# HW2

AUTHOR
Margaret Miles

## STATS 506 - HW2

Margaret Miles

## Problem 1 - Modified Random Walk

Consider a 1-dimensional random walk with the following rules:

Start at 0. At each step, move +1 or -1 with 50/50 probability. If +1 is chosen, 5% of the time move +10 instead. If -1 is chosen, 20% of the time move -3 instead. Repeat steps 2-4 times. (Note that if the +10 is chosen, it's not +1 then +10, it is just +10.)

Write a function to determine the end position of this random walk.

The input and output should be:

Input: The number of steps

Output: The final position of the walk

random_walk(10) [1] 4

random_walk(10) [1] -11

We're going to implement this in different ways and compare them.

**a. Implement the random walk in these three versions:**

Version 1: using a loop.

```
#' Version 1 of random walk
#'
#' Takes a random step number count based on input starting at 0, and returns a random ou
#'
#' @params n = number of steps in the walk
#' @returns final = final position of the walk
#'
#' @examples
#' ver1(10) = 4
#' ver1(10) = -11
#'
ver1 <- function(n){
  # start at 0
```

```r
  walk <- 0
  steps <- 1
  # At each step from 1 to n input
  for (steps in 1:n){
    # move +1 or -1 with 50/50 probability
    move <- sample(c(1,-1), size = 1, prob = c(0.5, 0.5))
    # take a step in that direction
    # print(move)
    walk <- walk + move
    # +1 is chosen, 5% of the time move +10 instead (9 because you already stepped 1)
    if (move > 0) {
      walk <- walk + sample(c(0, 9), 1, prob = c(0.95, 0.05))
      # print(walk)
    } else {
      # If -1 is chosen, 20% of the time move -3 instead. (-2 because you already stepped
      walk <- walk + sample(c(0, -2), 1, prob = c(0.80, 0.20))
      # print(walk)
    }
  }
  final <- walk
  return(final)
}

ver1(10)
```

```
[1] 2
```

```r
ver1(10)
```

```
[1] 9
```

Version 2: using built-in R vectorized functions. (Using no loops.) (Hint: Does the order of steps matter?)

```r
#' Version 2 of random walk
#'
#' Takes a random step number count based on input starting at 0, and returns a random ou
#' using vectorized functions
#'
#' @params n = number of steps in the walk
#' @returns final = final position of the walk
#'
#' @examples
#' ver1(10) = 4
#' ver1(10) = -11
#'
ver2 <- function(n){
  # set up moves +1 or -1
  steps <- sample(c(1, -1), n, replace = TRUE)
  # print(steps)
```

```
  # +10 jump 5% of the time when base is +1
  steps[steps == 1] <- 1 + rbinom(sum(steps == 1), 1, 0.05) * 9
  # print(steps)

  # -3 jump 20% of the time
  steps[steps == -1] <- -1 +rbinom(sum(steps == -1), 1, 0.20) * -2
  # print(steps)

  # then sum to find final spot
  final <- sum(steps)
  return(final)
}

ver2(10)
```

```
[1] -14
```

```
ver2(10)
```

```
[1] -6
```

Version 3: Implement the random walk using one of the “apply” functions.

```
#' Version 3 of random walk
#'
#' Takes a random step number count based on input starting at 0, and returns a random ou
#' using apply functions
#'
#' @params n = number of steps in the walk
#' @returns final = final position of the walk
#'
#' @examples
#' ver1(10) = 4
#' ver1(10) = -11
#'
ver3 <- function(n){
  # set up moves +1 or -1
  steps <- sample(c(1, -1), n, replace = TRUE)

  # using apply function, +10 jump 5% of the time when base is +1
  # and -3 jump 20% of the time when base is -1
  walk <- vapply(steps, function(x){
    if(x == 1){
      x <- sample(c(1, 10), 1, prob = c(0.95, 0.05))
    } else {
      x <- sample(c(-1, -3), 1, prob = c(0.80, 0.20))
    }
  }, numeric(1))
  # print(walk)
```

```
  return(sum(walk))
}

ver3(10)
```

```
[1] -4
```

```
ver3(10)
```

```
[1] -4
```

Demonstrate that all versions work by running the following: random_walk1(10) random_walk2(10) random_walk3(10) random_walk1(1000) random_walk2(1000) random_walk3(1000)

```
random_walk1 <- ver1
random_walk2 <- ver2
random_walk3 <- ver3

random_walk1(10)
```

```
[1] -4
```

```
random_walk2(10)
```

```
[1] 2
```

```
random_walk3(10)
```

```
[1] 7
```

```
random_walk1(1000)
```

```
[1] 12
```

```
random_walk2(1000)
```

```
[1] 172
```

```
random_walk3(1000)
```

```
[1] 148
```

### b. Demonstrate that the three versions can give the same result. Show this for both n=10 and n=1000. (You will need to add a way to control the randomization.)

```
# version #1 walk for same result
random_walk1_same <- function(n) {
```

```r
  # set up with +1 or -1
  steps <- sample(c(1, -1), n, replace = TRUE)

  # check to see if start is the same
  # print(steps)

  # At each step from 0 to n input
  for (i in 1:n){
    # +1 is chosen, 5% of the time move +10
    if (steps[i] > 0) {
      steps[i] <- ifelse(runif(1) < 0.05, 10, 1)
    } else {
      # If -1 is chosen, 20% of the time move -3
      steps[i] <- ifelse(runif(1) < 0.20, -3, -1)
    }
  }

  # print(steps)
  # sum
  final <- sum(steps)
  return(final)
}

# version #2 walk for same result
random_walk2_same <- function(n) {

  # set up with +1 or -1
  steps <- sample(c(1, -1), n, replace = TRUE)

  # check to see if start is the same
  # print(steps)

  # uniform random draws
  u <- runif(n)

  # step 1: replace the +1's
  steps[steps == 1]  <- ifelse(u[steps == 1] < 0.05, 10, 1)

  # step 2: replace the -1's
  steps[steps == -1] <- ifelse(u[steps == -1] < 0.20, -3, -1)

  # print(steps)
  # then sum to find final spot
  final <- sum(steps)
  return(final)
}

# version #3 walk for same result
random_walk3_same <- function(n) {
```

```r
  # set up with +1 or -1
  steps <- sample(c(1, -1), n, replace = TRUE)

  # check to see if start is the same
  # print(steps)

  # using apply function, +10 jump 5% of the time when base is +1
  # and -3 jump 20% of the time when base is -1
  walk <- vapply(steps, function(x){
    if(x == 1){
      ifelse(runif(1) < 0.05, 10, 1)
    } else {
      ifelse(runif(1) < 0.20, -3, -1)
    }
  }, numeric(1))

  # print(walk)
  return(sum(walk))
}

set.seed(67)
random_walk1_same(10)
```

```
[1] 2
```

```r
set.seed(67)
random_walk2_same(10)
```

```
[1] 2
```

```r
set.seed(67)
random_walk3_same(10)
```

```
[1] 2
```

```r
set.seed(67)
random_walk1_same(1000)
```

```
[1] 28
```

```r
set.seed(67)
random_walk2_same(1000)
```

```
[1] 28
```

```r
set.seed(67)
random_walk3_same(1000)
```

```
[1] 28
```

**c. Use the microbenchmark package to clearly demonstrate the speed of the implementations. Compare performance with a low input (1,000) and a large input (100,000). Discuss the results.**

```
library(microbenchmark)

# Benchmark with n = 1,000
set.seed(67)
microbenchmark(
  walk1 = random_walk1_same(1000),
  walk2 = random_walk2_same(1000),
  walk3 = random_walk3_same(1000)
)
```

```
Warning in microbenchmark(walk1 = random_walk1_same(1000), walk2 =
random_walk2_same(1000), : less accurate nanosecond times to avoid potential
integer overflows

Unit: microseconds
  expr      min        lq       mean    median        uq      max neval cld
 walk1  851.119  870.2455  939.52320  899.9910  917.8055 3903.036   100 a
 walk2   42.681   45.4485   49.34883   47.1295   52.5620  104.755   100  b
 walk3 1033.200 1085.1265 1144.49532 1109.3165 1124.5685 1979.972   100   c
```

```
# Benchmark with n = 100,000
set.seed(67)
microbenchmark(
  walk1 = random_walk1_same(100000),
  walk2 = random_walk2_same(100000),
  walk3 = random_walk3_same(100000)
)
```

```
Unit: milliseconds
  expr        min         lq       mean     median         uq        max neval
 walk1  89.823456  91.121147  92.896674  92.261562  93.350481 117.133105   100
 walk2   3.859494   3.992293   4.247253   4.097848   4.213755   7.094025   100
 walk3 109.645152 111.034068 115.304869 112.629399 114.825297 159.695738   100
 cld
 a
  b
   c
```

The results show that even in small implementation, vectorization was significantly faster. There is not much of a difference between a loop and apply, however loop is faster actually. This shows up even stronger when you run it for 10,000 times. Its extremely much faster to vectorize. My apply is longer because it calls two functions instead of 1 for the loop.

**d. What is the probability that the random walk ends at 0 if the number of steps is 10? 100? 1000? Defend your answers with evidence based upon a Monte Carlo simulation.**

```r
#' Monte Carlo Simulation
#'
#'
#'
#' @params n = number of steps
#' @params trials = number of trials
#' @params seed = seed for randomness
#' @returns results with all the information of the runs
#'
#' @examples
#' ver1(10) = 4
#' ver1(10) = -11
#'
mc_sim_prob <- function(n, trials, seed){
  set.seed(seed)

  # set up vectors for storage
  sums <- vector("list", 3)
  hits <- numeric(3)

  # run each random walk over # of trials
  sums[[1]] <- replicate(trials, random_walk1_same(n))  # N draws random walk 1(n)
  sums[[2]] <- replicate(trials, random_walk2_same(n))  # N draws random walk 2(n)
  sums[[3]] <- replicate(trials, random_walk3_same(n))  # N draws random walk 3(n)

  # store how many times it ends at 0
  hits[1] <- sum(sums[[1]] == 0)
  hits[2] <- sum(sums[[2]] == 0)
  hits[3] <- sum(sums[[3]] == 0)

  # results in a data frame
  results <- data.frame(
    n = n,
    trials = trials,

    walk1_hits   = hits[1],
    walk1_p_hat  = hits[1] / trials,
    walk1_ci_low = binom.test(hits[1], trials)$conf.int[1],
    walk1_ci_up  = binom.test(hits[1], trials)$conf.int[2],

    walk2_hits   = hits[2],
    walk2_p_hat  = hits[2] / trials,
    walk2_ci_low = binom.test(hits[2], trials)$conf.int[1],
    walk2_ci_up  = binom.test(hits[2], trials)$conf.int[2],

    walk3_hits   = hits[3],
    walk3_p_hat  = hits[3] / trials,
    walk3_ci_low = binom.test(hits[3], trials)$conf.int[1],
    walk3_ci_up  = binom.test(hits[3], trials)$conf.int[2]
  )
```

```
  return(results)
}

# random walk ends at 0 if the number of steps is 10? 100? 1000?
mc1 = mc_sim_prob(10, 10000, 67)
mc2 = mc_sim_prob(100, 10000, 67)
mc3 = mc_sim_prob(1000, 10000, 67)

cat("Number of steps:", mc1$n, "\n",
    "Number of MC sims:", mc1$trials, "\n",
    "Probability of 0 steps for Walk 1:", mc1$walk1_p_hat*100,
    "% Lower Bound:", mc1$walk1_ci_low,
    " Upper Bound:", mc1$walk1_ci_up, "\n",
    "Probability of 0 steps for Walk 2:", mc1$walk2_p_hat*100,
    "% Lower Bound:", mc1$walk2_ci_low,
    " Upper Bound:", mc1$walk2_ci_up, "\n",
    "Probability of 0 steps for Walk 3:", mc1$walk3_p_hat*100,
    "% Lower Bound:", mc1$walk3_ci_low,
    " Upper Bound:", mc1$walk3_ci_up, "\n", "\n")
```

```
Number of steps: 10
 Number of MC sims: 10000
 Probability of 0 steps for Walk 1: 13.51 % Lower Bound: 0.1284572  Upper Bound:
0.1419561
 Probability of 0 steps for Walk 2: 12.8 % Lower Bound: 0.121511  Upper Bound: 0.1347065
 Probability of 0 steps for Walk 3: 12.85 % Lower Bound: 0.1219999  Upper Bound:
0.1352172
```

```
cat("Number of steps:", mc2$n, "\n",
    "Number of MC sims:", mc2$trials, "\n",
    "Probability of 0 steps for Walk 1:", mc2$walk1_p_hat*100,
    "% Lower Bound:", mc2$walk1_ci_low,
    " Upper Bound:", mc2$walk1_ci_up, "\n",
    "Probability of 0 steps for Walk 2:", mc2$walk2_p_hat*100,
    "% Lower Bound:", mc2$walk2_ci_low,
    " Upper Bound:", mc2$walk2_ci_up, "\n",
    "Probability of 0 steps for Walk 3:", mc2$walk3_p_hat*100,
    "% Lower Bound:", mc2$walk3_ci_low,
    " Upper Bound:", mc2$walk3_ci_up, "\n", "\n")
```

```
Number of steps: 100
 Number of MC sims: 10000
 Probability of 0 steps for Walk 1: 1.94 % Lower Bound: 0.01678737  Upper Bound:
0.02229755
 Probability of 0 steps for Walk 2: 1.89 % Lower Bound: 0.01632191  Upper Bound:
0.02176339
 Probability of 0 steps for Walk 3: 2.14 % Lower Bound: 0.01865372  Upper Bound:
0.0244297
```

```
cat("Number of steps:", mc3$n, "\n",
    "Number of MC sims:", mc3$trials, "\n",
    "Probability of 0 steps for Walk 1:", mc3$walk1_p_hat*100,
    "% Lower Bound:", mc3$walk1_ci_low,
    " Upper Bound:", mc3$walk1_ci_up, "\n",
    "Probability of 0 steps for Walk 2:", mc3$walk2_p_hat*100,
    "% Lower Bound:", mc3$walk2_ci_low,
    " Upper Bound:", mc3$walk2_ci_up, "\n",
    "Probability of 0 steps for Walk 3:", mc3$walk3_p_hat*100,
    "% Lower Bound:", mc3$walk3_ci_low,
    " Upper Bound:", mc3$walk3_ci_up, "\n", "\n")
```

```
Number of steps: 1000
 Number of MC sims: 10000
 Probability of 0 steps for Walk 1: 0.49 % Lower Bound: 0.00362718  Upper Bound:
0.006472945
 Probability of 0 steps for Walk 2: 0.56 % Lower Bound: 0.004232871  Upper Bound:
0.007265981
 Probability of 0 steps for Walk 3: 0.63 % Lower Bound: 0.004844389  Upper Bound:
0.008053335
```

## Problem 2 - Mean of Mixture of Distributions

The number of cars passing an intersection is a classic example of a Poisson distribution. At a particular intersection, Poisson is an appropriate distribution most of the time, but during rush hours (hours of 8am and 5pm) the distribution is really normally distributed with a much higher mean.

**Using a Monte Carlo simulation, estimate the average number of cars that pass an intersection under the following assumptions:**

- From midnight until 7 AM, the distribution of cars per hour is Poisson with mean 1.
- From 9am to 4pm, the distribution of cars per hour is Poisson with mean 8.
- From 6pm to 11pm, the distribution of cars per hour is Poisson with mean 12.
- During rush hours (8am and 5pm), the distribution of cars per hour is Normal with mean 60 and variance 12 Accomplish this without using any loops.

(Hint: This can be done with extremely minimal code.)

```
# trails
n = 10000

# From midnight until 7:59 AM, the distribution of cars per hour is Poisson with mean 1.
time1 <- mean(rpois(n, 1))

# From 9am to 4pm, the distribution of cars per hour is Poisson with mean 8.
time2 <- mean(rpois(n, 8))
```

```
# From 6pm to 11:59pm, the distribution of cars per hour is Poisson with mean 12.
time3 <- mean(rpois(n, 12))

# During rush hours (8am and 5pm), the distribution of cars per hour is
# Normal with mean 60 and variance 12
time4 <- mean(rnorm(n, mean = 60, sd = 12))

#sum over all hours the average for a day
cars <- time1*8 + time2*7 + time3*6 + time4*2
print(cars)
```

```
[1] 255.5458
```

## Problem 3 - Linear Regression

Use the following code to download the YouTube Superbowl commercials data:

```
youtube <- read.csv('https://raw.githubusercontent.com/rfordatascience/tidytuesday/master
```

Information about this data can be found at https://github.com/rfordatascience/tidytuesday/tree/main/data/2021/2021-03-02. The research question for this project is to decide which of several attributes, if any, is associated with increased YouTube engagement metrics.

**a. Often in data analysis, we need to de-identify it. This is more important for studies of people, but let's carry it out here. Remove any column that might uniquely identify a commercial. This includes but isn't limited to things like brand, any URLs, the YouTube channel, or when it was published. Report the dimensions of the data after removing these columns.**

```
# remove all idenfying columns
youtube_deID <- youtube[, !(names(youtube) %in%
   c("brand", "superbowl_ads_dot_com_url", "youtube_url",
     "title", "description", "thumbnail", "channel_title"))]

dim(youtube_deID)
```

```
[1] 247  18
```

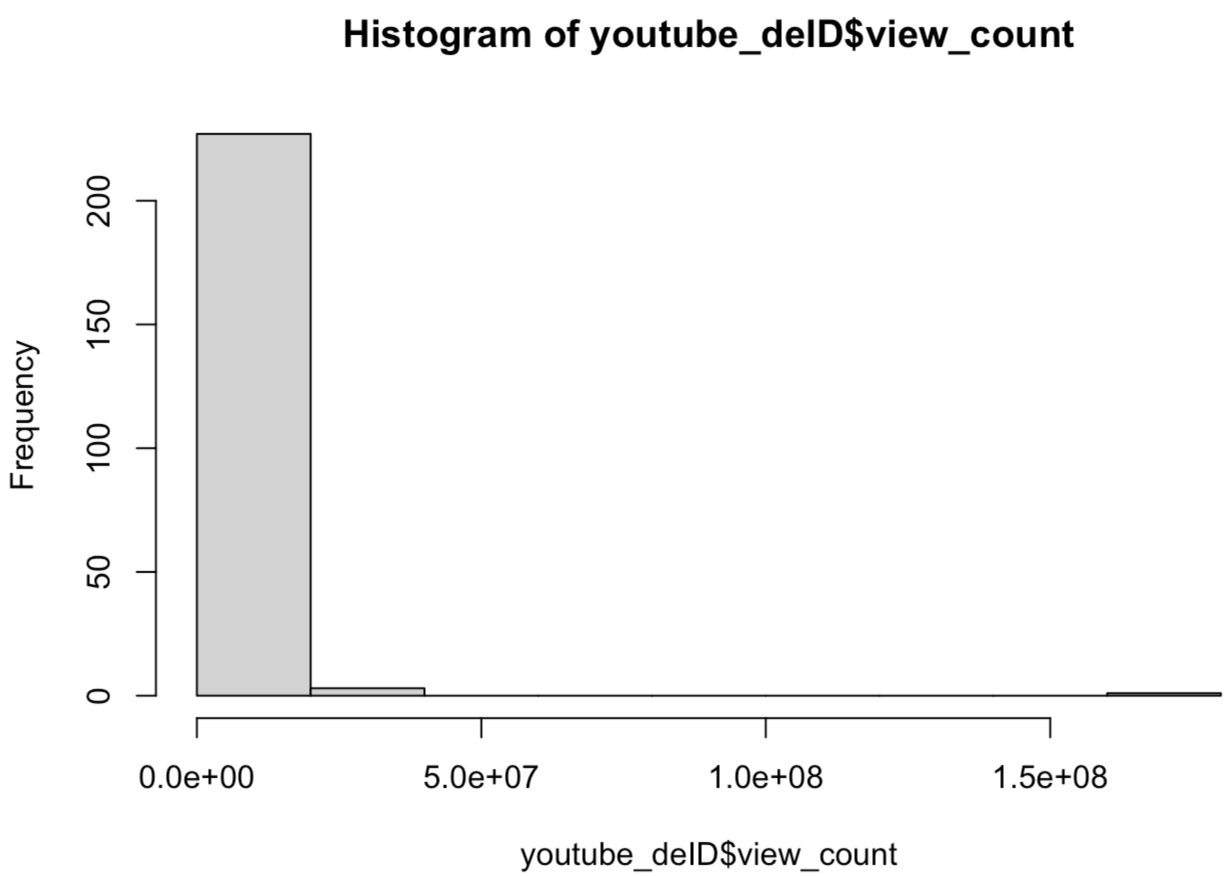
**b. For each of the following variables, examine their distribution.**

Determine whether i) The variable could be used as is as the outcome in a linear regression model, ii) The variable can use a transformation prior to being used as the outcome in a linear regression model, or iii) The variable would not be appropriate to use as the outcome in a linear regression model.

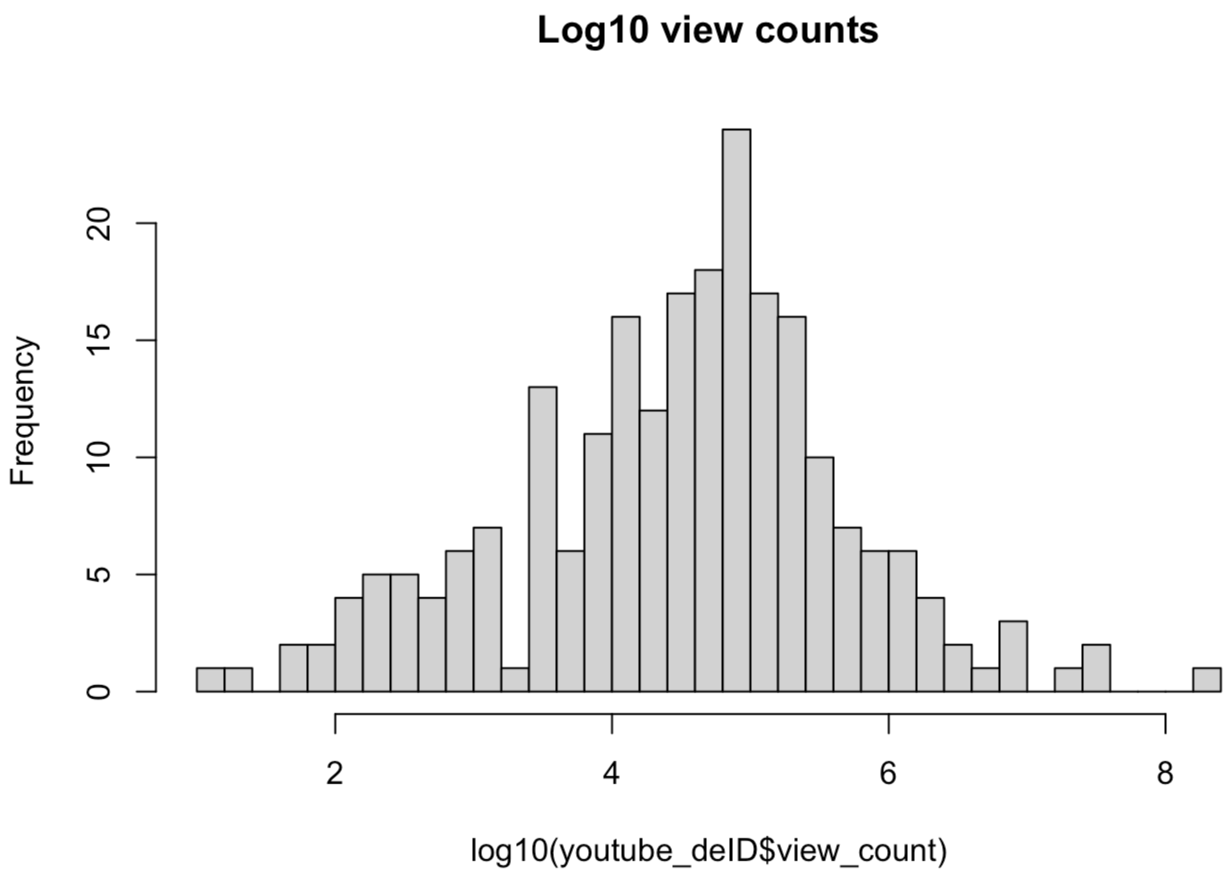
For each variable, report which category it falls in. If it requires a transformation, carry such a transformation out and use that transformation going forward.

- View counts
- Like counts
- Dislike counts
- Favorite counts
- Comment counts (Hint: At least the majority of these variables are appropriate to use.)

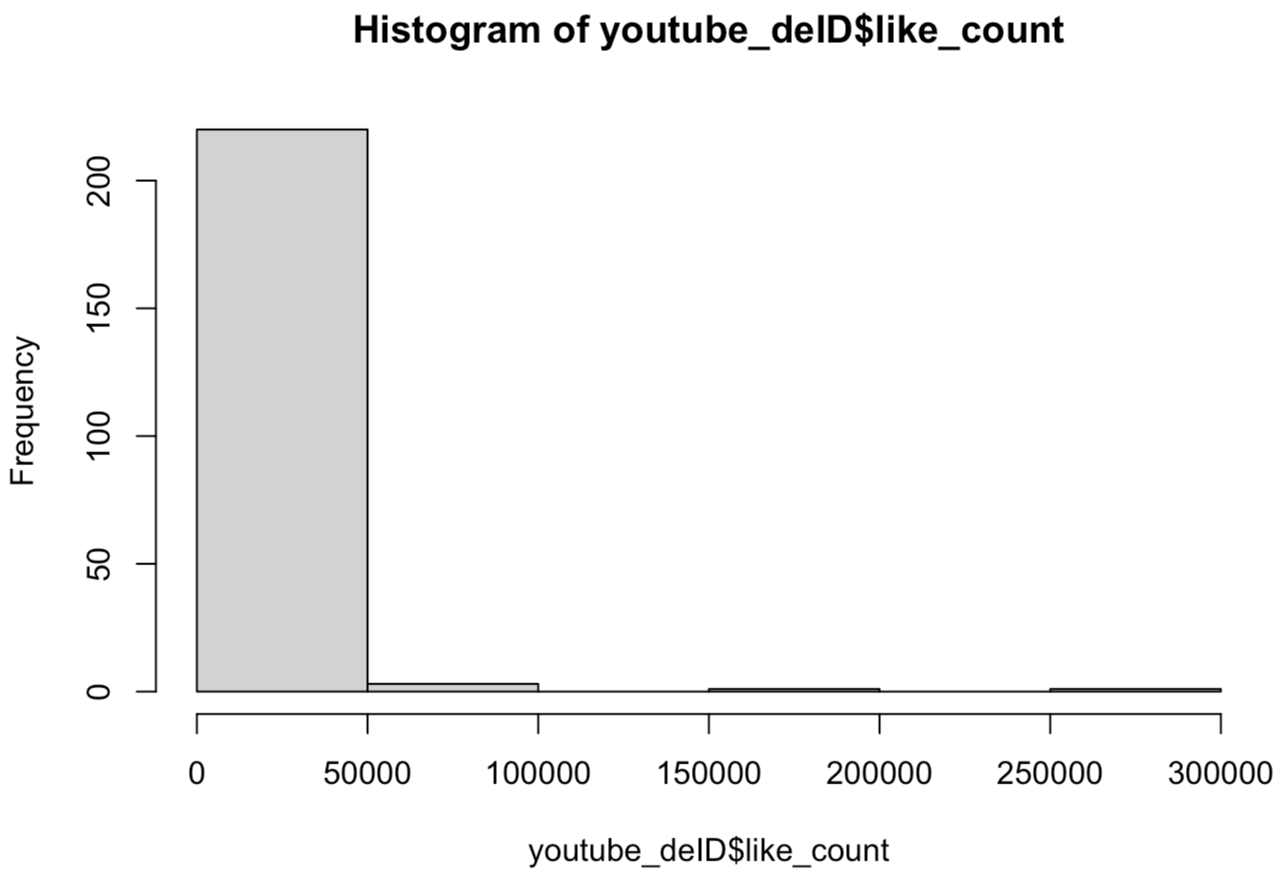
```
# examine distribution of view count
hist(youtube_deID$view_count)
```



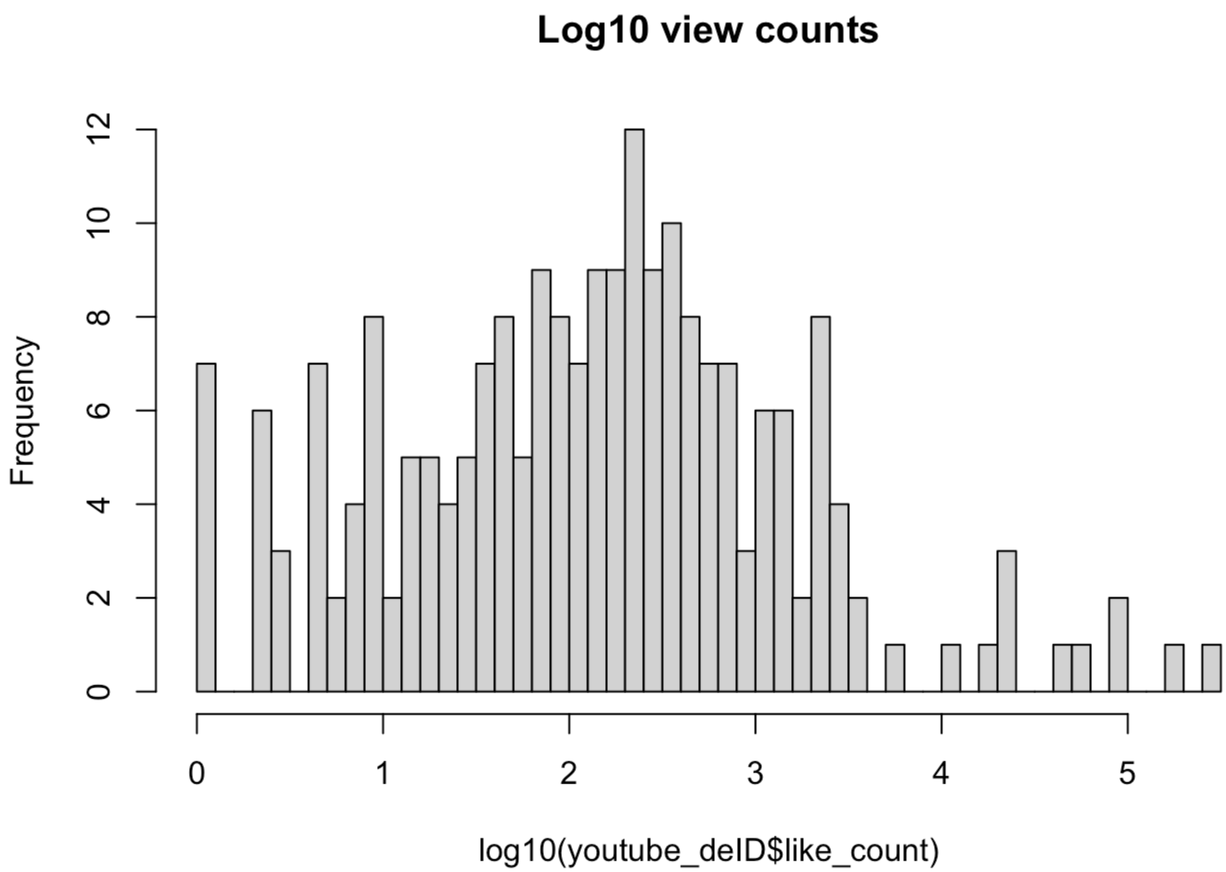

```
hist(log10(youtube_deID$view_count), breaks = 50, main="Log10 view counts")
```



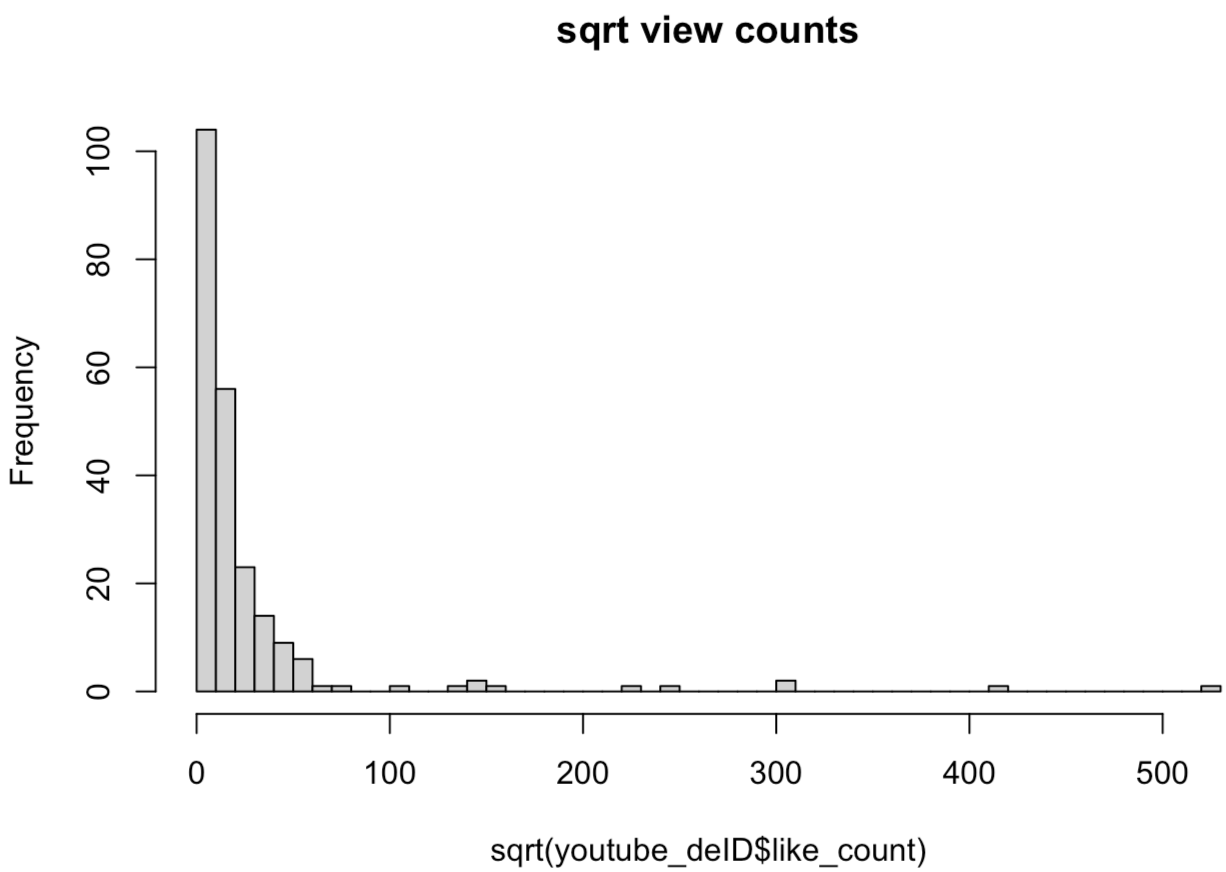

```
# view count has some very large numbers, meaning that if I do a log transformation I can
youtube_deID$view_count <- log10(youtube_deID$view_count)
# remove view counts that are NA
youtube_deID <- subset(youtube_deID, !is.na(view_count))

#examine distribution of like count
hist(youtube_deID$like_count)
```



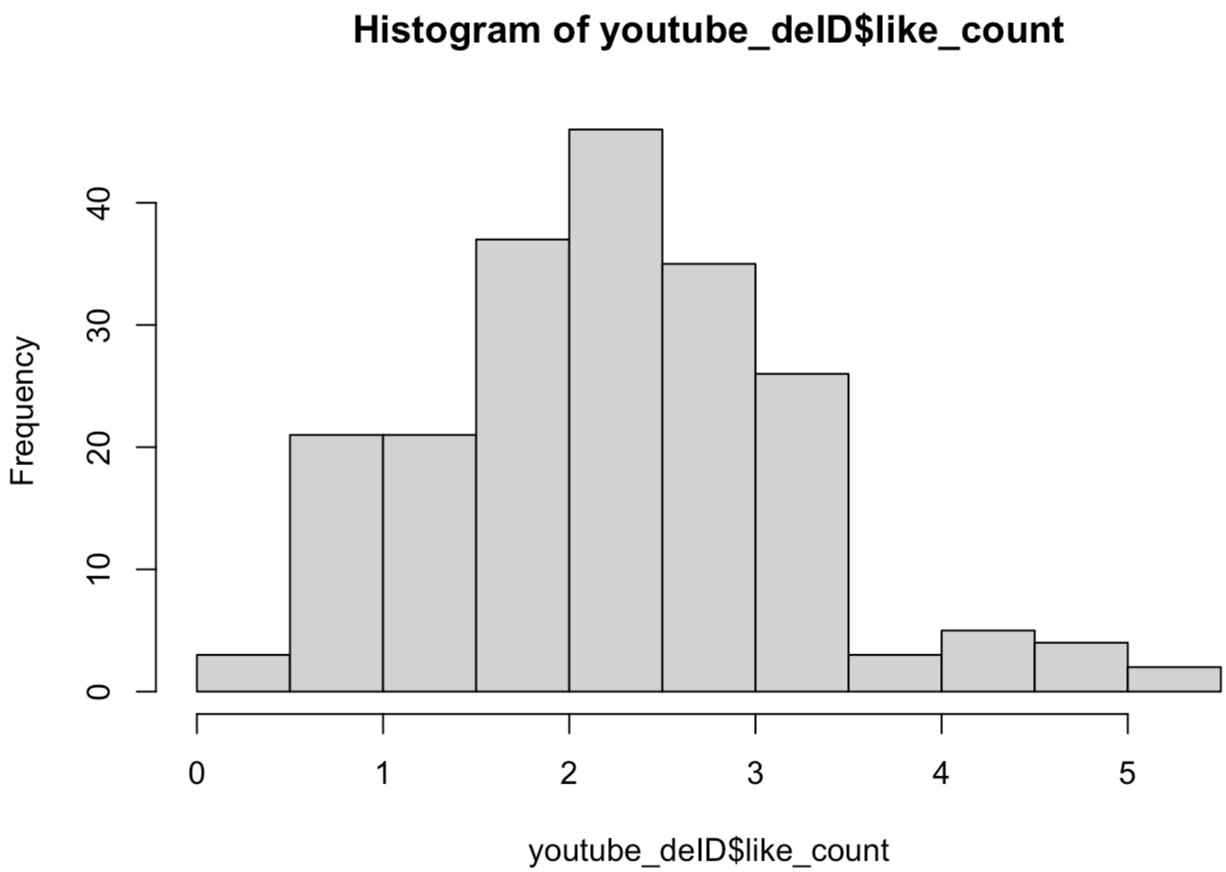

```
hist(log10(youtube_deID$like_count), breaks = 50, main="Log10 view counts")
```



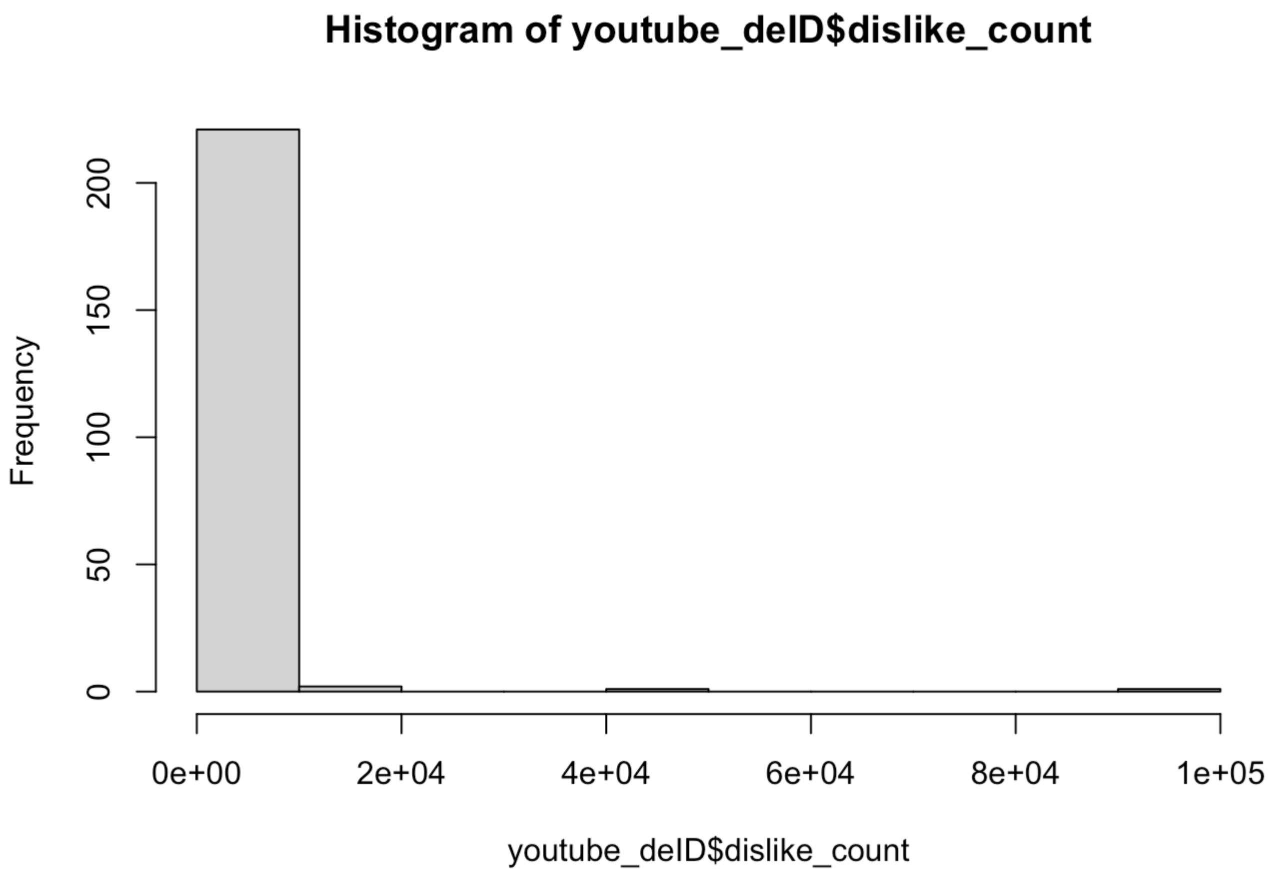

```
hist(sqrt(youtube_deID$like_count), breaks = 50, main="sqrt view counts")
```



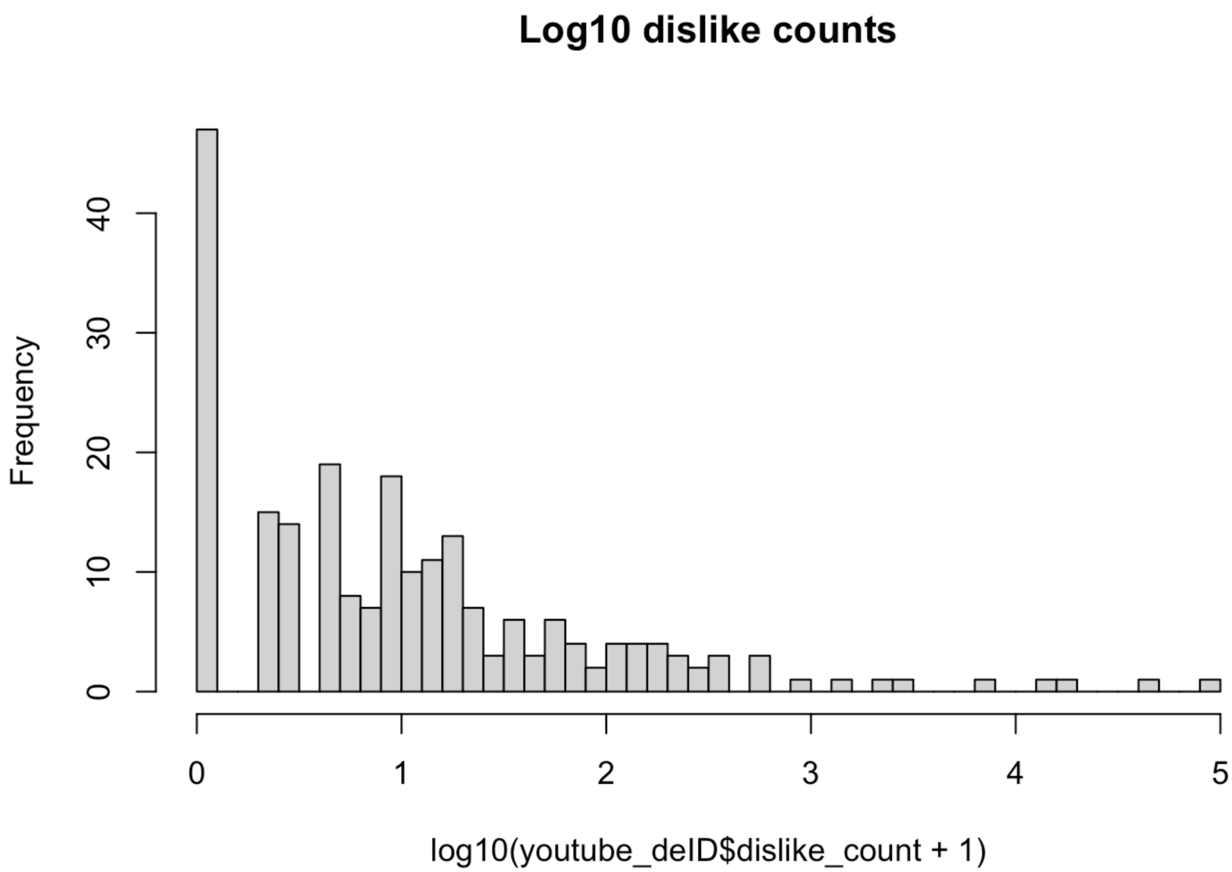

```
# like count has a lot of zeros, so it might be helpful to separate those out into their
youtube_deID$zero_likes <- youtube_deID$like_count == 0
youtube_deID$like_count[youtube_deID$like_count == 0] <- NA
# try to also do it with 1 or 0
youtube_deID$zero_likes <- youtube_deID$like_count < 3
youtube_deID$like_count[youtube_deID$like_count < 3] <- NA

# this looks reasonably normal with these edits, so I would just log transform it
youtube_deID$like_count <- log10(youtube_deID$like_count)
hist(youtube_deID$like_count)
```



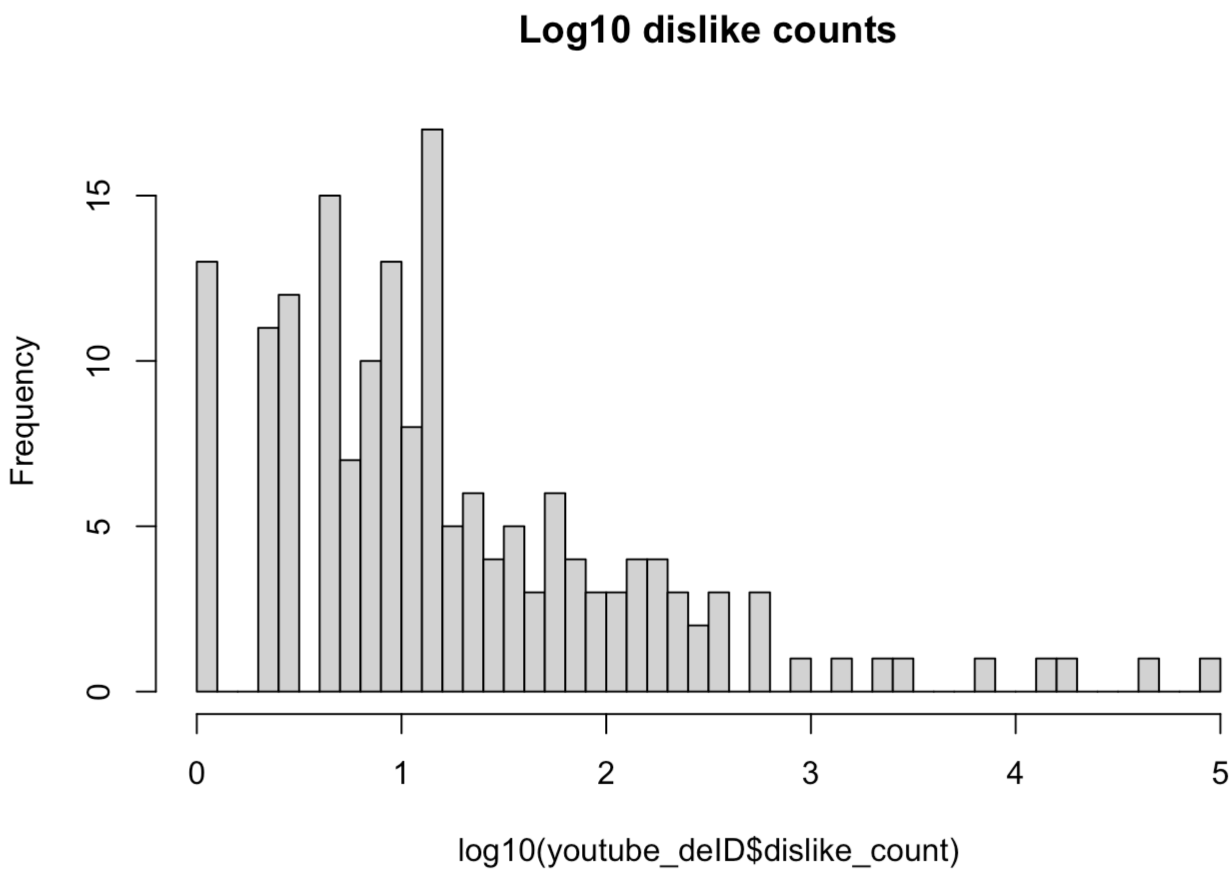

```r
# examine distribution of dislike count
hist(youtube_deID$dislike_count)
```



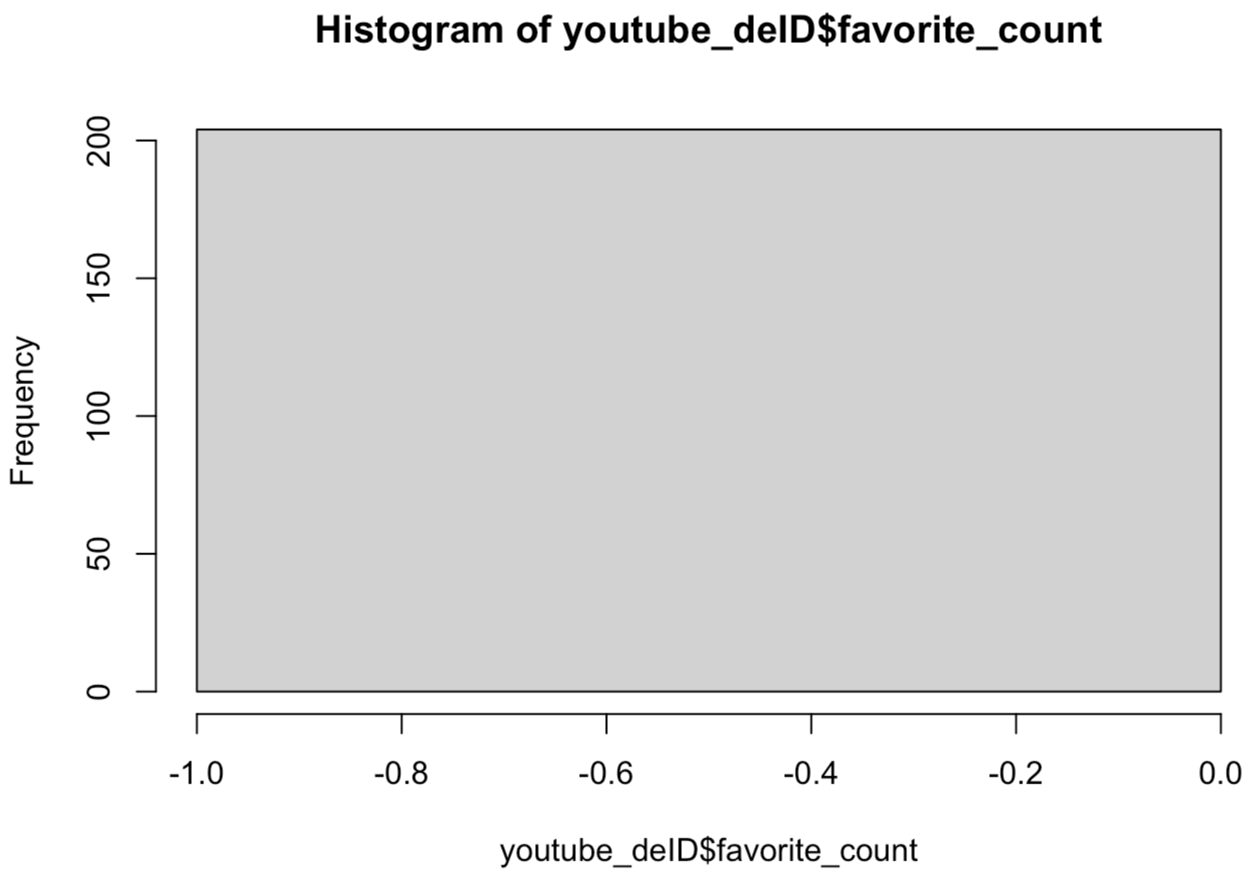

```r
hist(log10(youtube_deID$dislike_count + 1), breaks = 50, main="Log10 dislike counts")
```



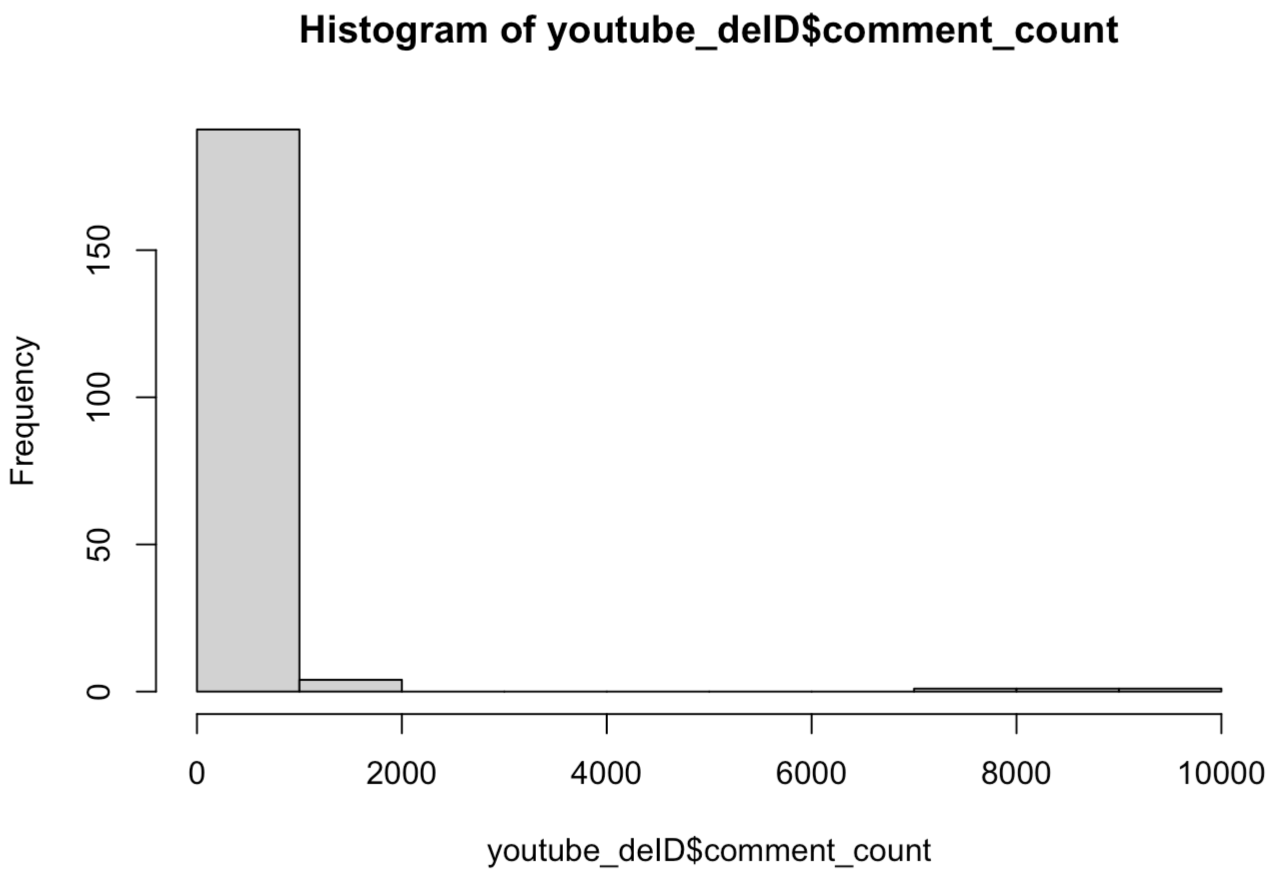

```
# lots of zeros again, and a few 1s so remove them
youtube_deID$zero_dislikes <- youtube_deID$dislike_count < 1
youtube_deID$dislike_count[youtube_deID$like_count < 1] <- NA
# remove counts that are NA
youtube_deID <- subset(youtube_deID, !is.na(dislike_count))
hist(log10(youtube_deID$dislike_count), breaks = 50, main="Log10 dislike counts")
```



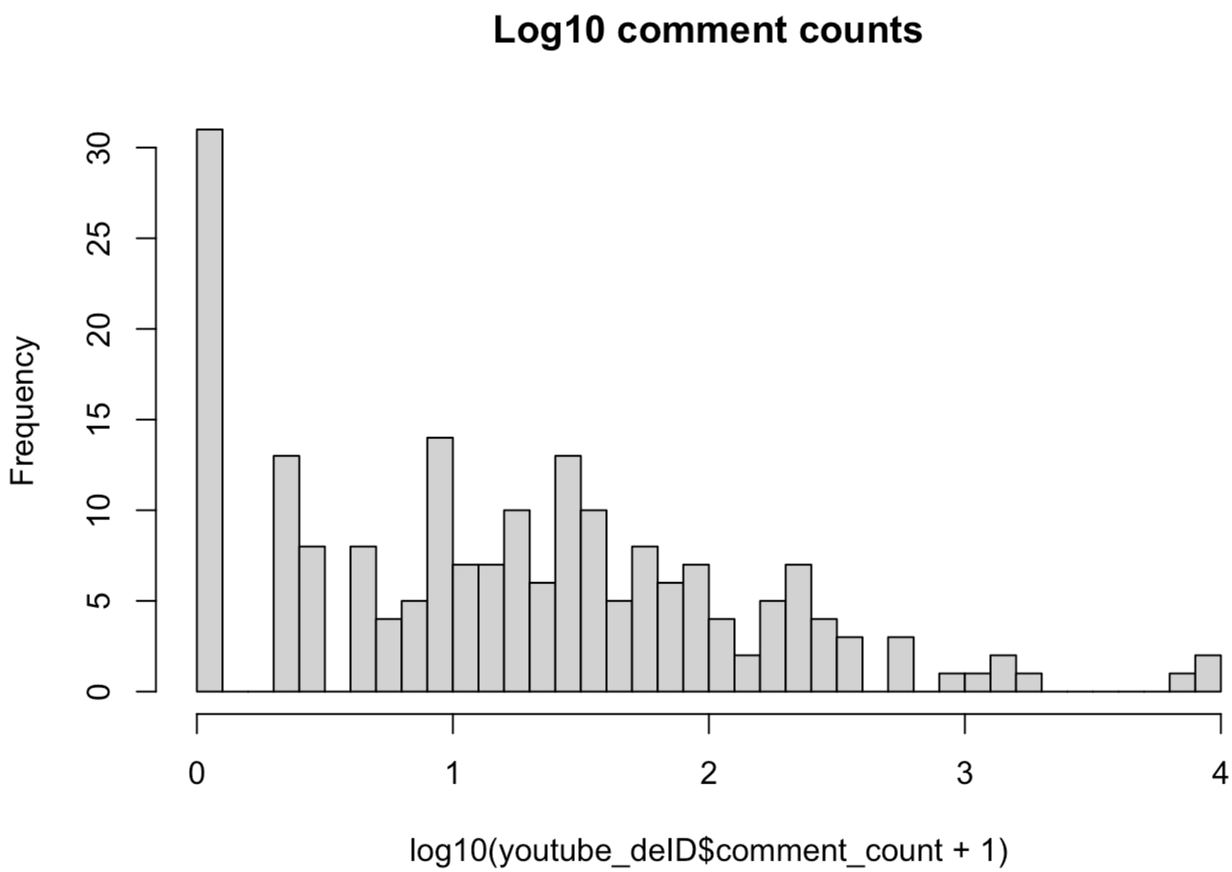

```
# this looks good now to use for a linear regression

# examine distribution of fav count
hist(youtube_deID$favorite_count)
```



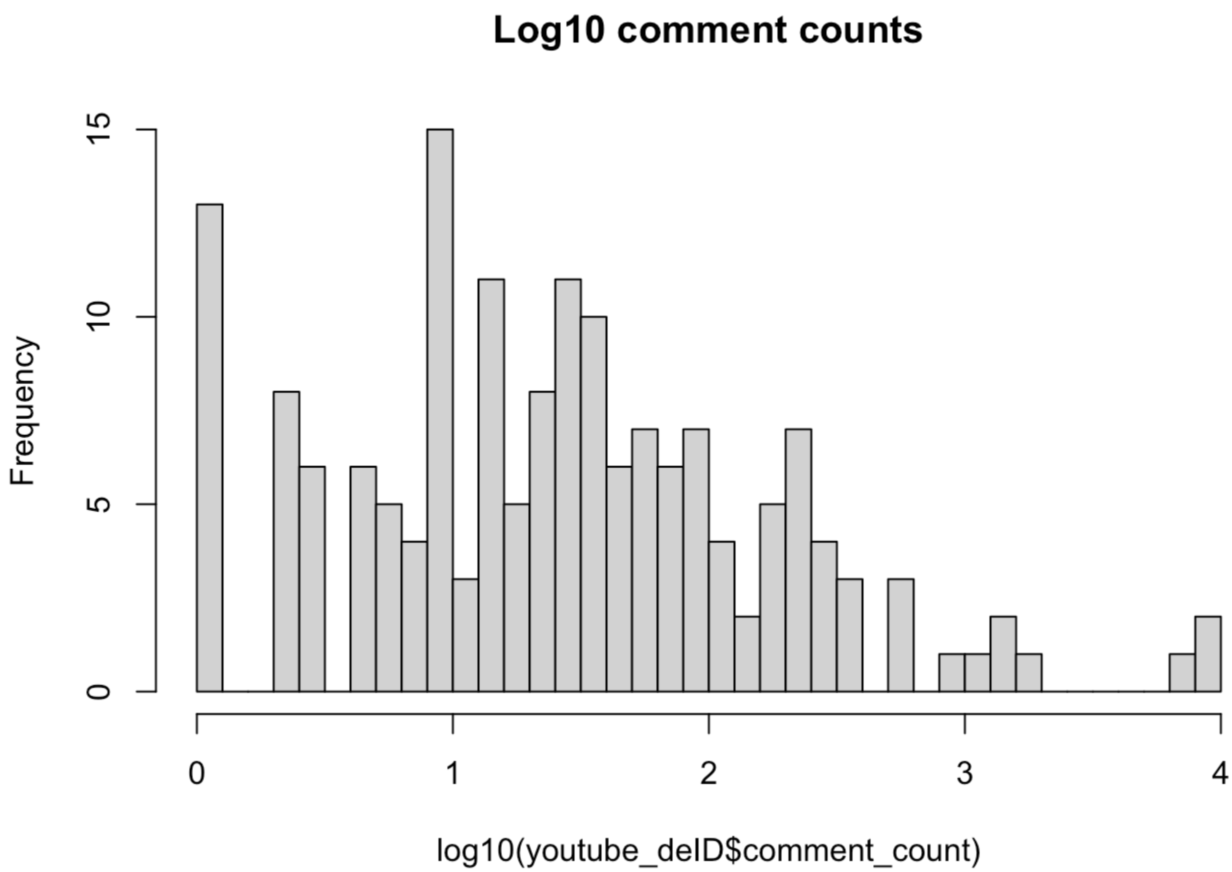

```r
# favorite is almost all zero, meaning that we should not use it at all for the linear re

# examine distribution of comment count
hist(youtube_deID$comment_count)
```




```r
hist(log10(youtube_deID$comment_count + 1), breaks = 50, main="Log10 comment counts")
```




```
# lots of zeros again, and a few 1s so remove them
youtube_deID$zero_comments <- youtube_deID$comment_count < 1
youtube_deID$comment_count[youtube_deID$comment_count < 1] <- NA
# remove counts that are NA
youtube_deID <- subset(youtube_deID, !is.na(comment_count))
hist(log10(youtube_deID$comment_count), breaks = 50, main="Log10 comment counts")
```




```
# this looks good now to use for a linear regression
```

**c. For each variable in part b. that are appropriate, fit a linear regression model predicting them based upon each of the seven binary flags for characteristics of the ads, such as whether it is funny. Control for year as a continuous covariate.**

Discuss the results. Identify the direction of any statistically significant results.

```
summary(youtube_deID)
```

```
      year          funny          show_product_quickly patriotic      
 Min.   :2000   Mode :logical   Mode :logical        Mode :logical  
 1st Qu.:2006   FALSE:49        FALSE:48             FALSE:140      
 Median :2009   TRUE :118       TRUE :119            TRUE :27       
 Mean   :2010                                                       
 3rd Qu.:2015                                                       
 Max.   :2020                                                       

 celebrity         danger         animals         use_sex       
 Mode :logical   Mode :logical   Mode :logical   Mode :logical  
 FALSE:116       FALSE:109       FALSE:106       FALSE:126      
 TRUE :51        TRUE :58        TRUE :61        TRUE :41       
```

```
      id                kind                etag             view_count   
 Length:167         Length:167         Length:167         Min.   :2.479  
 Class :character   Class :character   Class :character   1st Qu.:4.472  
 Mode  :character   Mode  :character   Mode  :character   Median :4.931  
                                                          Mean   :4.985  
                                                          3rd Qu.:5.426  
                                                          Max.   :8.246  
                                                                         
   like_count    dislike_count   favorite_count comment_count   
 Min.   :1.000   Min.   :    0   Min.   :0      Min.   :   1.0  
 1st Qu.:1.903   1st Qu.:    5   1st Qu.:0      1st Qu.:   7.5  
 Median :2.368   Median :   12   Median :0      Median :  25.0  
 Mean   :2.478   Mean   : 1120   Mean   :0      Mean   : 250.7  
 3rd Qu.:2.881   3rd Qu.:   55   3rd Qu.:0      3rd Qu.:  82.5  
 Max.   :5.440   Max.   :92990   Max.   :0      Max.   :9190.0  
 NA's   :1                                                      
 published_at        category_id    zero_likes      zero_dislikes  
 Length:167         Min.   : 1.00   Mode :logical   Mode :logical  
 Class :character   1st Qu.:17.00   FALSE:166       FALSE:159      
 Mode  :character   Median :23.00   TRUE :1         TRUE :8        
                    Mean   :19.04                                  
                    3rd Qu.:24.00                                  
                    Max.   :27.00                                  
                                                                   
 zero_comments  
 Mode :logical  
 FALSE:167      
```

```r
# Fit models
m_view <- lm(view_count ~ funny + show_product_quickly + patriotic + celebrity + danger +
m_like <- lm(like_count ~ funny + show_product_quickly + patriotic + celebrity + danger +
m_dislike <- lm(dislike_count ~ funny + show_product_quickly + patriotic + celebrity + da
m_comment <- lm(comment_count ~ funny + show_product_quickly + patriotic + celebrity + da

#### print model results ####
summary(m_view)
```

```
Call:
lm(formula = view_count ~ funny + show_product_quickly + patriotic + 
    celebrity + danger + animals + use_sex + year, data = youtube_deID)
```

```
Residuals:
    Min      1Q  Median      3Q     Max 
-2.4500 -0.6000 -0.0367  0.4045  3.1629 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)  
(Intercept)              -41.92454   25.42598  -1.649   0.1012  
funnyTRUE                  0.12979    0.17134   0.758   0.4499  
show_product_quicklyTRUE  -0.01718    0.14894  -0.115   0.9083  
patrioticTRUE              0.44126    0.20151   2.190   0.0300 *
celebrityTRUE             -0.16500    0.15751  -1.048   0.2964  
dangerTRUE                -0.03072    0.15123  -0.203   0.8393  
animalsTRUE               -0.04819    0.14478  -0.333   0.7397  
use_sexTRUE               -0.05314    0.16501  -0.322   0.7478  
year                       0.02331    0.01265   1.842   0.0673 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8603 on 158 degrees of freedom
Multiple R-squared:  0.06339,   Adjusted R-squared:  0.01596 
F-statistic: 1.337 on 8 and 158 DF,  p-value: 0.2291
```

```r
# Weak fit, low R^2, patriotic sig. positive correlation
summary(m_like)
```

```

Call:
lm(formula = like_count ~ funny + show_product_quickly + patriotic + 
    celebrity + danger + animals + use_sex + year, data = youtube_deID)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.35929 -0.58643 -0.06116  0.41161  2.91541 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)              -88.53101   24.25875  -3.649 0.000357 ***
funnyTRUE                 -0.02322    0.16432  -0.141 0.887818    
show_product_quicklyTRUE   0.04055    0.14208   0.285 0.775716    
patrioticTRUE              0.26774    0.19258   1.390 0.166413    
celebrityTRUE              0.06753    0.15048   0.449 0.654225    
dangerTRUE                 0.01794    0.14404   0.125 0.901015    
animalsTRUE               -0.01844    0.13800  -0.134 0.893873    
use_sexTRUE               -0.06135    0.15717  -0.390 0.696829    
year                       0.04525    0.01207   3.748 0.000250 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8194 on 157 degrees of freedom
  (1 observation deleted due to missingness)
```

```
Multiple R-squared:  0.1323,	Adjusted R-squared:  0.08804 
F-statistic: 2.991 on 8 and 157 DF,  p-value: 0.003786
```

```
# Modest/Weak fit = ok R^2, only year sig. positive correlation
summary(m_dislike)
```

```

Call:
lm(formula = dislike_count ~ funny + show_product_quickly + patriotic + 
    celebrity + danger + animals + use_sex + year, data = youtube_deID)

Residuals:
   Min     1Q Median     3Q    Max 
 -3573  -1827  -1062   -251  90598 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              -269210.7   241406.4  -1.115    0.266
funnyTRUE                   -242.2     1626.7  -0.149    0.882
show_product_quicklyTRUE     594.9     1414.1   0.421    0.675
patrioticTRUE               -507.0     1913.2  -0.265    0.791
celebrityTRUE              -1636.1     1495.5  -1.094    0.276
dangerTRUE                   375.9     1435.8   0.262    0.794
animalsTRUE                 -677.2     1374.6  -0.493    0.623
use_sexTRUE                 -870.9     1566.7  -0.556    0.579
year                         134.8      120.1   1.122    0.263

Residual standard error: 8168 on 158 degrees of freedom
Multiple R-squared:  0.02047,	Adjusted R-squared:  -0.02912 
F-statistic: 0.4128 on 8 and 158 DF,  p-value: 0.912
```

```
# Bad fit, no sig. predictors
summary(m_comment)
```

```

Call:
lm(formula = comment_count ~ funny + show_product_quickly + patriotic + 
    celebrity + danger + animals + use_sex + year, data = youtube_deID)

Residuals:
    Min      1Q  Median      3Q     Max 
-1298.9  -373.2  -167.9   144.2  7597.5 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)  
(Intercept)              -79229.14   32183.75  -2.462   0.0149 *
funnyTRUE                   -67.34     216.87  -0.310   0.7566  
show_product_quicklyTRUE   -244.86     188.52  -1.299   0.1959  
patrioticTRUE               631.02     255.06   2.474   0.0144 *
```

```
celebrityTRUE              -25.69     199.38  -0.129   0.8977
dangerTRUE                 325.16     191.42   1.699   0.0914 .
animalsTRUE               -210.62     183.26  -1.149   0.2522
use_sexTRUE                -79.02     208.86  -0.378   0.7057
year                        39.60      16.02   2.472   0.0145 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1089 on 158 degrees of freedom
Multiple R-squared:  0.1181,	Adjusted R-squared:  0.0735
F-statistic: 2.646 on 8 and 158 DF,  p-value: 0.009476
```

```
# /Weak fit = low R^2, patriotic and year sig. positive correlation.
```

**d. Consider only the outcome of view counts. Calculate manually (without using lm) by first creating a proper design matrix, then using matrix algebra to estimate. Confirm that you get the same result as lm did in part c.**

```
# Use the same filtered modeling data
# youtube_deID

# y is view count with log transformation
y <- youtube_deID$view_count

# Model matrix including intercept
X <- model.matrix(~ funny + show_product_quickly + patriotic + celebrity + danger + anima

# Closed-form OLS solution
b_hat <- solve(t(X) %*% X, t(X) %*% y)

# Compare to part c
print(coef(m_view))
```

```
         (Intercept)            funnyTRUE show_product_quicklyTRUE
        -41.92454466           0.12978817              -0.01718497
       patrioticTRUE        celebrityTRUE               dangerTRUE
          0.44126113          -0.16500406              -0.03071907
         animalsTRUE          use_sexTRUE                     year
         -0.04819420          -0.05314177               0.02330788
```

```
print(b_hat)
```

```
                                [,1]
(Intercept)              -41.92454466
funnyTRUE                  0.12978817
show_product_quicklyTRUE  -0.01718497
patrioticTRUE              0.44126113
celebrityTRUE             -0.16500406
dangerTRUE                -0.03071907
```

```
animalsTRUE              -0.04819420
use_sexTRUE              -0.05314177
year                      0.02330788
```

```
# they are the same result
```