the right, agree=0.931, adj=0.462, (0 split)
##
## Node number 7: 9 observations
##   mean=124666.7, MSE=1.162444e+09
##
## Node number 8: 529 observations
##   mean=3001.735, MSE=8899958
##
## Node number 9: 348 observations
##   mean=9455.747, MSE=5.301896e+07
##
## Node number 10: 334 observations
##   mean=12240.42, MSE=5.324768e+07
##
## Node number 11: 147 observations
##   mean=24782.31, MSE=2.409424e+08
##
## Node number 12: 89 observations,    complexity param=0.01616416
##   mean=36213.48, MSE=3.726848e+08
##   left son=24 (73 obs) right son=25 (16 obs)
##   Primary splits:
```

```
##       Category    splits as  ---------L--L---R----L, improve=0.24954480, (0 missing)
##       Released    < 30          to the right, improve=0.09665358, (0 missing)
##       Subscribers < 24550       to the right, improve=0.08817957, (0 missing)
##       afinn_score < -0.09233514 to the left,  improve=0.06772828, (0 missing)
##       Length      < 11.5        to the right, improve=0.04553668, (0 missing)
##   Surrogate splits:
##       Released < 17.5        to the right, agree=0.843, adj=0.125, (0 split)
##
## Node number 13: 13 observations
##   mean=81153.85, MSE=7.265976e+09
##
## Node number 24: 73 observations
##   mean=31698.63, MSE=1.994434e+08
##
## Node number 25: 16 observations
##   mean=56812.5, MSE=6.457773e+08
```

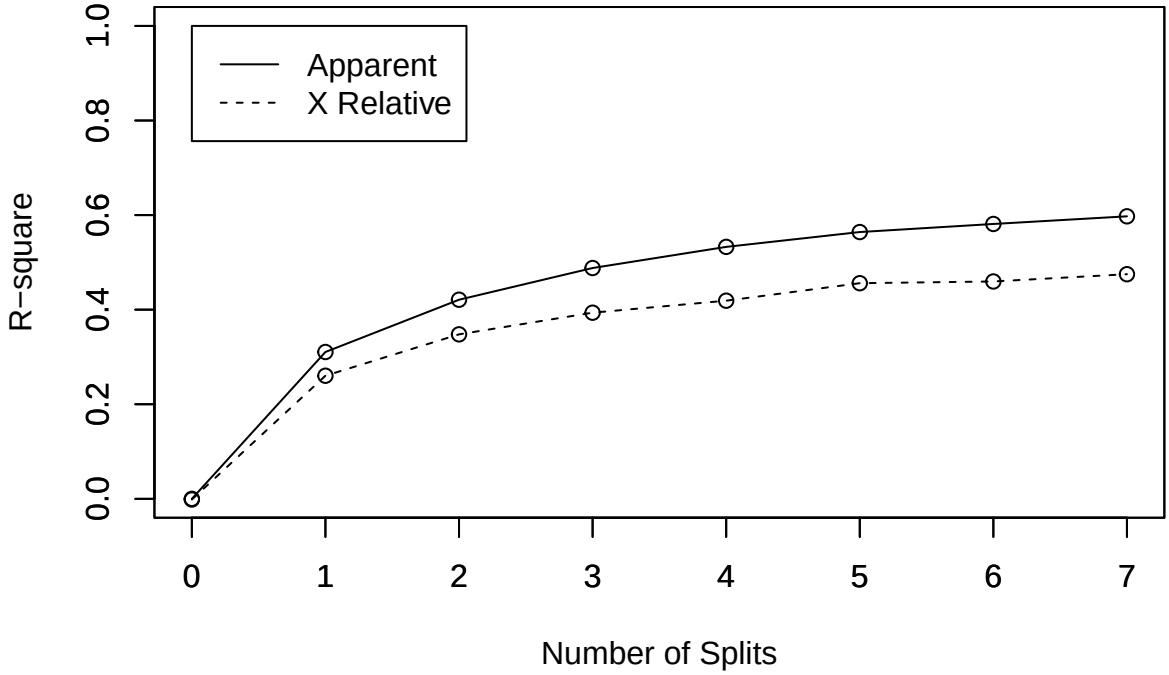
```
# Plot the desicion tree
rpart.plot(t1)
```

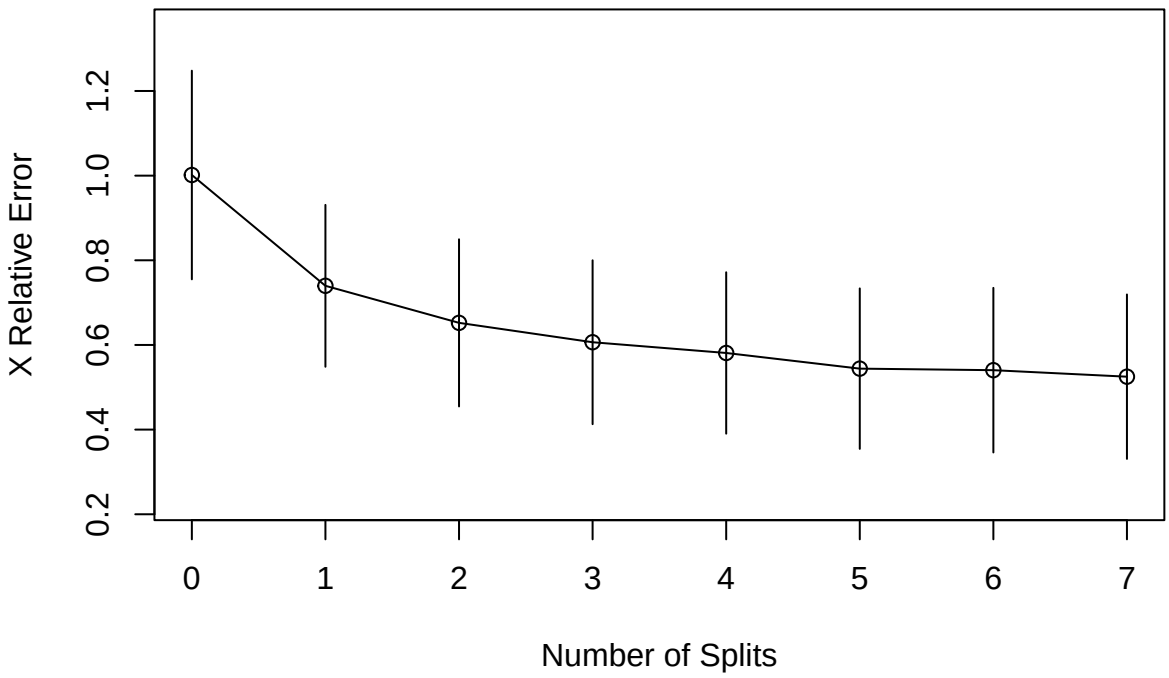



```
# Plot R-square vs Splits and the Relative Error vs Splits.
rsq.rpart(t1)
```

```
##
## Regression tree:
```

```
## rpart(formula = Views ~ CC + Released + Category + Length + Subscribers +
##     afinn_score + afinn_title_score, data = df_train, method = "anova")
##
## Variables actually used in tree construction:
## [1] Category    Length      Subscribers
##
## Root node error: 5.1207e+11/1469 = 348582113
##
## n= 1469
##
##         CP nsplit rel error  xerror    xstd
## 1 0.310493      0   1.00000 1.00150 0.24648
## 2 0.110528      1   0.68951 0.73970 0.19123
## 3 0.067016      2   0.57898 0.65220 0.19748
## 4 0.044738      3   0.51196 0.60642 0.19361
## 5 0.031356      4   0.46722 0.58104 0.19069
## 6 0.017075      5   0.43587 0.54405 0.18956
## 7 0.016164      6   0.41879 0.54040 0.19446
## 8 0.010000      7   0.40263 0.52502 0.19427
```





Make predictions on the test set and compute the RMSE

```
# Make prediction
pred_tree <- predict(t1, newdata = df_test)

# Compute the RMSE
t1_RMSE <- RMSE(df_test$Views, pred_tree); t1_RMSE
```

```
## [1] 7977.73
```

```
# test R^2
t1_R2 <- cor(df_test$Views, pred_tree)^2; t1_R2
```

```
## [1] 0.7801641
```

Example of interptiation:

Since the test set R2 for the second model is higher (closer to 1) it performs better. The interpretation is that about 67% of the variability in Sale_Price, on the test set, is explained by predictions from the linear regression model with Gr_Liv_Area and Year_Built as predictor variables.

Random Forest

Fit a Random Forest on the training set usinng the defaults for mtry and ntree = 500.

default mtry: p/3 = 28/3 = 9 (mtry: Number of predictors randomly sampled as candidates at each split.)

```
length(lm_full$coefficients)
```

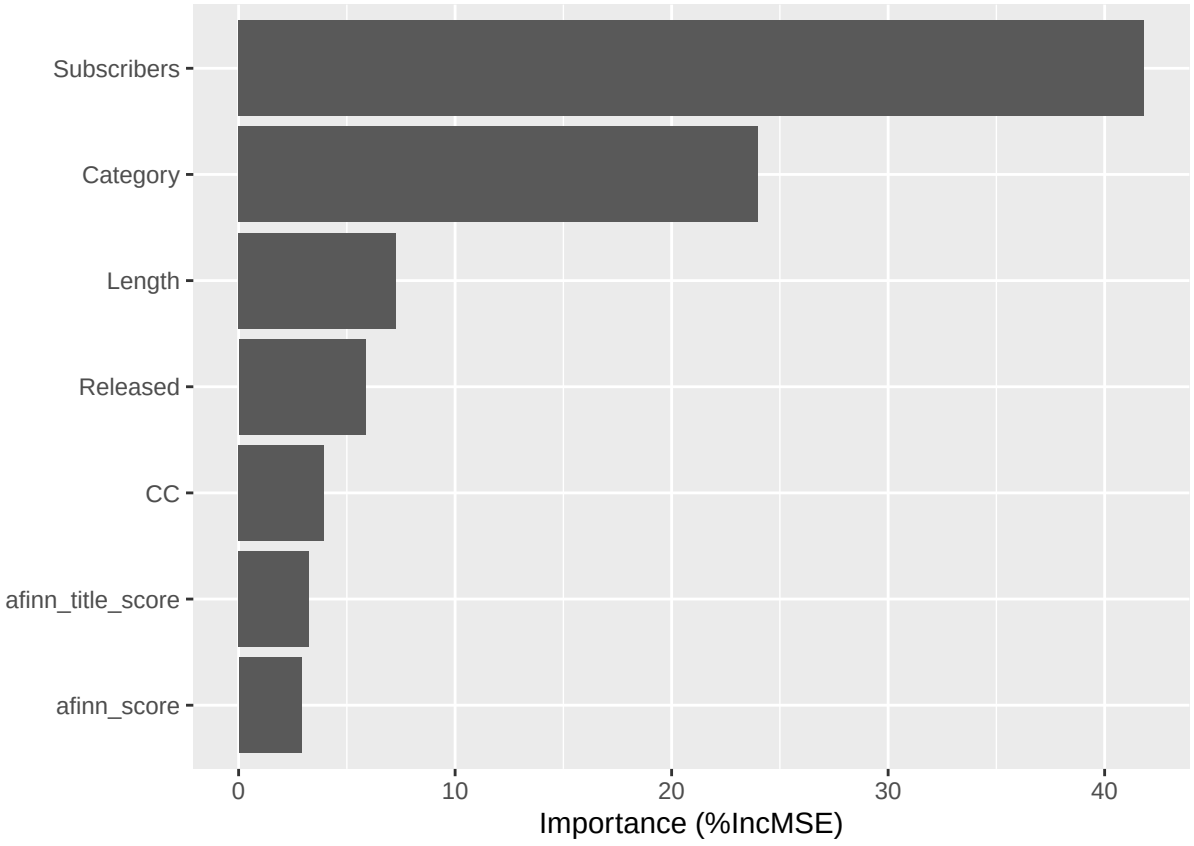
```
## [1] 28
```

```
set.seed(652)
rf1 <- randomForest(Views ~ CC + Released + Category +
                      Length + Subscribers + afinn_score +
                      afinn_title_score, importance = TRUE,
                    data = df_train)
rf1
```

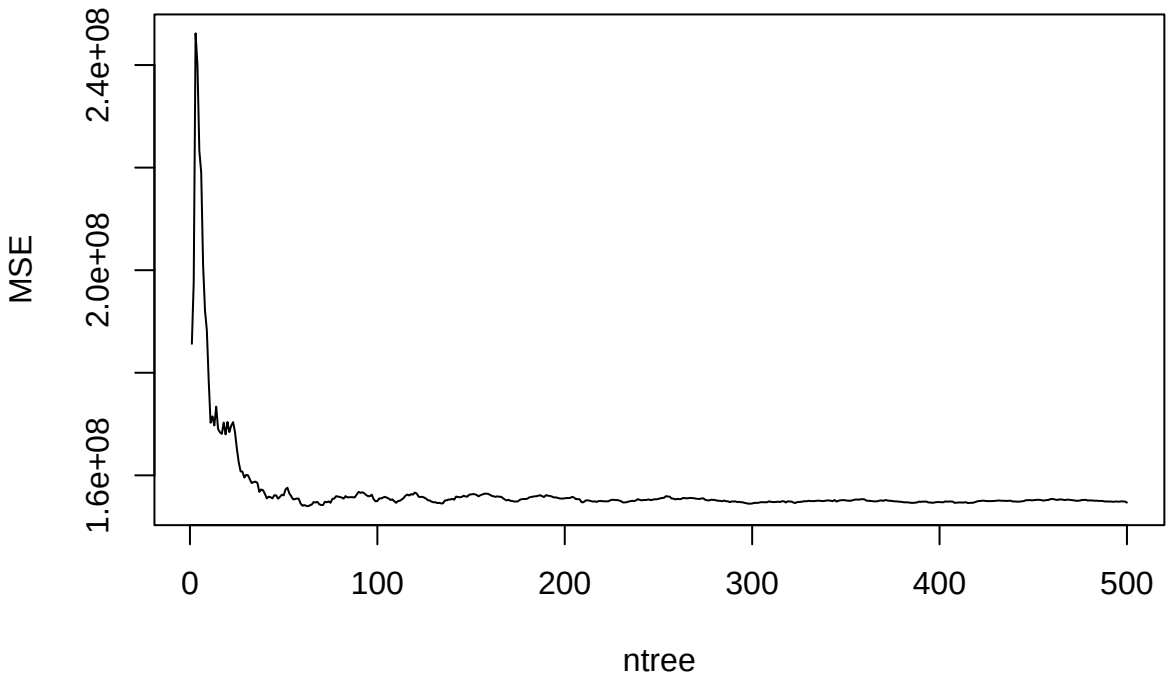
```
##
## Call:
##  randomForest(formula = Views ~ CC + Released + Category + Length +      Subscribers + afinn_score +
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 2
##
##           Mean of squared residuals: 154686582
##                     % Var explained: 55.62
```

Use the `vip()` function to make a variable importance plot. # Use below to do interpreation with random forests. ## i.e. In this rf model, we know that to predict the Views of a youtube viedo, the most important predictor is Subscribers of Channel, and then is the Video's Category, and the Length of Video.

```
vip(rf1, num_features = 14,  include_type = TRUE)
```




```
plot(c(1: 500), rf1$mse, xlab="ntree", ylab="MSE", type="l")
```



Make predictions on the test set and compute the RMSE

```
# Make prediction
pred_rf <- predict(rf1, newdata = df_test); length(pred_rf)
```

```
## [1] 629
```

```
# Compute the RMSE
rf1_RMSE <- RMSE(df_test$Views, pred_rf); rf1_RMSE
```

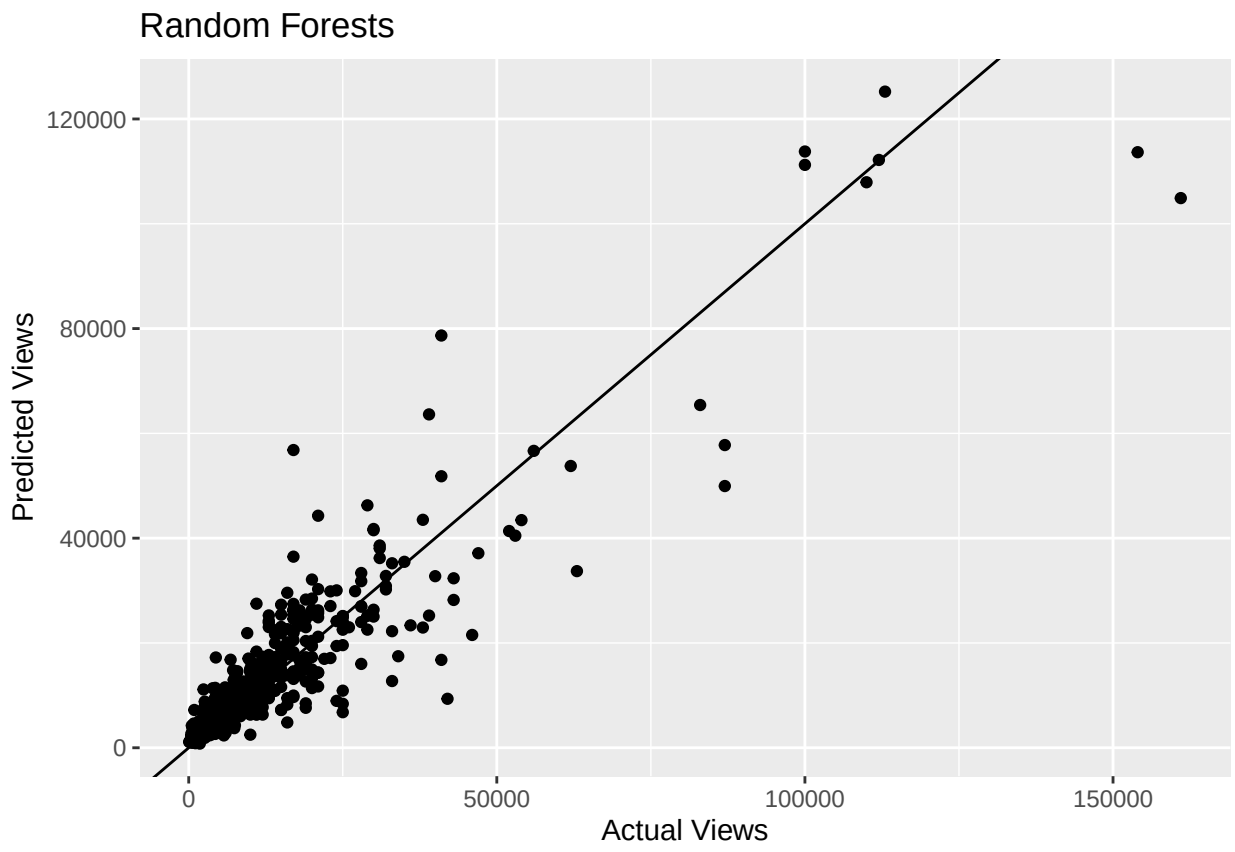
```
## [1] 6660.282
```

```
# test R^2
rf1_R2 <- cor(df_test$Views, pred_rf)^2; rf1_R2
```

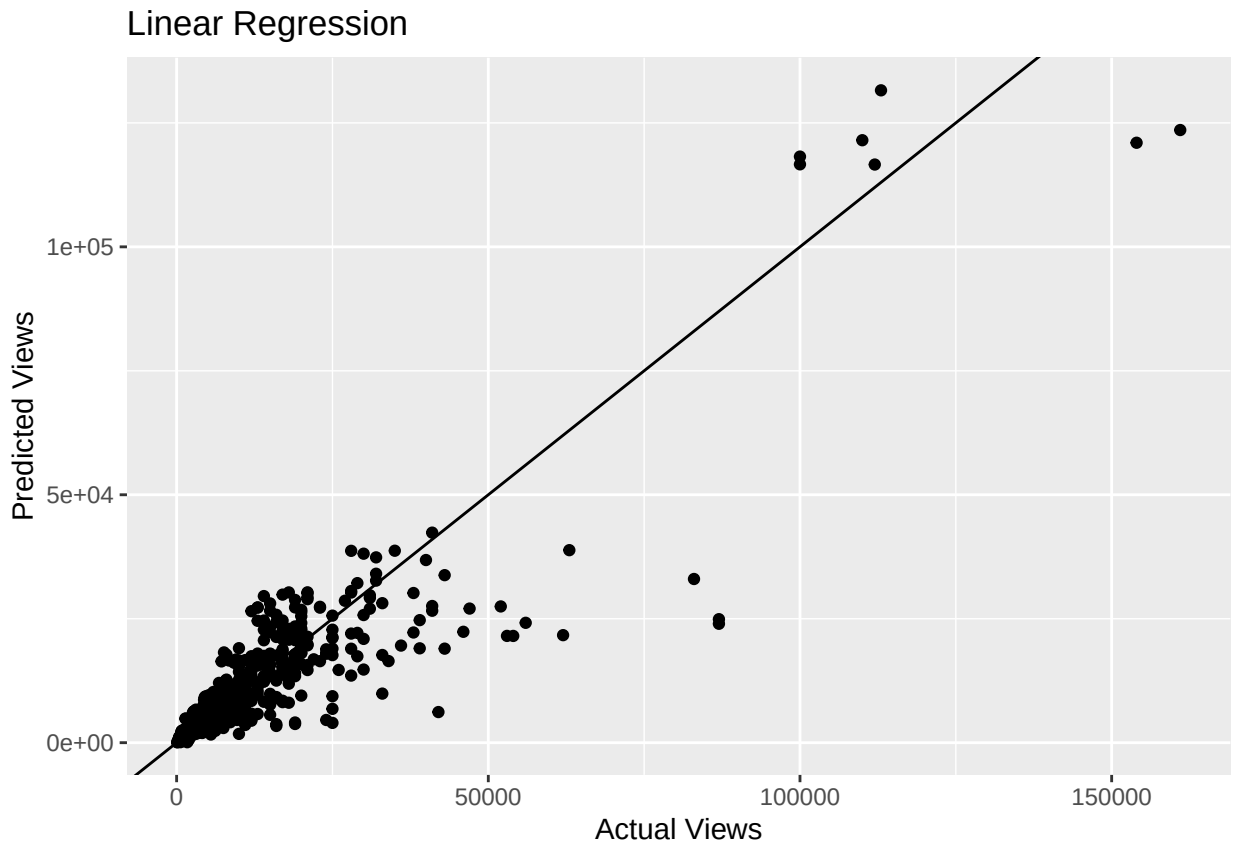
```
## [1] 0.836752
```

```
pred_df <- data.frame(
  Actual = df_test$Views,
  Pred_RF = pred_rf,
  Pred_LM = pred_lm5
)
```

```
ggplot(pred_df, aes(x = Actual, y = Pred_RF)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1) +
  xlab("Actual Views") + ylab("Predicted Views") +
  ggtitle("Random Forests")
```




```
ggplot(pred_df, aes(x = Actual, y = Pred_LM)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1) +
  xlab("Actual Views") + ylab("Predicted Views") +
  ggtitle("Linear Regression")
```



Conclusion(TODO)

```
# lm(Views ~ CC + Released + Length + Subscribers + Category + afinn_score+ afinn_title_score, data=df1
summary(lm_full)$r.squared
```

```
## [1] 0.5998046
```

```
# lm(log(Views) ~ CC + log(Released) + log(Length) + log(Subscribers) + Category + afinn_score+ afinn_t
summary(lm1)$r.squared
```

```
## [1] 0.8154339
```

```
# lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score + afinn_title_score, dat
summary(lm2)$r.squared
```

```
## [1] 0.8154009
```

```
# lm(log(Views) ~ CC  + log(Length) + log(Subscribers) + Category, data=df1)
summary(lm3)$r.squared
```

```
## [1] 0.8150697
```

```r
# lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score, data = df1)
summary(lm4)$r.squared
```

```
## [1] 0.8152674
```

```r
# lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score, data = df_train)
summary(lm5)$r.squared
```

```
## [1] 0.8162162
```

```r
summary(lm_full)$adj.r.squared
```

```
## [1] 0.5945846
```

```r
summary(lm1)$adj.r.squared
```

```
## [1] 0.8130265
```

```r
summary(lm2)$adj.r.squared
```

```
## [1] 0.8130834
```

```r
summary(lm3)$adj.r.squared
```

```
## [1] 0.8129286
```

```r
summary(lm4)$adj.r.squared
```

```
## [1] 0.8130385
```

```r
summary(lm5)$adj.r.squared
```

```
## [1] 0.8130322
```

```r
t1_R2 # regression tree's R2
```

```
## [1] 0.7801641
```

```r
rf1_R2 # Random forest' R2
```

```
## [1] 0.836752
```

```r
lm_RMSE # lm5's RMSE
```

```
## [1] 7618.171
```

```
t1_RMSE # regression tree's RMSE
```

```
## [1] 7977.73
```

```
rf1_RMSE # Random forest' R2
```

```
## [1] 6660.282
```

```
# test R^2 for regression tree
cor(df_test$Views, pred_tree)^2
```

```
## [1] 0.7801641
```

```
# test R^2 for random forest
cor(df_test$Views, pred_rf)^2
```

```
## [1] 0.836752
```

Linear Regression vs Regression Tree VS Random Forest

```
data.frame(Model=c("full model without transformation", "lm1", "lm2", "lm3", "lm4", "lm5"),
           R_squared = c(summary(lm_full)$r.squared,
                         summary(lm1)$r.squared,
                         summary(lm2)$r.squared,
                         summary(lm3)$r.squared,
                         summary(lm4)$r.squared,
                         summary(lm5)$r.squared),
           adj_R_squared = c(summary(lm_full)$adj.r.squared,
                             summary(lm1)$adj.r.squared,
                             summary(lm2)$adj.r.squared,
                             summary(lm3)$adj.r.squared,
                             summary(lm4)$adj.r.squared,
                             summary(lm5)$adj.r.squared),
           formula = c("lm(Views ~ CC + Released + Length + Subscribers + Category + afinn_score+ afinn
                       "lm(log(Views) ~ CC + log(Released) + log(Length) + log(Subscribers) + Category
                       "lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score + a
                       "lm(log(Views) ~ CC  + log(Length) + log(Subscribers) + Category, data=df1)",
                       "lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score, da
                       "lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score, da
                       ))
```

```
##                               Model R_squared adj_R_squared
## 1 full model without transformation 0.5998046     0.5945846
## 2                                 lm1 0.8154339     0.8130265
## 3                                 lm2 0.8154009     0.8130834
## 4                                 lm3 0.8150697     0.8129286
## 5                                 lm4 0.8152674     0.8130385
## 6                                 lm5 0.8162162     0.8130322
##
```

```
## 1                     lm(Views ~ CC + Released + Length + Subscribers + Category + afinn_score+ afinn
## 2 lm(log(Views) ~ CC + log(Released) + log(Length) + log(Subscribers) + Category + afinn_score+ afinn
## 3                lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_score + afinn
## 4                                                    lm(log(Views) ~ CC  + log(Length) + log(Subscribers
## 5                                    lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + a
## 6                              lm(log(Views) ~ CC + log(Length) + log(Subscribers) + Category + afinn_
```

```
data.frame(Model=c("linear regression", "regression tree", "random forest"),
           R_squared = c(summary(lm5)$r.squared,
                         cor(df_test$Views, pred_tree)^2,
                         cor(df_test$Views, pred_rf)^2),
           RMSE = c(lm_RMSE,
                    t1_RMSE,
                    rf1_RMSE))
```

```
##               Model R_squared     RMSE
## 1 linear regression 0.8162162 7618.171
## 2   regression tree 0.7801641 7977.730
## 3     random forest 0.8367520 6660.282
```

Aggregated/ensemble models are not universally better than their "single" counterparts, they are better if and only if the single models suffer of instability. With XX training rows and only XX columns, we are in a comfortable training sample size situation in which even a decision tree may get reasonably stable.

make this prediction and to calculate a 95% prediction interval.

```
df1[300, ]
```

```
## # A tibble: 1 x 13
##   Id    Channel Subscribers Title CC    URL   Released Views Category Transcript
##   <chr> <chr>         <dbl> <chr> <fct> <chr>    <dbl> <dbl> <fct>    <chr>
## 1 uxRf~ Joma T~        1590 i fi~ 0     http~       24   922 Tech,Co~ yes so so~
## # ... with 3 more variables: Length <dbl>, afinn_score <dbl>,
## #   afinn_title_score <dbl>
```

```
new_x <- data.frame(CC = "0", Length = 12,  Subscribers = 1590, Category = "Tech,Comedy", afinn_score =
exp(predict(lm5, newdata = new_x, interval="prediction"))
```

```
##        fit      lwr     upr
## 1 1731.504 580.2379 5167.03
```

```
df1[2000, ]
```

```
## # A tibble: 1 x 13
##   Id    Channel Subscribers Title CC    URL   Released Views Category Transcript
##   <chr> <chr>         <dbl> <chr> <fct> <chr>    <dbl> <dbl> <fct>    <chr>
## 1 jwu2~ Gordon~       18700 The ~ 1     http~       72 20000 Food     this is t~
## # ... with 3 more variables: Length <dbl>, afinn_score <dbl>,
## #   afinn_title_score <dbl>
```

```r
new_x <- data.frame(CC = "1", Length = 7,  Subscribers = 18700, Category = "Food", afinn_score = 0.4008
exp(predict(lm5, newdata = new_x, interval="prediction"))
```

```
##       fit      lwr      upr
## 1 33082.6 11372.88 96234.08
```