

# STA302H1 – Final Project Descriptive Statistics

Danny Chen

August 10, 2021

## Import STA302H1 Study Time and COVID Contemplation Time vs. Quiz Performance Dataset

### Data Cleaning

First, I'll clean my data.

```
cleaned_sta302_performance_data <- sta302_performance_data %>%  
  # Create a new "country" column, which is just "Country" but whose entries are factors.  
  mutate(country = as.factor(Country)) %>%  
  
  # TODO: Replace quiz grades, covid hours, and sta302h1 study hours with their  
  # TODO: median counterparts.  
  
  # Remove the "X" column: it's simply the row number, which isn't very useful.  
  # Remove the "Country" column: column "country" already exists  
  dplyr::select(-X, -Country) %>%  
  
  # Rearrange similar columns side-by-side.  
  relocate(country,  
            COVID.hours..W1., COVID.hours..W2., COVID.hours..W3., COVID.hours..W4.,  
            STA302.hours..W1., STA302.hours..W2., STA302.hours..W3., STA302.hours..W4.,  
            Quiz_1_score, Quiz_2_score, Quiz_3_score, Quiz_4_score)
```

## Helper Functions

```
num_column_NAs = function(predictor_variable) {  
  sum(is.na(predictor_variable))  
}
```

```
row_nums_of_NA_columns = function(data, predictor_variable) {  
  which(is.na(predictor_variable))  
}
```

```
rows_with_num_NAs = function(data, num_NAs) {  
  return (rowSums(is.na(data)) == num_NAs)  
}
```

```
row_nums_of_NA_rows = function(data, num_NAs) {  
  return (which(rows_with_num_NAs(data, num_NAs)))  
}
```

```
display_histogram <- function(data, predictor_variable, histogram_title, x_axis_label) {  
  ggplot(data = tibble(data), mapping = aes(x = predictor_variable)) +  
    geom_histogram(col = "black", fill = "red", bins = 30) +  
    labs(title = histogram_title, y = "Frequency", x = x_axis_label) +  
    geom_vline(mapping = aes(xintercept = mean(predictor_variable, na.rm = TRUE)),  
              color = "blue", linetype = "solid") +  
    geom_vline(mapping = aes(xintercept = median(predictor_variable, na.rm = TRUE)),  
              color = "dark green", linetype = "dotted")  
}
```

```
display_boxplot <- function(data, predictor_variable, boxplot_title, y_axis_label) {  
  ggplot(mapping = aes(x = Country, y = predictor_variable, color = Country)) +  
    geom_boxplot(mapping = aes(x = Country, y = predictor_variable)) +  
    labs(title = boxplot_title, x = "Country", y = y_axis_label)  
}
```

```
get_row_nums_to_exclude <- function(data) {  
  row_nums_with_3_NAs = which(rows_with_num_NAs(data, 3))  
  row_nums_with_4_NAs = which(rows_with_num_NAs(data, 4))  
  row_nums_to_exclude <- union(row_nums_with_3_NAs,  
                               row_nums_with_4_NAs)  
  return (row_nums_to_exclude)  
}
```

```
display_correlation_by_country <- function(country_data) {  
  colnames(country_data) <- c("W1COV", "W2COV", "W3COV", "W4COV",  
                              "W1302", "W2302", "W3302", "W4302",  
                              "Q1", "Q2", "Q3", "Q4")  
  round(cor(country_data, use = "pairwise.complete.obs", method = "pearson"), 2)  
}
```

## Special Tables

### Rows With At Least One NA

Rows with at least one NA deserve closer examination.

Some of the rows might only have 1 - 2 NAs and are therefore salvageable, which is OK.

Other rows may contain 3 or more NAs, and might indicate students who have dropped STA302H1. We'd like to exclude them from our analysis.

Here are the number of rows with 0 - 4 NAs.

```
##   nrows_0_NAs nrows_1_NAs nrows_2_NAs nrows_3_NAs nrows_4_NAs
## 1           143           9           16           19           1
```

### Columns with NAs

```
##   week1_covid week2_covid week3_covid week4_covid
## 1           26           22           21           40
```

```
##   week1_sta302 week2_sta302 week3_sta302 week4_sta302
## 1           26           22           20           40
```

```
##   quiz1_score quiz2_score quiz3_score quiz4_score
## 1           13           36           31           34
```

### Number of Missed Quizzes

```
##   miss_0_quizzes miss_1_quizzes miss_2_quizzes miss_3_quizzes miss_4_quizzes
## 1           176           20           3           24           4
```

### Who to Exclude from the Dataset?

Identify rows with at least 3 missing quiz marks. These indicate students who have dropped STA302H1, and who should be excluded from the final data.

Notice that we didn't check the number of NAs for country of origin, COVID hours, and STA302H1 hours, since some students either forgot or abstained. So there's no reason to exclude these students from our final dataset.

```
row_nums_to_exclude <- get_row_nums_to_exclude(quiz_grades)
cleaned_sta302_performance_data2 =
  cleaned_sta302_performance_data[-row_nums_to_exclude,]
```

## Rows with Mistyped Columns

Rows whose columns are mis-typed may need to be corrected via imputation.

```
rows_with_mistyped_columns = cleaned_sta302_performance_data2[c(38, 83, 84, 117),]
# row 83: Country -> "canada" -- DONE
# row 84: Country -> "canada" -- DONE

# row 117: COVID.hours..W4. -> 0.5 hours -- DONE

# row 38: STA302.hours..W3. -> 5.5<U+00A0> -- DONE
# row 117: STA302.hours..W4. -> 7.5 hours -- DONE

# library(janitor)
# use it to clean up data.
```

## Rows Without Country Entry

Taking out the country column can come in handy for functions like `cor()` where factors aren't allowed.

```
rows_with_no_country = cleaned_sta302_performance_data2 %>%
  dplyr::select(-country)
```

## Rows Filtered by Country

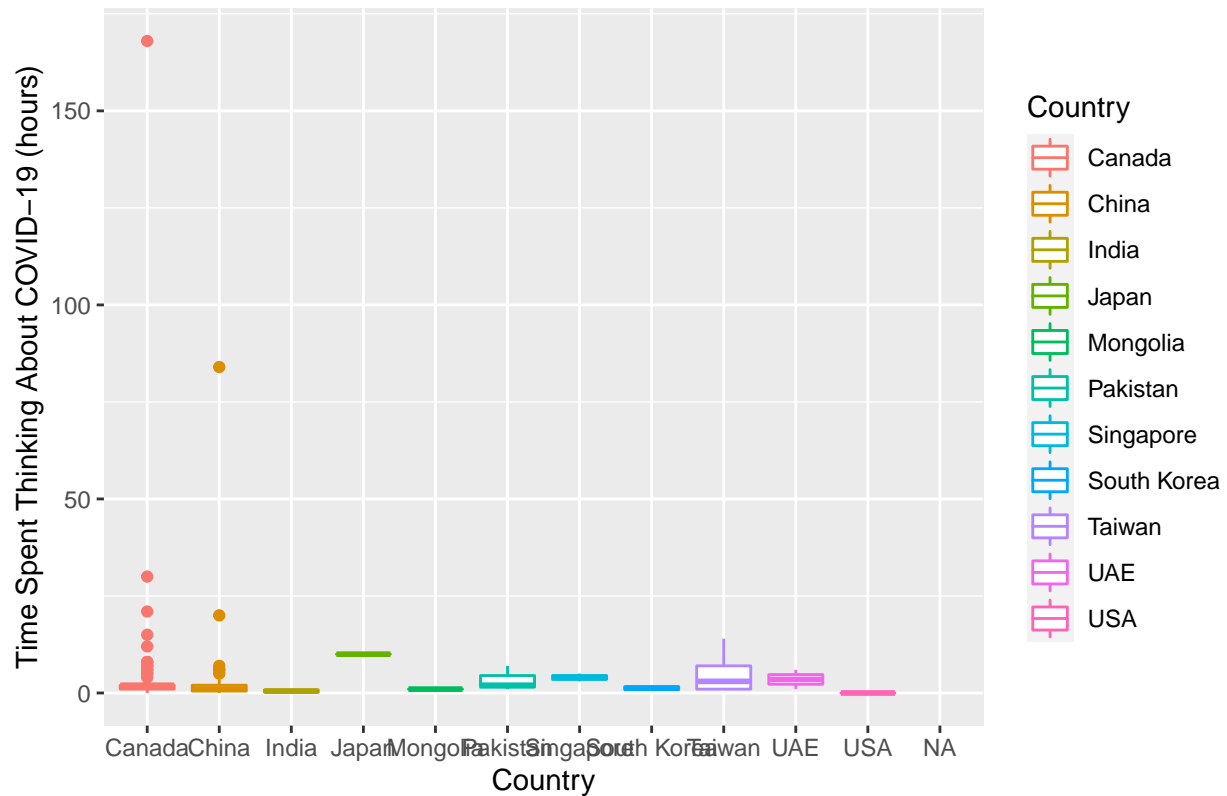
This is useful if we want data for individual countries.  
Only the first and last code snippets are shown.

```
canada <- cleaned_sta302_performance_data2 %>%
  filter(as.character(country) == "Canada") %>%
  dplyr::select(-country)

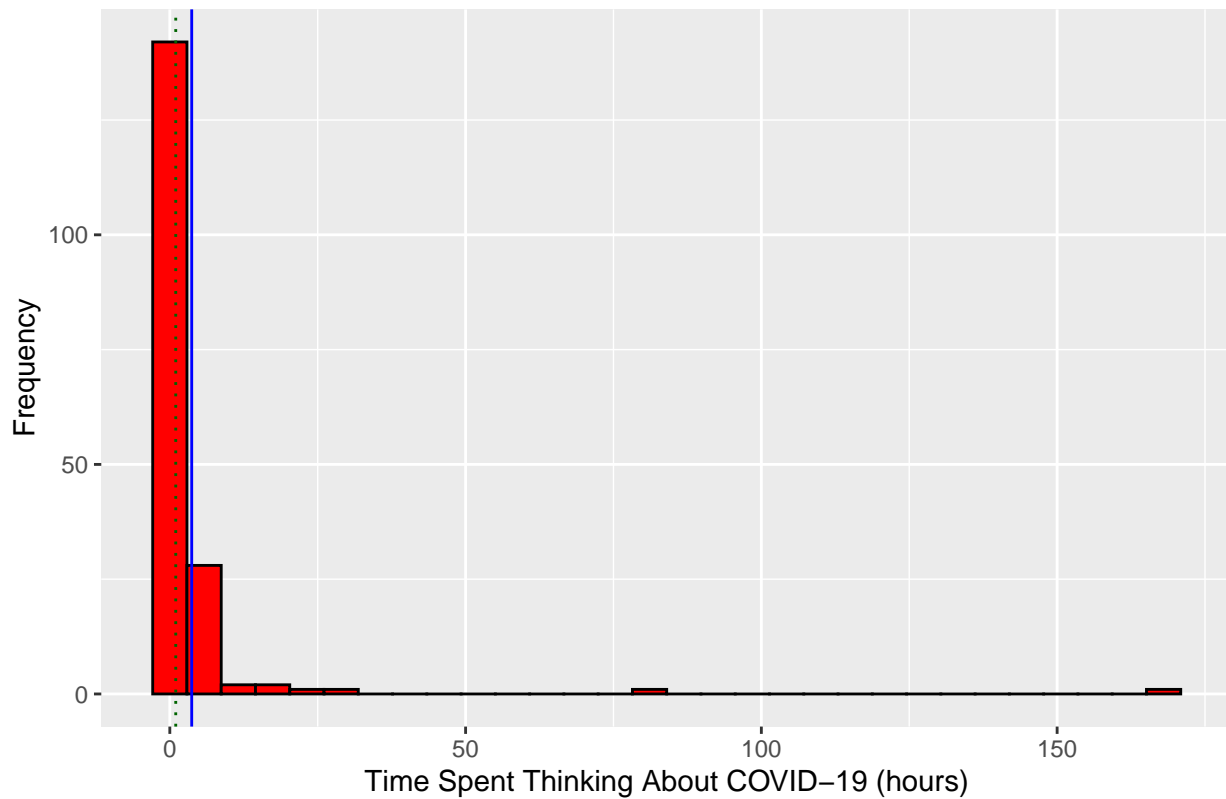
unknown <- cleaned_sta302_performance_data2 %>%
  filter(is.na(as.character(country))) %>%
  dplyr::select(-country)
```

##	Country
## Canada	97
## China	63
## India	2
## Japan	1
## Mongolia	1
## Pakistan	3
## Singapore	2
## South_Korea	2
## Taiwan	3
## UAE	2
## USA	2
## Unknown	21

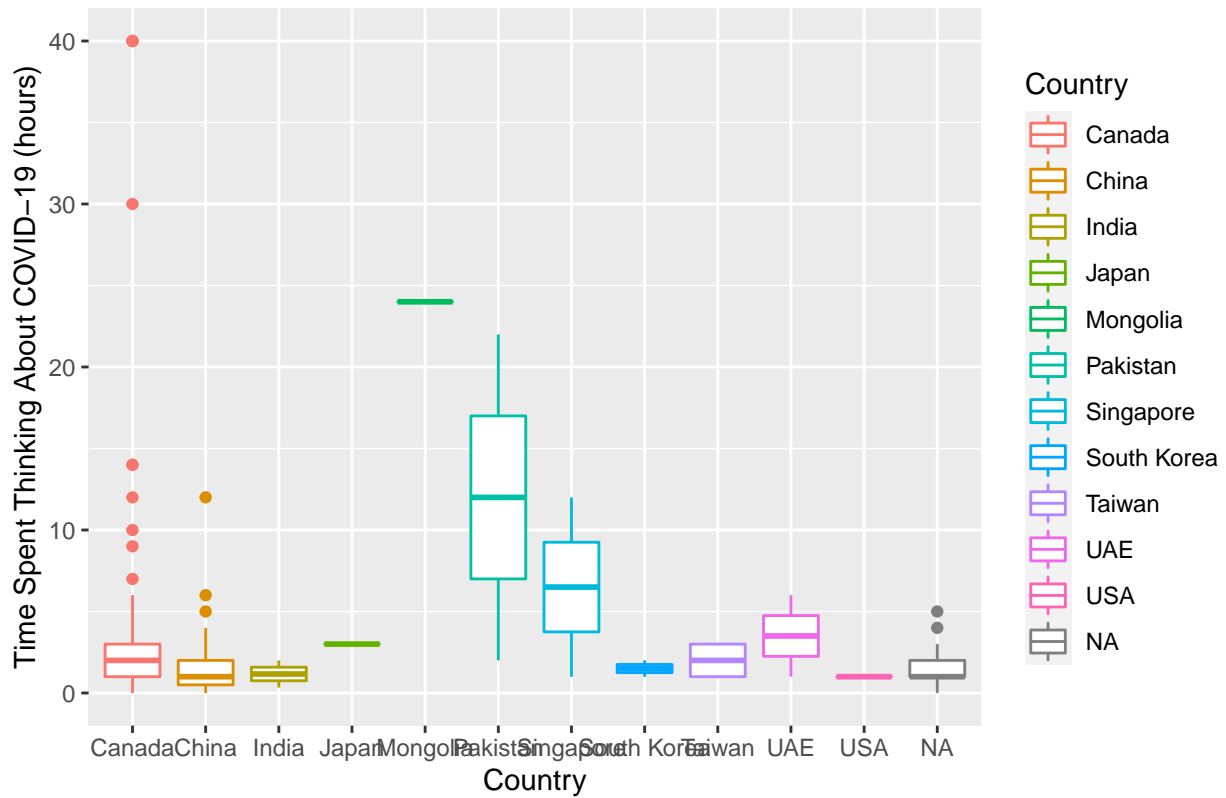
Country vs. Week 1 Time Spent Thinking About COVID-19



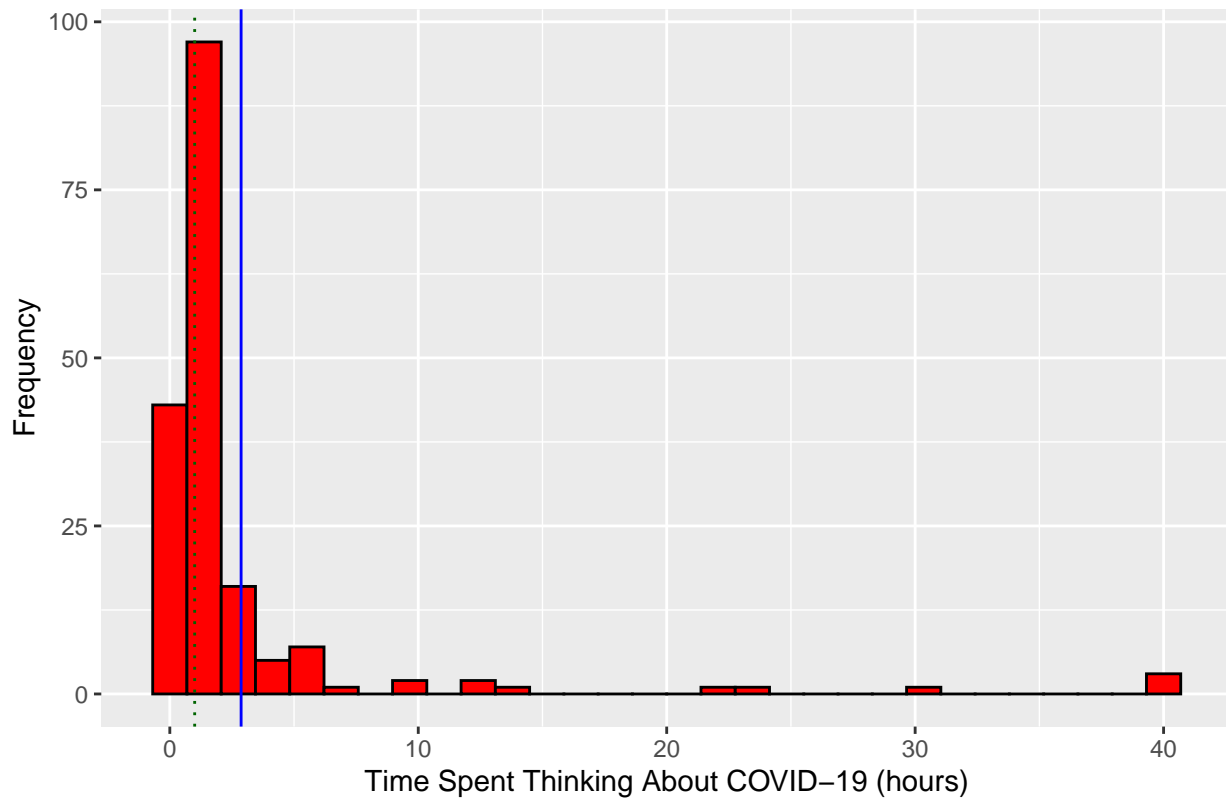
Histogram of Week 1 Time Spent Thinking About COVID-19



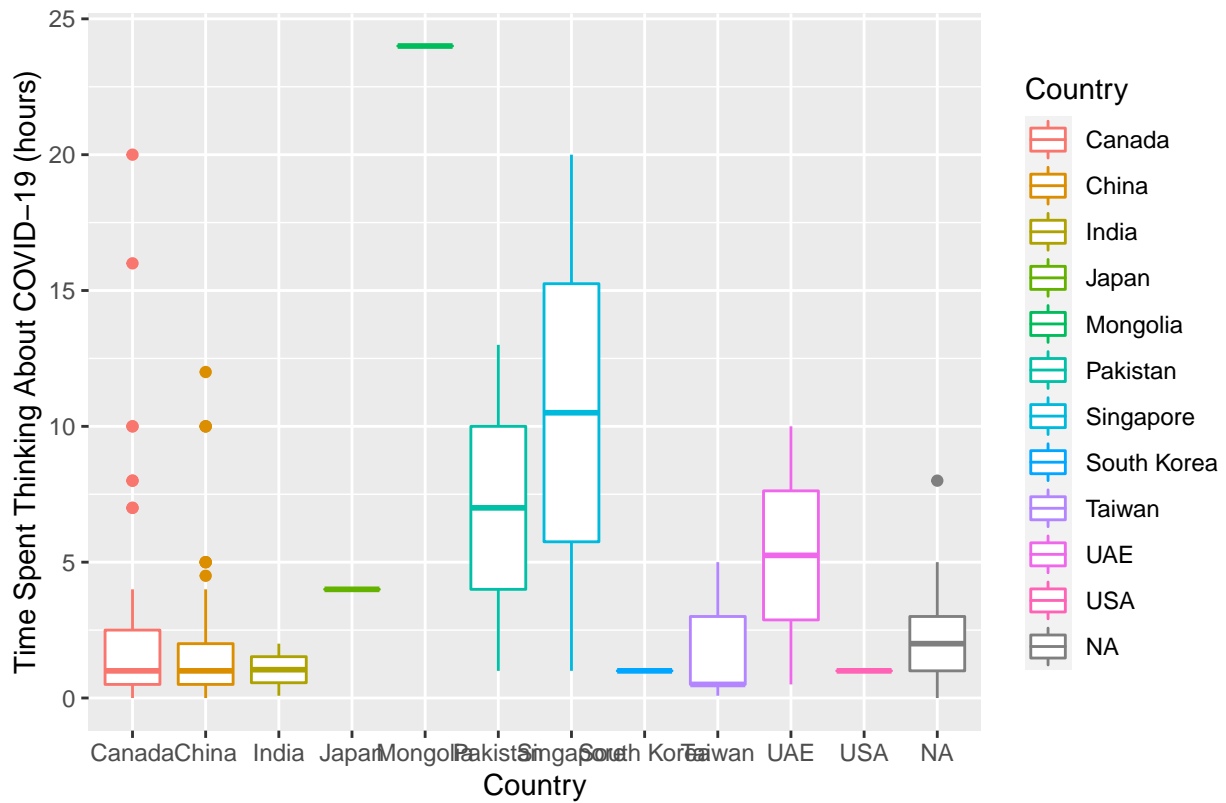
Country vs. Week 2 Time Spent Thinking About COVID-19



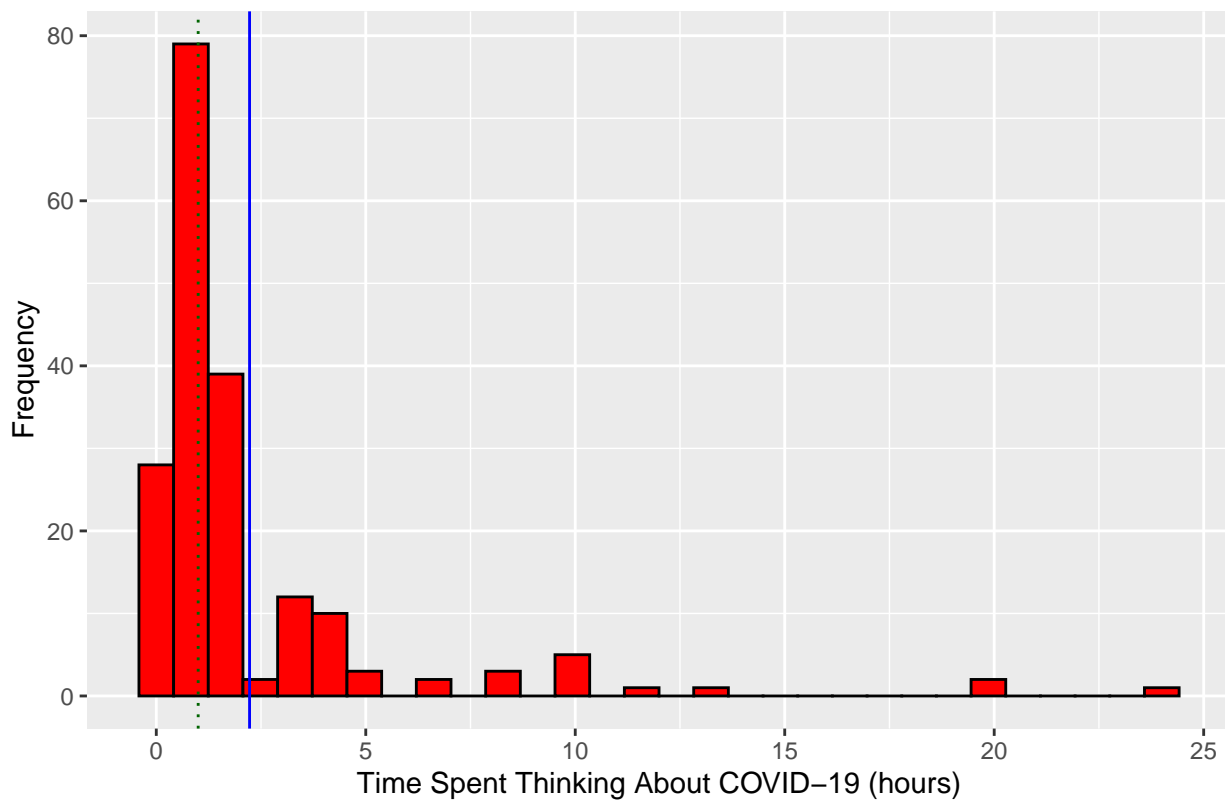
Histogram of Week 2 Time Spent Thinking About COVID-19



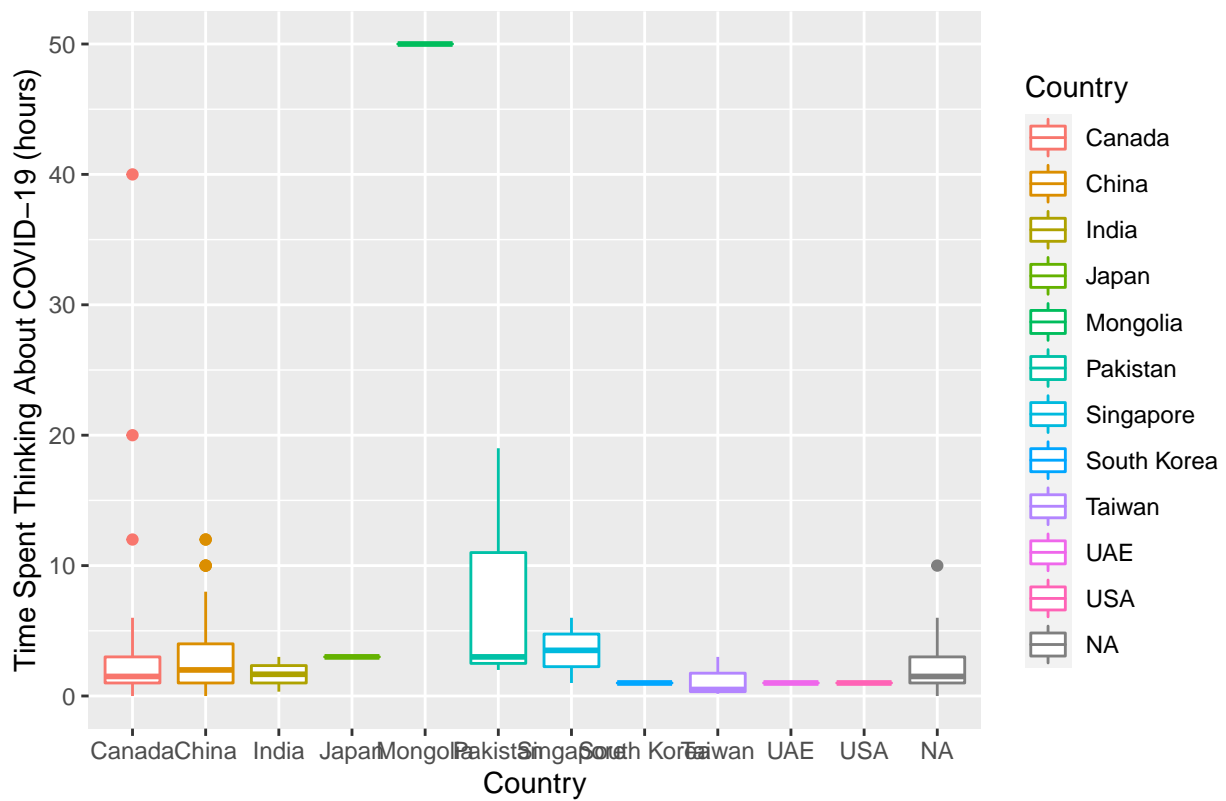
Country vs. Week 3 Time Spent Thinking About COVID-19



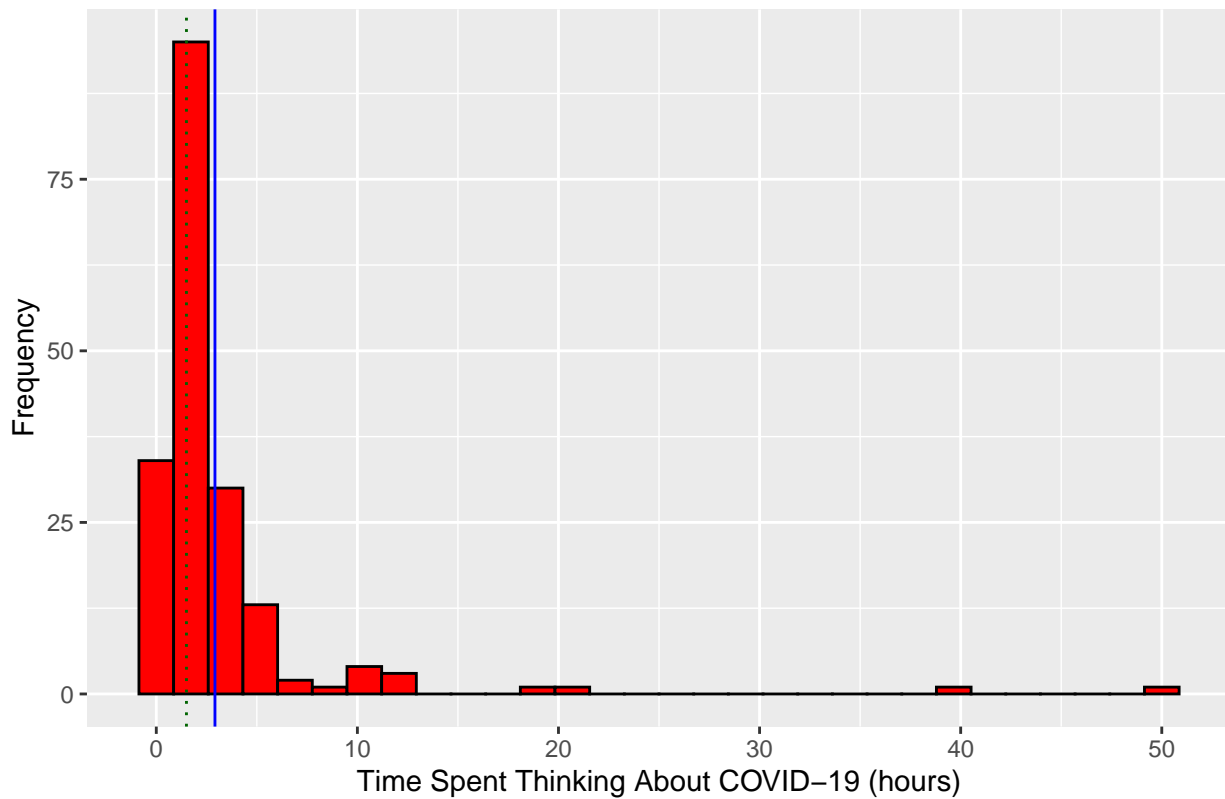
Histogram of Week 3 Time Spent Thinking About COVID-19



Country vs. Week 4 Time Spent Thinking About COVID-19

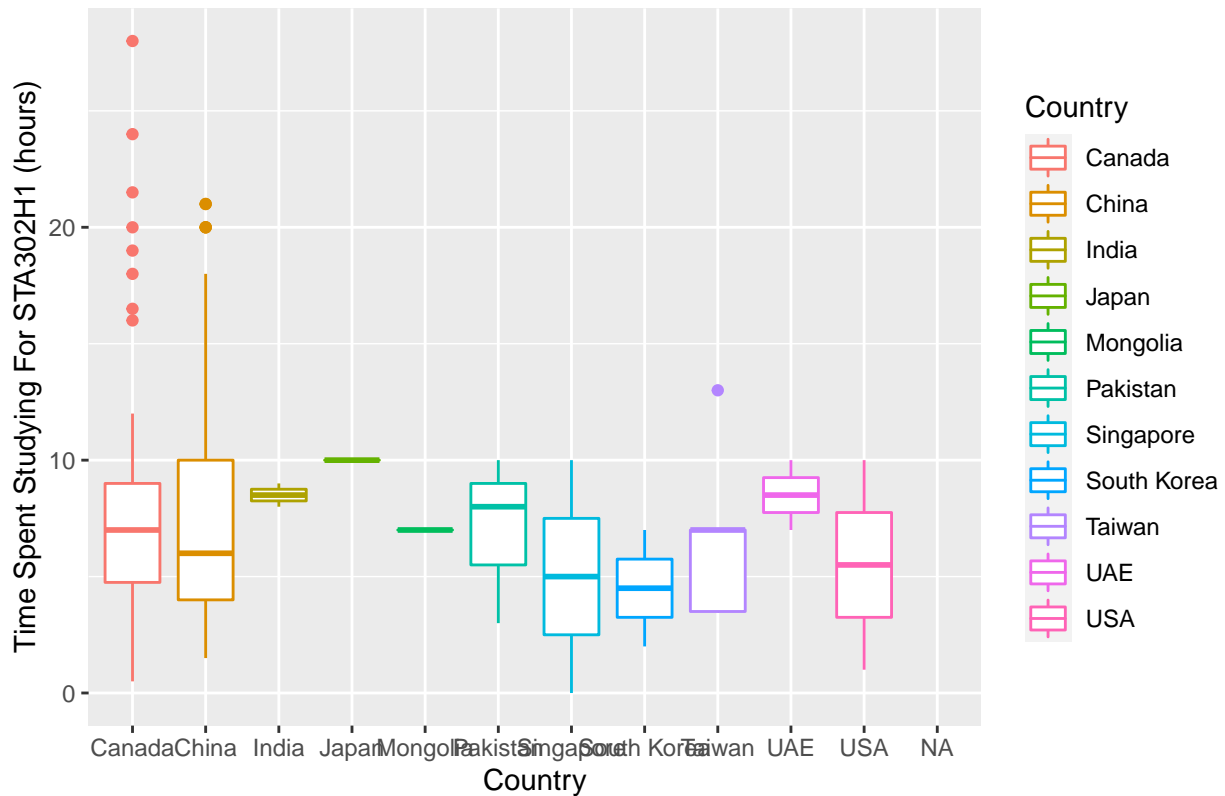


Histogram of Week 4 Time Spent Thinking About COVID-19

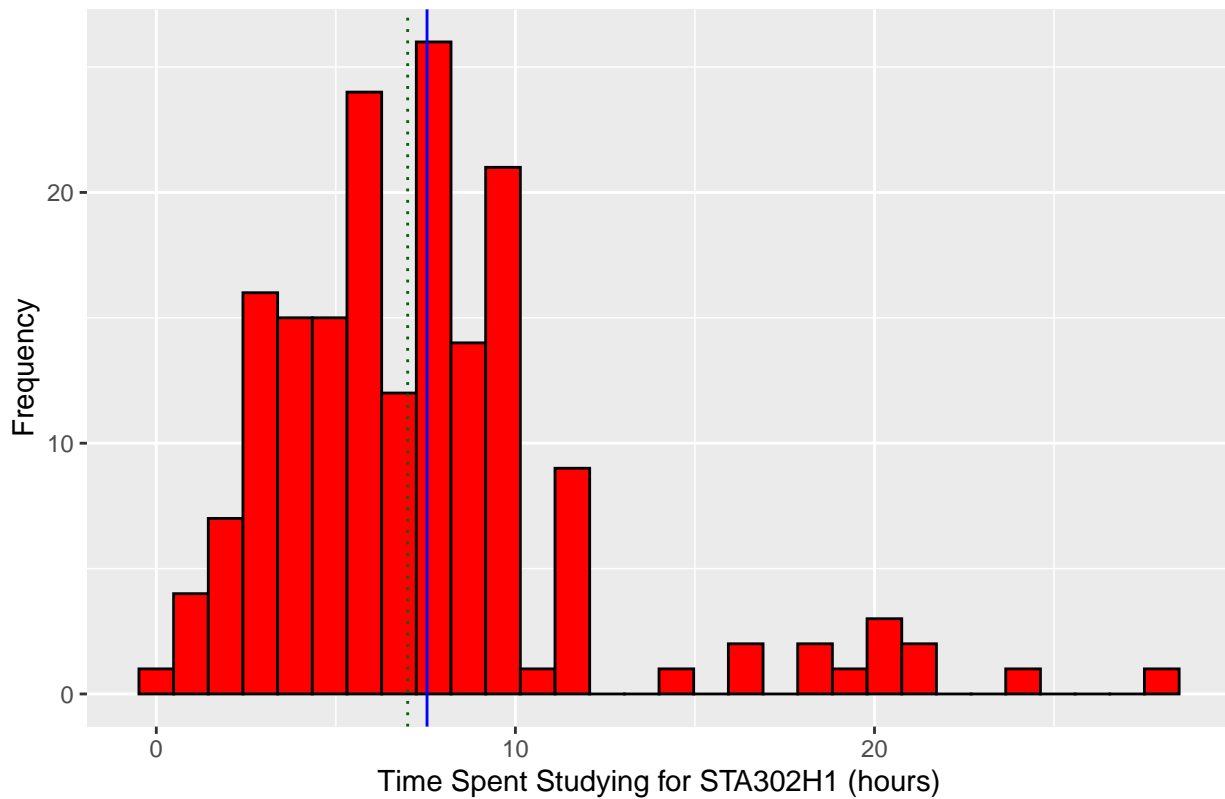


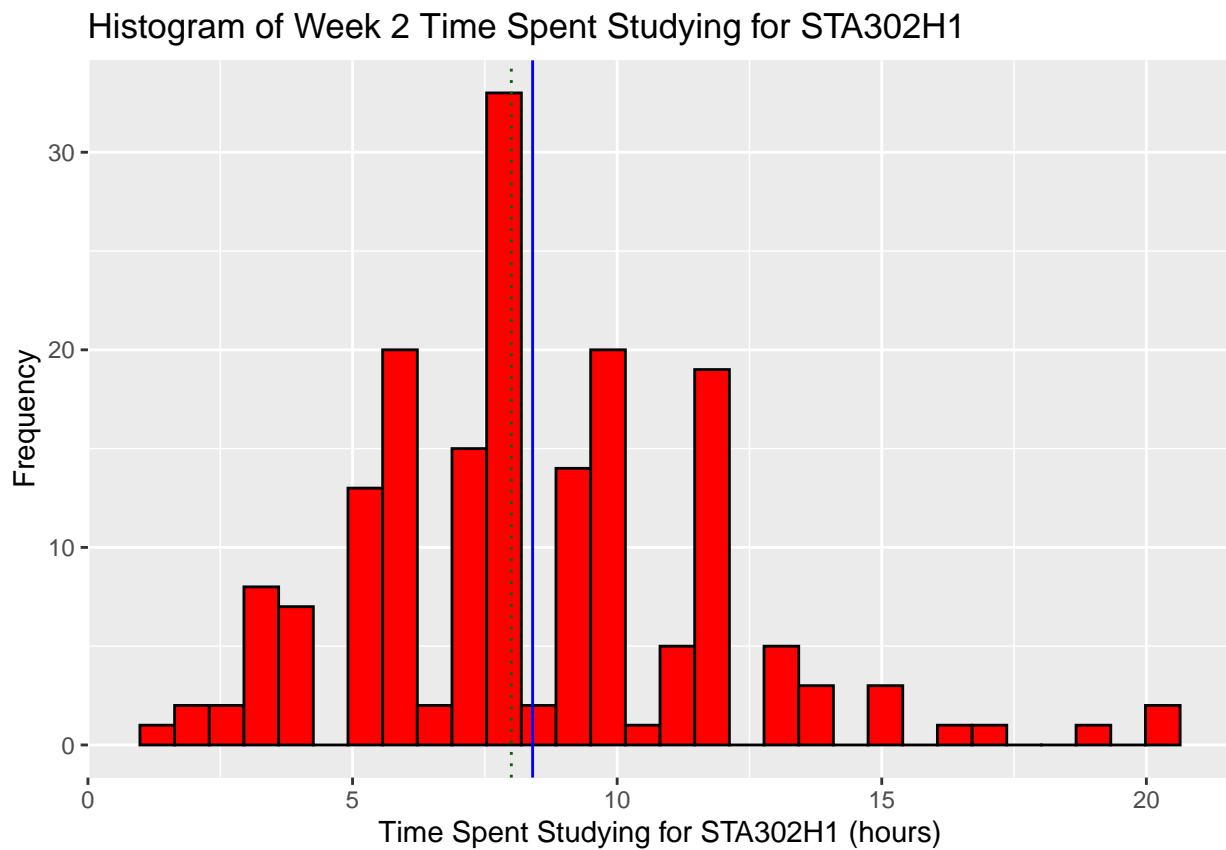
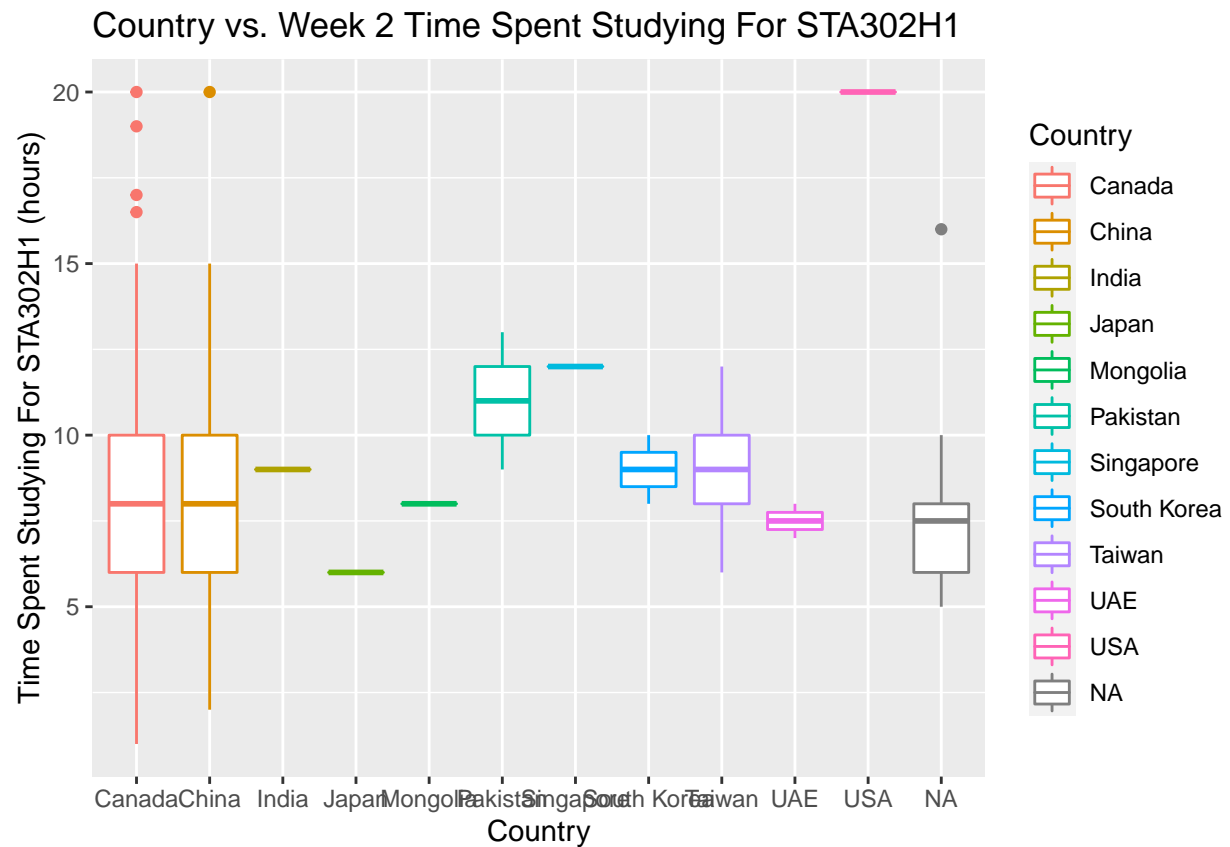


Country vs. Week 1 Time Spent Studying For STA302H1

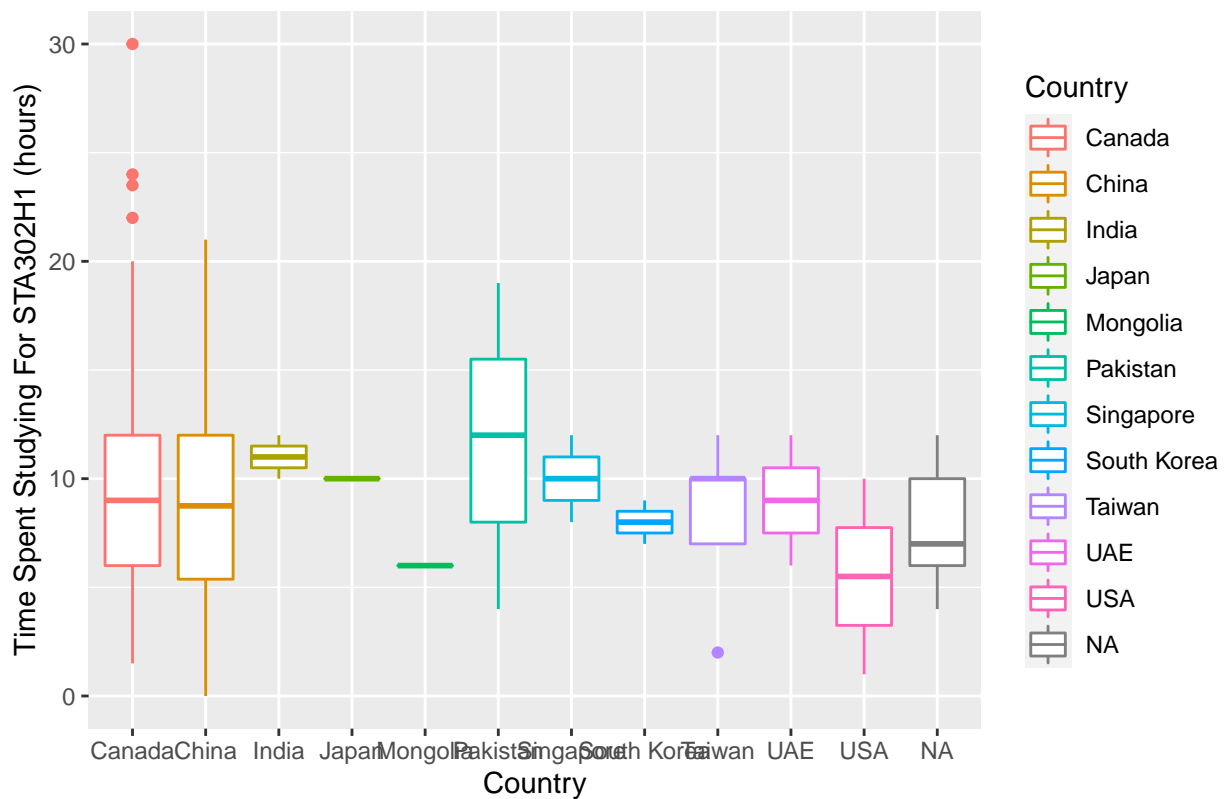


Histogram of Week 1 Time Spent Studying for STA302H1

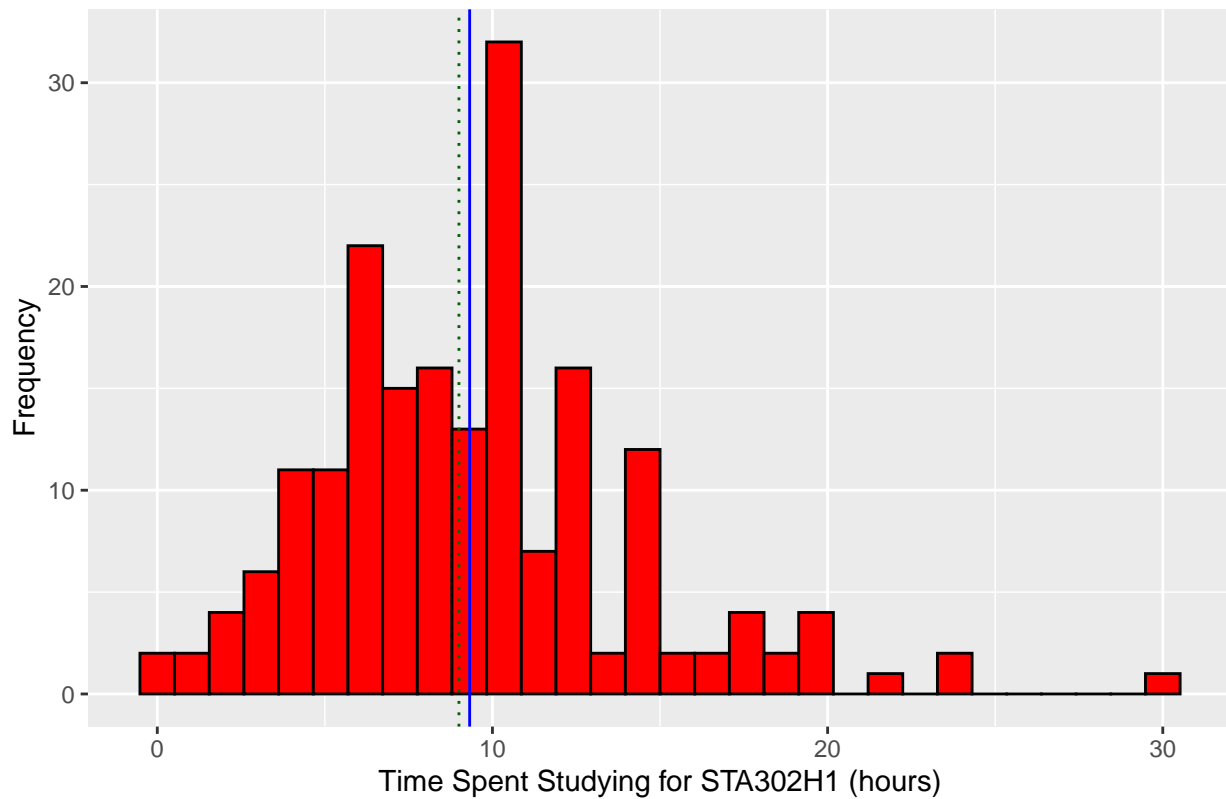




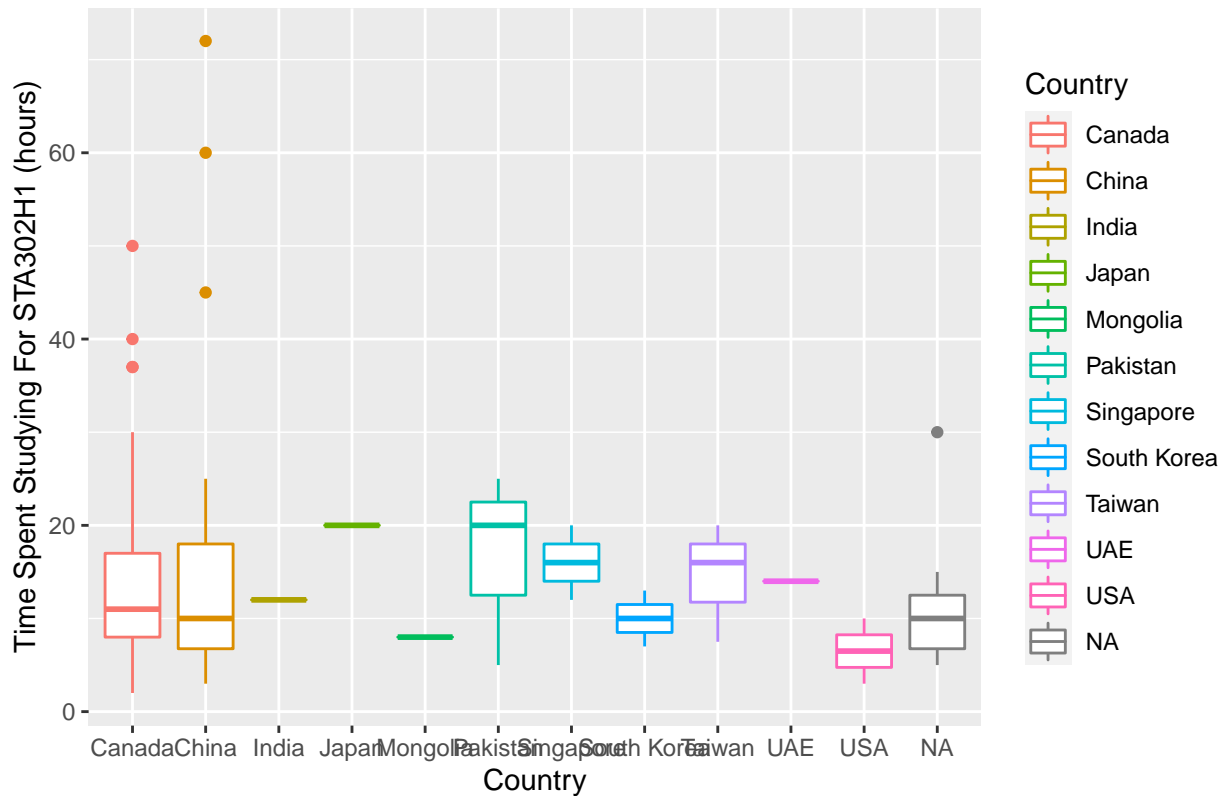
Country vs. Week 3 Time Spent Studying For STA302H1



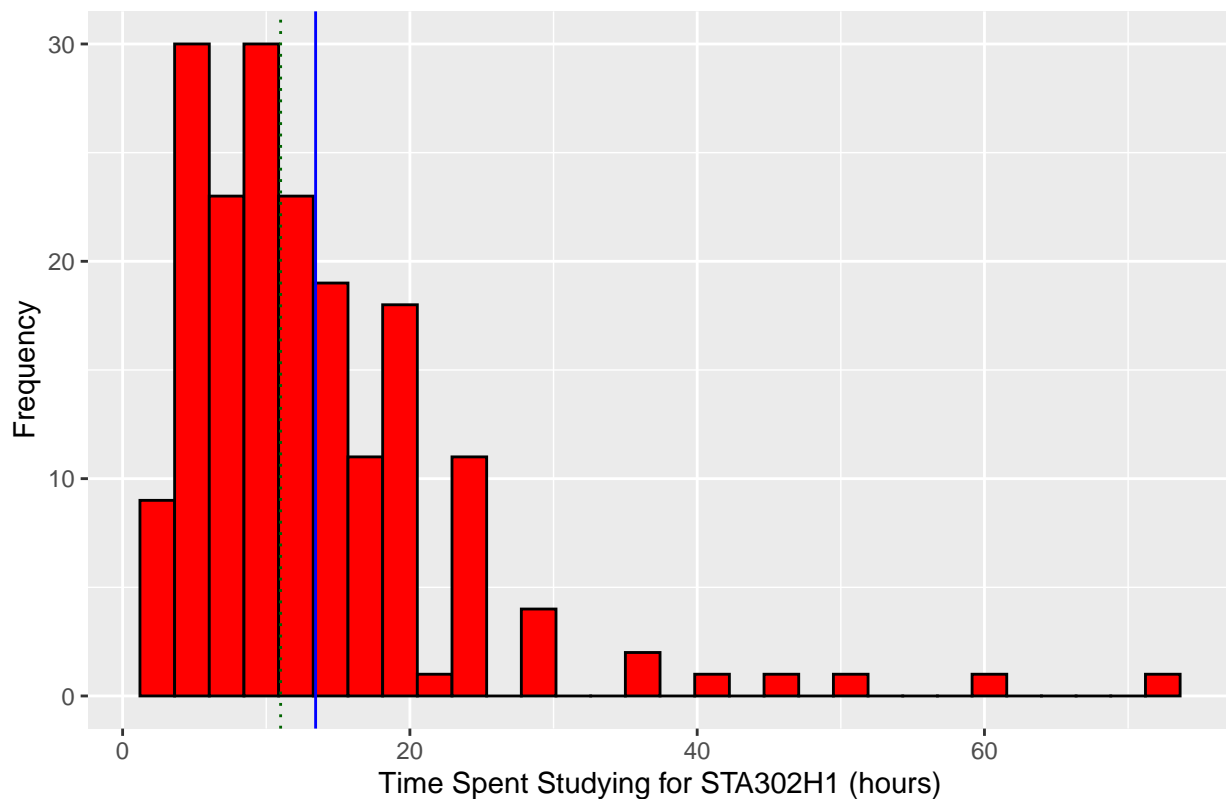
Histogram of Week 3 Time Spent Studying for STA302H1

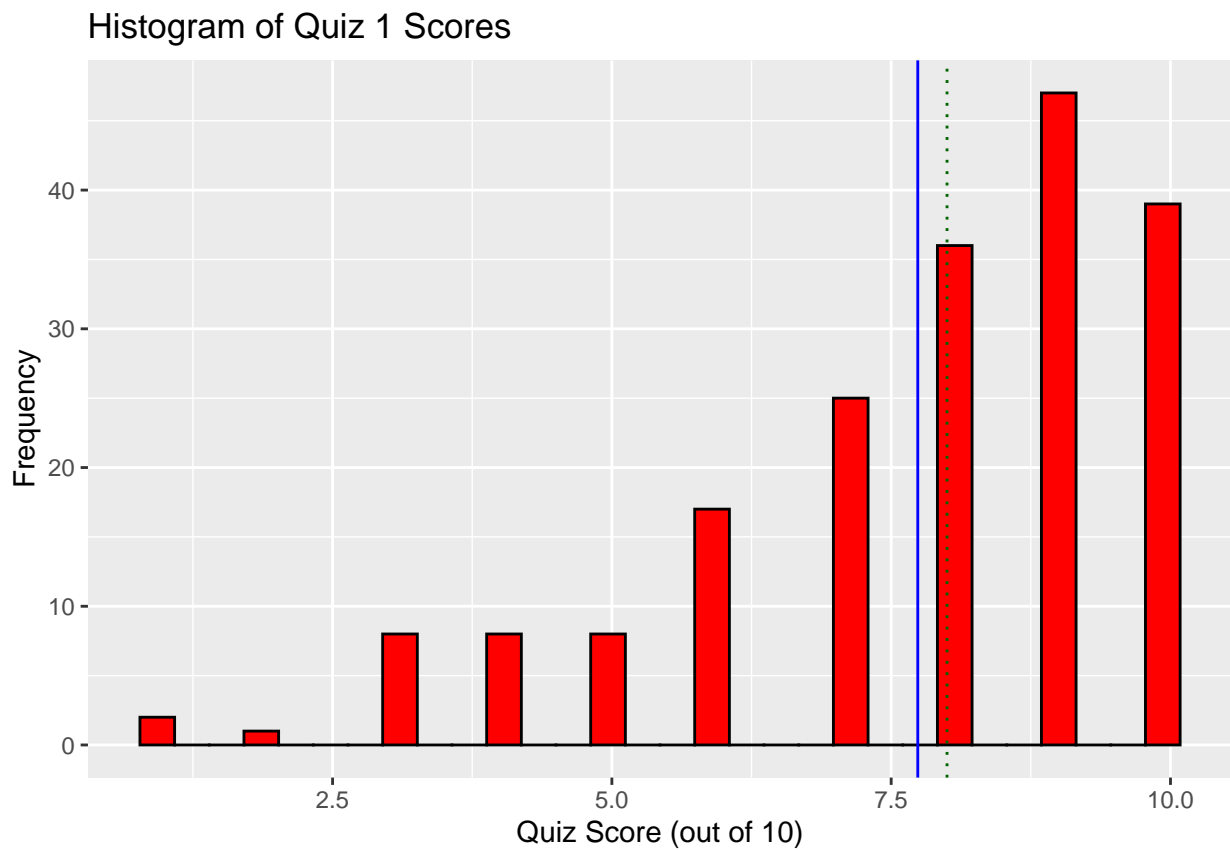
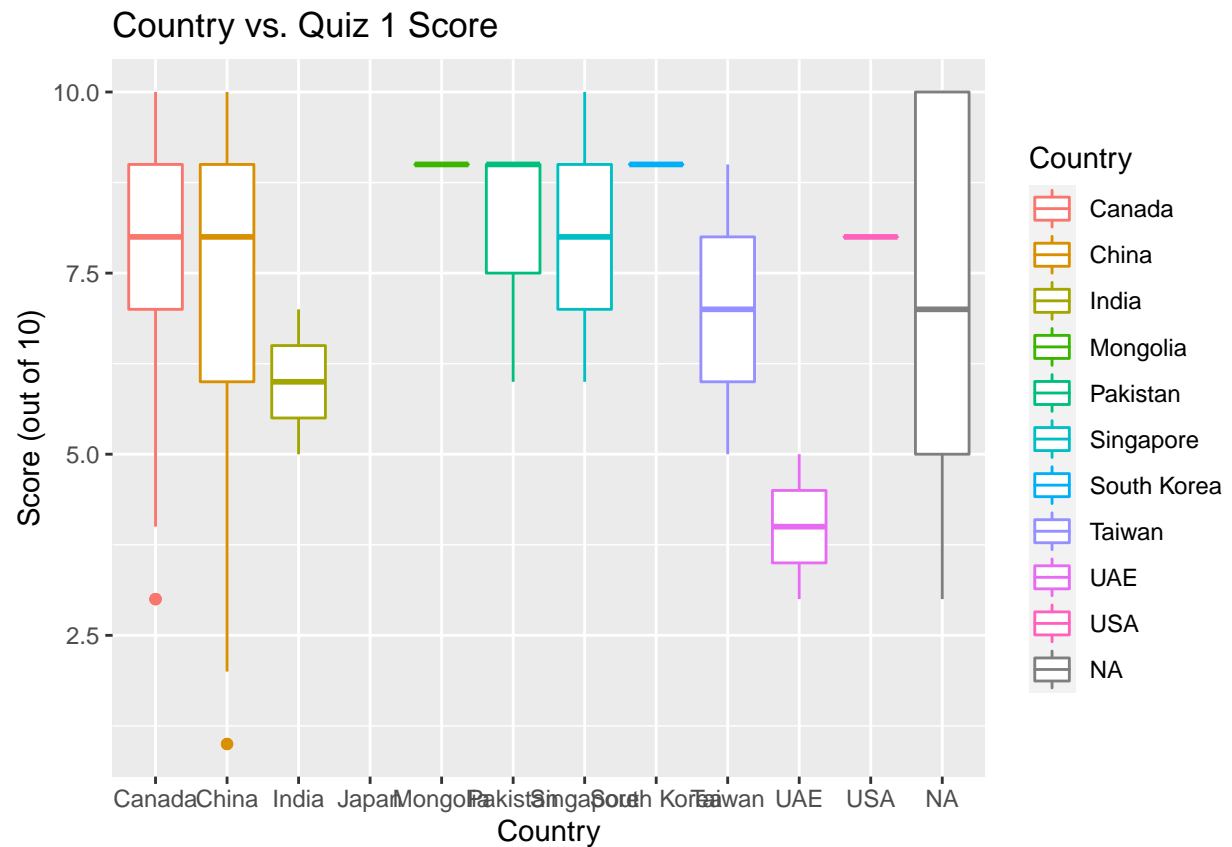


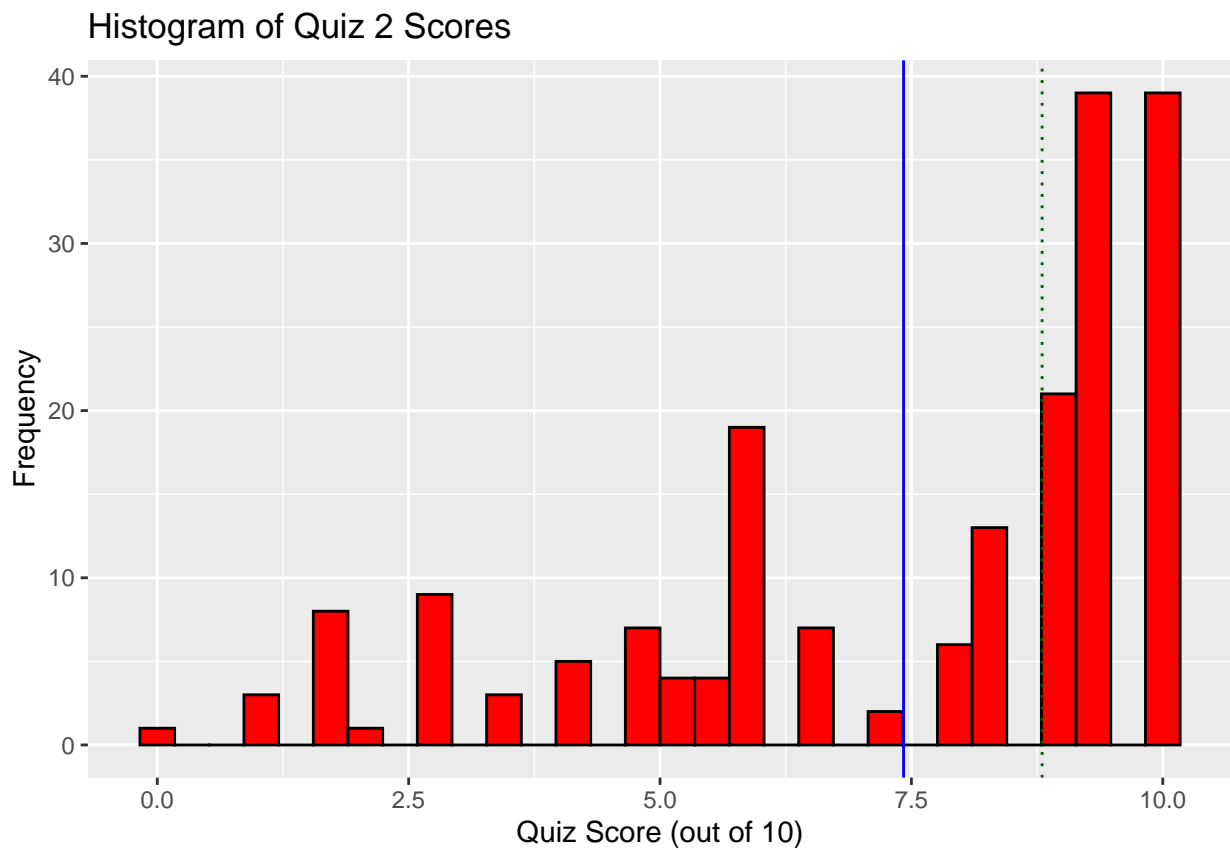
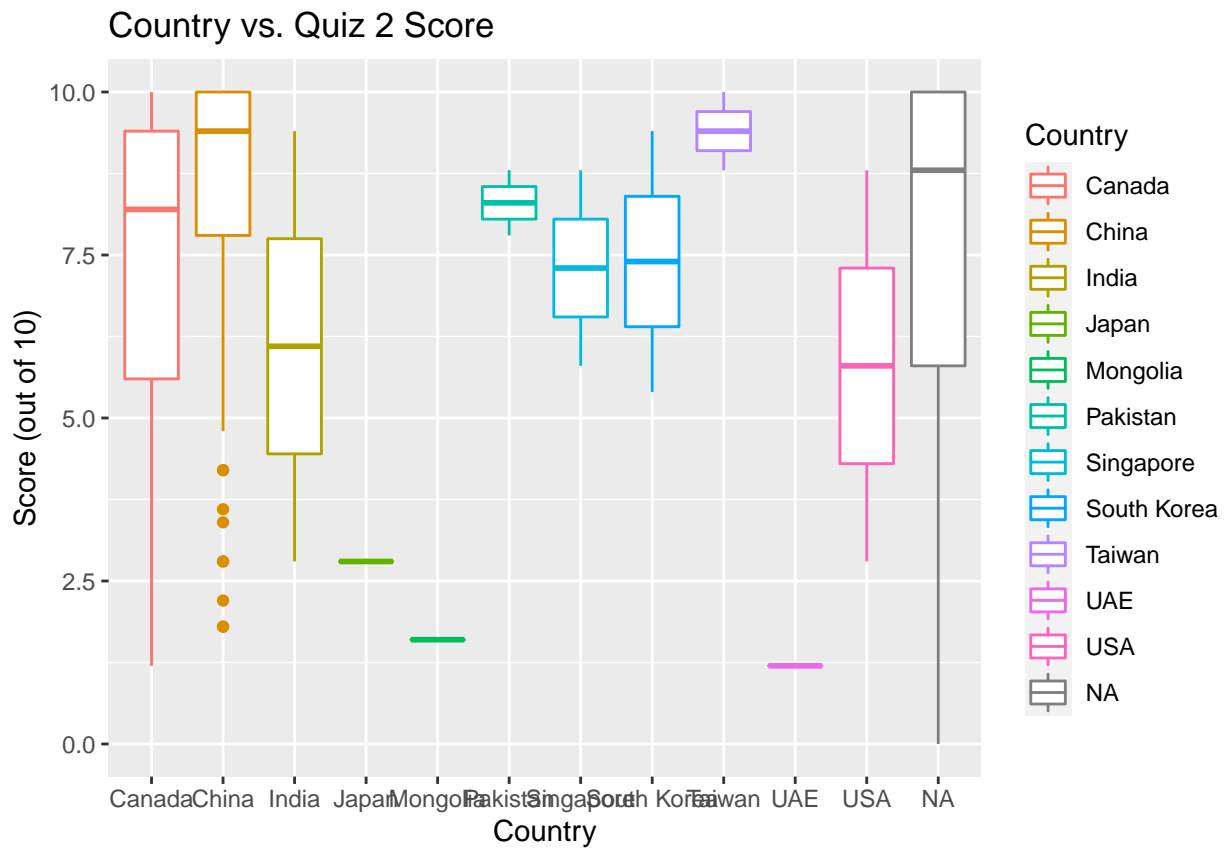
Country vs. Week 4 Time Spent Studying For STA302H1

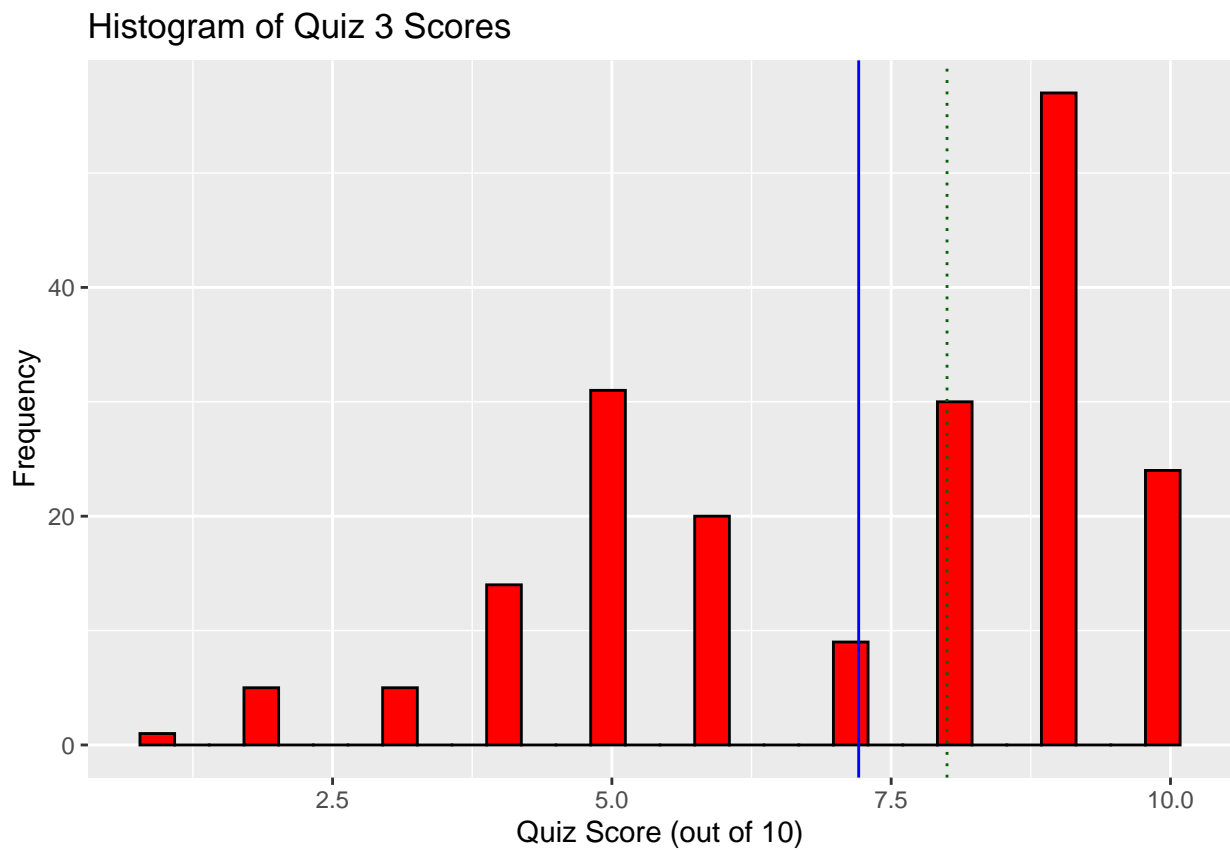
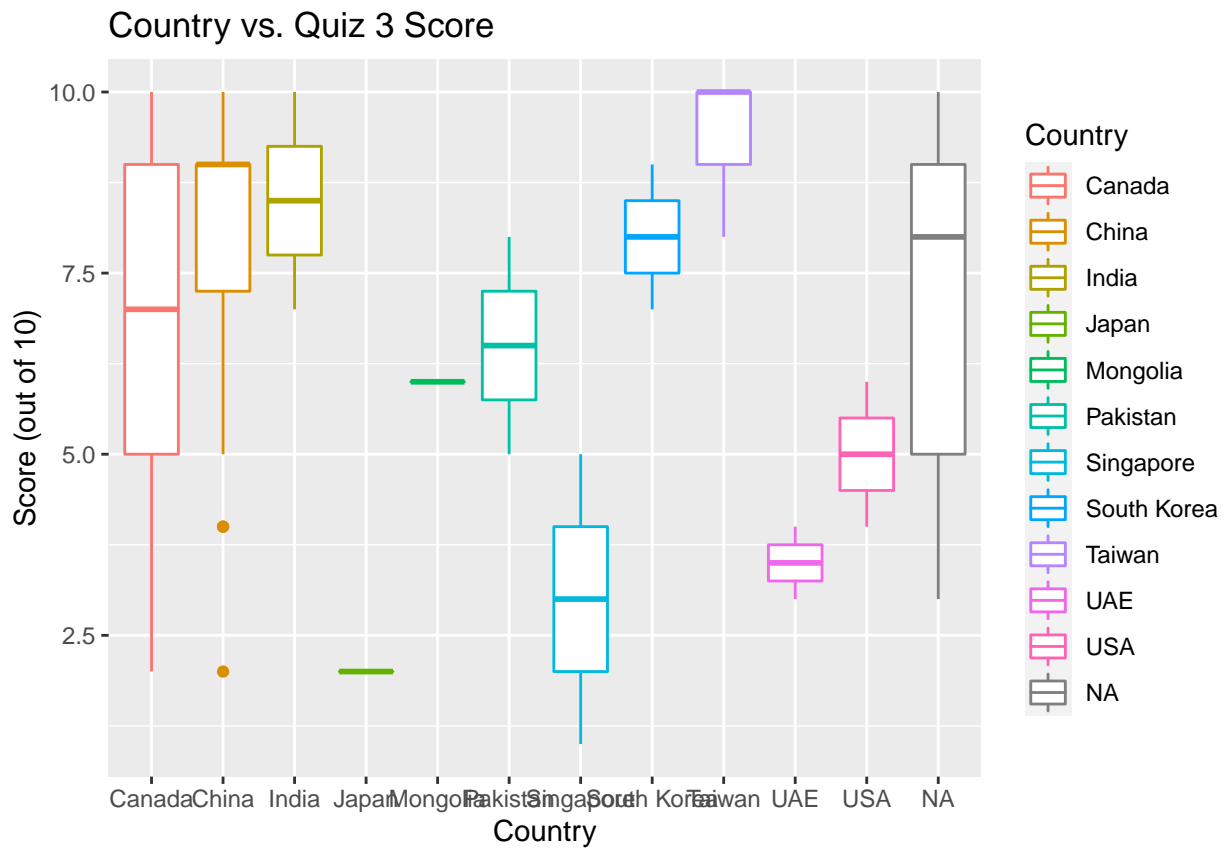


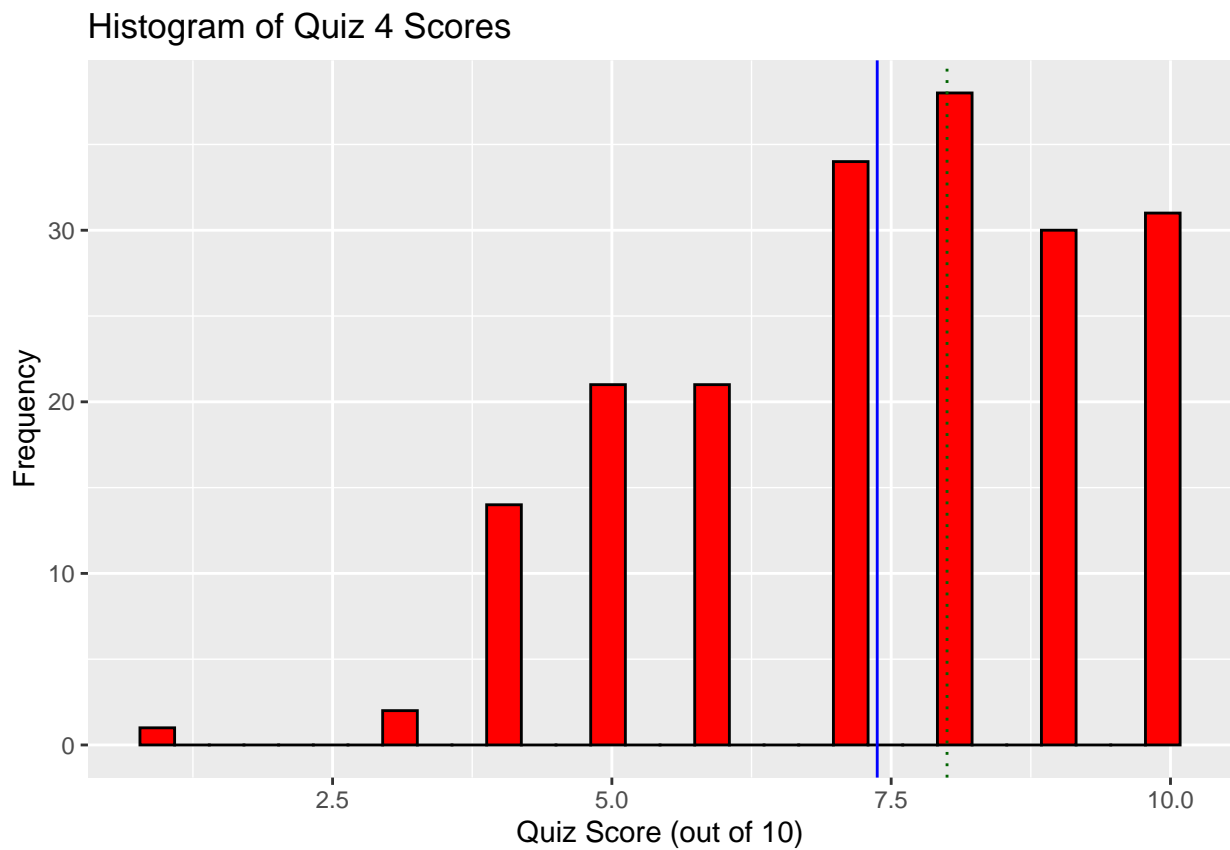
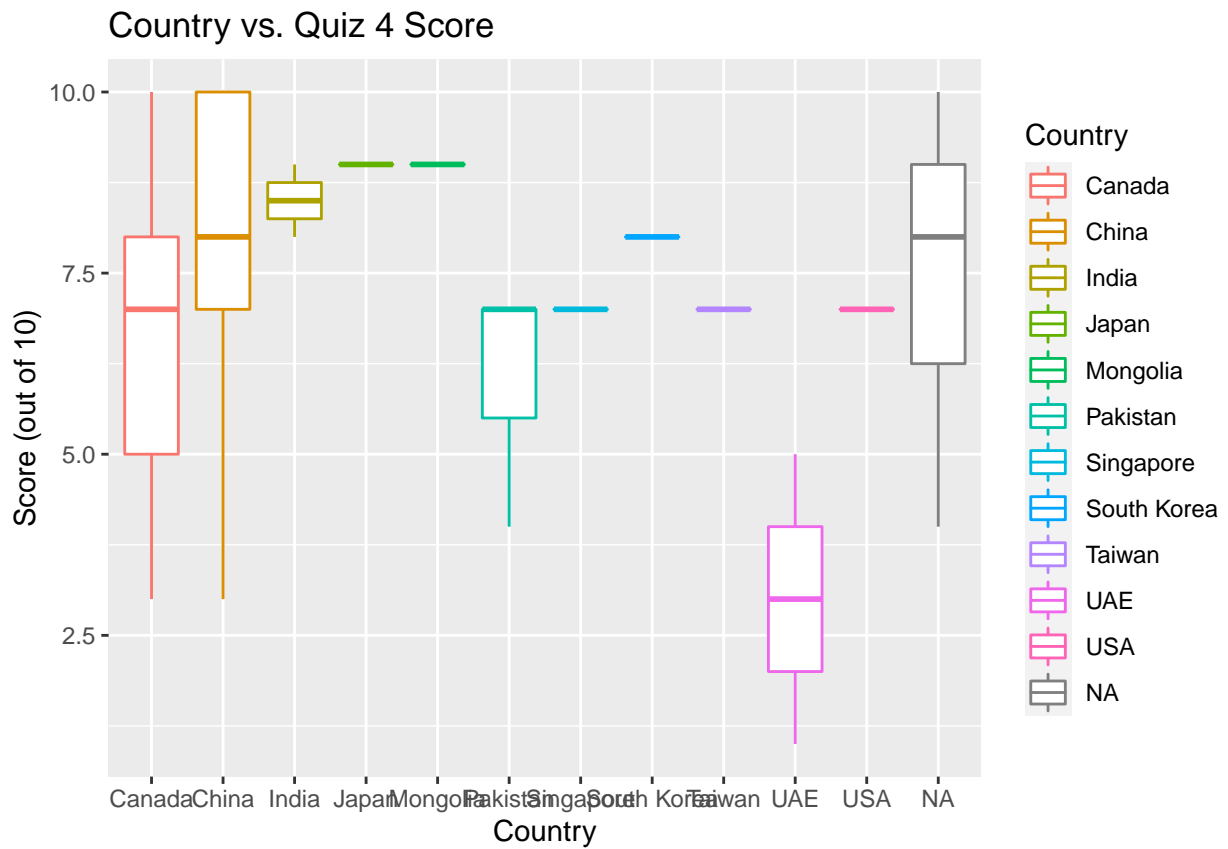
Histogram of Week 4 Time Spent Studying for STA302H1













## 5-Number Summary Statistics

```
summary(cleaned_sta302_performance_data2$COVID.hours..W1.)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	0.0	1.0	1.0	3.7	2.0	168.0	21

```
summary(cleaned_sta302_performance_data2$COVID.hours..W2.)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	0.000	1.000	1.000	2.869	2.000	40.000	19

```
summary(cleaned_sta302_performance_data2$COVID.hours..W3.)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	0.000	0.500	1.000	2.227	2.000	24.000	11

```
summary(cleaned_sta302_performance_data2$COVID.hours..W4.)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	0.000	1.000	1.500	2.917	3.000	50.000	13

```
summary(cleaned_sta302_performance_data2$STA302.hours..W1.)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	0.000	5.000	7.000	7.539	9.000	28.000	21

```
summary(cleaned_sta302_performance_data2$STA302.hours..W2.)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	1.000	6.000	8.000	8.403	10.000	20.000	19

```
summary(cleaned_sta302_performance_data2$STA302.hours..W3.)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	0.00	6.00	9.00	9.32	12.00	30.00	10

```
summary(cleaned_sta302_performance_data2$STA302.hours..W4.)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
##	2.00	7.00	11.00	13.44	16.00	72.00	13

```
summary(cleaned_sta302_performance_data2$Quiz_1_score)
```

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.     Max.    NA's  
##    1.000   7.000   8.000   7.738   9.000  10.000      8
```

```
summary(cleaned_sta302_performance_data2$Quiz_2_score)
```

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.     Max.    NA's  
##    0.000   5.800   8.800   7.422   9.400  10.000      8
```

```
summary(cleaned_sta302_performance_data2$Quiz_3_score)
```

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.     Max.    NA's  
##    1.000   5.000   8.000   7.209   9.000  10.000      3
```

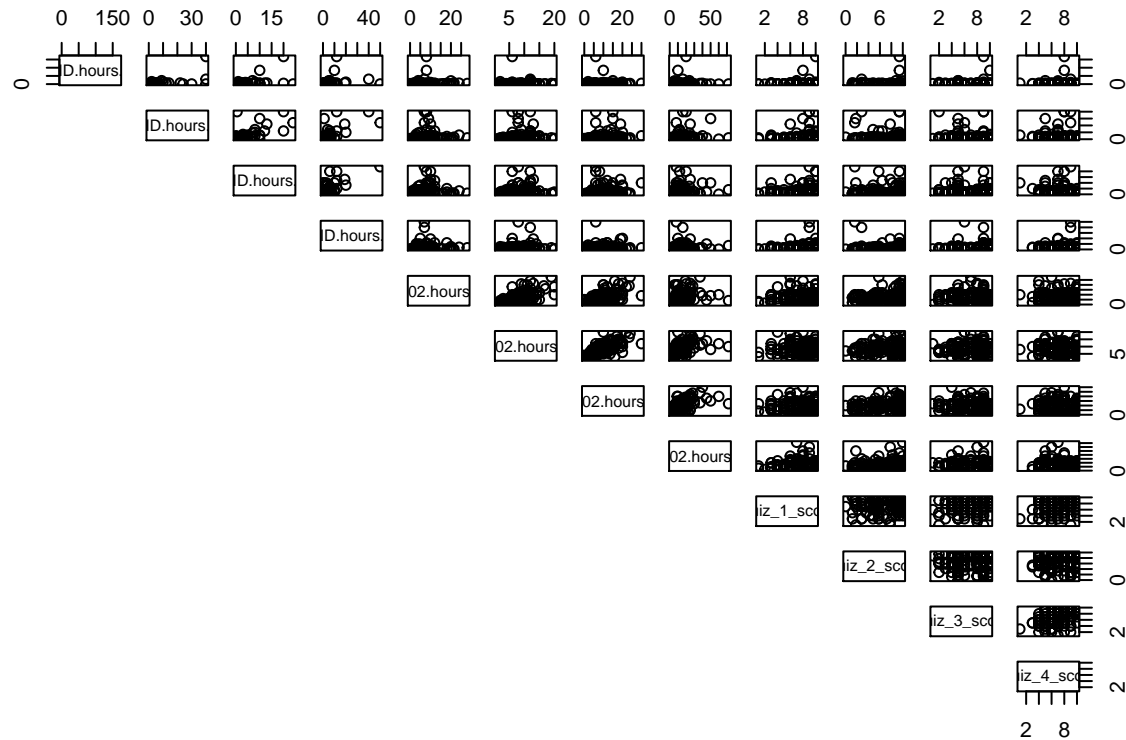
```
summary(cleaned_sta302_performance_data2$Quiz_4_score)
```

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.     Max.    NA's  
##    1.000   6.000   8.000   7.375   9.000  10.000      7
```

# Scatterplots

## Comprehensive pairwise scatterplot

```
pairs(~COVID.hours..W1. + COVID.hours..W2. + COVID.hours..W3. + COVID.hours..W4. +
      STA302.hours..W1. + STA302.hours..W2. + STA302.hours..W3. + STA302.hours..W4. +
      Quiz_1_score + Quiz_2_score + Quiz_3_score + Quiz_4_score,
      data = cleaned_sta302_performance_data2, lower.panel = NULL)
```

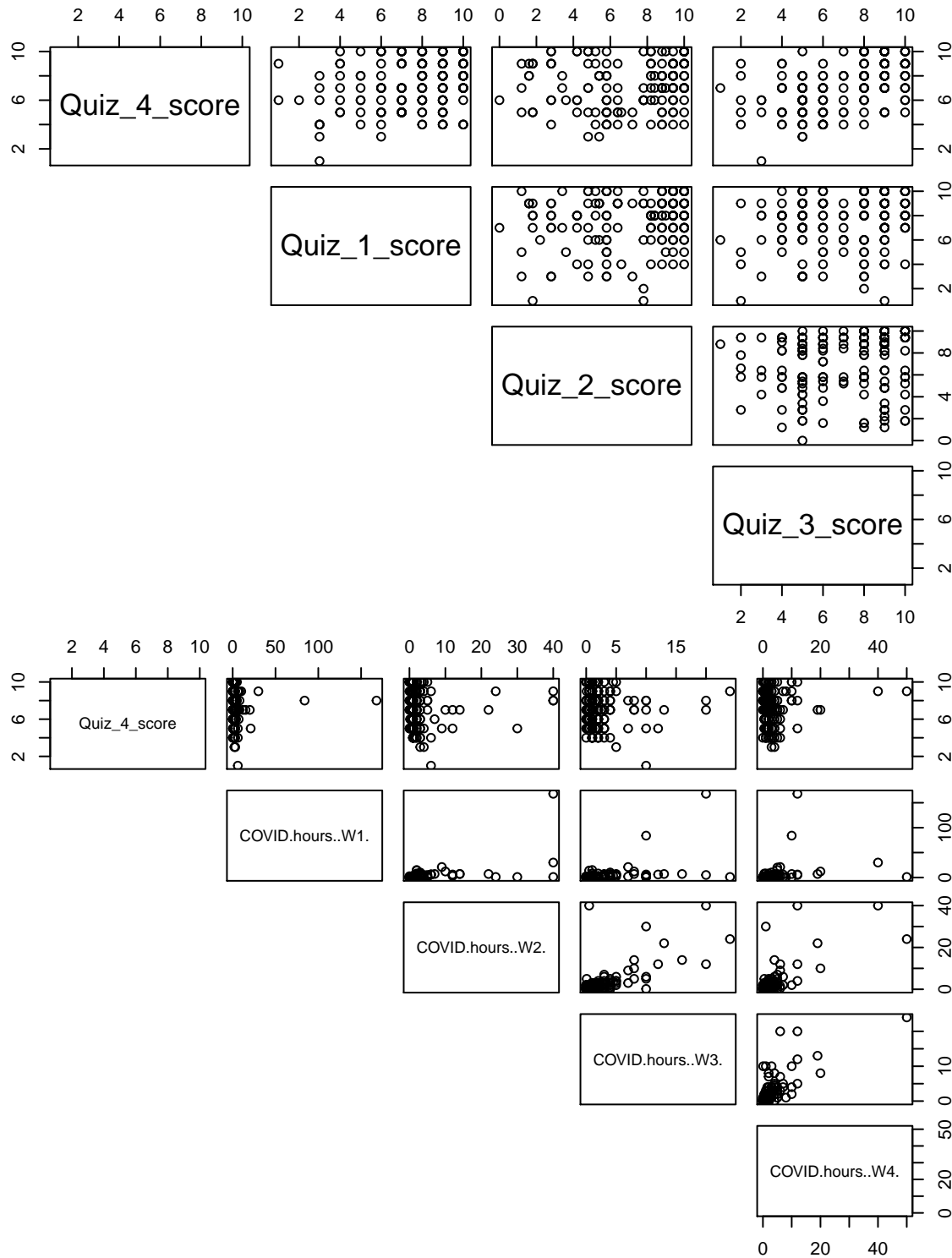


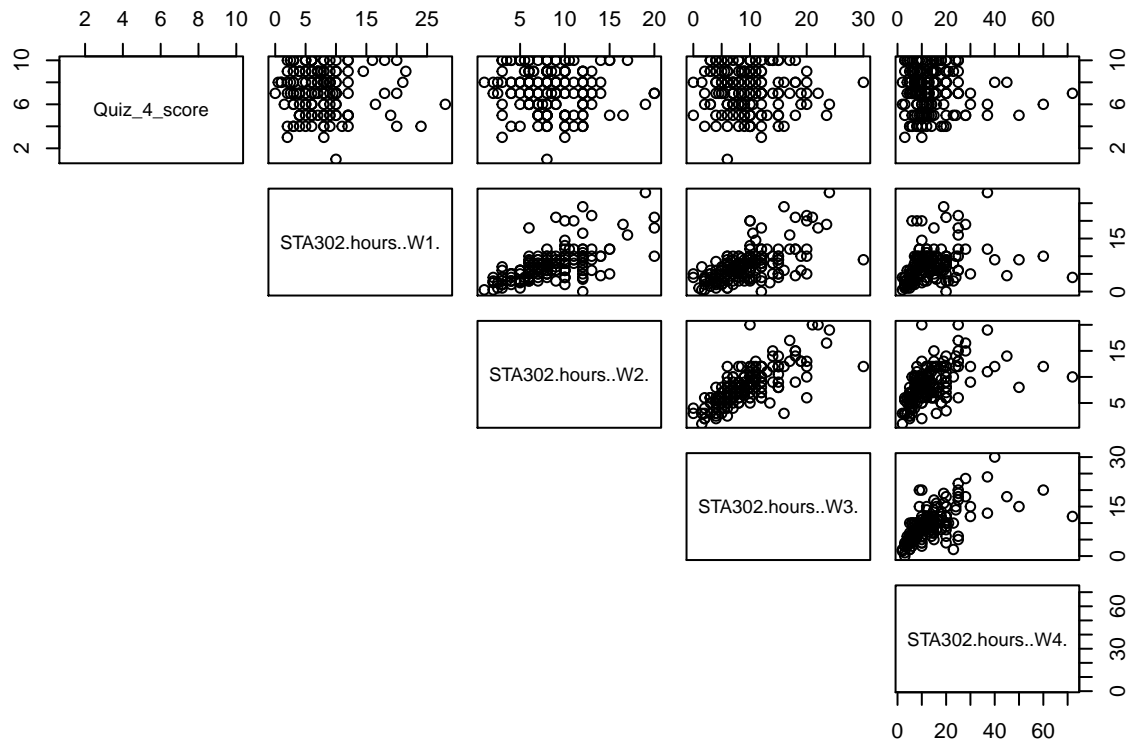
```
## GGally
# ggpairs -- removes bottom half of pairs plot
# ggpairs(data = cleaned_sta302_performance_data2)
```

## Slightly Zoomed In Pairwise Scatterplots

We can zoom in a bit by creating 3 - 4 pairs() functions:

- quiz4 ~ quiz 1, 2, 3
- quiz4 ~ covid 1, 2, 3, 4
- quiz4 ~ sta302h1 1, 2, 3, 4





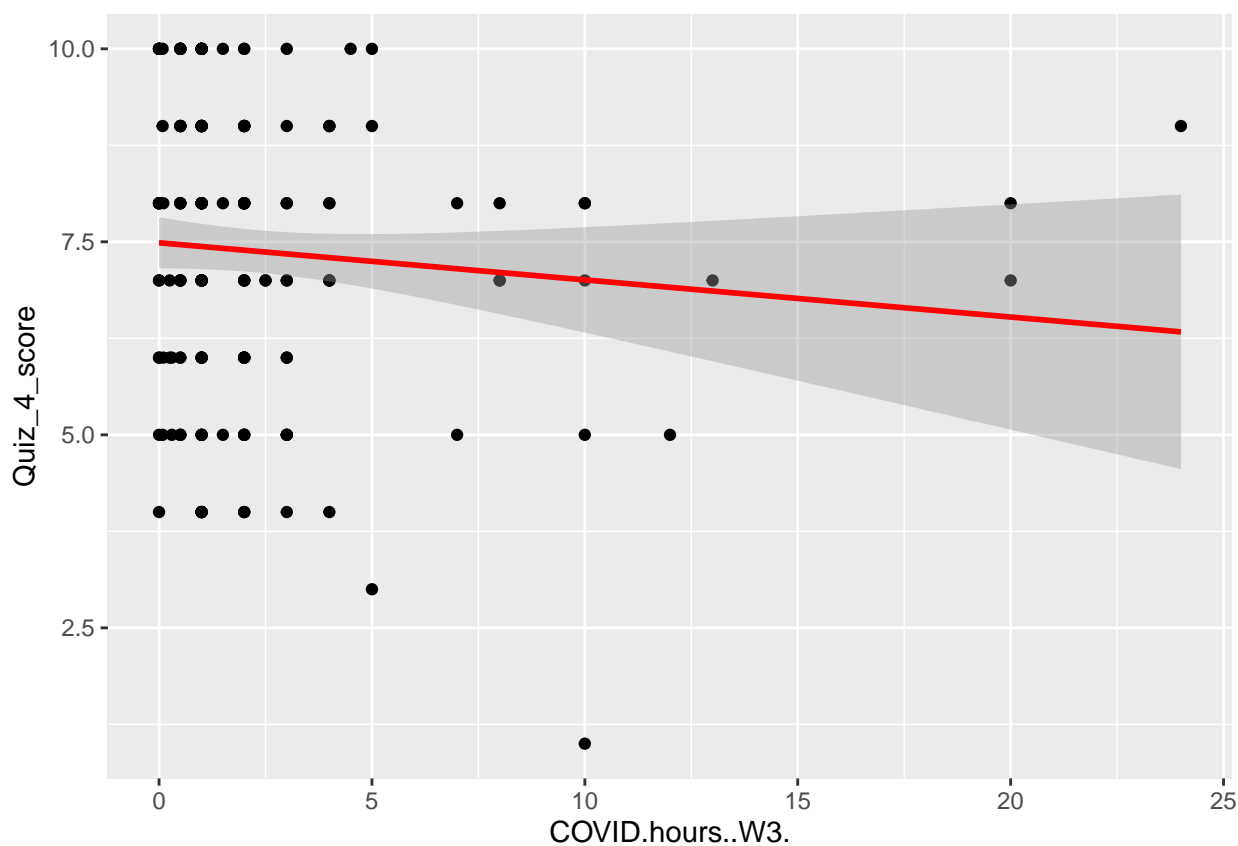
## Top 4 - 5 Interesting Scatterplots

On page 28 “Correlation Matrix,” when I look at the row labelled “Q4” (Quiz 4), I obtained the top 4 - 5 predictor variables based on their correlation:

- Quiz 3 Score ( $R = 0.55$ ), significant
- Quiz 1 Score ( $R = 0.29$ ), significant
- Quiz 2 Score ( $R = 0.19$ ), moderately significant
- Week 2 STA302H1 Hours ( $R = -0.11$ ), not significant at all
- Week 3 COVID Hours ( $R = -0.09$ ), not significant at all

Here are all of their scatterplots, linear regressions, and p-values.

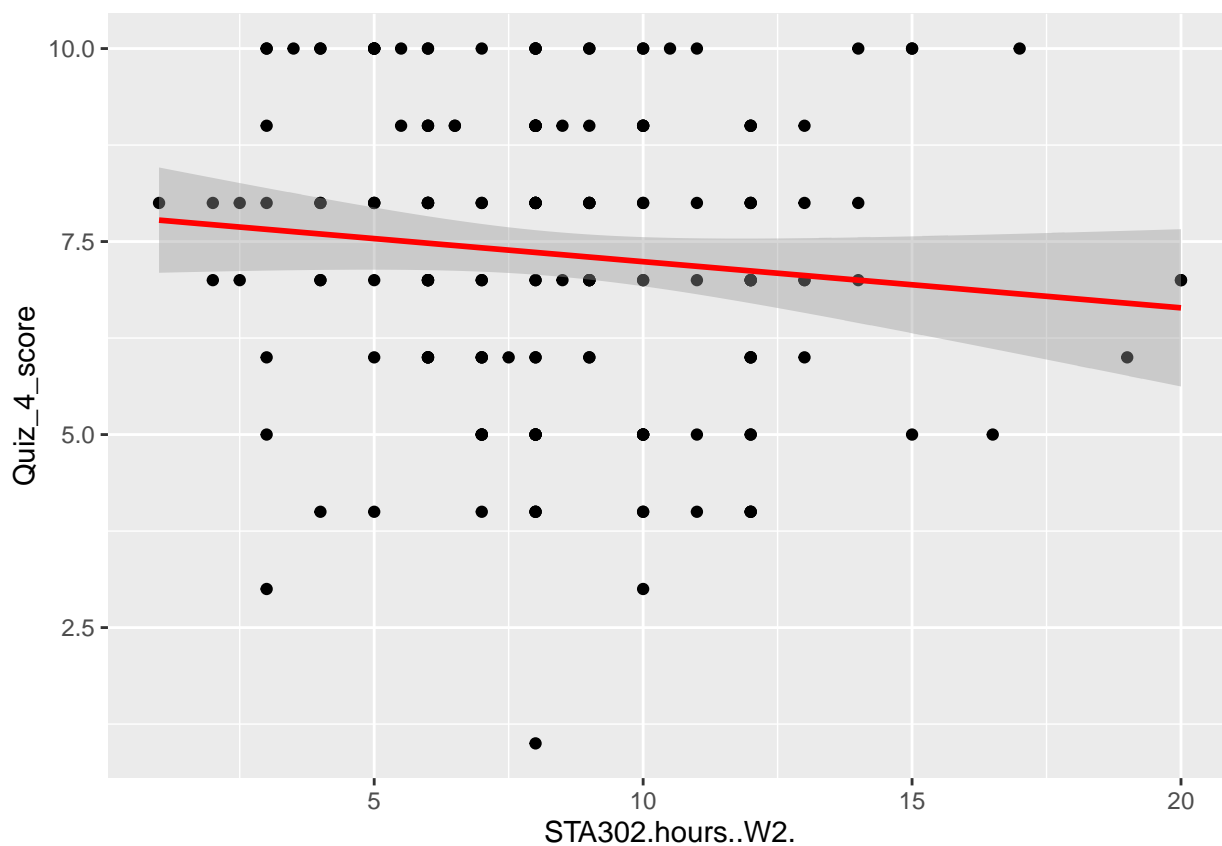
```
ggplot(data = cleaned_sta302_performance_data2, mapping = aes(x = COVID.hours..W3., y = Quiz_4_score)) +  
  geom_point() +  
  geom_smooth(method = "lm", col = "red", formula = y ~ x)
```



```
summary(lm(formula = Quiz_4_score ~ COVID.hours..W3.))$coefficients
```

```
##              Estimate Std. Error  t value    Pr(>|t|)  
## (Intercept)    7.4878594  0.16726635  44.766083 1.713615e-99  
## COVID.hours..W3. -0.0480875  0.04092781  -1.174935 2.415728e-01
```

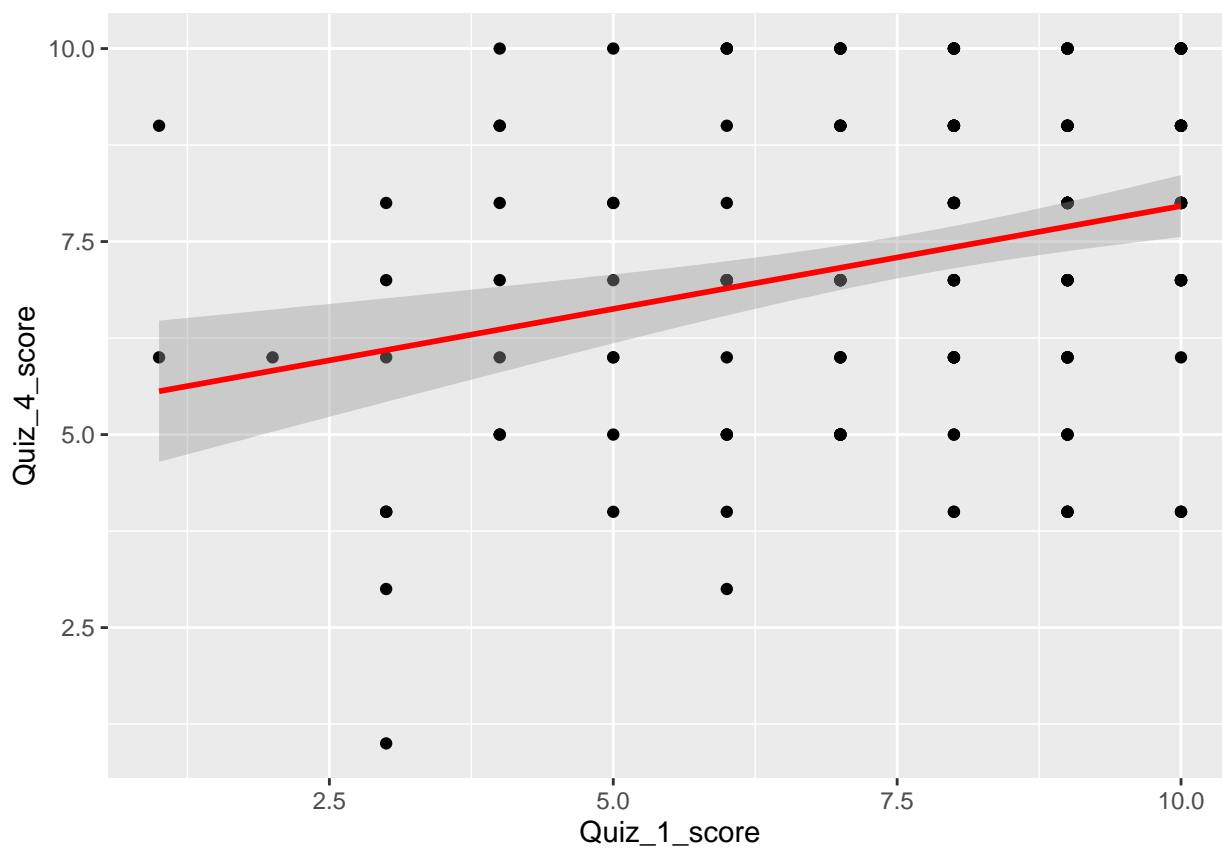
```
ggplot(data = cleaned_sta302_performance_data2, mapping = aes(x = STA302.hours..W2., y = Quiz_4_score))
  geom_point() +
  geom_smooth(method = "lm", col = "red", formula = y ~ x)
```



```
summary(lm(formula = Quiz_4_score ~ STA302.hours..W2.))$coefficients
```

```
##              Estimate Std. Error  t value    Pr(>|t|)
## (Intercept)   7.83737079 0.38459115 20.378448 7.564391e-48
## STA302.hours..W2. -0.05979501 0.04256155 -1.404907 1.618420e-01
```

```
ggplot(data = cleaned_sta302_performance_data2, mapping = aes(x = Quiz_1_score, y = Quiz_4_score)) +
  geom_point() +
  geom_smooth(method = "lm", col = "red", formula = y ~ x)
```

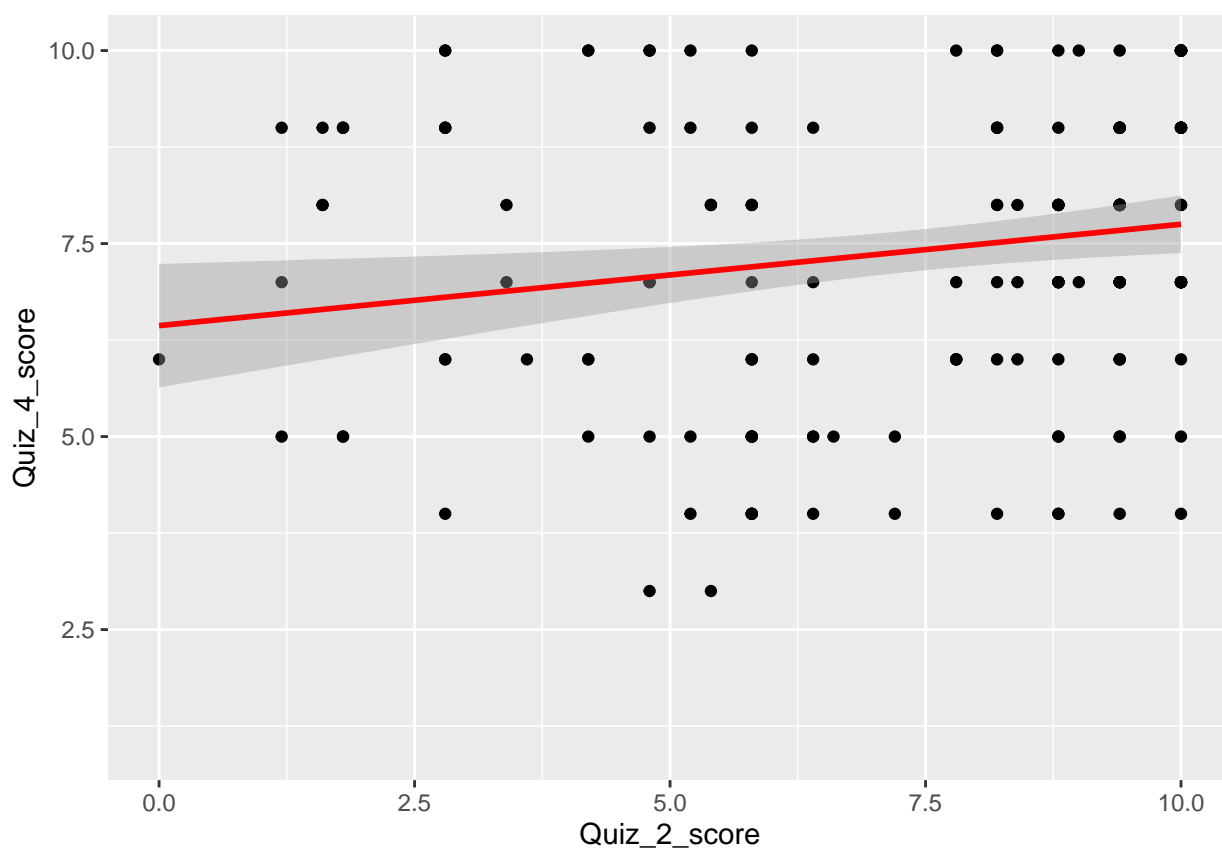


```
summary(lm(formula = Quiz_4_score ~ Quiz_1_score))$coefficients
```

```
##           Estimate Std. Error t value    Pr(>|t|)
## (Intercept)  5.294618  0.52656215  10.05507 3.389243e-19
## Quiz_1_score  0.266566  0.06581747   4.05008 7.569858e-05
```



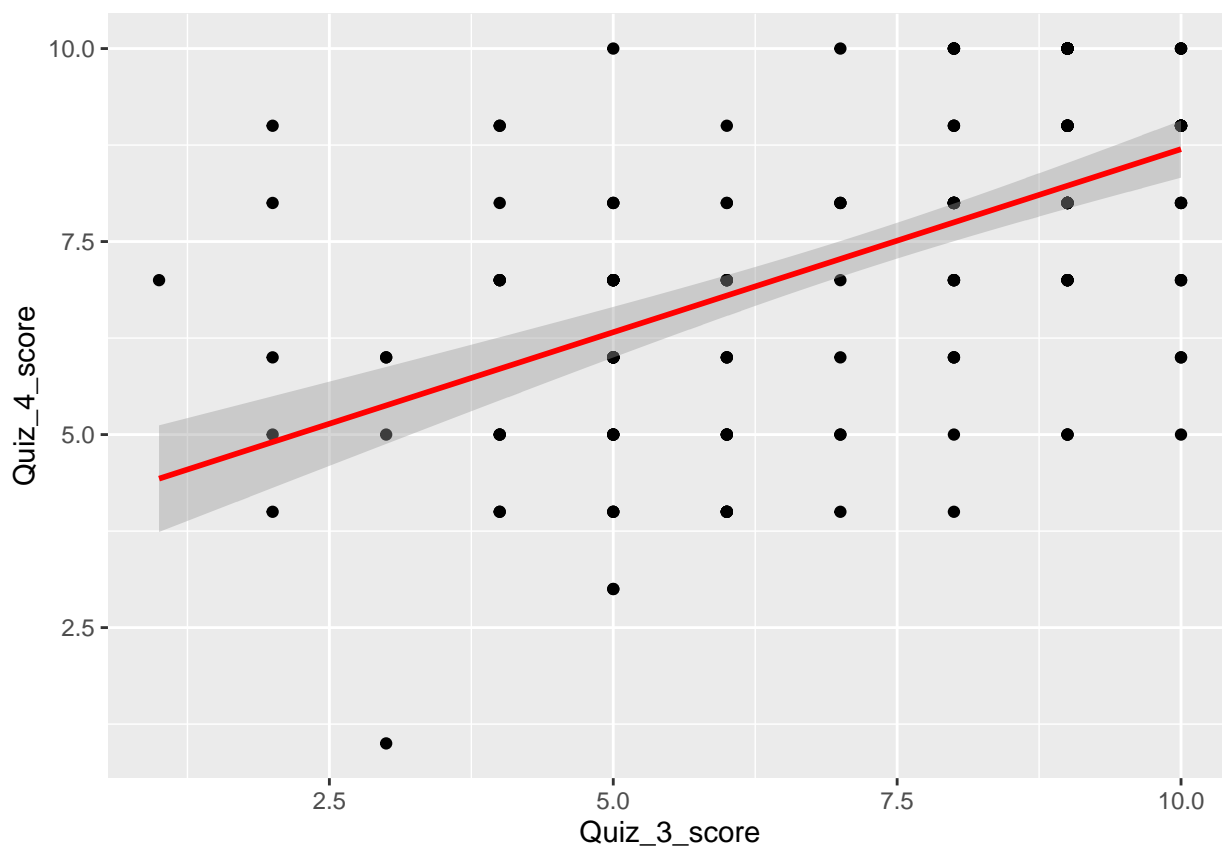
```
ggplot(data = cleaned_sta302_performance_data2, mapping = aes(x = Quiz_2_score, y = Quiz_4_score)) +
  geom_point() +
  geom_smooth(method = "lm", col = "red", formula = y ~ x)
```



```
summary(lm(formula = Quiz_4_score ~ Quiz_2_score))$coefficients
```

```
##           Estimate Std. Error  t value    Pr(>|t|)
## (Intercept)  6.4369424  0.40505781 15.891417 3.115470e-36
## Quiz_2_score  0.1312884  0.05134437  2.557017 1.137315e-02
```

```
ggplot(data = cleaned_sta302_performance_data2, mapping = aes(x = Quiz_3_score, y = Quiz_4_score)) +  
  geom_point() +  
  geom_smooth(method = "lm", col = "red", formula = y ~ x)
```



```
summary(lm(formula = Quiz_4_score ~ Quiz_3_score))$coefficients
```

```
##           Estimate Std. Error t value    Pr(>|t|)  
## (Intercept)  3.9548096 0.40042387  9.876558 8.520117e-19  
## Quiz_3_score  0.4742257 0.05296413  8.953715 3.324360e-16
```

I'll back up my choices with their correlations (R value).

## Correlation Matrix

### All Countries

We can find the correlation matrix to determine candidate significant predictor values.

##		W1COV	W2COV	W3COV	W4COV	W1302	W2302	W3302	W4302	Q1	Q2	Q3	Q4
##	W1COV	1.00	0.56	0.48	0.27	0.04	-0.03	-0.01	0.04	0.08	0.06	0.07	0.02
##	W2COV	0.56	1.00	0.67	0.71	0.05	0.08	0.17	0.19	0.13	-0.10	-0.12	-0.01
##	W3COV	0.48	0.67	1.00	0.72	0.08	0.08	0.14	0.13	0.09	-0.07	-0.11	-0.09
##	W4COV	0.27	0.71	0.72	1.00	0.02	0.07	0.09	0.07	0.12	-0.10	0.02	0.06
##	W1302	0.04	0.05	0.08	0.02	1.00	0.61	0.58	0.30	0.05	0.13	-0.04	-0.08
##	W2302	-0.03	0.08	0.08	0.07	0.61	1.00	0.70	0.48	0.00	0.06	-0.05	-0.11
##	W3302	-0.01	0.17	0.14	0.09	0.58	0.70	1.00	0.62	-0.01	0.08	-0.12	-0.08
##	W4302	0.04	0.19	0.13	0.07	0.30	0.48	0.62	1.00	-0.01	0.04	-0.05	-0.06
##	Q1	0.08	0.13	0.09	0.12	0.05	0.00	-0.01	-0.01	1.00	0.25	0.29	0.29
##	Q2	0.06	-0.10	-0.07	-0.10	0.13	0.06	0.08	0.04	0.25	1.00	0.23	0.19
##	Q3	0.07	-0.12	-0.11	0.02	-0.04	-0.05	-0.12	-0.05	0.29	0.23	1.00	0.55
##	Q4	0.02	-0.01	-0.09	0.06	-0.08	-0.11	-0.08	-0.06	0.29	0.19	0.55	1.00

## By Individual Country

We could also create separate correlation matrices for each country.

```
display_correlation_by_country(canada)
```

```
##          W1COV W2COV W3COV W4COV W1302 W2302 W3302 W4302  Q1  Q2  Q3  Q4
## W1COV    1.00  0.60  0.72  0.39 -0.01 -0.05 -0.05  0.10  0.10  0.06  0.11  0.06
## W2COV    0.60  1.00  0.67  0.72  0.00  0.02  0.15  0.29  0.13 -0.07 -0.06  0.05
## W3COV    0.72  0.67  1.00  0.61 -0.01 -0.01  0.23  0.31  0.09  0.03 -0.08 -0.07
## W4COV    0.39  0.72  0.61  1.00 -0.04  0.04  0.16  0.02  0.10 -0.04  0.10  0.04
## W1302   -0.01  0.00 -0.01 -0.04  1.00  0.70  0.64  0.55 -0.09  0.09 -0.02 -0.16
## W2302   -0.05  0.02 -0.01  0.04  0.70  1.00  0.73  0.62 -0.15 -0.09 -0.01 -0.11
## W3302   -0.05  0.15  0.23  0.16  0.64  0.73  1.00  0.68 -0.09  0.05 -0.13 -0.12
## W4302    0.10  0.29  0.31  0.02  0.55  0.62  0.68  1.00 -0.12 -0.08 -0.09 -0.12
## Q1       0.10  0.13  0.09  0.10 -0.09 -0.15 -0.09 -0.12  1.00  0.16  0.38  0.35
## Q2       0.06 -0.07  0.03 -0.04  0.09 -0.09  0.05 -0.08  0.16  1.00  0.07  0.14
## Q3       0.11 -0.06 -0.08  0.10 -0.02 -0.01 -0.13 -0.09  0.38  0.07  1.00  0.50
## Q4       0.06  0.05 -0.07  0.04 -0.16 -0.11 -0.12 -0.12  0.35  0.14  0.50  1.00
```

```
display_correlation_by_country(china)
```

```
##          W1COV W2COV W3COV W4COV W1302 W2302 W3302 W4302  Q1  Q2  Q3  Q4
## W1COV    1.00  0.70  0.51  0.40  0.12  0.08  0.05 -0.07  0.06  0.09  0.10 -0.01
## W2COV    0.70  1.00  0.67  0.67  0.25  0.34  0.27  0.08  0.14 -0.05  0.05 -0.12
## W3COV    0.51  0.67  1.00  0.62  0.15  0.28  0.19  0.04  0.14  0.04  0.20 -0.19
## W4COV    0.40  0.67  0.62  1.00  0.13  0.25  0.19  0.28  0.24  0.07  0.08 -0.10
## W1302    0.12  0.25  0.15  0.13  1.00  0.56  0.49  0.02  0.21  0.28 -0.06  0.07
## W2302    0.08  0.34  0.28  0.25  0.56  1.00  0.76  0.42  0.15  0.27 -0.02 -0.08
## W3302    0.05  0.27  0.19  0.19  0.49  0.76  1.00  0.57  0.11  0.14 -0.07  0.00
## W4302   -0.07  0.08  0.04  0.28  0.02  0.42  0.57  1.00  0.07  0.15  0.04 -0.03
## Q1       0.06  0.14  0.14  0.24  0.21  0.15  0.11  0.07  1.00  0.44  0.36  0.25
## Q2       0.09 -0.05  0.04  0.07  0.28  0.27  0.14  0.15  0.44  1.00  0.19  0.15
## Q3       0.10  0.05  0.20  0.08 -0.06 -0.02 -0.07  0.04  0.36  0.19  1.00  0.61
## Q4      -0.01 -0.12 -0.19 -0.10  0.07 -0.08  0.00 -0.03  0.25  0.15  0.61  1.00
```

```
display_correlation_by_country(other)
```

```
##          W1COV W2COV W3COV W4COV W1302 W2302 W3302 W4302  Q1  Q2  Q3  Q4
## W1COV    1.00  0.33  0.37  0.10  0.43 -0.20  0.29  0.60 -0.26 -0.11 -0.54 -0.15
## W2COV    0.33  1.00  0.90  0.87  0.29  0.17  0.24  0.18  0.14 -0.19 -0.24  0.03
## W3COV    0.37  0.90  1.00  0.82  0.36  0.09  0.03  0.10  0.12 -0.21 -0.26 -0.02
## W4COV    0.10  0.87  0.82  1.00  0.18  0.04  0.04  0.01  0.12 -0.25 -0.10  0.22
## W1302    0.43  0.29  0.36  0.18  1.00  0.01  0.40  0.35 -0.16 -0.16  0.02  0.00
## W2302   -0.20  0.17  0.09  0.04  0.01  1.00  0.34  0.19  0.09  0.23 -0.02 -0.01
## W3302    0.29  0.24  0.03  0.04  0.40  0.34  1.00  0.72 -0.21  0.15 -0.06  0.08
## W4302    0.60  0.18  0.10  0.01  0.35  0.19  0.72  1.00 -0.05  0.10 -0.28  0.02
## Q1      -0.26  0.14  0.12  0.12 -0.16  0.09 -0.21 -0.05  1.00  0.26  0.29  0.45
## Q2      -0.11 -0.19 -0.21 -0.25 -0.16  0.23  0.15  0.10  0.26  1.00  0.49  0.24
## Q3      -0.54 -0.24 -0.26 -0.10  0.02 -0.02 -0.06 -0.28  0.29  0.49  1.00  0.49
## Q4      -0.15  0.03 -0.02  0.22  0.00 -0.01  0.08  0.02  0.45  0.24  0.49  1.00
```

## Select Predictor Variables Based on Criterion

Here are our tentative models:

- $\text{quiz4} \sim \text{quiz 1, 2, 3 grades (out of 10)}$
- $\text{quiz4} \sim \text{weeks 1, 2, 3, 4 covid19 hours}$
- $\text{quiz4} \sim \text{weeks 1, 2, 3, 4 sta302h1 hours}$

This R code snippet below produces the model  $\text{quiz4} = \text{quiz3}$ . This model seems to under-fit though.

```
quiz_grades.fit = lm(quiz4 ~ quiz1 + quiz2 + quiz3)
step = stepAIC(quiz_grades.fit, direction = "both")
step$anova
```

```
summary(quiz_grades.fit)$r.squared
summary(quiz_grades.fit)$adj.r.squared
```

This R code snippet below produces the model

$\text{quiz4} = \text{quiz1} + \text{I}(\text{quiz2}^2) + \text{I}(\text{quiz3}^2) + \text{I}(\text{quiz1} \text{ quiz3}) + \text{I}(\text{quiz2} \text{ quiz3})$ .

This model seems to be a good fit.

```
quiz_grades.fit2 = lm(
  quiz4 ~ quiz1 + quiz2 + quiz3
  + I(quiz1 ^ 2) + I(quiz2 ^ 2) + I(quiz3 ^ 2)
  + I(quiz1 * quiz2) + I(quiz1 * quiz3) + I(quiz2 * quiz3))
step2 = stepAIC(quiz_grades.fit2, direction = "both")
step2$anova
```

```
summary(quiz_grades.fit2)$r.squared
summary(quiz_grades.fit2)$adj.r.squared
```

This R code snippet below produces the model  $\text{quiz4} = 1$ . This model seems to under-fit though.

```
study_hours.fit = lm(quiz4 ~ study1 + study2 + study3 + study4)
step3 = stepAIC(study_hours.fit, direction = "both")
step3$anova
```

```
summary(study_hours.fit)$r.squared
summary(study_hours.fit)$adj.r.squared
```

This R code snippet below produces the model  $\text{quiz4} = 1$ . This model seems to be a good fit.

```
study_hours.fit2 = lm(
  quiz4 ~ study1 + study2 + study3 + study4 +
  I(study1 ^ 2) + I(study2 ^ 2) + I(study3 ^ 2) + I(study4 ^ 2) +
  I(study1 * study2) + I(study1 * study3) + I(study1 * study4) +
  I(study2 * study3) + I(study2 * study4) + I(study3 * study4))
step4 = stepAIC(study_hours.fit2, direction = "both")
step4$anova
```

```
summary(study_hours.fit2)$r.squared  
summary(study_hours.fit2)$adj.r.squared
```

This R code snippet below produces the model  $\text{quiz4} = 1$ . This model seems to under-fit though.

```
covid_hours.fit = lm(quiz4 ~ covid1 + covid2 + covid3 + covid4)
step5 = stepAIC(covid_hours.fit, direction = "both")
step5$anova
```

```
summary(covid_hours.fit)$r.squared
summary(covid_hours.fit)$adj.r.squared
```

This R code snippet below produces the model

$$\text{quiz4} = \text{covid3} + I(\text{covid3}^2).$$

This model seems to be a good fit.

```
covid_hours.fit2 = lm(
  quiz4 ~ covid1 + covid2 + covid3 + covid4 +
    I(covid1^2) + I(covid2^2) + I(covid3^2) + I(covid4^2) +
    I(covid1 * covid2) + I(covid1 * covid3) + I(covid1 * covid4) +
    I(covid2 * covid3) + I(covid2 * covid4) + I(covid3 * covid4))
step6 = stepAIC(covid_hours.fit2, direction = "both")
step6$anova
```

```
summary(covid_hours.fit2)$r.squared
summary(covid_hours.fit2)$adj.r.squared
```

This R code snippet below produces the model  $\text{quiz4} = \text{quiz3}$ . This model seems to under-fit though.

```
full_model.fit = lm(quiz4 ~
  quiz1 + quiz2 + quiz3 +
  covid1 + covid2 + covid3 + covid4 +
  study1 + study2 + study3 + study4)
step7 = stepAIC(full_model.fit, direction = "both")
step7$anova
```

```
summary(full_model.fit)$r.squared
summary(full_model.fit)$adj.r.squared
```

This R code snippet below produces the model

$$\text{quiz4} = \text{quiz3} + I(\text{study1 study2}) + I(\text{study2 study3}) + I(\text{study3 study4}).$$

This model seems to be a good fit.

```
full_model.fit2 = lm(
  quiz4 ~ quiz1 + quiz2 + quiz3
  + I(covid1 * covid2) + I(covid2 * covid3) + I(covid2 * covid4) + I(covid3 * covid4)
  + I(study1 * study2) + I(study1 * study3) + I(study2 * study3) + I(study3 * study4))
step8 = stepAIC(full_model.fit2, direction = "both")
step8$anova
```

```
summary(full_model.fit2)$r.squared  
summary(full_model.fit2)$adj.r.squared
```



With just Canada, we get the model

$\text{quiz4} \sim \text{quiz3} + \text{I}(\text{covid1 covid2}) + \text{I}(\text{covid2 covid3}) + \text{I}(\text{study2 study3}) + \text{I}(\text{study2 study4})$

```
full_model_canada.fit = lm(
  quiz4 ~ quiz1 + quiz2 + quiz3
  + I(covid1 * covid2) + I(covid1 * covid3) + I(covid2 * covid3) + I(covid2 * covid4)
  + I(covid3 * covid4)

  + I(study1 * study2) + I(study1 * study3) + I(study1 * study4) + I(study2 * study3)
  + I(study2 * study4) + I(study3 * study4))
step9 = stepAIC(full_model_canada.fit, direction = "both")
step9$anova
```

```
summary(full_model_canada.fit)$r.squared
summary(full_model_canada.fit)$adj.r.squared
```

With just China, we get the model

$\text{quiz4} \sim \text{quiz3} + \text{I}(\text{covid1 covid2}) + \text{I}(\text{covid2 covid3}) + \text{I}(\text{study2 study3}) + \text{I}(\text{study3 study4})$

```
full_model_china.fit = lm(
  quiz4 ~ quiz1 + quiz2 + quiz3
  + I(covid1 * covid2) + I(covid1 * covid3) + I(covid2 * covid3) + I(covid2 * covid4)
  + I(covid3 * covid4)

  + I(study1 * study2) + I(study2 * study3) + I(study3 * study4))
step10 = stepAIC(full_model_china.fit, direction = "both")
step10$anova
```

```
summary(full_model_china.fit)$r.squared
summary(full_model_china.fit)$adj.r.squared
```

With all other countries, we get the model

$\text{quiz4} \sim \text{quiz3} + \text{I}(\text{covid2 covid3})$

```
full_model_other.fit = lm(
  quiz4 ~ quiz1 + quiz2 + quiz3
  + I(covid2 * covid3) + I(covid2 * covid4) + I(covid3 * covid4)
  + I(study3 * study4))
step11 = stepAIC(full_model_other.fit, direction = "both")
step11$anova
```

```
summary(full_model_other.fit)$r.squared
summary(full_model_other.fit)$adj.r.squared
```

## Find Significance Predictor Variables

```
# use week 5b slides -- choose model selection criterion to pick predictor variables.
```

```
# use lm() on a bunch of predictor variables to determine significant  
# predictor variables.
```