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)
```

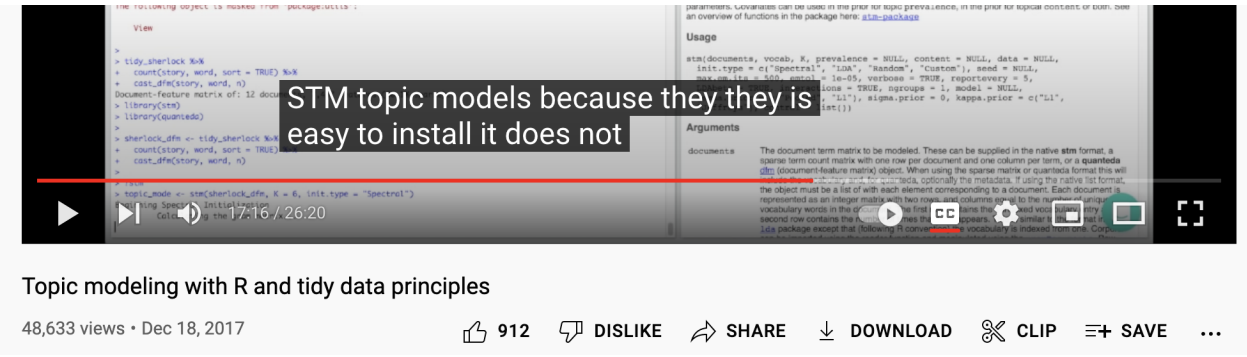
Research Data

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.
```

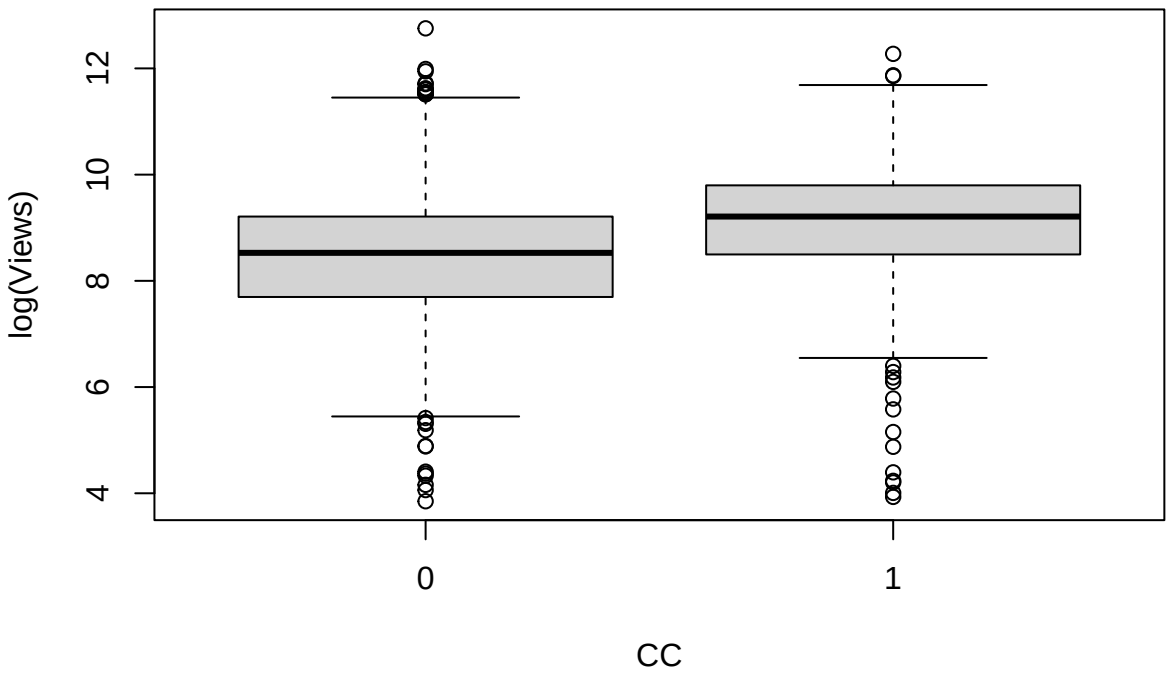
```
df$CC <- as.factor(df$CC)
df$Category <- as.factor(df$Category)
df$Subscribers <- as.numeric(df$Subscribers)

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>
```

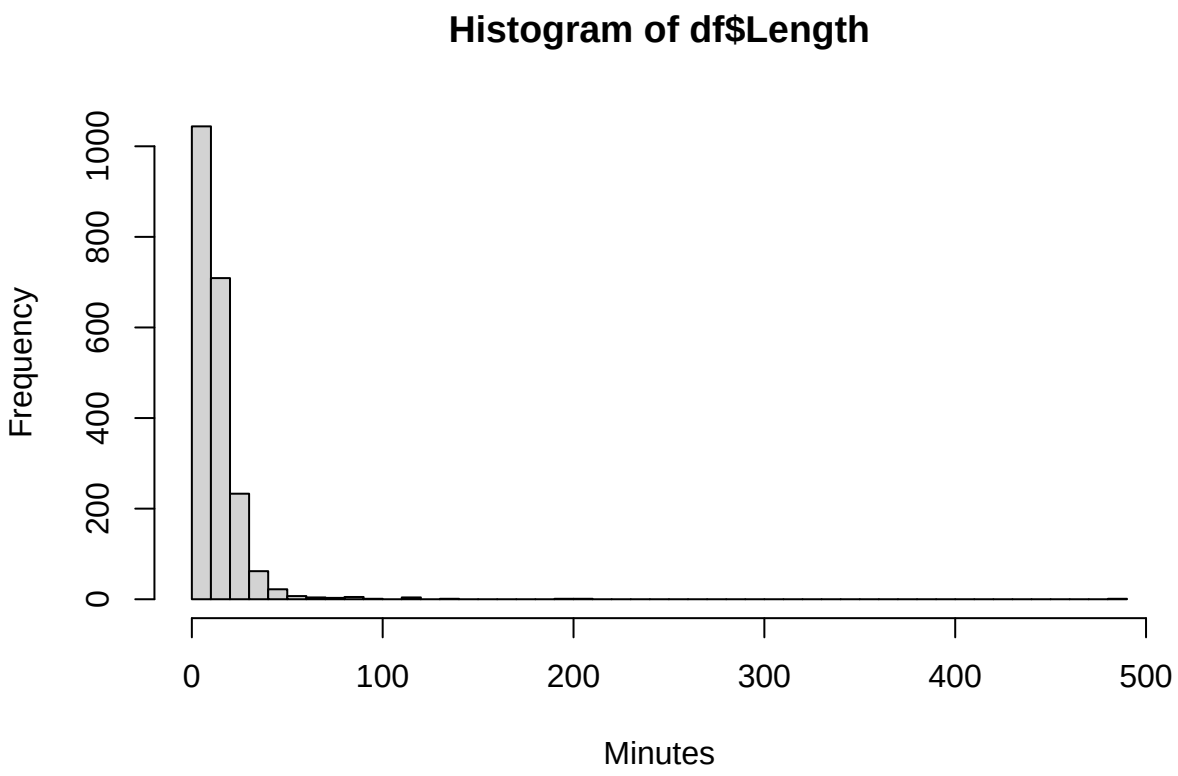
```
table(df$CC)
```

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

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




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



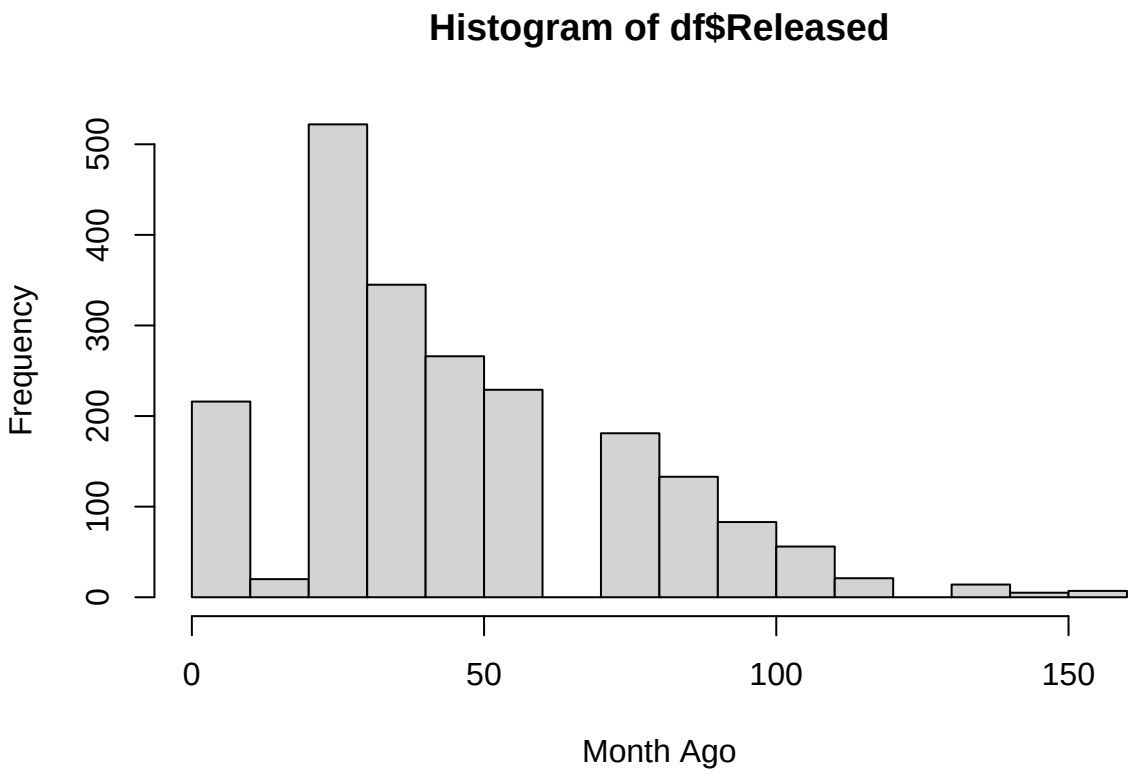

```
summary(df$Length)
```

```
##    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
```

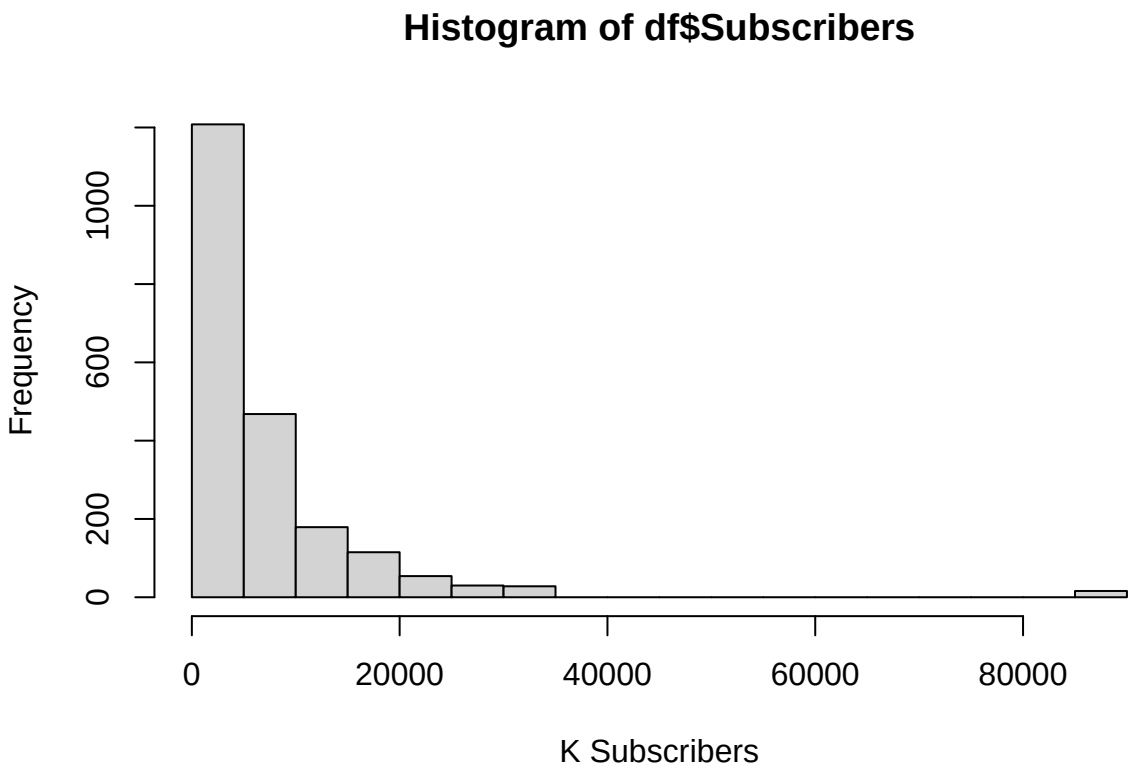
```
hist(df$Released, xlab = "Month Ago")
```



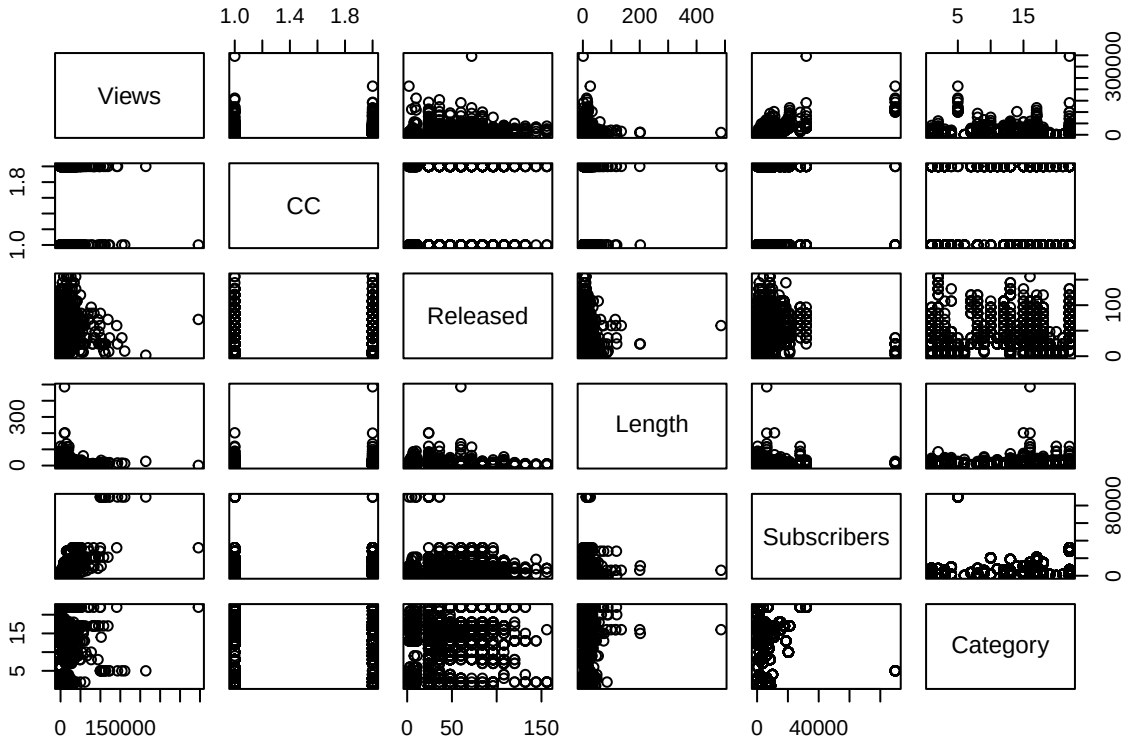

```
summary(df$Subscribers)
```

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

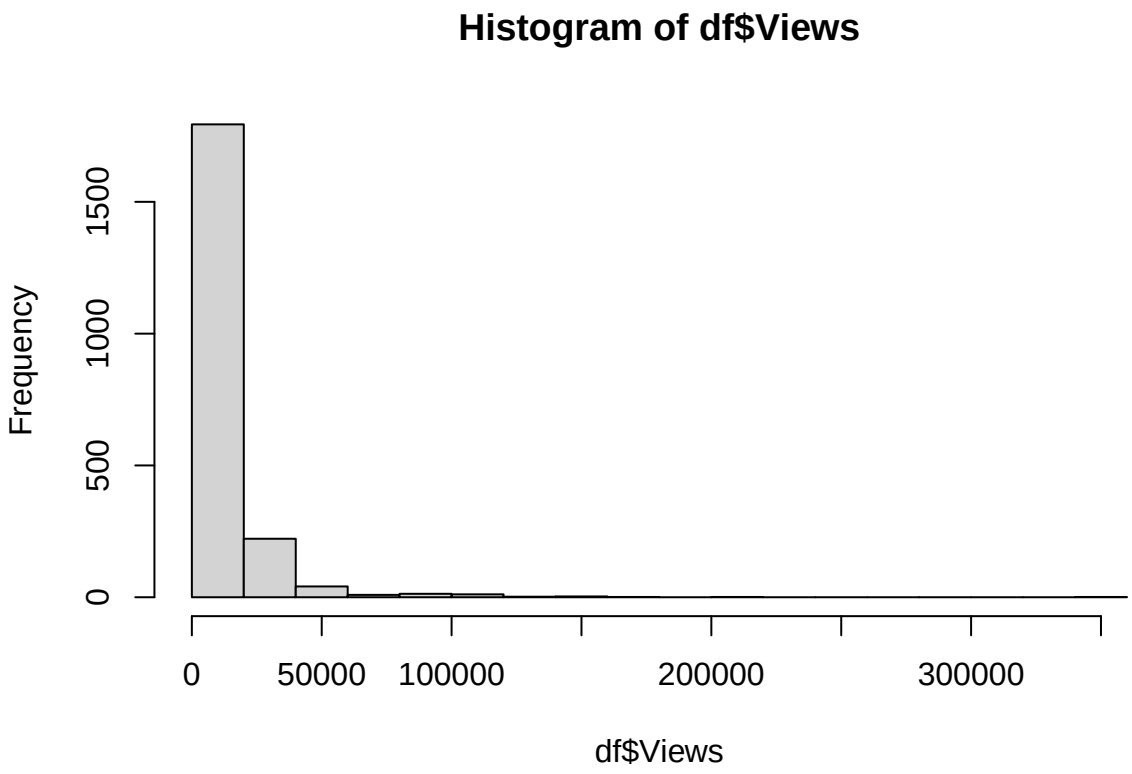
```
hist(df$Subscribers, xlab = "K Subscribers")
```




```
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 OZWGeidvrJw 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")
```

```
## # A tibble: 1 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 R~
## # ... with 1 more variable: Length <dbl>
```

```
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)
```

```
## # A tibble: 6 x 3
## # Groups:   Id [1]
##   Id          word1     word2
##   <chr>       <chr>     <chr>
## 1 FozCkl1xj-w joe       rogan
## 2 FozCkl1xj-w rogan     experience
## 3 FozCkl1xj-w epstein's friend
## 4 FozCkl1xj-w friend    toe
## 5 FozCkl1xj-w andrew    yeah
## 6 FozCkl1xj-w yeah      yeah
```

```
# 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
```

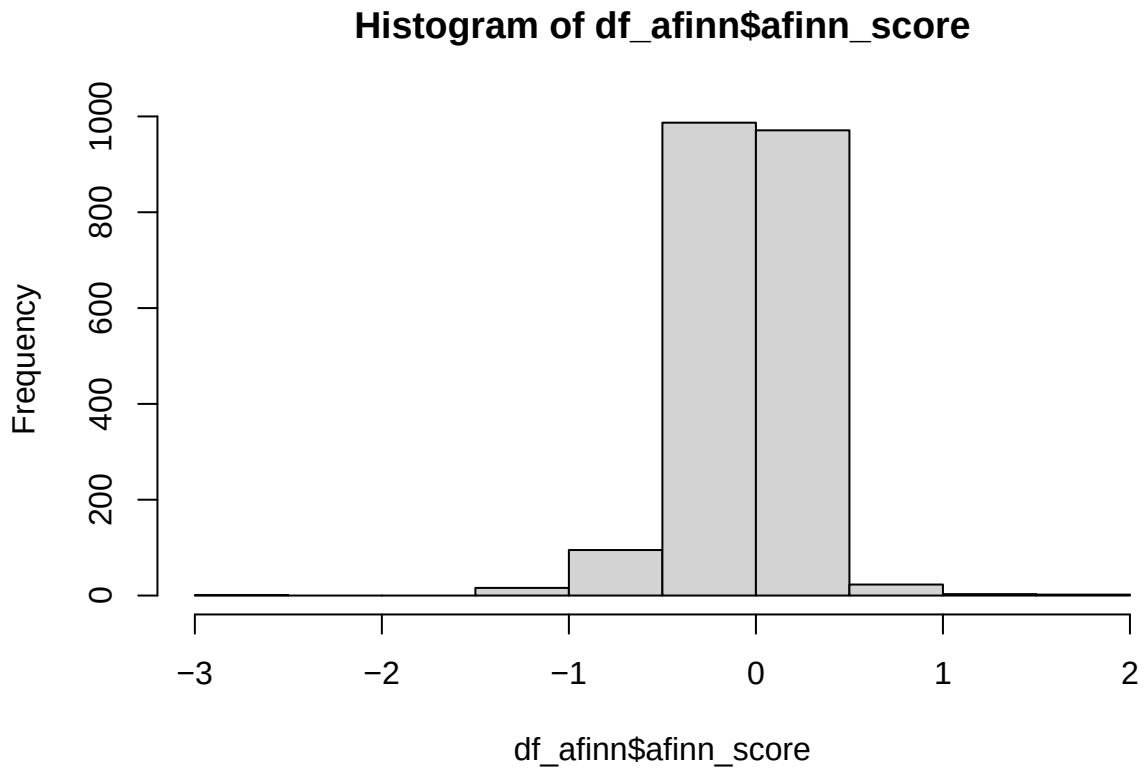
```
df_afinn <- df_afinn %>%
  dplyr::select(Id, afinn_score) %>%
  unique() %>%
  ungroup()

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
```

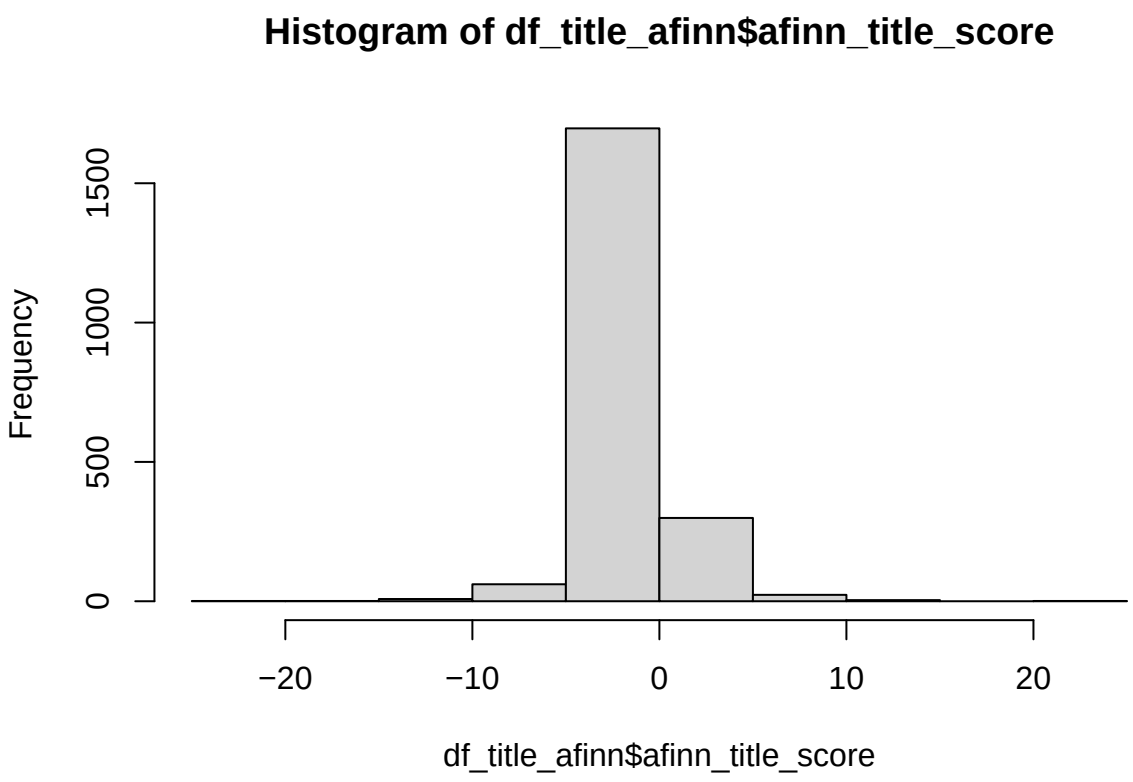
```
df_title_afinn <- df_title_afinn %>% dplyr::select(Id, afinn_title_score) %>%
  unique() %>%
  ungroup()

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>
```

```
# 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

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

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

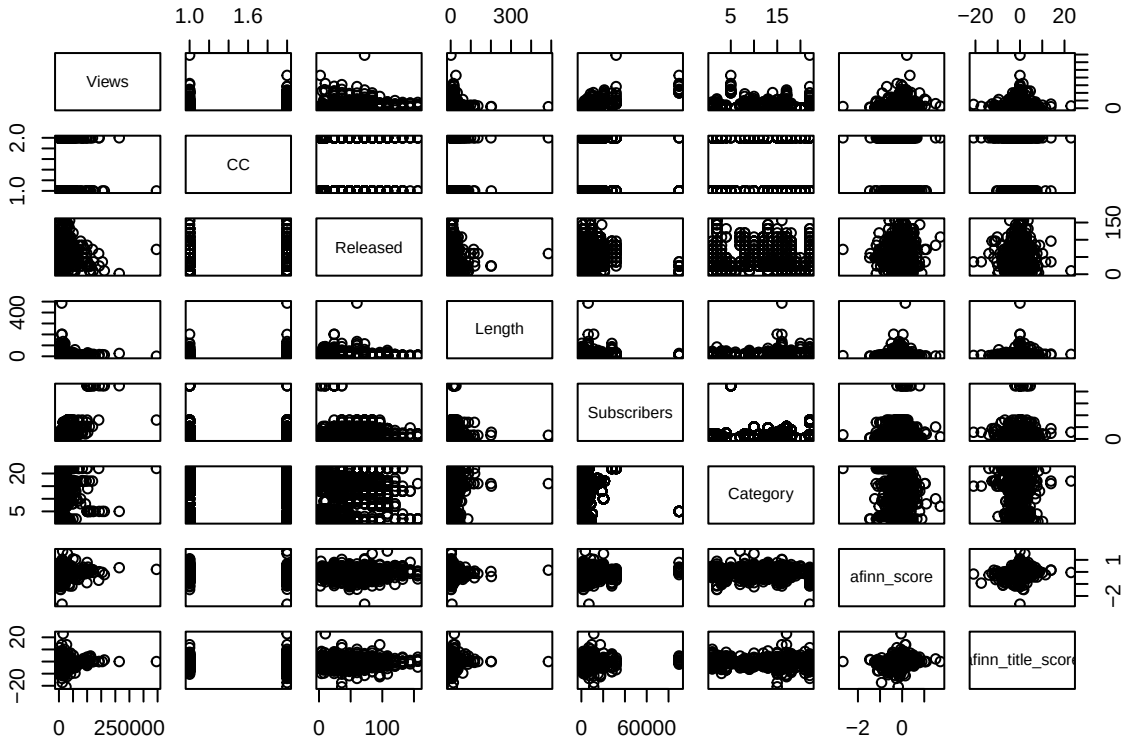
```
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (6): Id, Channel, Title, URL, Category, Transcript
## dbl (7): Subscribers, CC, Released, Views, Length, afinn_score, afinn_title_...
```

```
##
## 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.
```

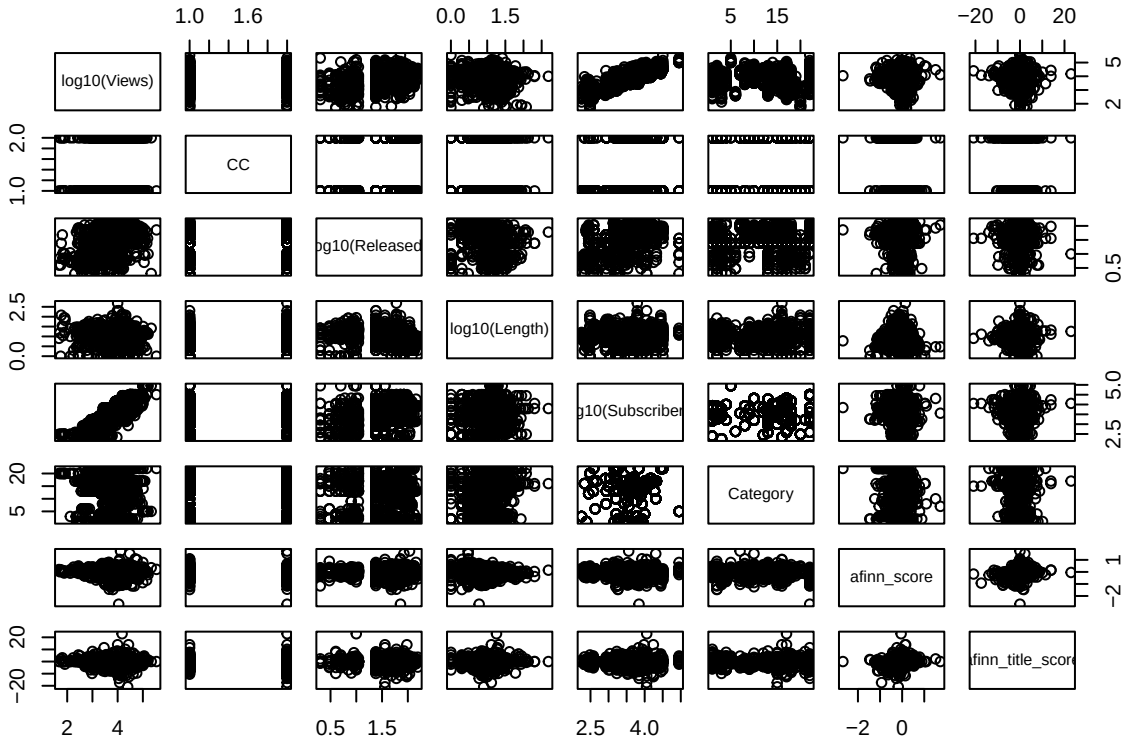
```
df1$CC <- as.factor(df1$CC)
df1$Category <- as.factor(df1$Category)
df1$Subscribers <- as.numeric(df1$Subscribers)

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

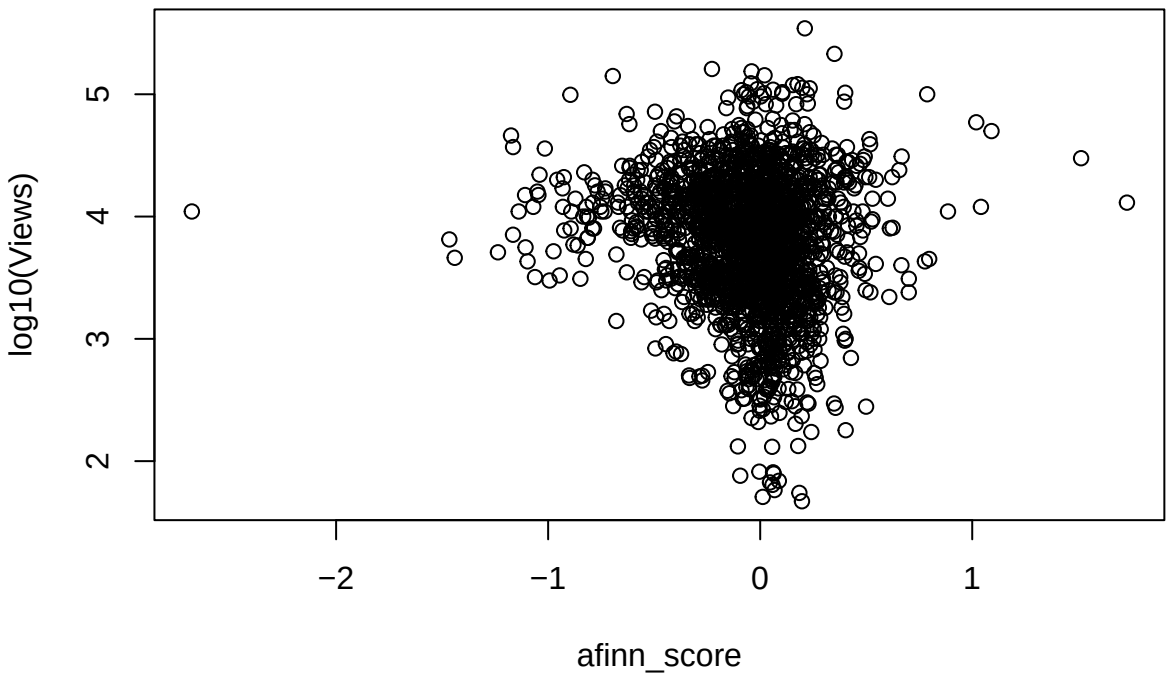
```
pairs(Views ~ CC + Released +
        Length + Subscribers + Category +
        afinn_score + afinn_title_score,
      data=df1)
```



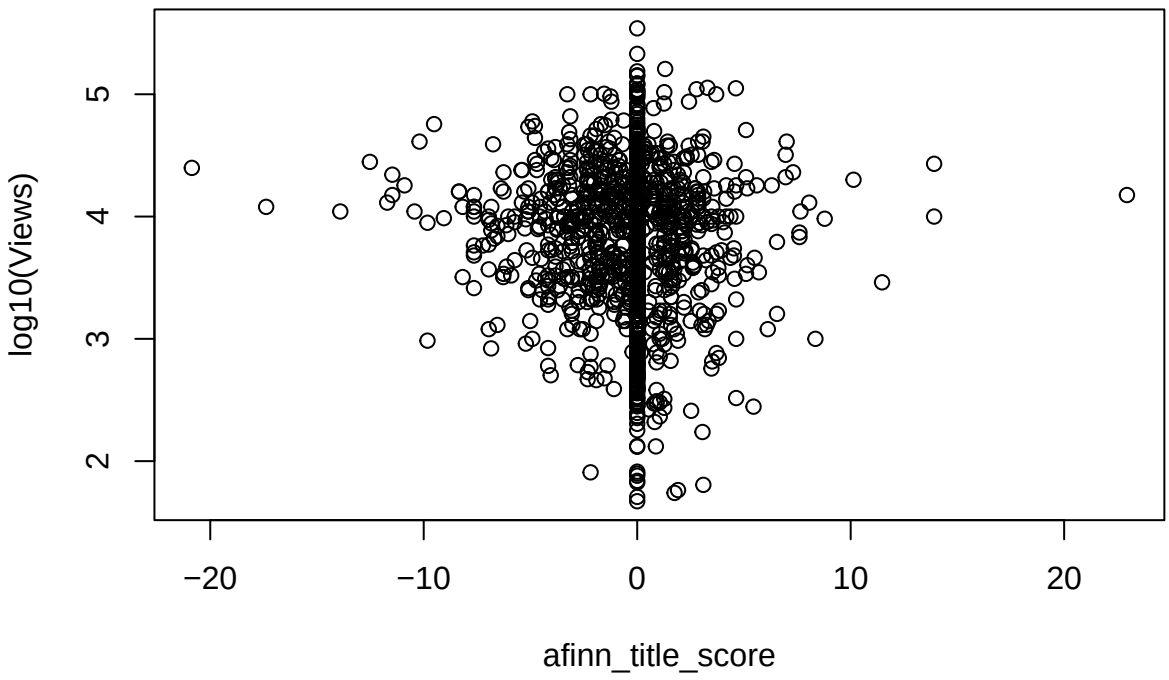

```
pairs(log10(Views) ~ CC + log10(Released) +
        log10(Length) + log10(Subscribers) + Category +
        afinn_score + afinn_title_score,
      data=df1)
```



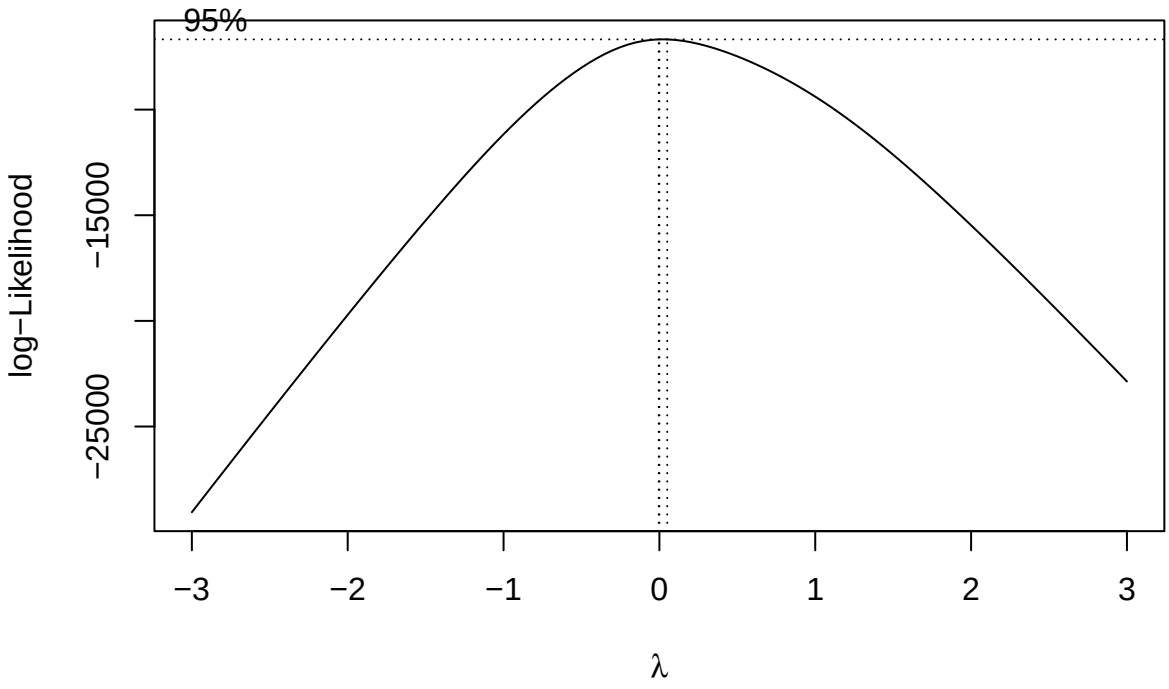

```
plot(log10(Views)~ afinn_score, data = df1)
```




```
plot(log10(Views)~ afinn_title_score, data = df1)
```




```
boxcox(Views ~ CC + log10(Released) + log10(Length) + log10(Subscribers) + Category + afinn_score + afi
       data=df1,
       lambda = seq(-3, 3, by = 0.05))
```




```
summary(powerTransform(Views ~
                         CC + log10(Released) + log10(Length) +
                         log10(Subscribers) + Category + afinn_score + afinn_title_score,
                       data=df1))
```

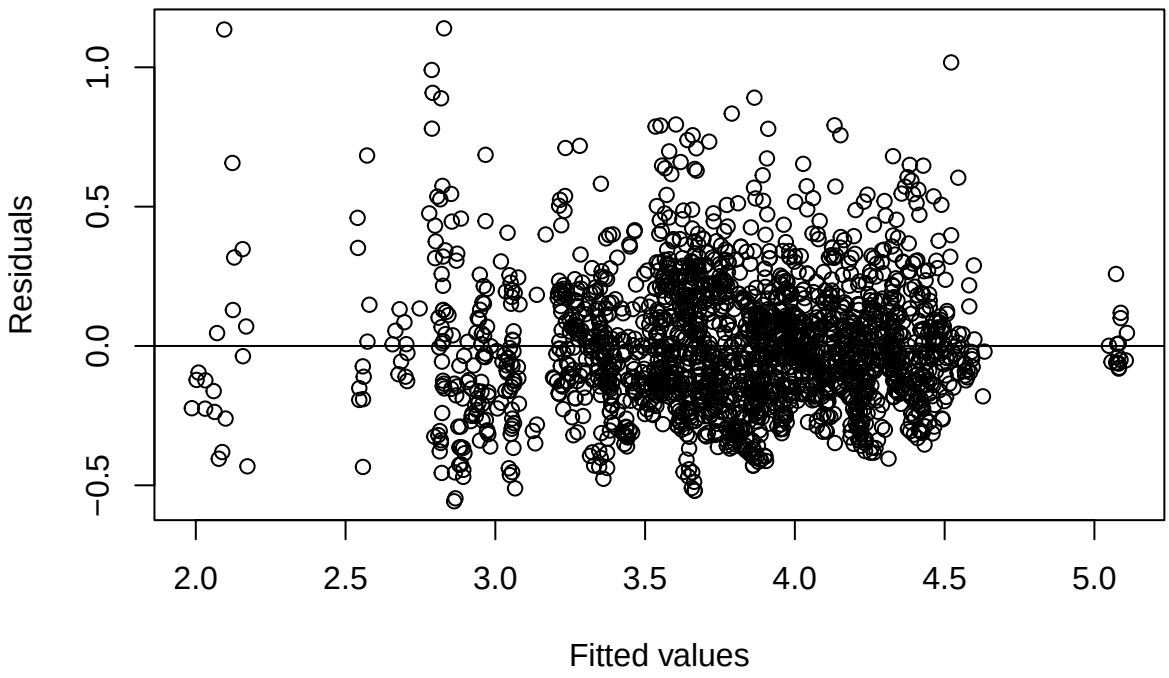
```
## bcPower Transformation to Normality
##    Est Power Rounded Pwr Wald Lwr Bnd Wald Upr Bnd
## Y1     0.021        0.02        7e-04       0.0412
##
## Likelihood ratio test that transformation parameter is equal to 0
##  (log transformation)
##                            LRT df     pval
## LR test, 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
```

```
lm1 <- lm(log10(Views) ~ CC + log10(Released) + log10(Length) + log10(Subscribers) + Category + afinn_s
summary(lm1)
```

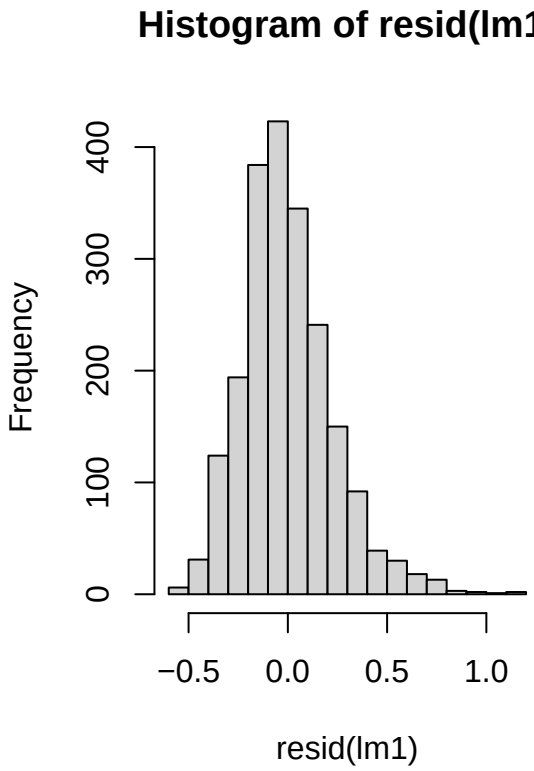
```
##
## Call:
## lm(formula = log10(Views) ~ CC + log10(Released) + log10(Length) +
##     log10(Subscribers) + Category + afinn_score + afinn_title_score,
```

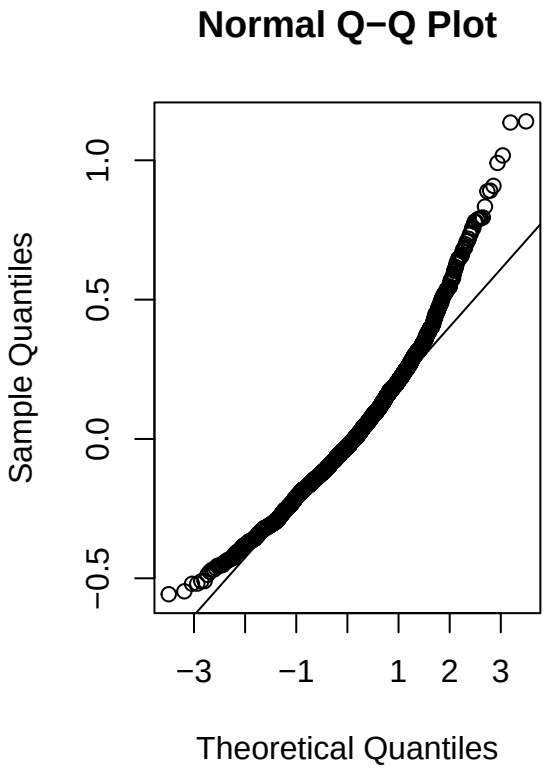
```
##     data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.55716 -0.15129 -0.02761  0.12819  1.13973
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   0.866095   0.049971  17.332  < 2e-16 ***
## CC1                           0.026619   0.011843   2.248 0.024702 *
## log10(Released)               0.010325   0.016986   0.608 0.543333
## log10(Length)                -0.081625   0.016780  -4.864 1.23e-06 ***
## log10(Subscribers)            0.828092   0.012171  68.038  < 2e-16 ***
## CategoryAutomobile,Comedy     0.175587   0.033178   5.292 1.34e-07 ***
## CategoryBlog                 -0.094845   0.027368  -3.465 0.000540 ***
## CategoryBlog,Comedy          -0.058156   0.039763  -1.463 0.143737
## CategoryBlog,Entertainment    0.199111   0.064003   3.111 0.001890 **
## CategoryBlog,Science         -0.272223   0.072664  -3.746 0.000184 ***
## CategoryComedy                0.413006   0.047244   8.742  < 2e-16 ***
## CategoryComedy,Entertainment  0.361365   0.031287  11.550  < 2e-16 ***
## CategoryComedy,Informative    0.341333   0.038953   8.763  < 2e-16 ***
## CategoryEntertainment         0.171039   0.036919   4.633 3.83e-06 ***
## CategoryEntertainment,Blog    0.139836   0.048066   2.909 0.003661 **
## CategoryEntertainment,Comedy  0.392950   0.031557  12.452  < 2e-16 ***
## CategoryFood                  0.128524   0.023704   5.422 6.58e-08 ***
## CategoryFood,Entertainment    0.222136   0.051517   4.312 1.69e-05 ***
## CategoryInformative           0.017522   0.025111   0.698 0.485392
## CategoryNews                  0.086774   0.027058   3.207 0.001362 **
## CategoryScience              -0.021460   0.023619  -0.909 0.363669
## CategoryTech                 -0.253227   0.025544  -9.914  < 2e-16 ***
## CategoryTech,Comedy          -0.165748   0.052488  -3.158 0.001612 **
## CategoryTech,Informative     -0.775347   0.057557 -13.471  < 2e-16 ***
## CategoryTech,News            -0.441156   0.059208  -7.451 1.35e-13 ***
## CategoryVideoGames           -0.087889   0.024473  -3.591 0.000337 ***
## afinn_score                  -0.024840   0.020043  -1.239 0.215366
## afinn_title_score            -0.002893   0.002338  -1.238 0.215996
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2299 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
```

```
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))
```



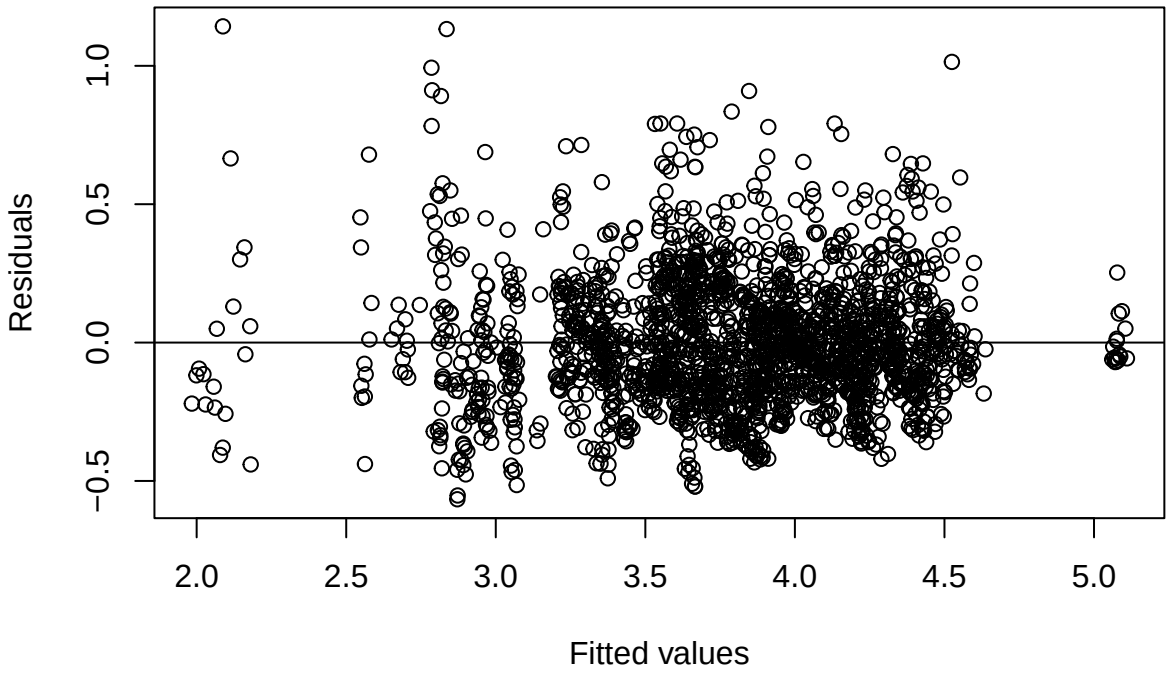



```
lm2 <- lm(log10(Views) ~ CC + log10(Length) + log10(Subscribers) + Category + afinn_score , data=df1)
summary(lm2)
```

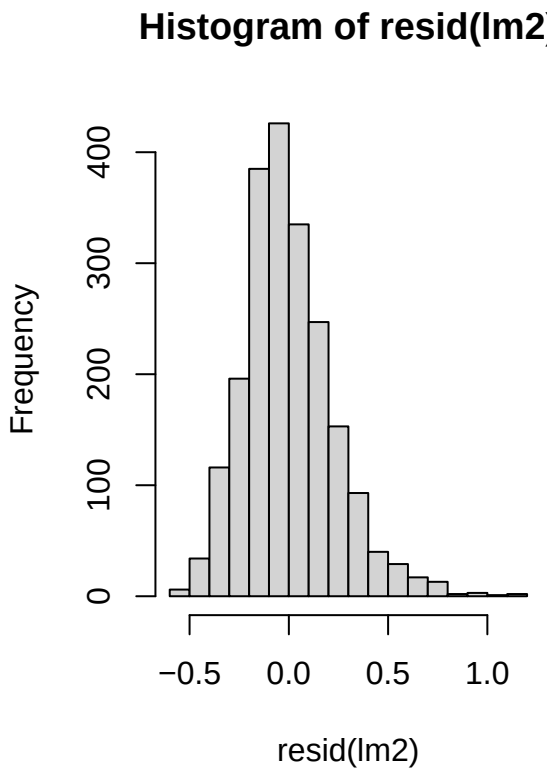
```
##
## Call:
## lm(formula = log10(Views) ~ CC + log10(Length) + log10(Subscribers) +
##     Category + afinn_score, data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.56617 -0.15068 -0.02771  0.12714  1.14261
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     0.87490    0.04663  18.761  < 2e-16 ***
## CC1                             0.02633    0.01177   2.237 0.025411 *
## log10(Length)                  -0.08380    0.01647  -5.087 3.97e-07 ***
## log10(Subscribers)              0.83081    0.01169  71.084  < 2e-16 ***
## CategoryAutomobile,Comedy       0.17267    0.03310   5.216 2.01e-07 ***
## CategoryBlog                   -0.09481    0.02724  -3.480 0.000512 ***
## CategoryBlog,Comedy            -0.05906    0.03961  -1.491 0.136110
## CategoryBlog,Entertainment      0.19031    0.06314   3.014 0.002608 **
## CategoryBlog,Science           -0.27575    0.07219  -3.820 0.000137 ***
## CategoryComedy                  0.41567    0.04719   8.808  < 2e-16 ***
## CategoryComedy,Entertainment    0.36335    0.03121  11.641  < 2e-16 ***
```

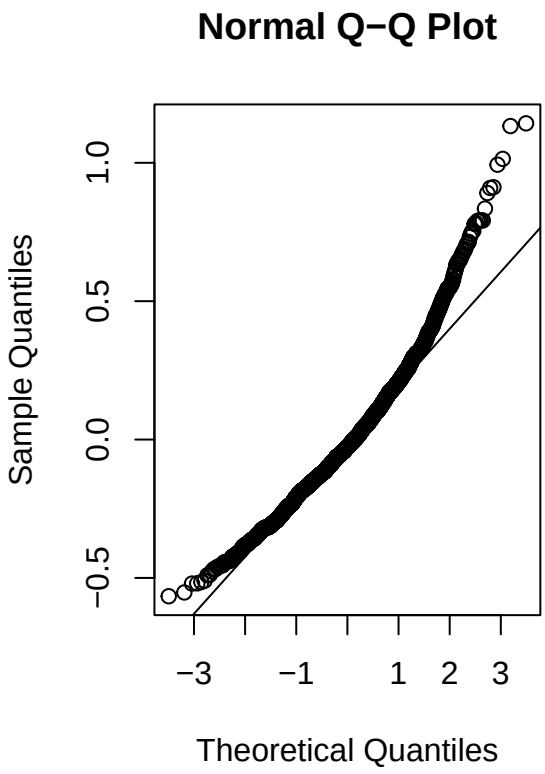
```
## CategoryComedy,Informative    0.34493    0.03876   8.898  < 2e-16 ***
## CategoryEntertainment         0.17274    0.03686   4.686 2.96e-06 ***
## CategoryEntertainment,Blog    0.13940    0.04799   2.905 0.003710 **
## CategoryEntertainment,Comedy  0.39354    0.03141  12.528  < 2e-16 ***
## CategoryFood                  0.12839    0.02360   5.439 5.98e-08 ***
## CategoryFood,Entertainment    0.22164    0.05151   4.303 1.76e-05 ***
## CategoryInformative           0.01889    0.02508   0.753 0.451476
## CategoryNews                  0.08725    0.02696   3.236 0.001230 **
## CategoryScience              -0.02134    0.02358  -0.905 0.365534
## CategoryTech                 -0.25290    0.02553  -9.908  < 2e-16 ***
## CategoryTech,Comedy          -0.16748    0.05232  -3.201 0.001391 **
## CategoryTech,Informative     -0.78025    0.05697 -13.695  < 2e-16 ***
## CategoryTech,News            -0.44191    0.05872  -7.526 7.74e-14 ***
## CategoryVideoGames           -0.08563    0.02434  -3.517 0.000446 ***
## afinn_score                  -0.02929    0.01966  -1.489 0.136523
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2299 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(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))
```



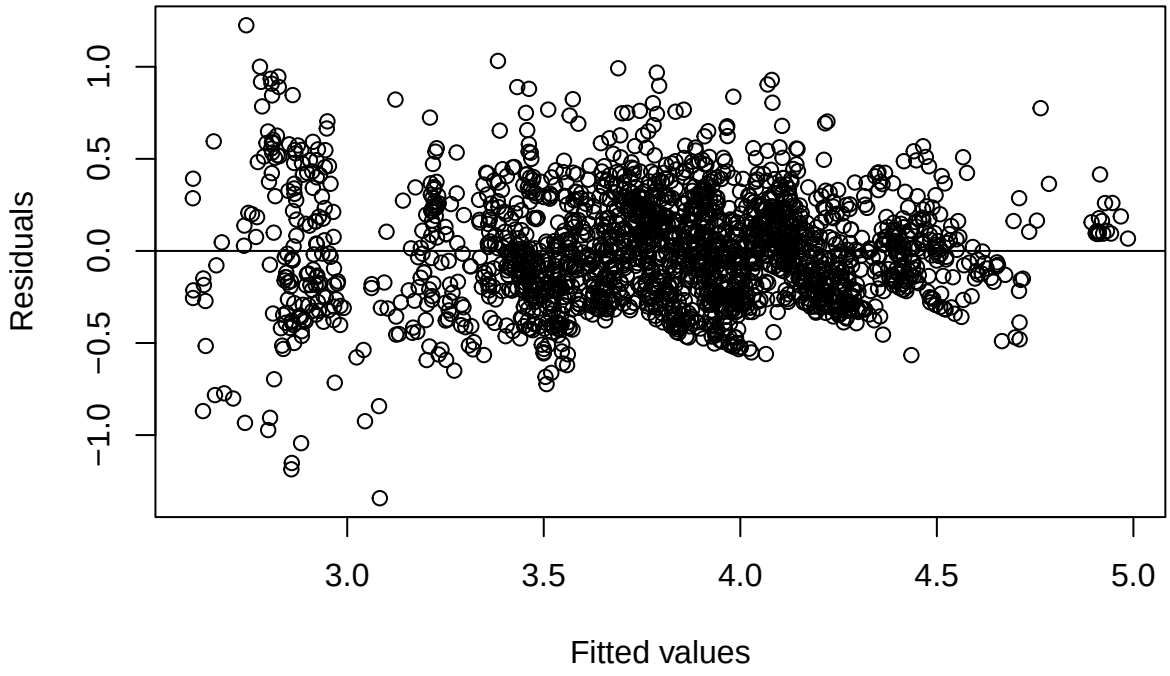



```
lm3 <- lm(log10(Views) ~ CC  + log10(Length) + log10(Subscribers) + afinn_score, data=df1)
summary(lm3)
```

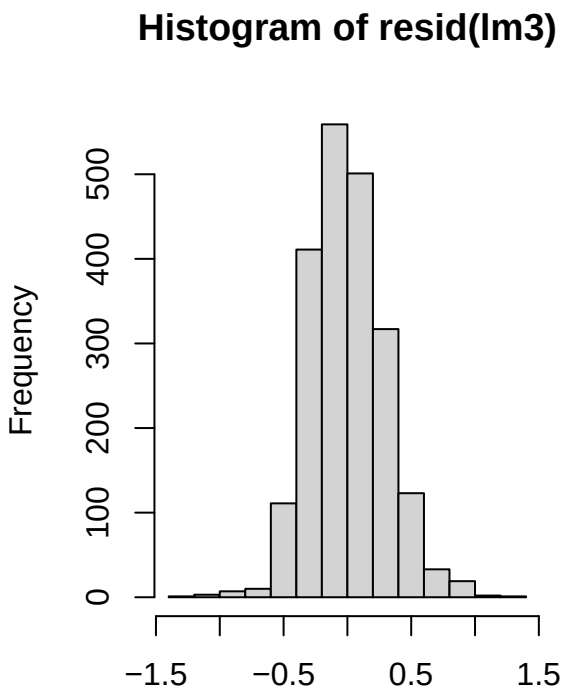
```
##
## Call:
## lm(formula = log10(Views) ~ CC + log10(Length) + log10(Subscribers) +
##     afinn_score, data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.34258 -0.20632 -0.02035  0.18661  1.22521
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.91078    0.04980  18.290  < 2e-16 ***
## CC1                 0.04795    0.01343   3.570 0.000365 ***
## log10(Length)      -0.19559    0.01923 -10.170  < 2e-16 ***
## log10(Subscribers)  0.85720    0.01332  64.347  < 2e-16 ***
## afinn_score        -0.03550    0.02323  -1.528 0.126613
## ---
```

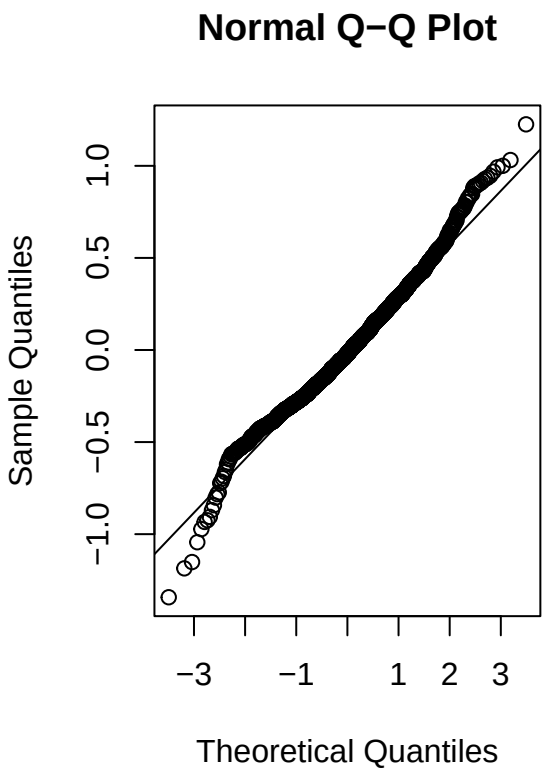
```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2936 on 2093 degrees of freedom
## Multiple R-squared:  0.6956, Adjusted R-squared:  0.695
## F-statistic:  1196 on 4 and 2093 DF,  p-value: < 2.2e-16
```

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




```
par(mfrow=c(1,2))
hist(resid(lm3))
qqnorm(resid(lm3))
qqline(resid(lm3))
```






```
# lm1 <- lm(log10(Views) ~ CC + log10(Released) + log10(Length) + log10(Subscribers) + Category + afinn
lm4 <- step(lm1)
```

```
## Start:  AIC=-6140.89
## log10(Views) ~ CC + log10(Released) + log10(Length) + log10(Subscribers) +
##     Category + afinn_score + afinn_title_score
##
##                       Df Sum of Sq    RSS     AIC
## - log10(Released)      1     0.020 109.42 -6142.5
## - afinn_title_score    1     0.081 109.48 -6141.3
## - afinn_score          1     0.081 109.48 -6141.3
## <none>                             109.40 -6140.9
## - CC                   1     0.267 109.67 -6137.8
## - log10(Length)        1     1.251 110.65 -6119.0
## - Category            21    69.503 178.91 -5151.0
## - log10(Subscribers)   1   244.656 354.06 -3678.9
##
## Step:  AIC=-6142.51
## log10(Views) ~ CC + log10(Length) + log10(Subscribers) + Category +
##     afinn_score + afinn_title_score
##
##                       Df Sum of Sq    RSS     AIC
## - afinn_title_score    1     0.079 109.50 -6143.0
## - afinn_score          1     0.079 109.50 -6143.0
## <none>                             109.42 -6142.5
```

```
## - CC                  1     0.282 109.70 -6139.1
## - log10(Length)       1     1.359 110.78 -6118.6
## - Category           21    71.007 180.43 -5135.2
## - log10(Subscribers)  1   265.992 375.41 -3558.1
##
## Step:  AIC=-6143
## log10(Views) ~ CC + log10(Length) + log10(Subscribers) + Category +
##     afinn_score
##
##                       Df Sum of Sq    RSS     AIC
## <none>                             109.50 -6143.0
## - afinn_score         1     0.117 109.62 -6142.8
## - CC                  1     0.264 109.76 -6139.9
## - log10(Length)       1     1.367 110.87 -6119.0
## - Category           21    70.946 180.45 -5137.0
## - log10(Subscribers)  1   267.037 376.54 -3553.8
```

```
summary(lm4)
```

```
##
## Call:
## lm(formula = log10(Views) ~ CC + log10(Length) + log10(Subscribers) +
##     Category + afinn_score, data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.56617 -0.15068 -0.02771  0.12714  1.14261
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    0.87490    0.04663  18.761  < 2e-16 ***
## CC1                            0.02633    0.01177   2.237 0.025411 *
## log10(Length)                 -0.08380    0.01647  -5.087 3.97e-07 ***
## log10(Subscribers)             0.83081    0.01169  71.084  < 2e-16 ***
## CategoryAutomobile,Comedy      0.17267    0.03310   5.216 2.01e-07 ***
## CategoryBlog                  -0.09481    0.02724  -3.480 0.000512 ***
## CategoryBlog,Comedy           -0.05906    0.03961  -1.491 0.136110
## CategoryBlog,Entertainment     0.19031    0.06314   3.014 0.002608 **
## CategoryBlog,Science          -0.27575    0.07219  -3.820 0.000137 ***
## CategoryComedy                 0.41567    0.04719   8.808  < 2e-16 ***
## CategoryComedy,Entertainment   0.36335    0.03121  11.641  < 2e-16 ***
## CategoryComedy,Informative     0.34493    0.03876   8.898  < 2e-16 ***
## CategoryEntertainment          0.17274    0.03686   4.686 2.96e-06 ***
## CategoryEntertainment,Blog     0.13940    0.04799   2.905 0.003710 **
## CategoryEntertainment,Comedy   0.39354    0.03141  12.528  < 2e-16 ***
## CategoryFood                   0.12839    0.02360   5.439 5.98e-08 ***
## CategoryFood,Entertainment     0.22164    0.05151   4.303 1.76e-05 ***
## CategoryInformative            0.01889    0.02508   0.753 0.451476
## CategoryNews                   0.08725    0.02696   3.236 0.001230 **
## CategoryScience               -0.02134    0.02358  -0.905 0.365534
## CategoryTech                  -0.25290    0.02553  -9.908  < 2e-16 ***
## CategoryTech,Comedy           -0.16748    0.05232  -3.201 0.001391 **
## CategoryTech,Informative      -0.78025    0.05697 -13.695  < 2e-16 ***
## CategoryTech,News             -0.44191    0.05872  -7.526 7.74e-14 ***
```

```
## CategoryVideoGames           -0.08563    0.02434  -3.517 0.000446 ***
## afinn_score                  -0.02929    0.01966  -1.489 0.136523
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2299 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
```

```
# fit lm4 (the final model in MLR part) to df_train
lm5 <- lm(log10(Views) ~ CC + log10(Length) + log10(Subscribers) + Category + afinn_score, data = df_tra

# make prediction
pred1 <- predict(lm5, newdata = df_test)

# Compute the RMSE
RMSE(df_test$Views, pred1)
```

```
## [1] 20224.33
```

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)
```

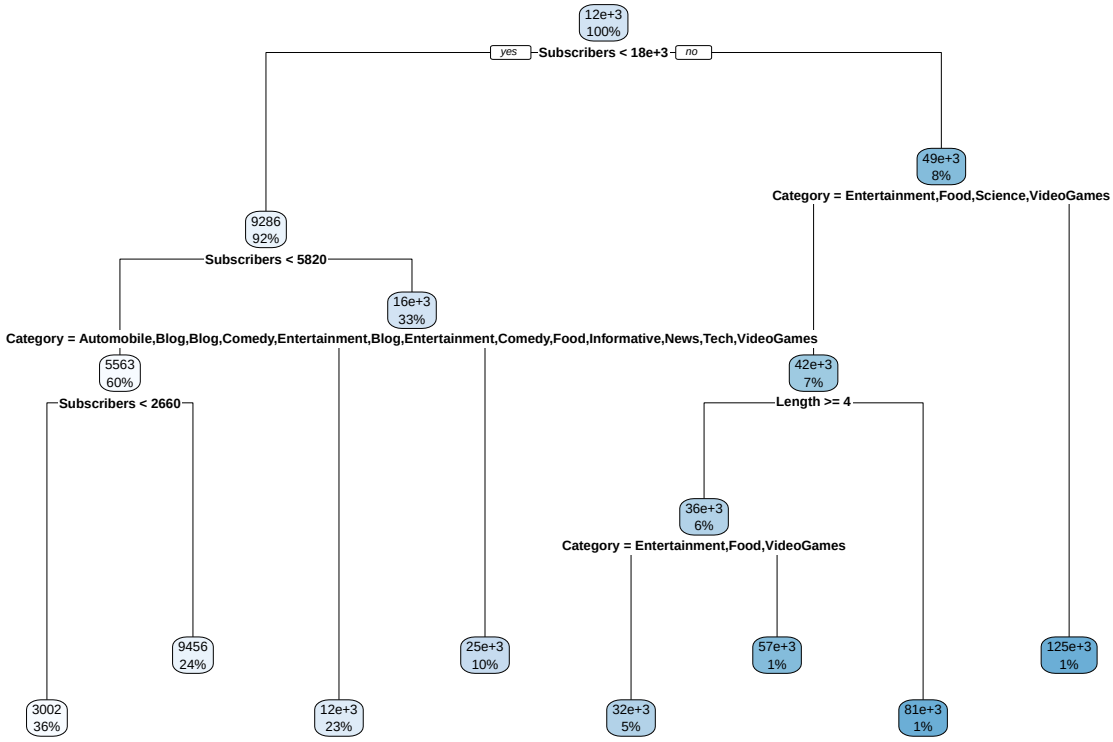
```
## Call:
## rpart(formula = Views ~ CC + Released + Category + Length + Subscribers +
##     afinn_score + afinn_title_score, data = df_train, method = "anova")
##   n= 1469
##
##           CP nsplit rel error    xerror      xstd
## 1 0.31049310      0 1.0000000 1.0015040 0.2464760
## 2 0.11052780      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
```

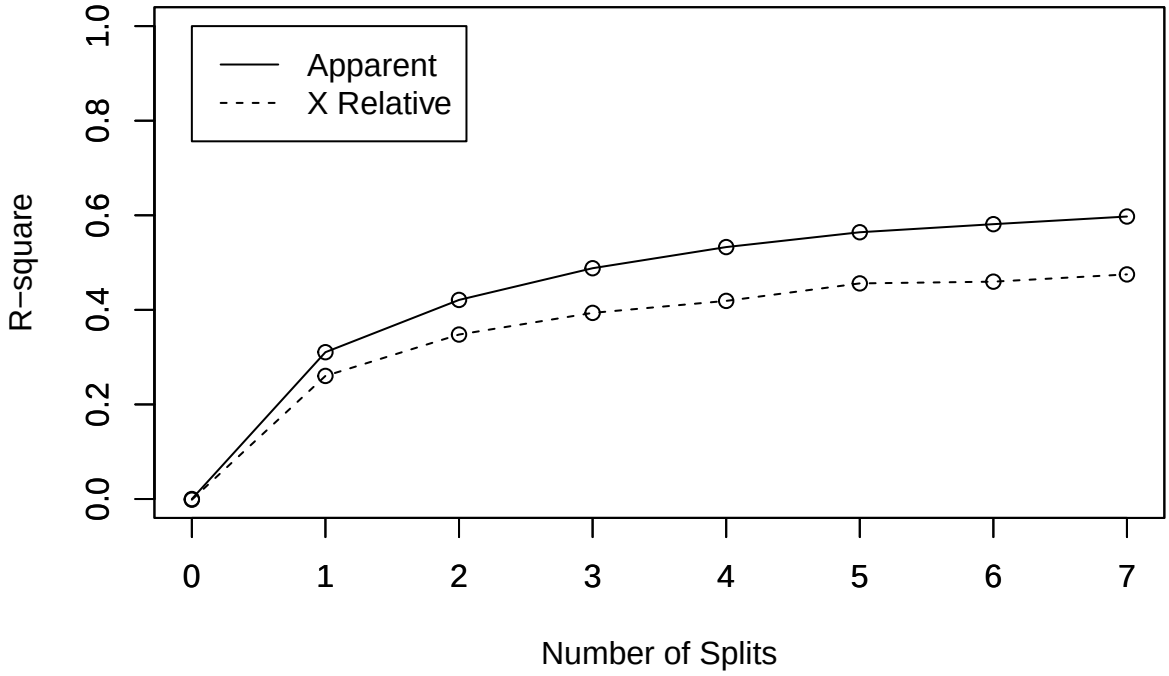
```
# Plot the desicion tree
rpart.plot(t1)
```

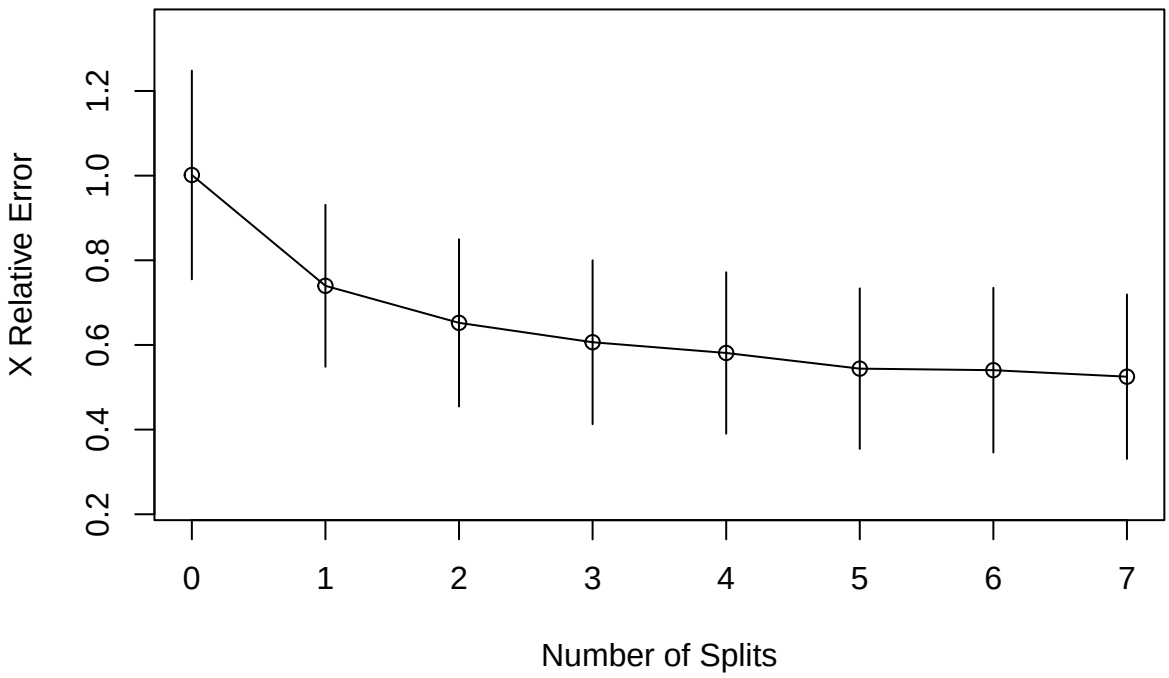



```
# Plot R-square vs Splits and the Relative Error vs Splits.
rsq.rpart(t1)
```

```
##
## 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
RMSE(df_test$Views, pred_tree)
```

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

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

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

Random Forest

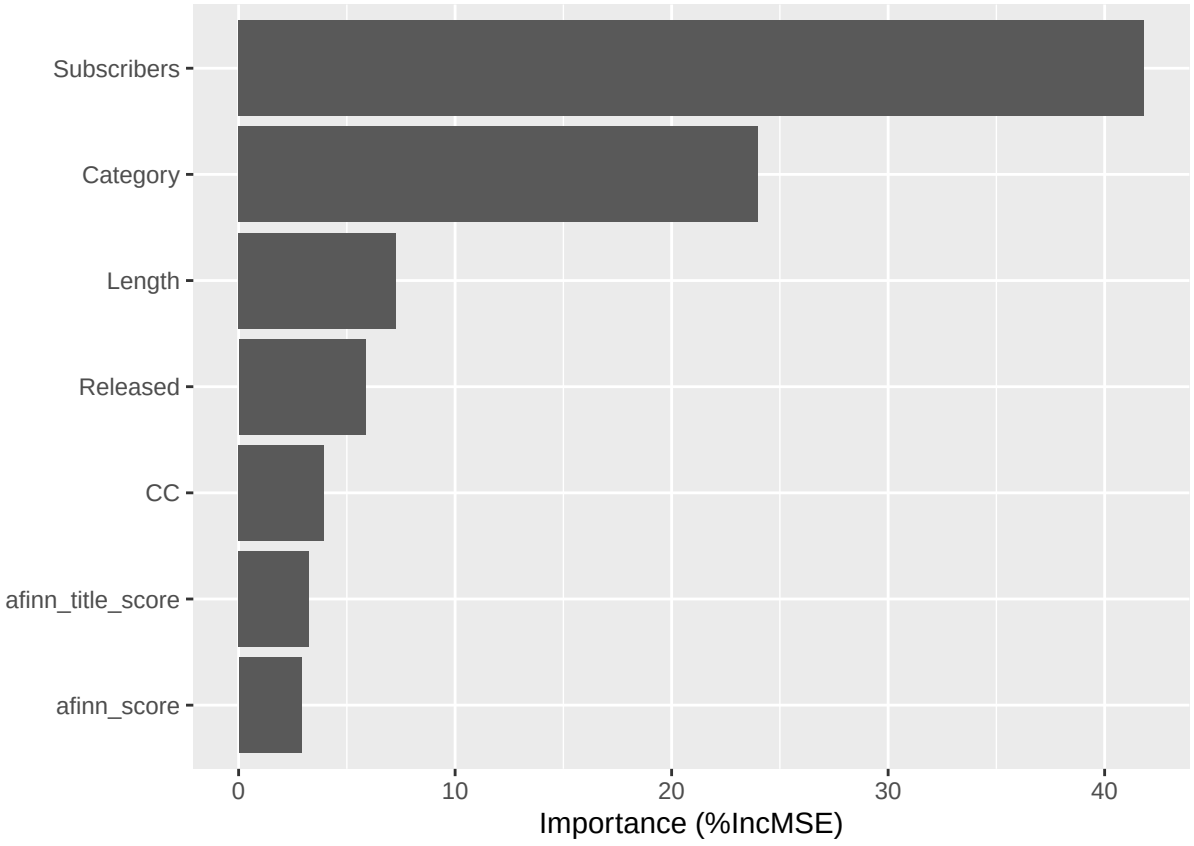
Fit a Random Forest on the training set usinng the defaults for mtry and ntree.

```
set.seed(652)
rf1 <- randomForest(Views ~ CC + Released + Category + Length + Subscribers + afinn_score + afinn_title
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.

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



Make predictions on the test set and compute the RMSE

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

# Compute the RMSE
RMSE(df_test$Views, pred_rf)
```

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

```r
# test R^2
cor(df_test$Views, pred_rf)^2
```

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

Conclusion(TODO)

Model	RMSE	R Squared	Number of Coefficients	performance	interpretability
linear regression	-	-	-	-	-
regression tree	-	-	-	-	-
random forest	-	-	-	-	-

Linear Regression vs Regression Tree VS Random Forest

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.