eda

```
install.packages("GGally")
install.packages("moments")
install.packages("corrplot")
```

```
library(GGally)
library(ggplot2)
library(lmtest)
library(moments)
library(sandwich)
library(stargazer)
library(tidyverse)
library(corrplot)
library(data.table)

source('./get_robust_se.R')
```

```
d <- read.csv('data/googleplaystore.csv')
summary(d)
```

```
##      App              Category           Rating         Reviews
##  Length:10841       Length:10841       Min.   : 1.000   Length:10841
##  Class :character   Class :character   1st Qu.: 4.000   Class :character
##  Mode  :character   Mode  :character   Median : 4.300   Mode  :character
##                                        Mean   : 4.193
##                                        3rd Qu.: 4.500
##                                        Max.   :19.000
##                                        NA's   :1474
##      Size              Installs            Type              Price
##  Length:10841       Length:10841       Length:10841       Length:10841
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  Content.Rating        Genres          Last.Updated       Current.Ver
##  Length:10841       Length:10841       Length:10841       Length:10841
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  Android.Ver
##  Length:10841
##  Class :character
##  Mode  :character
```

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

```
# Function to convert strings to numbers
str_to_num <- function(s) {
  n <- nchar(s)
  last <- substr(s, n, n + 1)
  if (last == "B") {
    number <- as.numeric(substr(s, 0, n - 1)) * 1.0e9
  } else if (last == "M") {
    number <- as.numeric(substr(s, 0, n - 1)) * 1.0e6
  } else if (last == "k") {
    number <- as.numeric(substr(s, 0, n - 1)) * 1.0e3
  } else if (last == "+") {
    number <- as.numeric(str_replace_all(s, "[+,]", ""))
  }
    else {
    number <- as.numeric(s)
  }
  return(number)
}

# Remove entries with bad values
d <- d[d$Installs != "Free", ]
d <- d[!is.nan(d$Rating), ]
d <- d[d$Size != "Varies with device", ]

# Convert strings to numbers
d$installs_clean <- sapply(d$Installs, str_to_num)
d$reviews_clean  <- sapply(d$Reviews, str_to_num)
d$size_clean     <- sapply(d$Size, str_to_num)
d$price_clean     <- as.numeric(gsub('\\$','',d$Price))

# Bins for install count

# install groups-- increments by 1, there are 19 of them.
install_groups <- data.table(table(d$installs_clean))
setnames(install_groups,c('V1','N'),c('installs_clean','count'))
install_groups[, install_group := 1:.N]
install_groups <- install_groups[,c('installs_clean','install_group')]
install_groups
```

```
##     installs_clean install_group
##  1:              1             1
##  2:              5             2
##  3:             10             3
##  4:             50             4
##  5:            100             5
##  6:            500             6
##  7:           1000             7
##  8:           5000             8
##  9:          10000             9
## 10:          50000            10
```

```
## 11:         100000            11
## 12:         500000            12
## 13:        1000000            13
## 14:        5000000            14
## 15:       10000000            15
## 16:       50000000            16
## 17:      100000000            17
## 18:      500000000            18
## 19:     1000000000            19
```

```
d <- merge(d,install_groups,by='installs_clean')

# summary of dataset
summary(d)
```

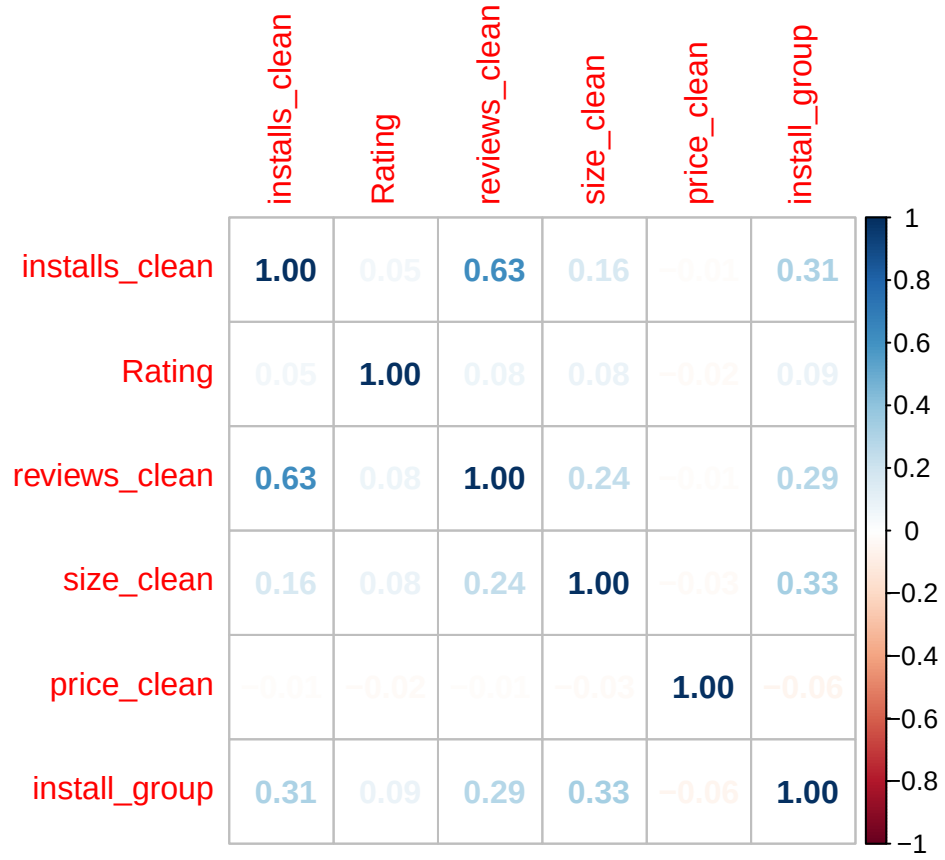
```
##  installs_clean           App              Category            Rating
##  Min.   :          1   Length:7729        Length:7729        Min.   :1.000
##  1st Qu.:      10000   Class :character   Class :character   1st Qu.:4.000
##  Median :     100000   Mode  :character   Mode  :character   Median :4.300
##  Mean   :    8417734                                         Mean   :4.174
##  3rd Qu.:    1000000                                         3rd Qu.:4.500
##  Max.   :1000000000                                          Max.   :5.000
##    Reviews              Size              Installs            Type
##  Length:7729        Length:7729        Length:7729        Length:7729
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##     Price           Content.Rating        Genres          Last.Updated
##  Length:7729        Length:7729        Length:7729        Length:7729
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##  Current.Ver        Android.Ver        reviews_clean        size_clean
##  Length:7729        Length:7729        Min.   :       1   Min.   :     8500
##  Class :character   Class :character   1st Qu.:     108   1st Qu.:  5300000
##  Mode  :character   Mode  :character   Median :    2328   Median : 14000000
##                                        Mean   :  294673   Mean   : 22957607
##                                        3rd Qu.:   38961   3rd Qu.: 33000000
##                                        Max.   :44893888   Max.   :100000000
##   price_clean      install_group
##  Min.   :  0.000   Min.   : 1
##  1st Qu.:  0.000   1st Qu.: 9
##  Median :  0.000   Median :11
##  Mean   :  1.128   Mean   :11
##  3rd Qu.:  0.000   3rd Qu.:13
##  Max.   :400.000   Max.   :19
```

```
# save a data.table version for some easier wrangling downstream
d_dt <- as.data.table(d)
```

```r
numeric_cols <- colnames(d)[unlist(lapply(d, is.numeric))]

# show distribution of numeric columns
create_quantile_table <- function(column) {
  probs <- sort(c(seq(0, 1, 0.25), 0.05, 0.95))
  result <-
    as.data.table(t(data.table(quantile(d[, column], probs = probs))))
  setnames(result, paste0(probs * 100, '%'))
  result[, variable := column]
  result[, diff_min_vs_max := `100%` - `0%`]
  return(result)

}

table_quantile_numeric <- rbindlist(lapply(numeric_cols,create_quantile_table))
table_quantile_numeric
```

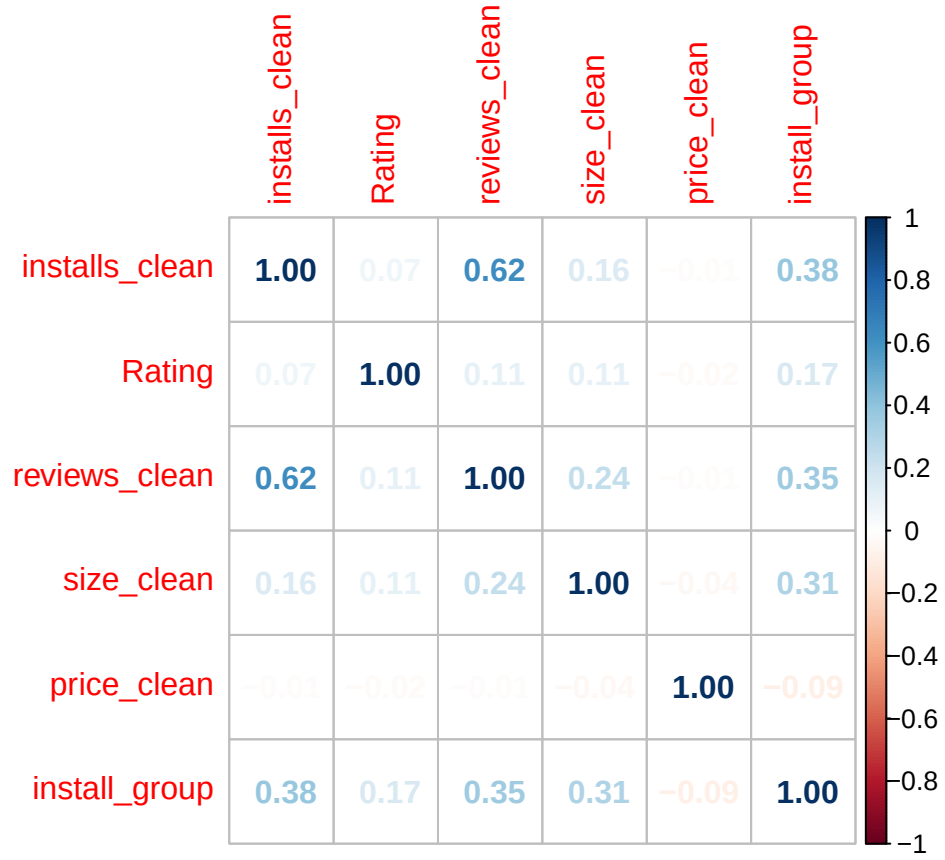
```
##      0%        5%     25%        50%        75%         95%       100%
## 1:    1     100.0   10000   100000.0  1000000.0 50000000.00 1000000000
## 2:    1       3.1       4        4.3        4.5        4.80          5
## 3:    1       6.0     108     2328.0    38961.0   855727.00   44893888
## 4: 8500 1500000.0 5300000 14000000.0 33000000.0 76000000.00  100000000
## 5:    0       0.0       0        0.0        0.0        1.99        400
## 6:    1       5.0       9       11.0       13.0       16.00         19
##          variable diff_min_vs_max
## 1: installs_clean       999999999
## 2:         Rating               4
## 3:  reviews_clean        44893887
## 4:     size_clean        99991500
## 5:    price_clean             400
## 6:  install_group              18
```

```r
# Corrplot across variables
corrplot(cor(d[,numeric_cols], use = "complete.obs"),
         method = 'number')
```



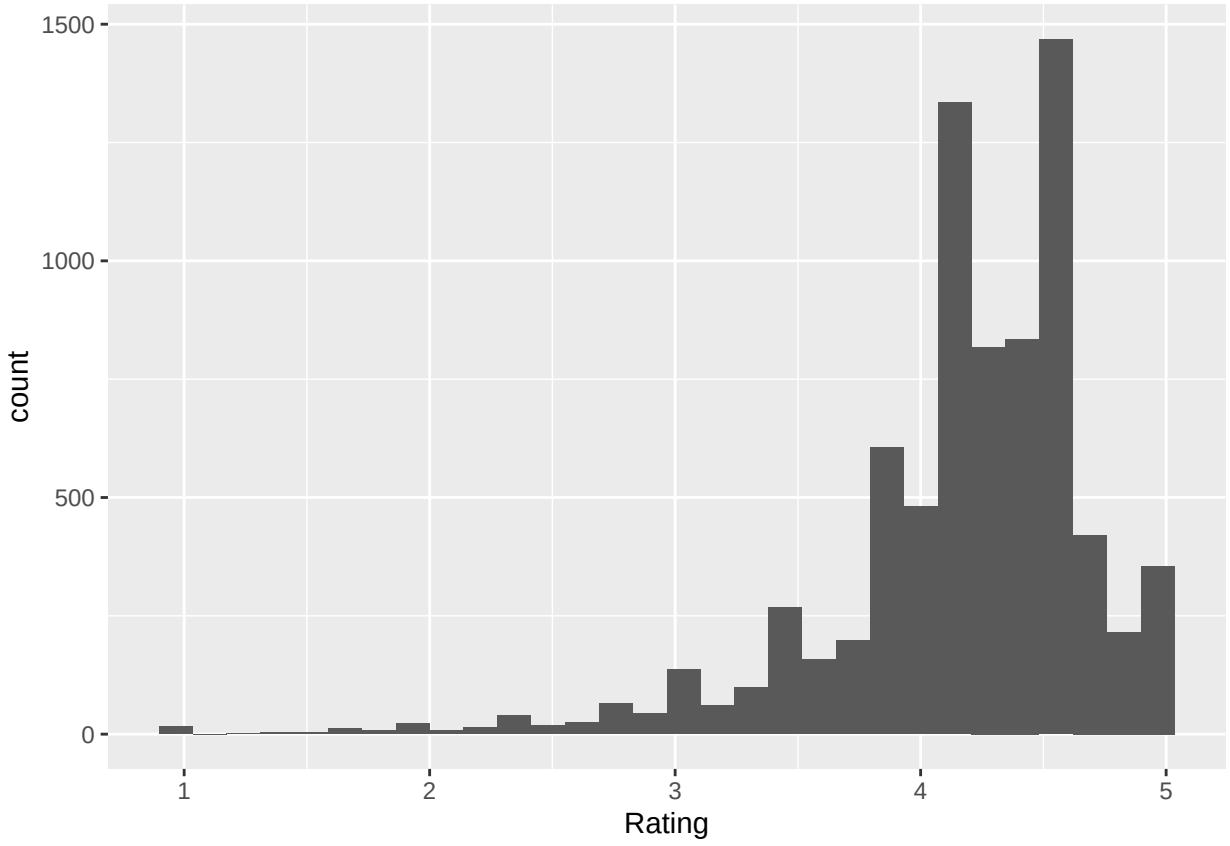

```
# Corrplot across variables (5th PCTL outliers removed)
corrplot(cor(d[d$reviews_clean >= 6,numeric_cols], use = "complete.obs"),
         method = 'number')
```


```
# Corrplot across variables (25th PCTL outliers removed)
corrplot(cor(d[d$reviews_clean >= 100,numeric_cols], use = "complete.obs"),
         method = 'number')
```



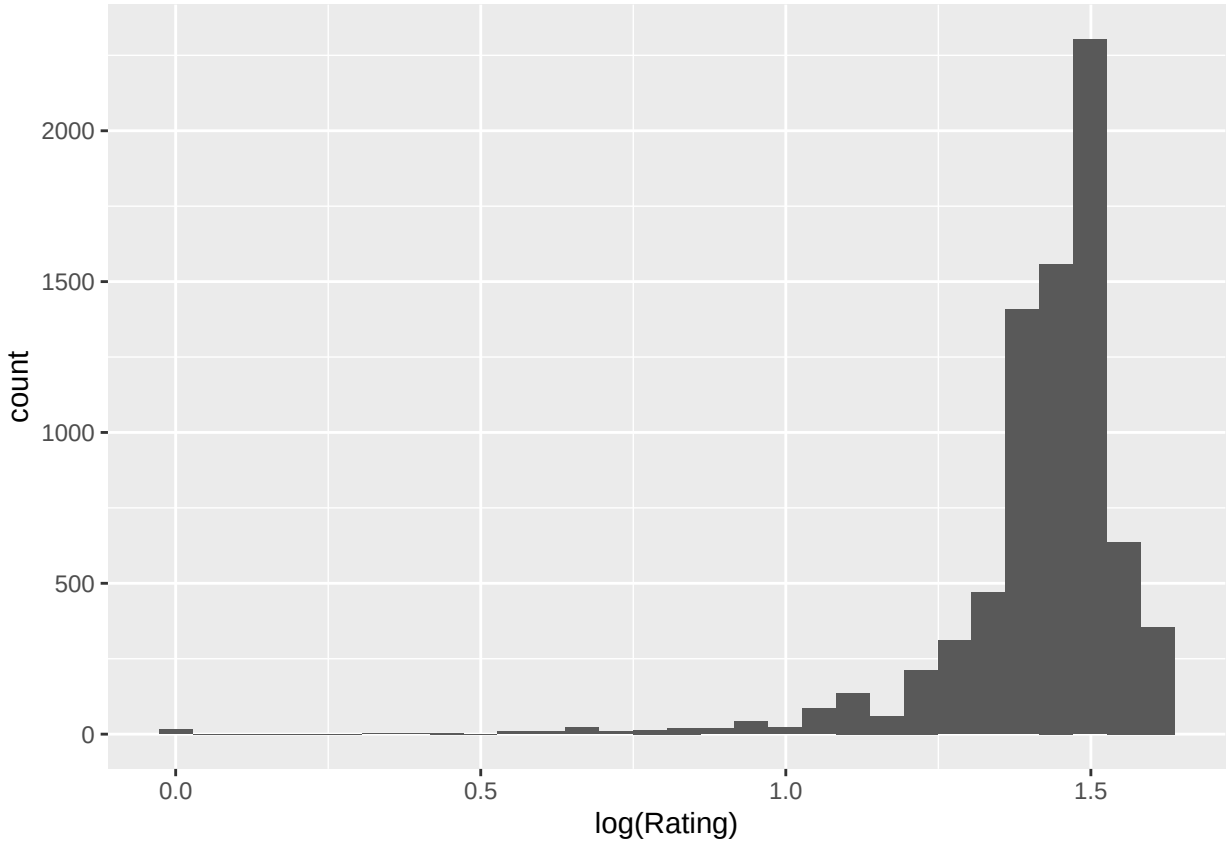

```
# Distribution of numeric columns
ggplot(data = d, aes(x = Rating)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



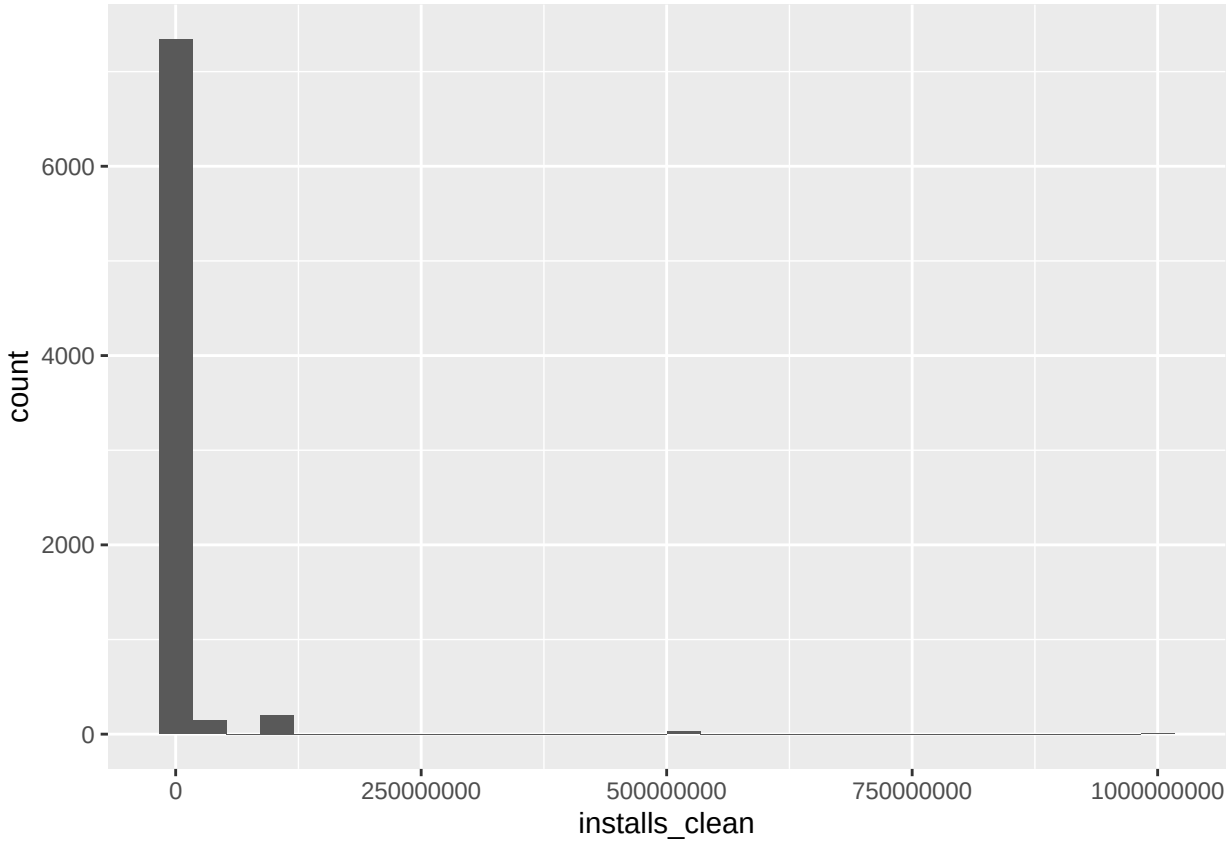

```
ggplot(data = d, aes(x = log(Rating))) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



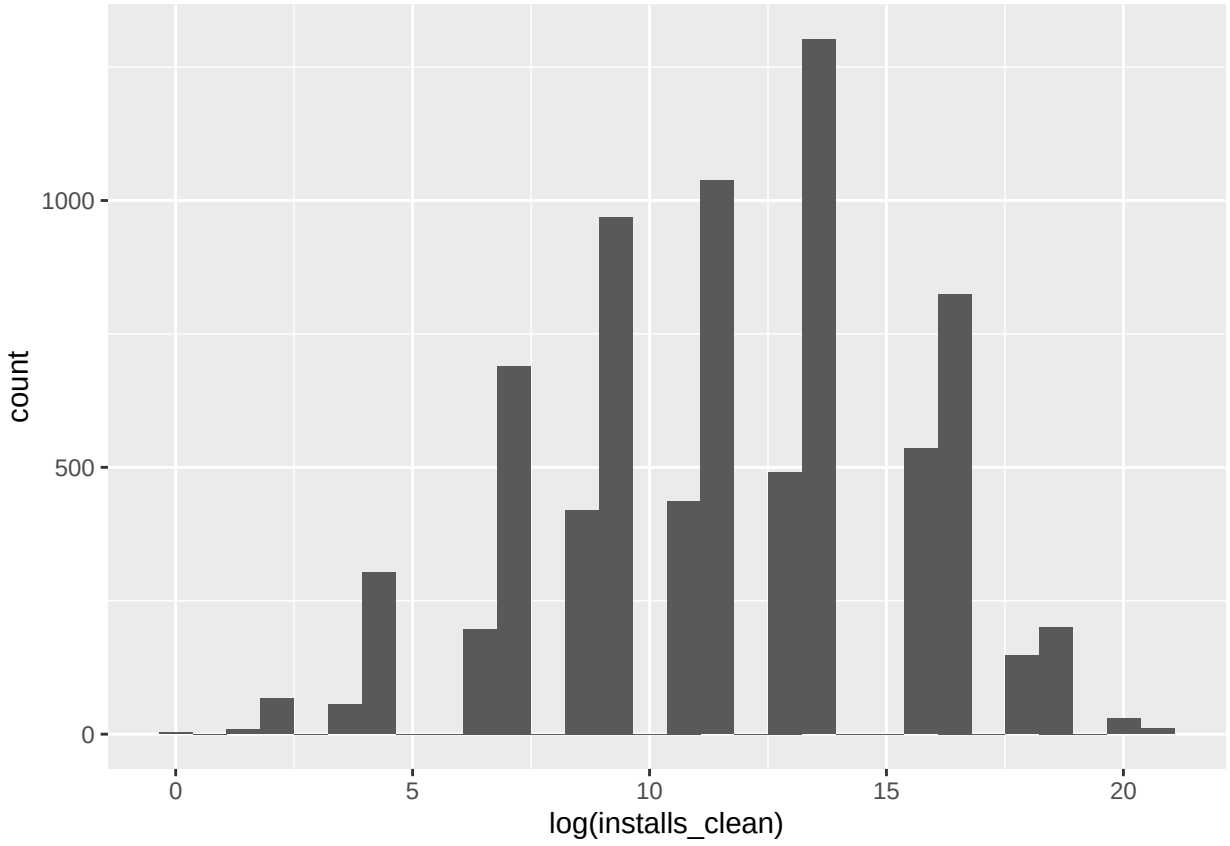

```
ggplot(data = d, aes(x = installs_clean)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



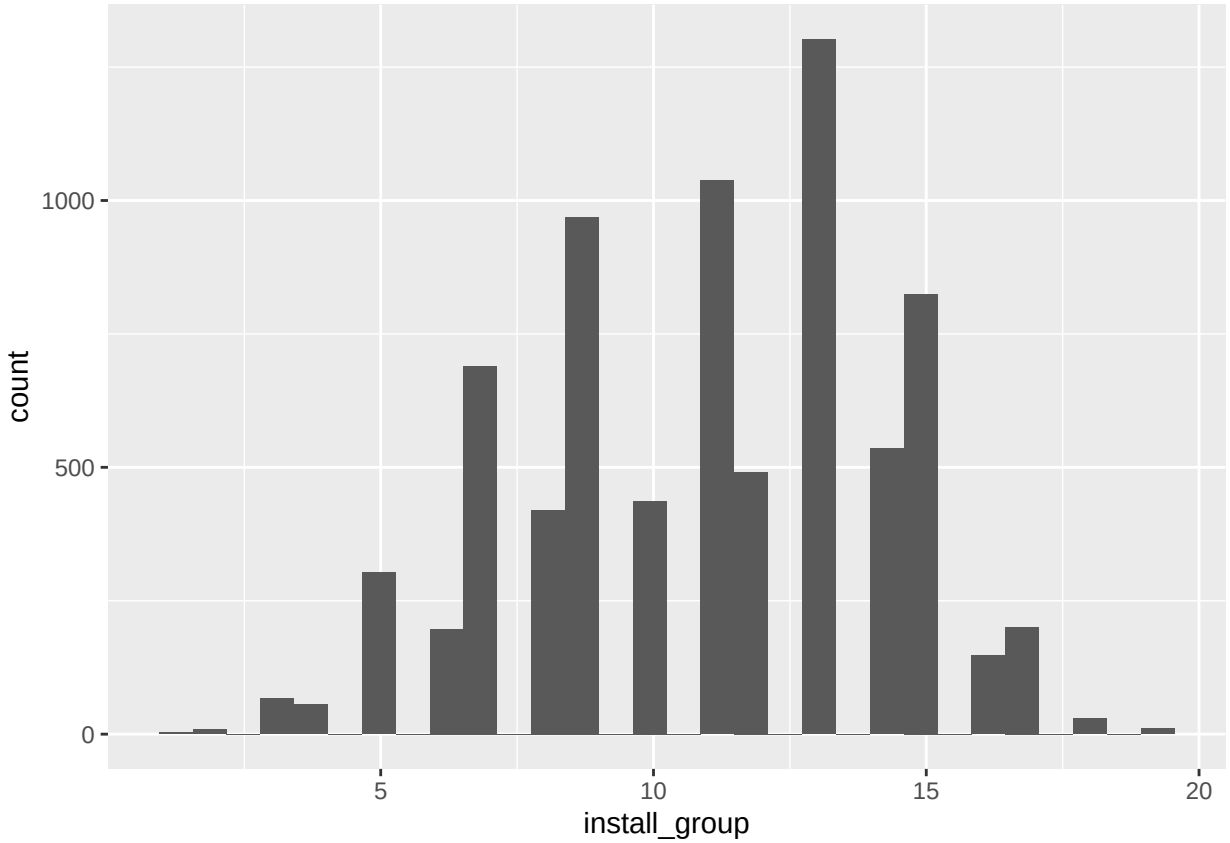

```
ggplot(data = d, aes(x = log(installs_clean))) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



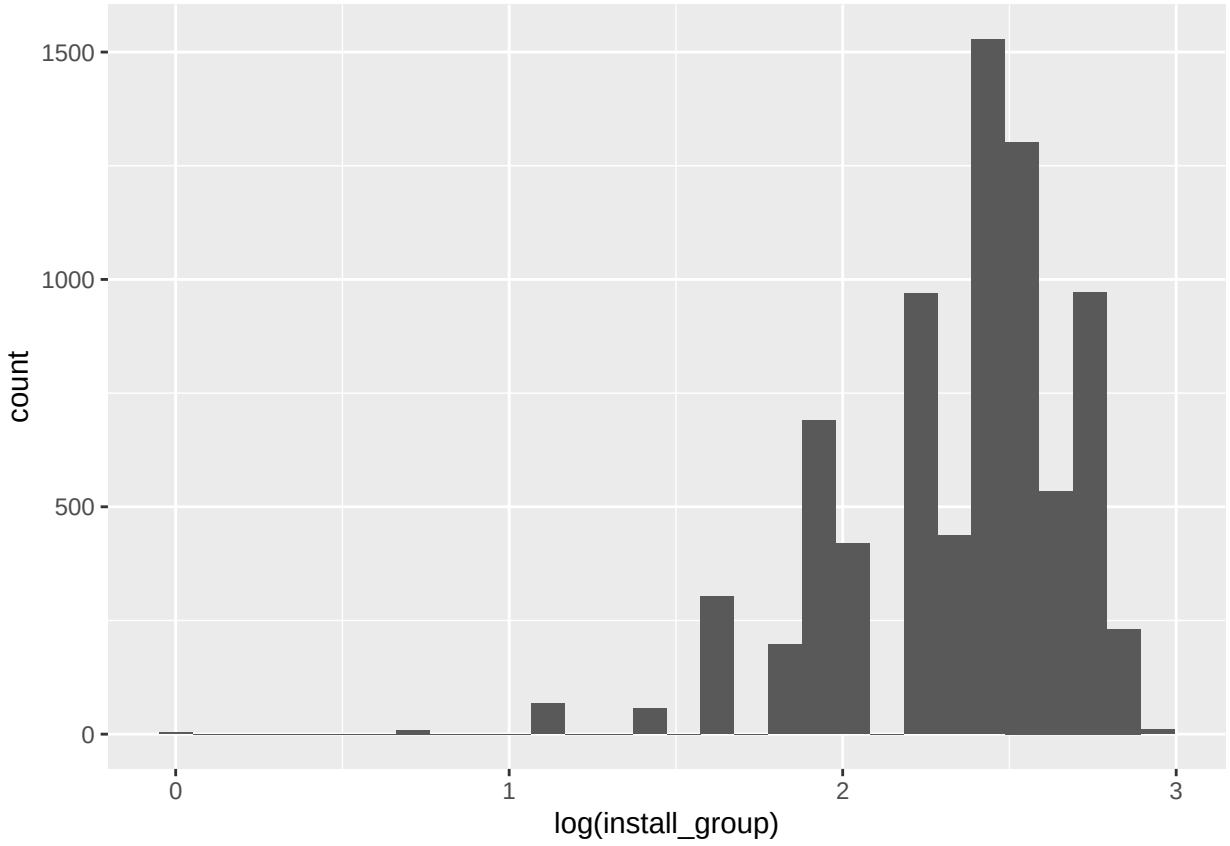

```
ggplot(data = d, aes(x = install_group)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



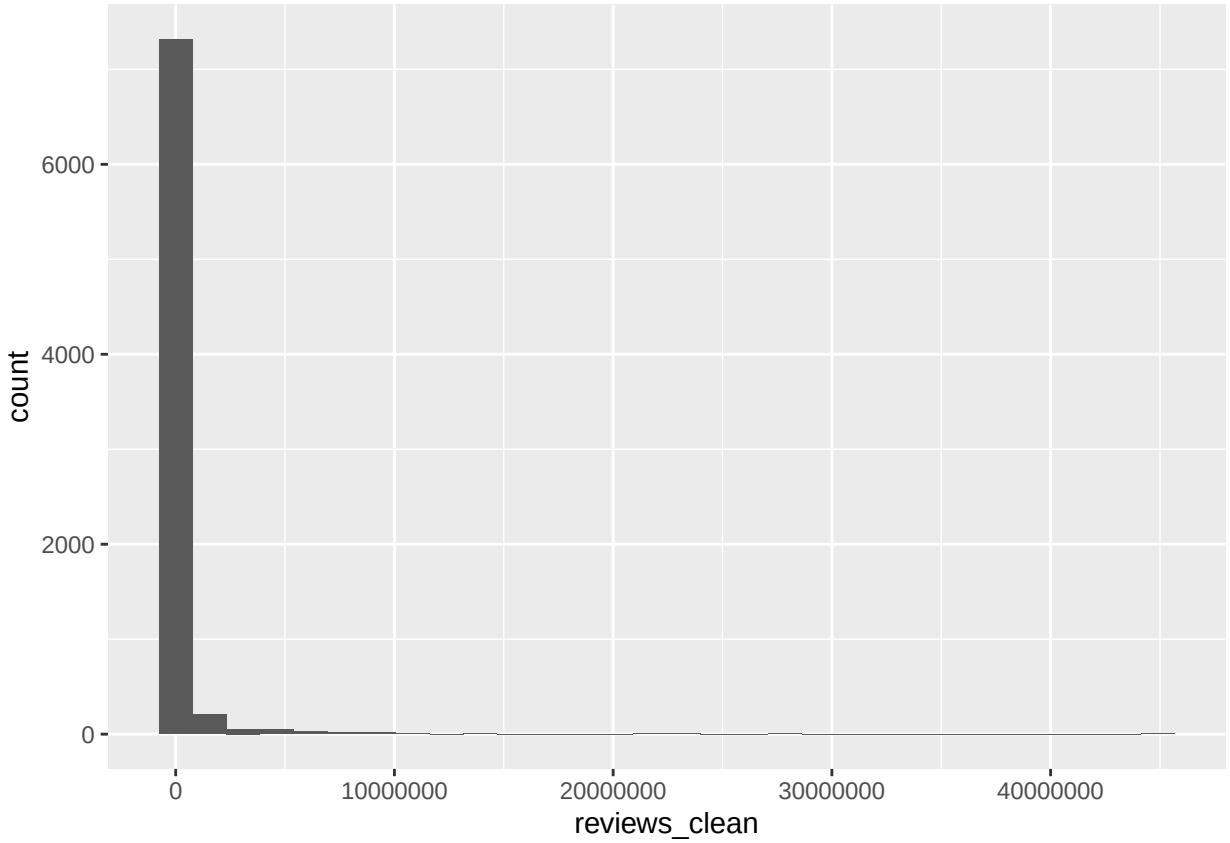

```
ggplot(data = d, aes(x = log(install_group))) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



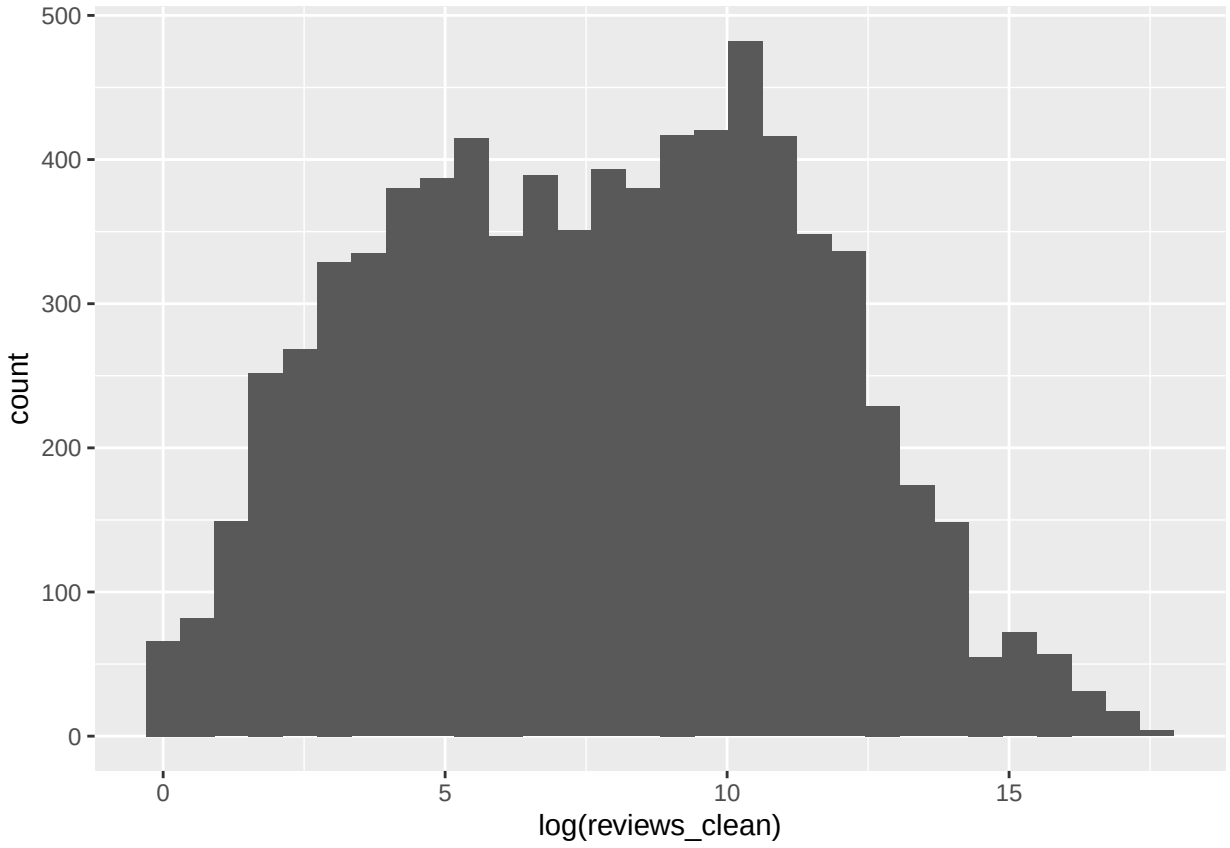

```
ggplot(data = d, aes(x = reviews_clean)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



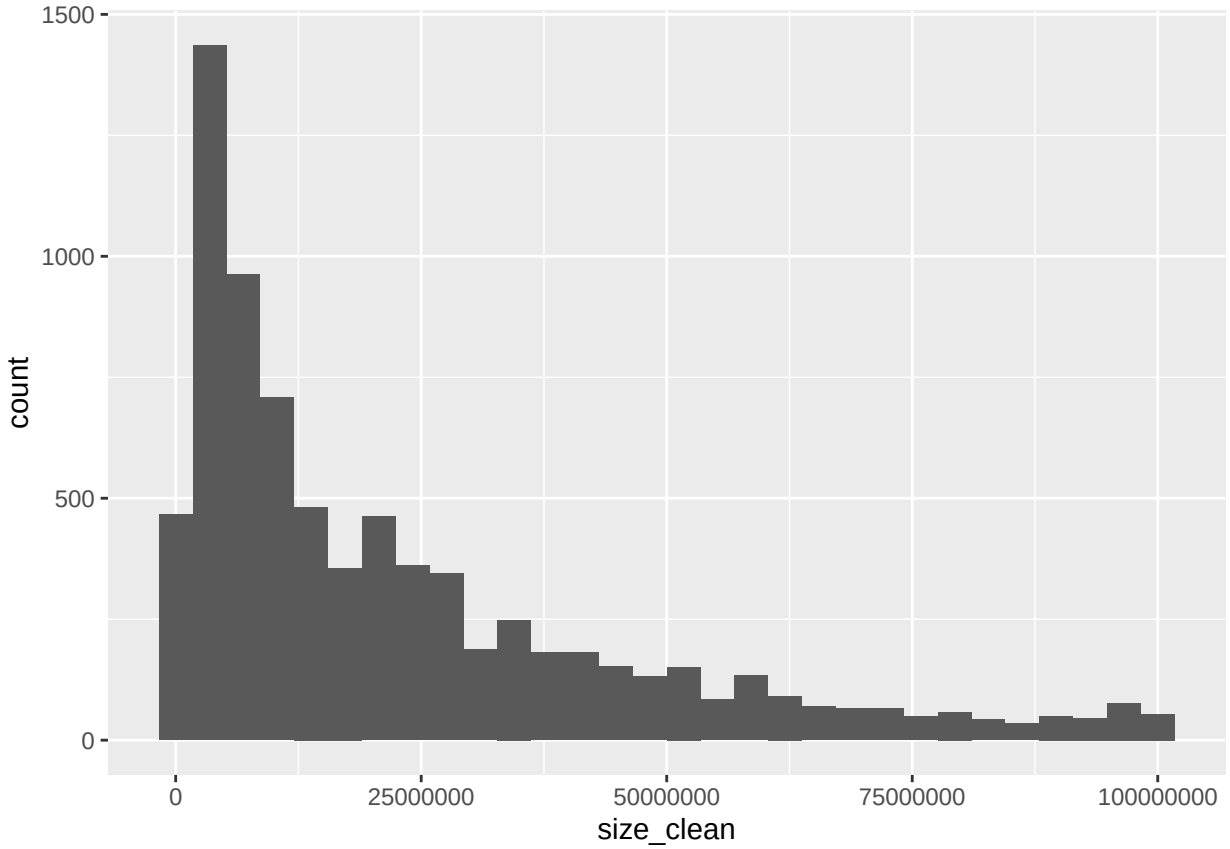

```
ggplot(data = d, aes(x = log(reviews_clean))) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



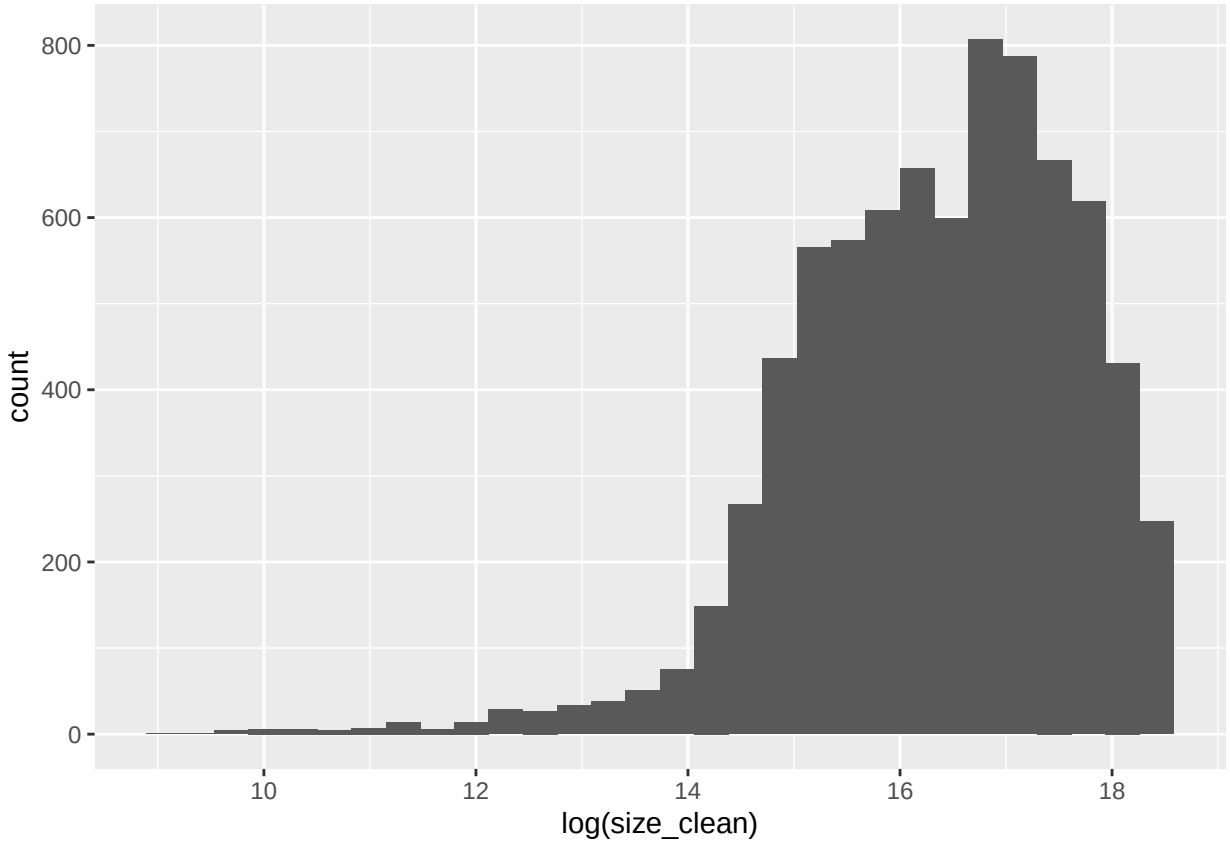

```
ggplot(data = d, aes(x = size_clean)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



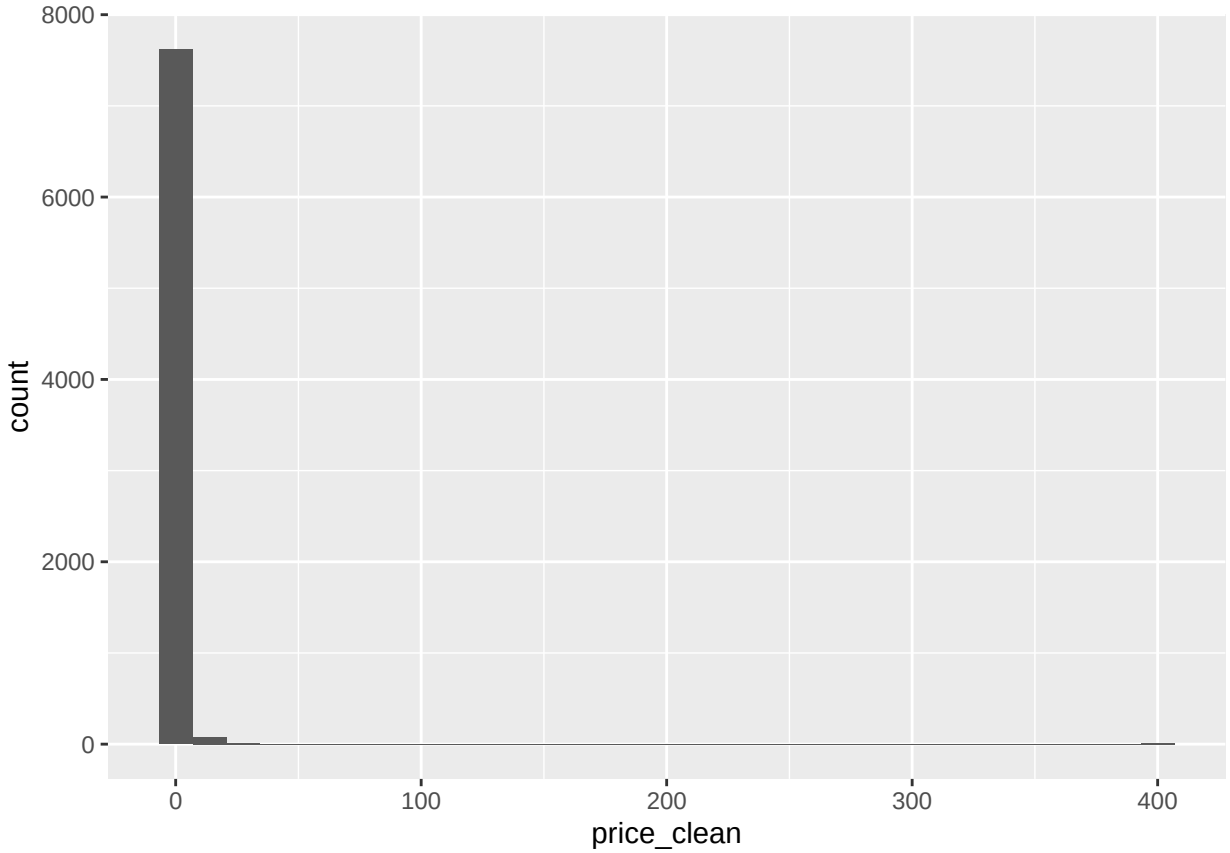

```
ggplot(data = d, aes(x = log(size_clean))) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(data = d, aes(x = price_clean)) +
  geom_histogram()
```

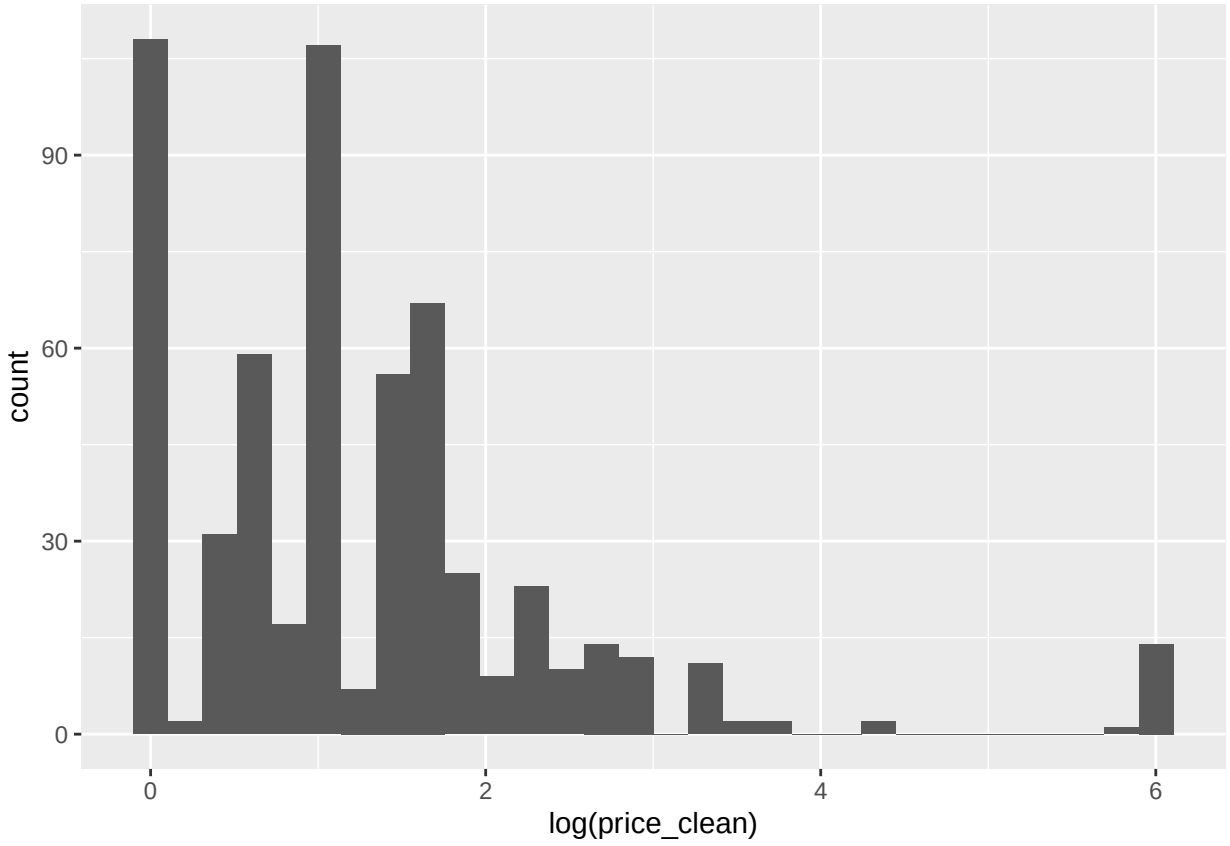
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(data = d, aes(x = log(price_clean))) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 7150 rows containing non-finite values (stat_bin).
```




```
categorical_cols <- c(
  'Category',
  'Type',
  'Content.Rating',
  'Current.Ver',
  'Android.Ver'
)

calc_stats_by_group <-
  function(column, quantile_table = FALSE) {

    # calc summary statistics per unique element in categorical column
    result <- d_dt[, .(count_apps = .N,
                       install_group_avg = mean(install_group, na.rm = TRUE),
                       install_count_med = median(installs_clean, na.rm = TRUE)),
                   by = column][count_apps > 100][order(-install_group_avg)]
    setnames(result, column, 'group_by_column')
    result[, variable := column]

    # create a table that shows the distribution across group averages
    if (quantile_table) {
      result <- as.data.table(t(data.table(quantile(
        result$install_group_avg
      ))))
      setnames(result, c('0%', '25%', '50%', '75%', '100%'))
      result[, variable := column]
```

```
    result[, diff_min_vs_max := `100%` - `0%`]
  }
  return(result)
}

# perform function across all categorical columns
table_long_cat <- rbindlist(lapply(categorical_cols, calc_stats_by_group))
table_quantile_cat <- rbindlist(lapply(categorical_cols, calc_stats_by_group,quantile_table=TRUE))

# compare mean install grp across variable values
table_long_cat
```

```
##         group_by_column count_apps install_group_avg install_count_med
##  1:                GAME        974         12.975359           1000000
##  2:           EDUCATION        110         12.627273           1000000
##  3:         PHOTOGRAPHY        236         12.389831           1000000
##  4:            SHOPPING        179         12.307263           1000000
##  5:       VIDEO_PLAYERS        116         11.655172            500000
##  6:              SPORTS        247         11.404858            500000
##  7:       COMMUNICATION        211         11.350711            500000
##  8:              SOCIAL        177         11.203390            500000
##  9:    TRAVEL_AND_LOCAL        160         11.181250            300000
## 10:  HEALTH_AND_FITNESS        223         11.103139            500000
## 11:        PRODUCTIVITY        235         10.872340            100000
## 12:              FAMILY       1617         10.679654            100000
## 13:  NEWS_AND_MAGAZINES        169         10.656805            100000
## 14:               TOOLS        634         10.517350            100000
## 15:              DATING        173         10.352601            100000
## 16:     PERSONALIZATION        280         10.275000             50000
## 17: BOOKS_AND_REFERENCE        144         10.159722             50000
## 18:             FINANCE        266         10.026316             10000
## 19:           LIFESTYLE        280          9.914286             50000
## 20:            BUSINESS        246          9.394309             10000
## 21:             MEDICAL        324          8.521605             10000
## 22:                Free       7150         11.243636            100000
## 23:                Paid        579          7.981002              5000
## 24:        Everyone 10+        318         12.764151           1000000
## 25:                Teen        868         11.995392           1000000
## 26:          Mature 17+        368         11.334239            500000
## 27:            Everyone       6172         10.747894            100000
## 28:                 1.3        120          9.533333             10000
## 29:                 2.0        118          9.067797             10000
## 30:                 1.2        126          8.714286             10000
## 31:                 1.1        195          8.446154             10000
## 32:                 1.0        458          7.967249              5000
## 33:          4.1 and up       1930         11.427979            500000
## 34:          4.4 and up        806         11.330025            500000
## 35:          5.0 and up        490         11.038776            100000
## 36:          4.0 and up       1109         11.025248            100000
## 37:          2.3 and up        566         11.014134            100000
## 38:          4.2 and up        318         10.933962            100000
## 39:        4.0.3 and up       1194         10.909548            100000
## 40:          2.1 and up        113         10.619469             50000
## 41:          4.3 and up        195         10.600000            100000
```

```
## 42:        2.3.3 and up        235         10.510638            100000
## 43:          3.0 and up        211         10.071090             50000
## 44:          2.2 and up        206          9.325243             10000
##         group_by_column count_apps install_group_avg install_count_med
##           variable
##  1:       Category
##  2:       Category
##  3:       Category
##  4:       Category
##  5:       Category
##  6:       Category
##  7:       Category
##  8:       Category
##  9:       Category
## 10:       Category
## 11:       Category
## 12:       Category
## 13:       Category
## 14:       Category
## 15:       Category
## 16:       Category
## 17:       Category
## 18:       Category
## 19:       Category
## 20:       Category
## 21:       Category
## 22:           Type
## 23:           Type
## 24: Content.Rating
## 25: Content.Rating
## 26: Content.Rating
## 27: Content.Rating
## 28:    Current.Ver
## 29:    Current.Ver
## 30:    Current.Ver
## 31:    Current.Ver
## 32:    Current.Ver
## 33:    Android.Ver
## 34:    Android.Ver
## 35:    Android.Ver
## 36:    Android.Ver
## 37:    Android.Ver
## 38:    Android.Ver
## 39:    Android.Ver
## 40:    Android.Ver
## 41:    Android.Ver
## 42:    Android.Ver
## 43:    Android.Ver
## 44:    Android.Ver
##           variable
```

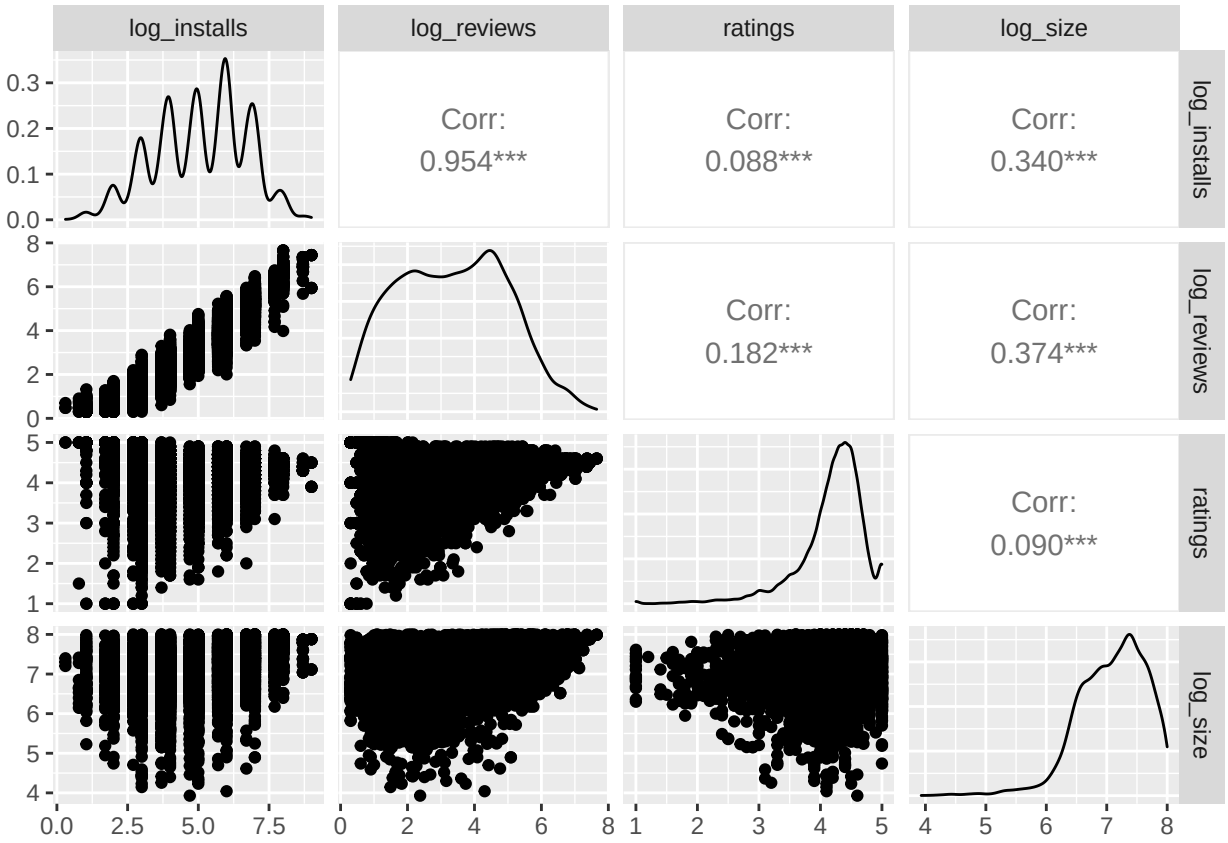
```
# compare distribution of mean install grp across variable values
table_quantile_cat
```

```
##           0%       25%       50%       75%      100%       variable
```

```
## 1:  8.521605 10.275000 10.872340 11.404858 12.975359       Category
## 2:  7.981002  8.796660  9.612319 10.427978 11.243636           Type
## 3: 10.747894 11.187653 11.664815 12.187582 12.764151 Content.Rating
## 4:  7.967249  8.446154  8.714286  9.067797  9.533333    Current.Ver
## 5:  9.325243 10.577660 10.921755 11.028630 11.427979    Android.Ver
##    diff_min_vs_max
## 1:        4.453754
## 2:        3.262635
## 3:        2.016257
## 4:        1.566084
## 5:        2.102737
```

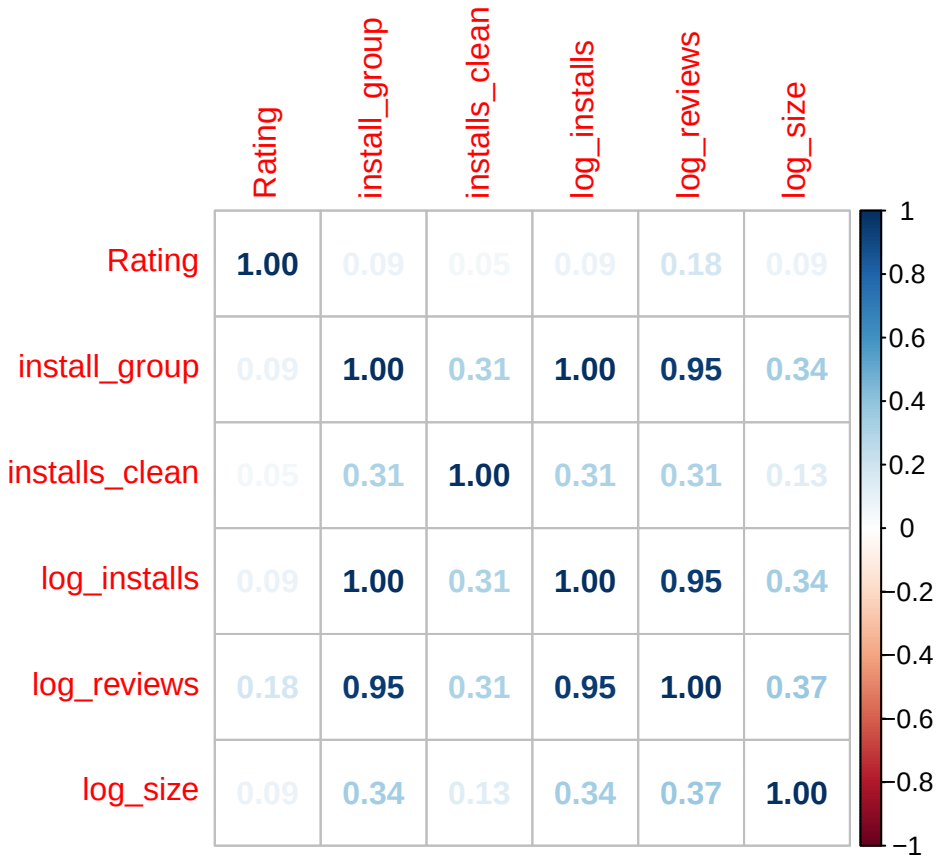
I.I.D. data: According to the Kaggle authors, this data set was collected by randomly scraping the Google Play Store. Since no clusters of applications were specifically targeted, we can reasonably use the entirety of the store as our reference population. We recognize that applications likely have some degree of interdependence, especially within genres. For example, the success of one application probably has a negative impact on other applications of the same type. Due to the large size of this data set (7729 records), however, we expect any dependencies to be negligible. We also have reason to believe that the data are identically distributed, as they are drawn from the same population of applications. One could argue that since the Google Play Store changes over time, the distribution also shifts in response. Because the authors do not mention the time frame across which the data was collected, we will assume that they originated from a single snapshot of the Play Store and that no shifts in the underlying distribution occurred.

```
d$log_installs <- log10(d$installs_clean + 1)
d$log_reviews  <- log10(d$reviews_clean + 1)
d$ratings      <- d$Rating
d$log_size     <- log10(d$size_clean + 1)
cols <- c('log_installs', 'log_reviews', 'ratings', 'log_size')
ggpairs(d[, cols])
```

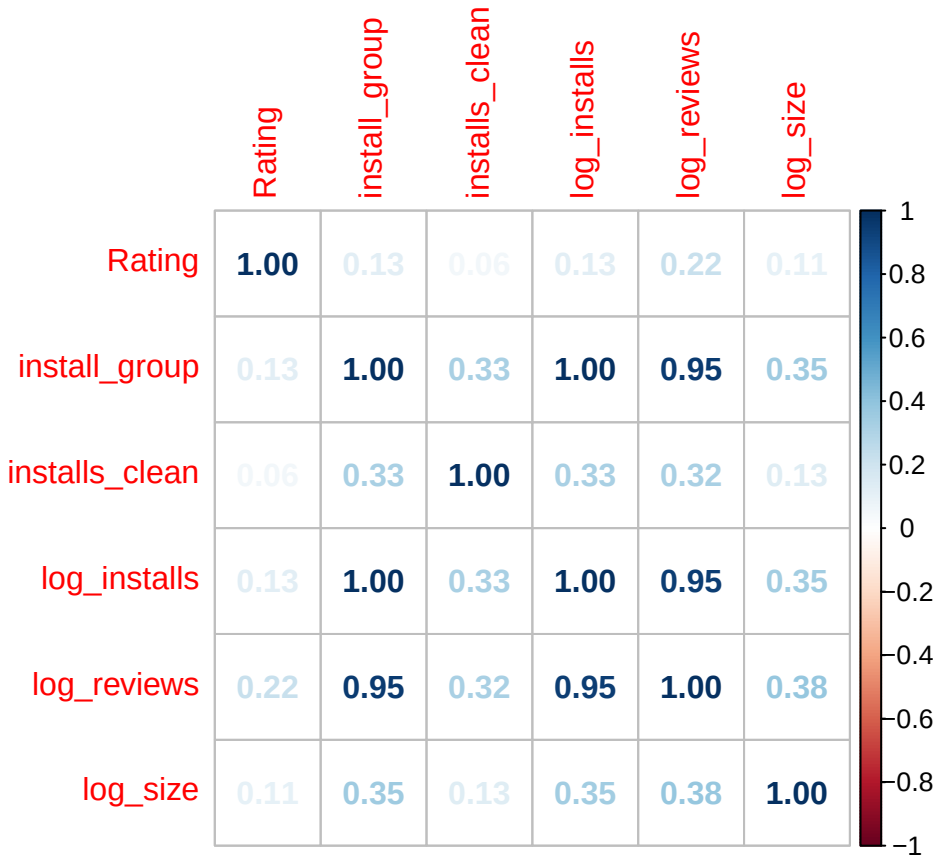



```
# save a data.table version for some easier wrangling downstream
d_dt <- as.data.table(d)
```

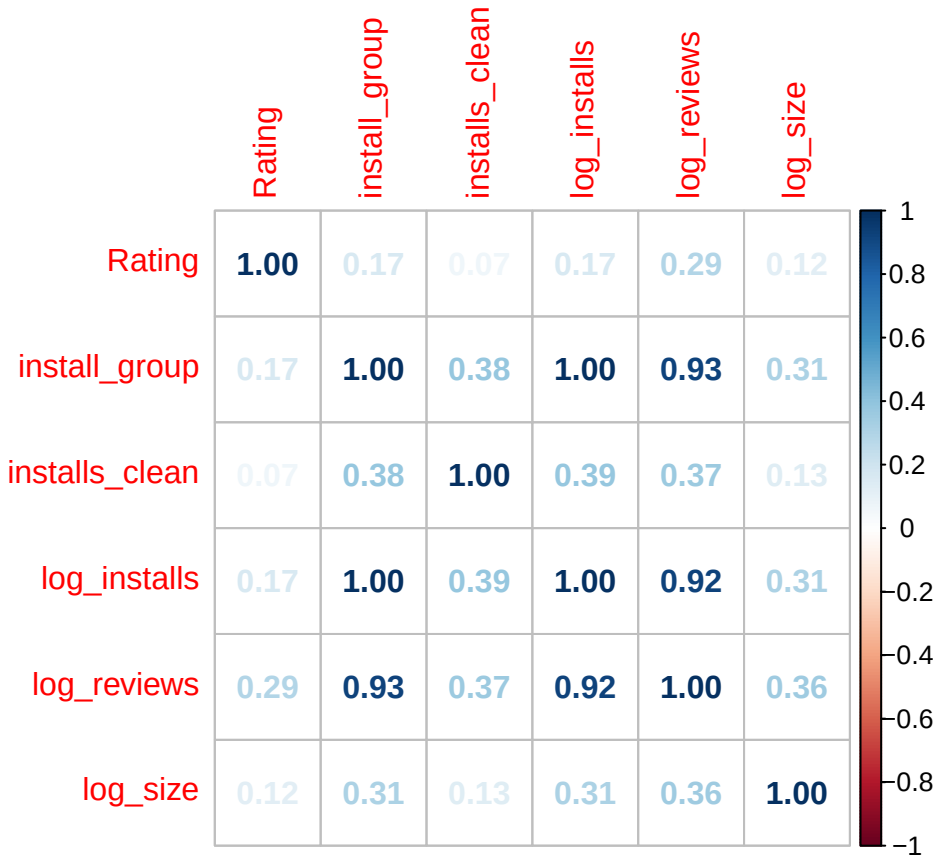
```
cols <- c('Rating','install_group','installs_clean', 'log_installs', 'log_reviews', 'log_size')

# Corrplot across variables
corrplot(cor(d[,
               cols], use = "complete.obs"),
         method = 'number')
```




```
# Corrplot across variables (5th PCTL outliers removed)
corrplot(cor(d[d$reviews_clean >= 6,cols], use = "complete.obs"),
         method = 'number')
```




```
# Corrplot across variables (25th PCTL outliers removed)
corrplot(cor(d[d$reviews_clean >= 100,cols], use = "complete.obs"),
         method = 'number')
```




```
model_small  <- lm(log_installs ~ 1 + log_reviews, data = d)
model_medium <- lm(log_installs ~ 1 + log_reviews + ratings + log_size, data = d)
model_large <- lm(log_installs ~ 1 + log_reviews + ratings + log_size + factor(Type), data = d)

stargazer(
  model_small,
  model_medium,
  model_large,
  type = 'text',
  se = list(get_robust_se(model_small), get_robust_se(model_medium))
)
```

```
##
## ===============================================================================================
##                                                Dependent variable:
##                    ---------------------------------------------------------------------------
##                                                    log_installs
##                                (1)                     (2)                     (3)
## -----------------------------------------------------------------------------------------------
## log_reviews                 0.955***                0.977***                0.959***
##                             (0.004)                 (0.004)                 (0.003)
##
## ratings                                             -0.261***               -0.239***
##                                                     (0.013)                 (0.009)
##
## log_size                                            -0.048***               -0.053***
```

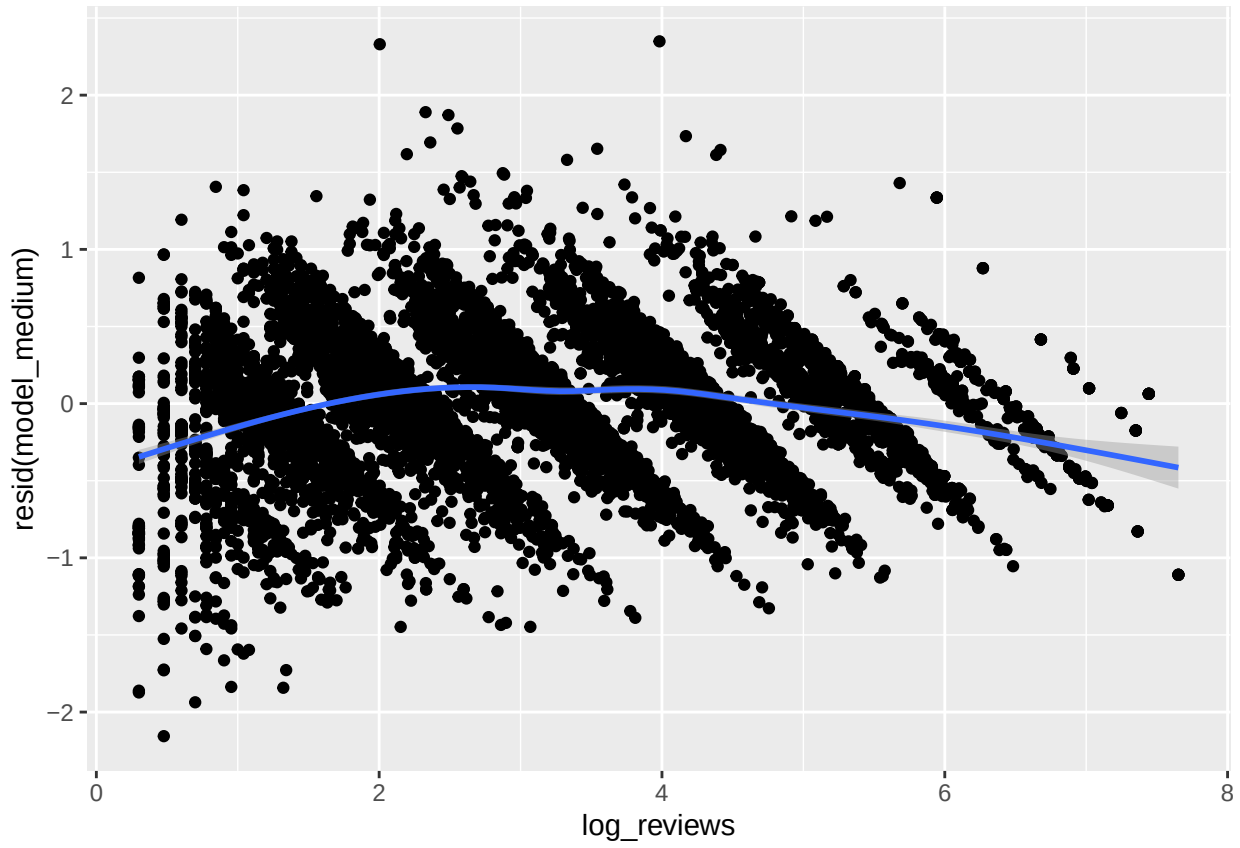
```
##                                                (0.010)                    (0.009)
##
## factor(Type)Paid                                                         -0.611***
##                                                                           (0.019)
##
## Constant                          1.860***                 3.213***      3.264***
##                                   (0.015)                  (0.083)       (0.073)
##
## ------------------------------------------------------------------------------------------
## Observations                       7,729                    7,729         7,729
## R2                                 0.909                    0.917         0.927
## Adjusted R2                        0.909                    0.917         0.927
## Residual Std. Error      0.484 (df = 7727)        0.462 (df = 7725)   0.435 (df = 7724)
## F Statistic         77,422.710*** (df = 1; 7727) 28,504.560*** (df = 3; 7725) 24,455.410*** (df = 4;
## ==========================================================================================
## Note:                                                          *p<0.1; **p<0.05; ***
```

2. **No Perfect Colinearity:** We can immediately conclude that `log_installs`, `log_reviews`, `ratings`, and `log_size` are not perfectly colinear as otherwise the regression above would have failed. We can also assess near perfect colinearity for these variables by observing the robust standard errors returned by the regression model. In general, highly colinear features will have large standard errors. Since the standard error of the coefficients are small relative to their magnitude, we can reasonably conclude that they are not nearly colinear.

3. **Linear Conditional Expectation:** To verify the assumption of linear conditional expectations, we seek to show that there is no relationship between the model residuals and any of the predictor variables. That is, the model does not systematically underpredict or overpredict in certain regions of the input space. Plots 1 through 3 show the relationships between the model residuals and individual predictors. The residuals are generally well-centered around zero, although the model seems to underpredict when `log_reviews` is high and `ratings` is low. The fourth plot shows the model residuals as a function of the model predictions. Here, the model seems to underpredict in the left-most and right-most regions, and slightly overpredict in the middle. Overall, there are no strong non-linear relationships between the model residuals and the input features, and we do not find enough evidence to reject the assumption of linear conditional expectation.

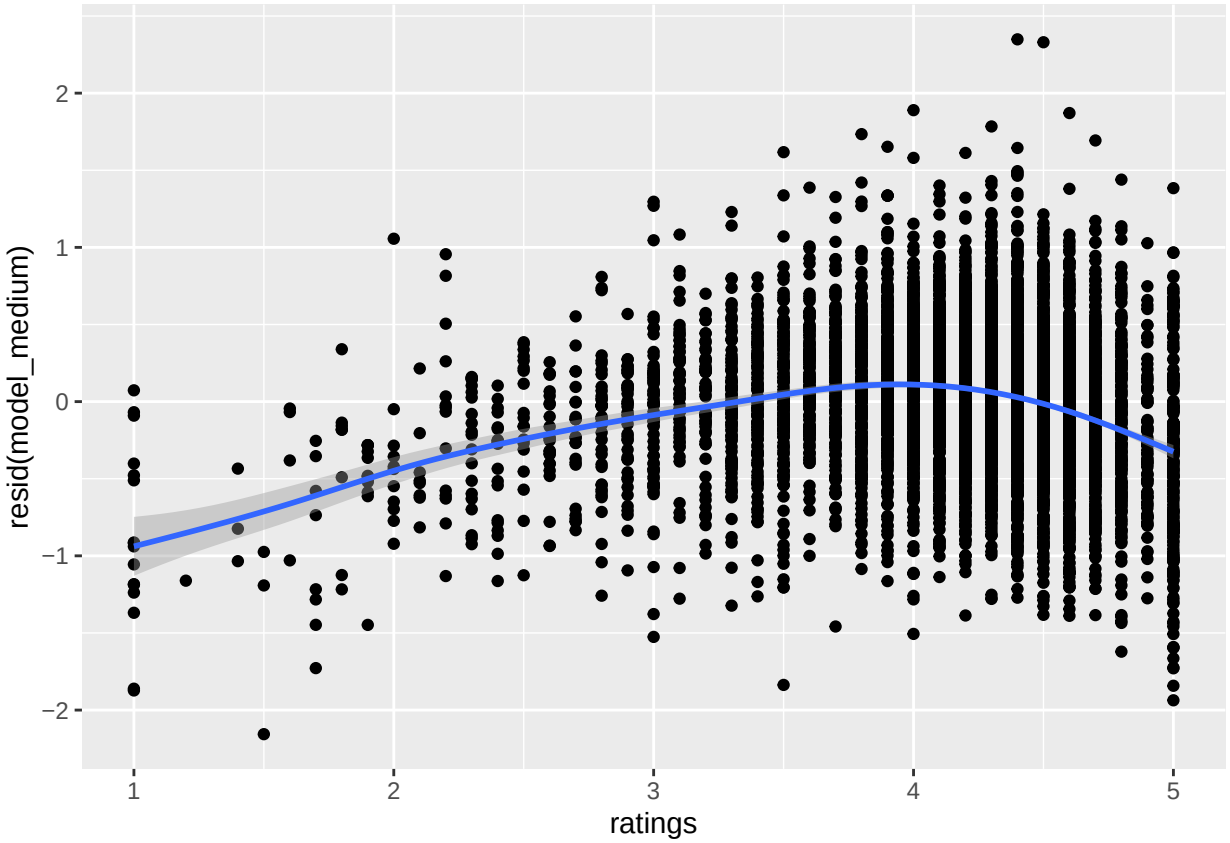
```
# Reviews versus residuals
plot_1 <- ggplot(data = d, mapping = aes(x = log_reviews, y = resid(model_medium))) +
  geom_point() + stat_smooth()
plot_1
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



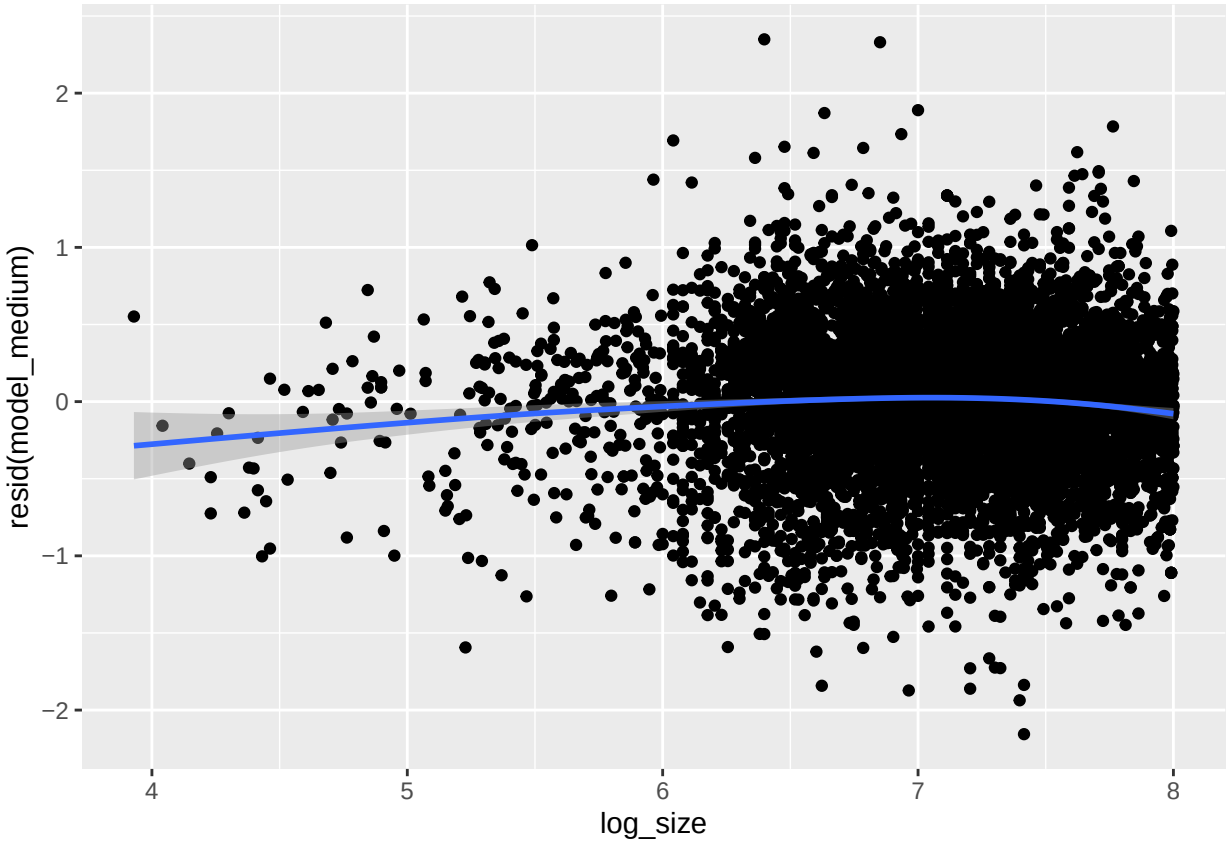

```
# Ratings versus residuals
plot_2 <- ggplot(data = d, mapping = aes(x = ratings, y = resid(model_medium))) +
  geom_point() + stat_smooth()
plot_2
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



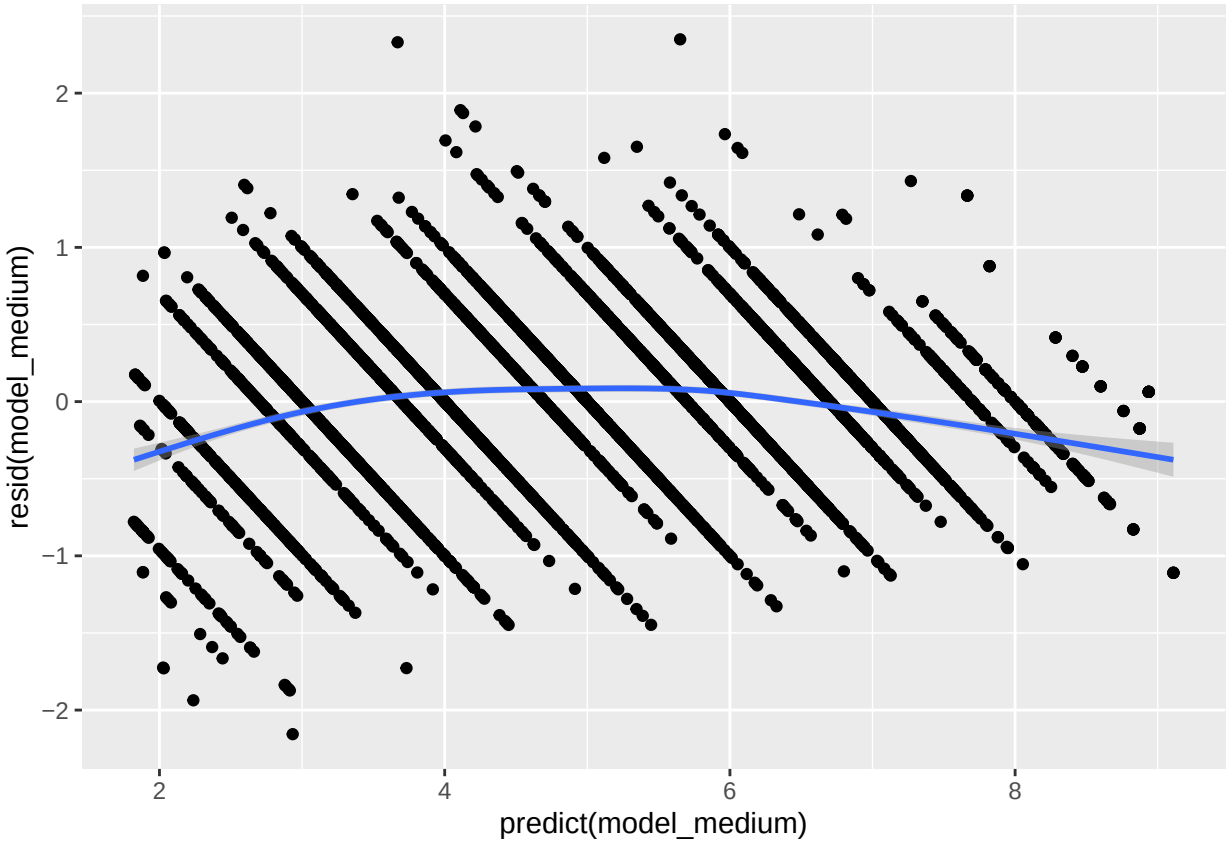

```
# Size versus residuals
plot_3 <- ggplot(data = d, mapping = aes(x = log_size, y = resid(model_medium))) +
  geom_point() + stat_smooth()
plot_3
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```




```
# Model predictions versus residuals
plot_4 <- ggplot(data = d, mapping = aes(x = predict(model_medium), y = resid(model_medium))) +
  geom_point() + stat_smooth()
plot_4
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



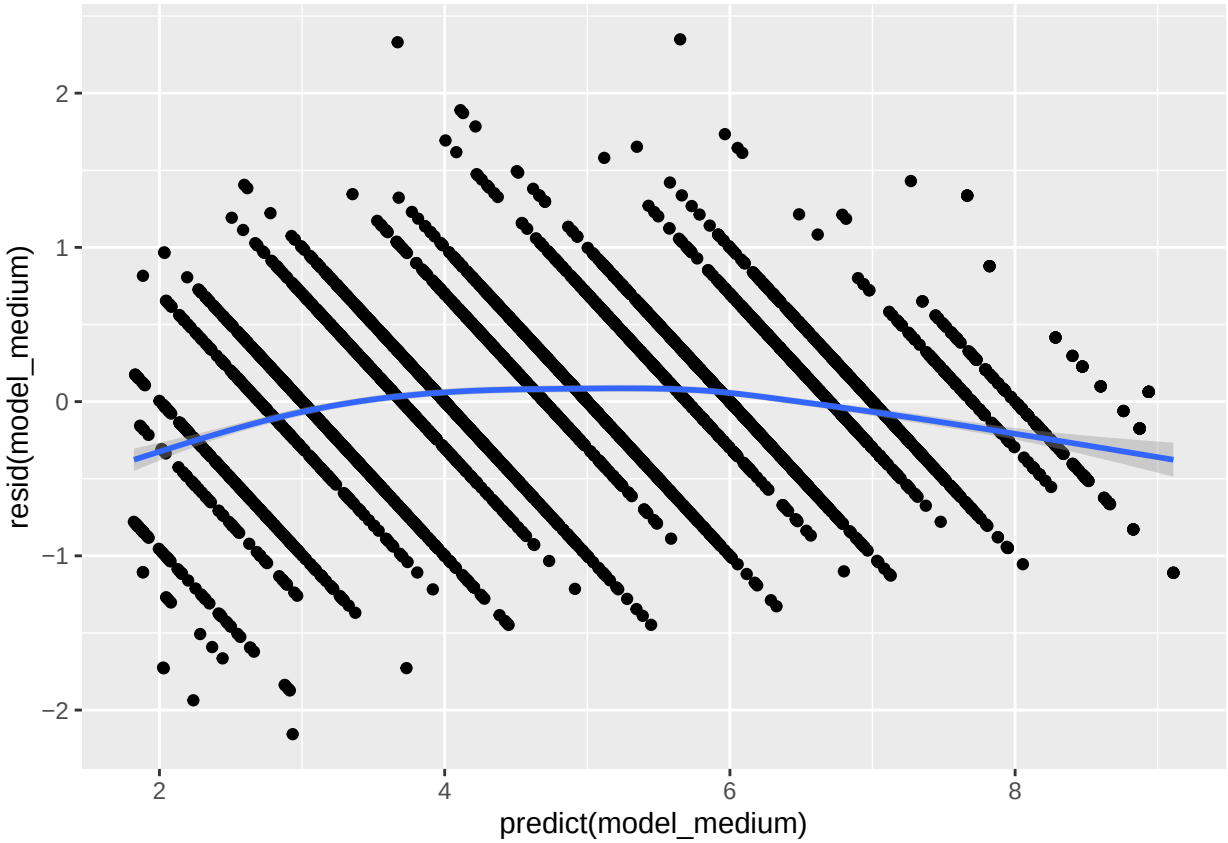
4. **Homoskedastic Errors:** When assessing homoskedastic errors, we seek to determine if there is a relationship between the variance of the model residuals and the predictors. If the homoskedastic assumption is satisfied, then we should observe a lack of relationship; conversely, if the data are heteroskedastic then the conditional variance will depend on the predictors. The first plot is an eyeball test of homoskedasticity, showing the model residuals as a function of the model predictions. We notice that the spread of the residuals is mostly consistent throughout the data, although the right-hand side is somewhat narrower. As a more concrete assessment, we also perform a Breush-Pagan test with the null hypothesis that there are no heteroskedastic errors in the model. Since the p-value falls below our significance threshold of 0.001, we find enough evidence to reject the null hypothesis. In response to this failed assumption, we report robust standard errors (adjusted for heteroskedasticity) instead of non-adjusted errors.

```
# Breusch-Pagan test
bp_test <- bptest(model_small)
bp_test
```

```
##
##  studentized Breusch-Pagan test
##
## data:  model_small
## BP = 235.66, df = 1, p-value < 0.00000000000000022
```

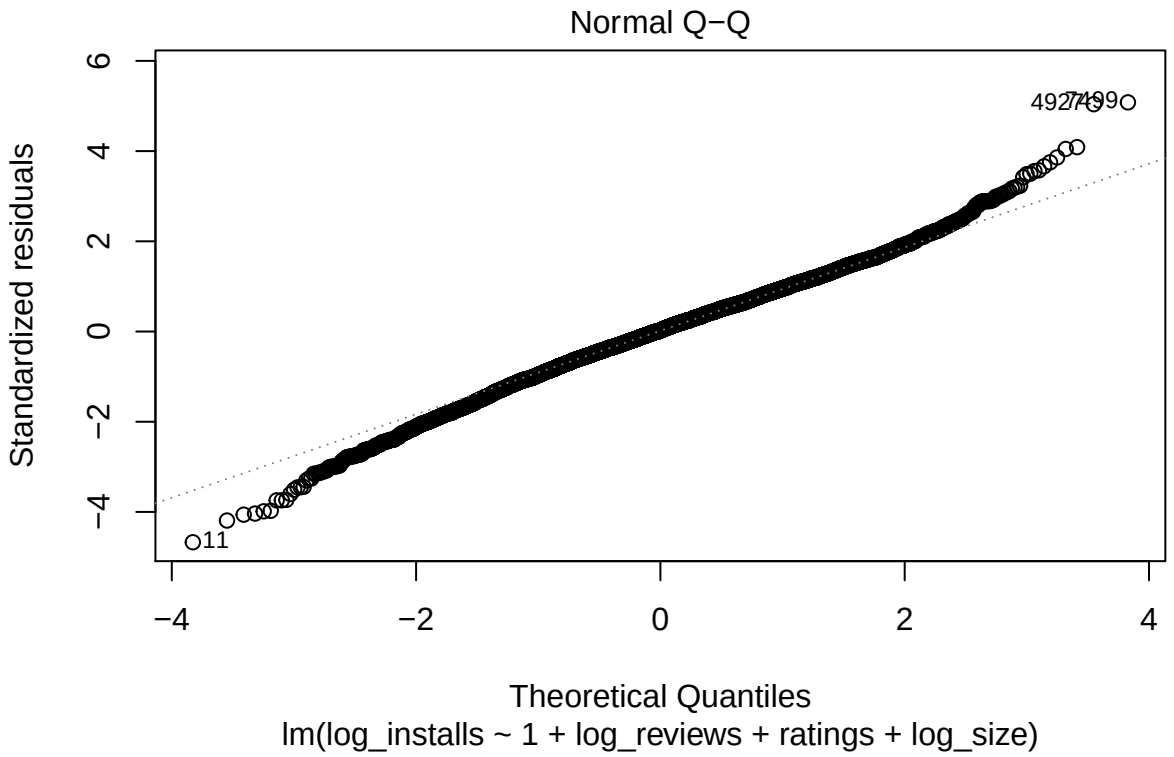
```
plot_4
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



5. **Normally Distributed Errors:** When assessing the normality of the error distribution, we seek to determine if the model residuals are approximately Gaussian. If so, then the sample quantiles of the residuals should closely match the theoretical quantiles of a normal distribution in a Q-Q plot. Below, we plot the Q-Q plot associated with our model. In general, the residuals seem to follow a normal distribution, as the middle quantiles match the corresponding theoretical quantiles. However, the tails of the residual distribution are fatter than expected; the first quantiles occur at smaller than expected values, and the last quantiles occur at larger than expected values. Overall, the assumption of normally distributed errors seems imperfect but reasonably justified.

```
# Q-Q plot
plot_5 <- plot(model_medium, which = 2)
```




```
plot_5
```

```
## NULL
```

** Reverse Causality: ** We have to consider the possibility that high average reviews could lead to a higher number of installations which could lead to a higher average review. We will want to test for a reverse causality relationship between these two variables to determine if the best linear predictor is valid. If we regress average reviews on installs, the installs coefficient (Gamma1) will have a positive slope. Since Beta1 (average review slope coefficent) > 0, we know higher average review leads to more installs. Since Gamma1 (installs slope cofficent for reverse causality) is > 0, this leads to positive feedback. Given we have two potentially positive coefficents, this could be a bias away from zero which is a concern that a reverse causality relationship exists between the two variables. We could consider dropping average reviews as a variable and determine if there are other leading variables that can explain the number of installs for an app.

```
model_small  <- lm(log_installs ~ 1 + log_reviews, data = d)
model_reverse  <- lm(log_reviews ~ 1 + log_installs, data = d)

stargazer(
  model_small,
  model_reverse,
  type = 'text',
  se = list(get_robust_se(model_small), get_robust_se(model_medium))
)
```

```
##
## ============================================================
##                                      Dependent variable:
```

```
##                                 ----------------------------
##                                  log_installs   log_reviews
##                                      (1)            (2)
## ------------------------------------------------------------
## log_reviews                        0.955***
##                                    (0.004)
##
## log_installs                                        0.952
##
##
## Constant                           1.860***      -1.467***
##                                    (0.015)        (0.083)
##
## ------------------------------------------------------------
## Observations                        7,729          7,729
## R2                                  0.909          0.909
## Adjusted R2                         0.909          0.909
## Residual Std. Error (df = 7727)     0.484          0.483
## F Statistic (df = 1; 7727)      77,422.710***  77,422.710***
## ============================================================
## Note:                           *p<0.1; **p<0.05; ***p<0.01
```