Project 1

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Introduction

Within the Project1.Rmd file and this Project1.pdf file, the user can create a linear regression between two variables; also, the user can use a bootstrapping function. Within the function myslr, the user estimates the relationship between two variables, as well show the confidence in those estimates.

Within the bootstrapping function myboot, the user can use a limited sample to infer information about a population's variance. The function will output a confidence interval, some summary statistics, and a histogram showing the possible outcomes of a given variable.

Data

Within the examples in this file, the mtcars data set provides meaningful information when estimating linear regressions and bootstrapping. This data set includes information from the 1974 *Motor Trends* US magazine, and "comprises fuel consumption," as well as "10 aspects" of each of the thirty-two cars in the data set. These "aspects" resemble the variables within the data, such as miles per gallon.

When considering the variables in the mtcars data set, it is useful to understand the types of data, which help best determine how to analyze the data. Please see the variables, their descriptions, and their data types below.

Variable Description	Data Type
Miles/(US) gallon	Ratio
Number of cylinders	Ratio
Displacement (cu.in.)	Ratio
Gross horsepower	Ratio
Rear axle ratio	Ratio
Weight (1000 lbs)	Ratio
1/4 mile time	Interval
Engine (0 = V-shaped, $1 = \text{straight}$)	Nominal
Transmission $(0 = automatic, 1 = manual)$	Nominal
Number of forward gears	Ratio
Number of carburetors	Ratio
	Miles/(US) gallon Number of cylinders Displacement (cu.in.) Gross horsepower Rear axle ratio Weight (1000 lbs) 1/4 mile time Engine (0 = V-shaped, 1 = straight) Transmission (0 = automatic, 1 = manual) Number of forward gears

Theory Used

$$Y = \beta_0 + \beta_i * X_i + \epsilon_i \tag{1}$$

Y Represents the dependent, or explained, variable.

$$\beta_0$$
 (2)

represents the estimated intercept.

$$\beta_i$$
 (3)

represents the slope of the estimated vector.

$$X_i$$
 (4)

represents the independent, or control, variable.

$$\epsilon_i$$
 (5)

represents some error term.

Application of SLR to the mtcars data set

Making the SLR function: myslr

```
myslr <- function(data,</pre>
                    y, yName,
                    x, xName,
                    sizeVar, sizeVarName,
                    colVar, colVarName,
                    titleVar)
  # Open Window to View Plot
    windows(title = "Linear Estimation Graph for Y on X")
  # Create Plot
    plot <- ggplot(</pre>
                  # Data
                    data,
                  # Aesthetic Mapping
                    aes(x, y,
                       color = colVar,
                       size = sizeVar)) +
                  # Add Scatter Layer
                    geom_point(alpha = 2/5) +
                  # Add Linear Estimation
                    geom_smooth(method = "lm",
                                formula = y \sim x,
                                color = "grey35") +
                  # Titles
                    labs(title = titleVar,
                         subtitle = " ",
                                  = xName,
                                  = yName,
                         у
                         col
                                   = colVarName,
                                   = sizeVarName) +
                         size
```

```
# Theme
                  theme get()
# show Plot
 print(plot)
# Save plot
  ggsave(filename = paste0(titleVar, ".png"),
         plot
                   = plot,
         height
                   = 6,
         width
                   = 8)
# Linear Estimation and Summary Output
  ## Linear Regression (returned)
    y.lm \leftarrow lm(y \sim x)
  ## Linear Regression Output (void)
    print(summary(y.lm))
  ## Confidence Interval at 95% (void)
    CI <- ciReg(y.lm)
    CI
    write.csv(CI, file = "Confidence Intervals.csv")
  ## Check assumptions and save .png
    png("Normal Interval Check.png", height = 150, width = 500)
    normcheck(y.lm)
    dev.off()
  ## Check residuals and save .png
    png("Fitted vs. residuals Plot.png", height = 250, width = 500)
    plot(y.lm, which = 1)
    dev.off()
  ## Linear Estimation
    return(y.lm)
```

Invoke myslr function using the mtcars data set

1Q Median

3Q

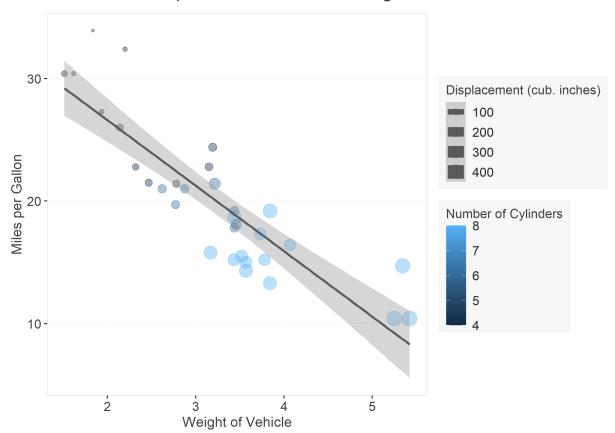
Max

Residuals: ## Min

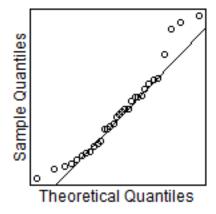
```
## -4.5432 -2.3647 -0.1252 1.4096 6.8727
##
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 37.2851
                          1.8776 19.858 < 2e-16 ***
## x
               -5.3445
                           0.5591 -9.559 1.29e-10 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.046 on 30 degrees of freedom
## Multiple R-squared: 0.7528, Adjusted R-squared: 0.7446
## F-statistic: 91.38 on 1 and 30 DF, p-value: 1.294e-10
##
##
               95 % C.I.lower
                                95 % C.I.upper
## (Intercept)
                    33.45050
                                      41.11975
                                       -4.20263
                     -6.48631
  # Coefficient list
    coefsList <- y.lm$coefficients</pre>
```

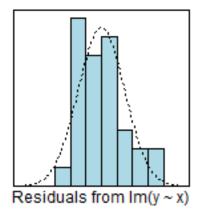
Plot Output

The Relationship between MPG and Weight of Vehicle

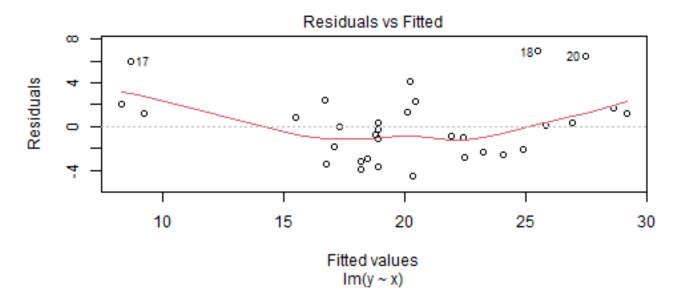


Normal Interval Check





Fitted vs. Residuals



Interpretation of Model

Within the model, it estimates that an increase of 1,000 pounds in weight of a given car decreases the miles per gallon of the vehicle by 5.34. Additionally, the model estimates that changes in weight account for 75.28% of the variation in the car's miles per gallon.

At a 95% level of confidence, the model estimates the lower bound to be a 6.49 decrease in miles per gallon when increasing the weight of a car by 1,000 pounds. Alternatively, the model estimates the upper bound to be a 4.20 decrease in miles per gallon when increasing the weight of a car by 1,000 pounds.

Validity of the Model

Although the model estimates a narrow confidence interval with a relatively high R-squared value, we may not assume that solely weight accounts for the full 76.28% variation in miles per gallon. This variable could easily be correlated with another relevant variable, thus confounding the simple linear regression.

Bootstrap

Make Bootstrap Function

```
myboot <- function(iter = 10000, # num iterations</pre>
                 x,  #
fun = "var", #
                                 # dataset
                  alpha = 0.05, # 95% confidence
                       = 1.5,
                  . . .
                  )
  # Get Sample size
   n = length(x)
  # Create Sample
   y = sample(x,
              n * iter,
              replace = TRUE)
  # Form Matrix from sample
   rs.mat = matrix(y, # data from sampling
                  nrow = n,
                  ncol = iter,
                  byrow = TRUE) # sort by row
  # Variance
   xstat = apply(rs.mat, 2, fun) # vector containing iter vals
  # Form confidence interval
   ci = quantile(xstat,
                 c(alpha / 2,
                  1 - alpha / 2)
  # Send summary Statistics to the console
   ## Confidence Interval Out
     print(pasteO("Confidence Interval at Alpha = ", alpha))
     print("----")
     print(ci)
   ## Form matrix of sample stats
   statNames <- c("Mean:", "Median:", "Standard Deviation:")</pre>
   statVals <- c(comma(mean (xstat), digits = 2),</pre>
                  comma(median(xstat), digits = 2),
                  comma(sd (xstat), digits = 2)
   summaryStats <- matrix(data = c(statNames,</pre>
                                  statVals),
                         nrow = 3.
                         ncol = 2)
   ## Sample Stats Out
```

```
print("Summary Statistics from Bootstrap Sampling:")
   print("----")
   print(summaryStats)
  # Create a histogram from Bootstrap sampling
   para <- hist(</pre>
                 xstat,
                 freq = FALSE, # along numberline, not freq
                 las = 1,
                 main = pasteO("Histogram of Bootstrap Sample Statistics",
                              "\n",
                              "Alpha = ", alpha, "; ",
                              "Iters = ", comma(iter, digits = 0)),
                 col = alpha("skyblue3", 2/5),
                 ...)
    # Save Bootstrap plot
     png("Bootstrap Estimate Plot.png", height = 150, width = 500)
     para
     dev.off()
    # write a file to current directory with sample data
     write.csv(xstat, "Bootstrap Estimations.csv")
   return(xstat)
}
```

Invoke myboot Function

Get data from mtcars, while only containing 4 cylinder cars

```
# Get dataset from mtcars
df <- mtcars %>%

## filter to only 4-cylinder cars
   filter(cyl == 4) %>%

## Only show vars of interest
   select(mpg)

## Store as vector
   df.vector <- df$mpg</pre>
```

Call myboot Function and Store Estimations in List

```
## [1] "______"

## [1] "Confidence Interval at Alpha = 0.05"

## [1] "----------"

## 2.5% 97.5%

## 8.506909 28.430909

## [1] "_____"

## [1] "Summary Statistics from Bootstrap Sampling:"

## [1] "---------"

## [1,1] [,2]

## [1,1] "Mean:" "18.4292932363636"

## [2,] "Median:" "18.3828181818182"

## [3,] "Standard Deviation:" "5.08501472032832"
```

Histogram of Bootstrap Sample Statistics Alpha = 0.05; Iters = 10,000

