Analyses 4 (Lab 5)

06/22/2021

IN THE CONTEXT OF YOUR FINAL PROJECT DATA:

Data Import and Merging

```
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 3.6.2
```

```
## -- Attaching packages --------------------------------- tidyverse 1.3.1 --
```

```
## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.1.2     v dplyr   1.0.6
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   1.4.0     v forcats 0.5.1
```

```
## Warning: package 'ggplot2' was built under R version 3.6.2
```

```
## Warning: package 'tibble' was built under R version 3.6.2
```

```
## Warning: package 'tidyr' was built under R version 3.6.2
```

```
## Warning: package 'readr' was built under R version 3.6.2
```

```
## Warning: package 'purrr' was built under R version 3.6.2
```

```
## Warning: package 'dplyr' was built under R version 3.6.2
```

```
## Warning: package 'forcats' was built under R version 3.6.2
```

```
## -- Conflicts ------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(ggpubr)
```

```
## Warning: package 'ggpubr' was built under R version 3.6.2
```

```
library(cluster)
```

```
## Warning: package 'cluster' was built under R version 3.6.2
```

```
library(factoextra)
```

```
## Warning: package 'factoextra' was built under R version 3.6.2
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```
library(interactions)
```

```
## Warning: package 'interactions' was built under R version 3.6.2
```

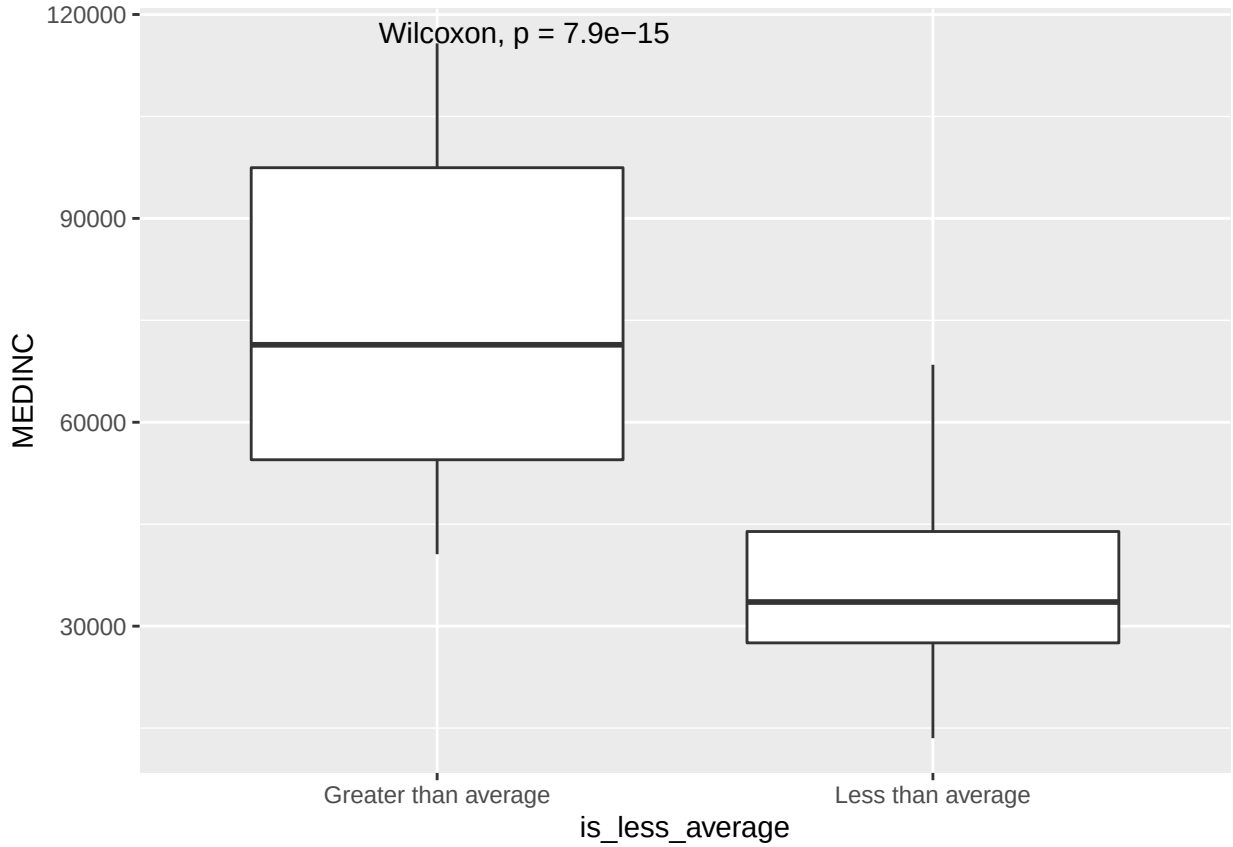
```
library(sandwich)
```

```
## Warning: package 'sandwich' was built under R version 3.6.2
```

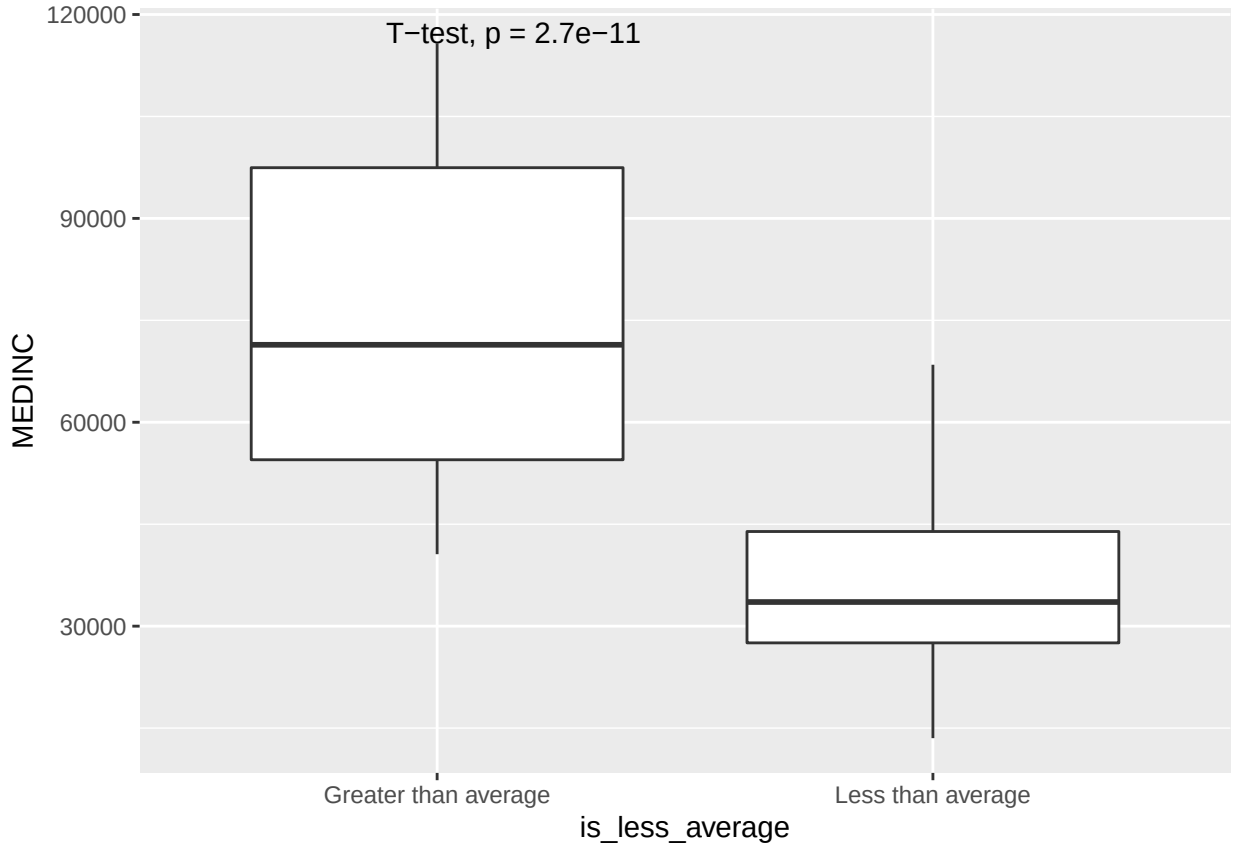
```
Chicago_census <- read.csv(url("https://datahub.cmap.illinois.gov/dataset/1d2dd970-f0a6-4736-96a1-3caeb

Chicago_socionomic <- read.csv(url("https://data.cityofchicago.org/api/views/kn9c-c2s2/rows.csv"))

Chicago_schools <- read.csv(url("https://data.cityofchicago.org/api/views/9xs2-f89t/rows.csv"))

Chicago_combined <- Chicago_socionomic %>%
  rename(GEOG = "COMMUNITY.AREA.NAME") %>%
  left_join(Chicago_census, by = "GEOG")
```

Perform T-test

```
ttest <- Chicago_combined %>%
  filter(WHITE > 0) %>%
  filter(TOT_POP > 0) %>%
  mutate(white_pct = WHITE/TOT_POP) %>%
  mutate(is_less_average = ifelse(white_pct < mean(white_pct), "Less than average", "Greater than avera
  select(is_less_average, everything())


a <- ggplot(data = ttest, mapping = aes(x = is_less_average, y = MEDINC)) +
  geom_boxplot()
a + stat_compare_means()
```




```
a + stat_compare_means(method = "t.test")
```



(INCLUDE VISUALIZATION) DESCRIBE OUTPUT: There is a statistically significant difference between median income of neighborhoods and the percentage of white citizens in neighborhoods.

Perform ANOVA(How does ethnicity affect safety?)

```
anova_alt_data_raw <- Chicago_schools %>%
  select(c( "Community.Area.Name","Safety.Score")) %>%
  transmute(GEOG = Community.Area.Name, Safety_Score = Safety.Score) %>%
  filter(!(Safety_Score == "NDA")) %>%
  group_by(GEOG) %>%
  summarise(Mean = mean(Safety_Score), n=n()) %>%
  select(c("GEOG", "Mean"))

anova_alt_dataa <- Chicago_combined %>%
  select(c("TOT_POP", "WHITE", "GEOG"))

anova_alt_data <- toupper(anova_alt_dataa$GEOG)

 anova_test_data1 <- cbind(anova_alt_dataa, anova_alt_data)
 anova_test_data <- anova_test_data1 %>%
   transmute(TOT_POP = TOT_POP, WHITE = WHITE, GEOG = anova_alt_data) %>%
   left_join(anova_alt_data_raw, by ="GEOG") %>%
   transmute(GEOG = GEOG, WHITE_percent = round(100*(WHITE / TOT_POP)), Safety = round(Mean, 1)) %>%
   drop_na()
```

```
anova_test_data
```

```
##                     GEOG WHITE_percent Safety
## 1             ROGERS PARK            44   43.0
## 2              WEST RIDGE            42   67.2
## 3                  UPTOWN            54   52.0
## 4           LINCOLN SQUARE            64   67.2
## 5             NORTH CENTER            78   85.2
## 6                LAKE VIEW            78   74.1
## 7             LINCOLN PARK            79   81.8
## 8          NEAR NORTH SIDE            71   68.4
## 9              EDISON PARK            83   78.0
## 10            NORWOOD PARK            80   77.4
## 11          JEFFERSON PARK            61   59.0
## 12             FOREST GLEN            69   99.0
## 13              NORTH PARK            52   81.6
## 14             ALBANY PARK            32   61.0
## 15            PORTAGE PARK            49   55.4
## 16             IRVING PARK            43   54.9
## 17                 DUNNING            62   69.2
## 18          BELMONT CRAGIN            13   47.7
## 19                 HERMOSA            10   39.7
## 20                AVONDALE            35   56.2
## 21            LOGAN SQUARE            48   51.5
## 22               WEST TOWN            63   60.3
## 23                  AUSTIN             5   39.8
## 24     WEST GARFIELD PARK              2   37.2
## 25     EAST GARFIELD PARK              6   49.5
## 26         NEAR WEST SIDE            41   54.2
## 27         NORTH LAWNDALE             3   49.3
## 28         SOUTH LAWNDALE             4   47.4
## 29        LOWER WEST SIDE            18   51.3
## 30        NEAR SOUTH SIDE            47   80.3
## 31          ARMOUR SQUARE            12   43.3
## 32                DOUGLAS            11   43.2
## 33             FULLER PARK             4   35.5
## 34        GRAND BOULEVARD              3   37.5
## 35                KENWOOD            18   46.6
## 36        WASHINGTON PARK              1   25.4
## 37              HYDE PARK            48   58.5
## 38               WOODLAWN             8   33.3
## 39             SOUTH SHORE             3   34.0
## 40                 CHATHAM             2   53.2
## 41             AVALON PARK             1   28.0
## 42           SOUTH CHICAGO             2   27.0
## 43                BURNSIDE             0   28.0
## 44        CALUMET HEIGHTS              1   56.0
## 45                ROSELAND             1   33.5
## 46                 PULLMAN            10   51.8
## 47           SOUTH DEERING             5   42.5
## 48               EAST SIDE            15   48.6
## 49            WEST PULLMAN             1   33.9
## 50               RIVERDALE             2   41.0
```

```
## 51              HEGEWISCH            39   50.0
## 52         GARFIELD RIDGE            43   56.0
## 53         ARCHER HEIGHTS            16   45.5
## 54          BRIGHTON PARK             7   48.1
## 55          MCKINLEY PARK            17   60.0
## 56             BRIDGEPORT            33   55.0
## 57               NEW CITY            12   38.6
## 58            WEST ELSDON            15   50.7
## 59              GAGE PARK             4   49.1
## 60               CLEARING            39   69.3
## 61              WEST LAWN            14   58.0
## 62           CHICAGO LAWN             4   31.9
## 63         WEST ENGLEWOOD             1   31.2
## 64              ENGLEWOOD             1   34.1
## 65 GREATER GRAND CROSSING             1   35.0
## 66                ASHBURN            10   45.0
## 67         AUBURN GRESHAM             1   32.3
## 68                BEVERLY            57   70.5
## 69        MOUNT GREENWOOD            84   86.5
## 70            MORGAN PARK            27   38.2
## 71              EDGEWATER            55   59.8
```

(INCLUDE VISUALIZATION)] DESCRIBE OUTPUT: There is a statistically significant difference between the white percentage in neighborhoods that are considered dangerous, moderate, or safe. The anova test suggests that the neighborhoods with high white percentages are safer due to historical systems.

Perform Multiple Regression (please try interaction terms, if possible.)

```r
Q2 <- Chicago_combined %>%
  select(c("PERCENT.AGED.25..WITHOUT.HIGH.SCHOOL.DIPLOMA",
           "GEOG", "PER.CAPITA.INCOME", "TOT_POP", "WHITE")) %>%
  mutate(Percent_Minorities = ((TOT_POP - WHITE)/TOT_POP) * 100,
         Income = PER.CAPITA.INCOME,
         Education = PERCENT.AGED.25..WITHOUT.HIGH.SCHOOL.DIPLOMA)

lm_1 = lm(Income ~ Percent_Minorities * Education, data = Q2)
summary(lm_1)
```

```
##
## Call:
## lm(formula = Income ~ Percent_Minorities * Education, data = Q2)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -22538  -4069   -315   2764  34654
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  72137.592   4694.979  15.365  < 2e-16 ***
```

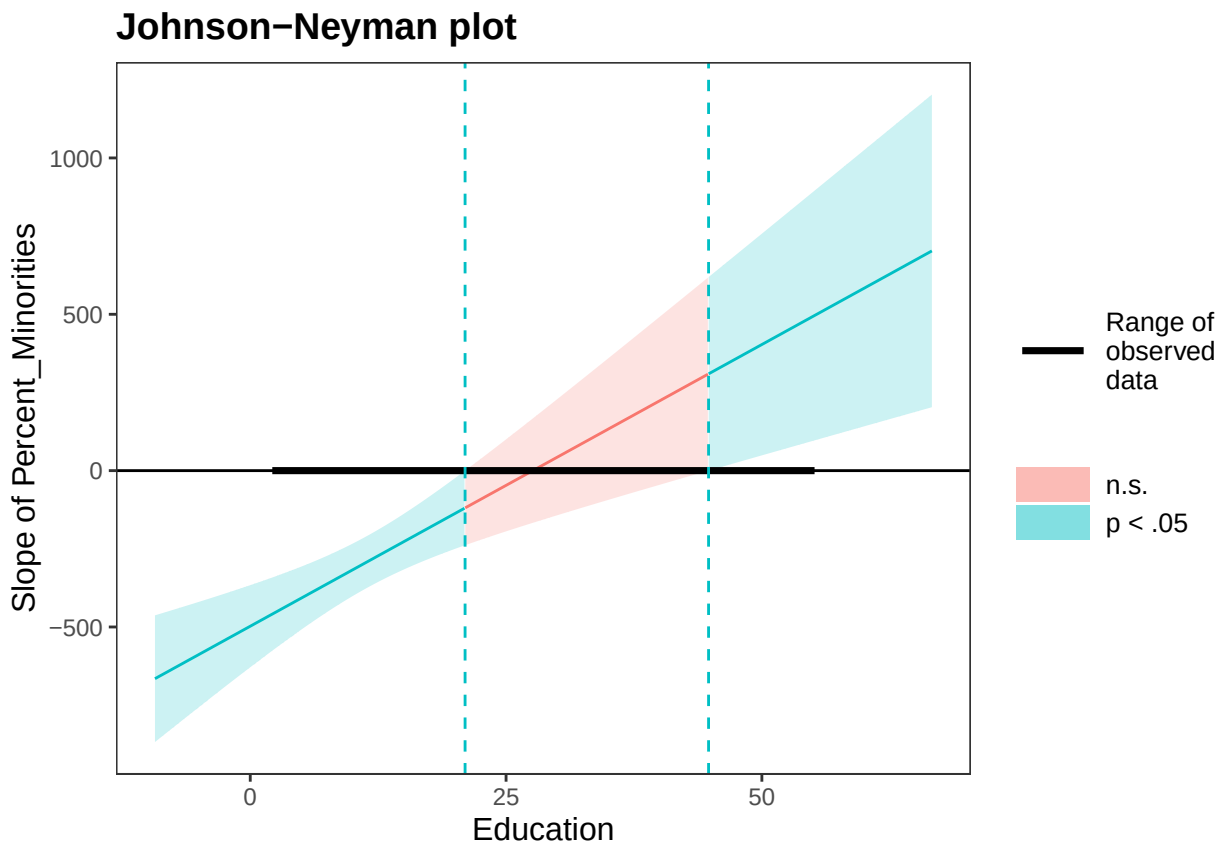
```
## Percent_Minorities            -497.555     65.790  -7.563 1.26e-10 ***
## Education                    -2001.213    387.362  -5.166 2.21e-06 ***
## Percent_Minorities:Education    18.018      4.475   4.027 0.000143 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7747 on 69 degrees of freedom
##   (5 observations deleted due to missingness)
## Multiple R-squared:  0.741,  Adjusted R-squared:  0.7297
## F-statistic: 65.79 on 3 and 69 DF,  p-value: < 2.2e-16
```

```
sim_slopes(lm_1, pred = Percent_Minorities, modx = Education, johnson_neyman =  FALSE)
```

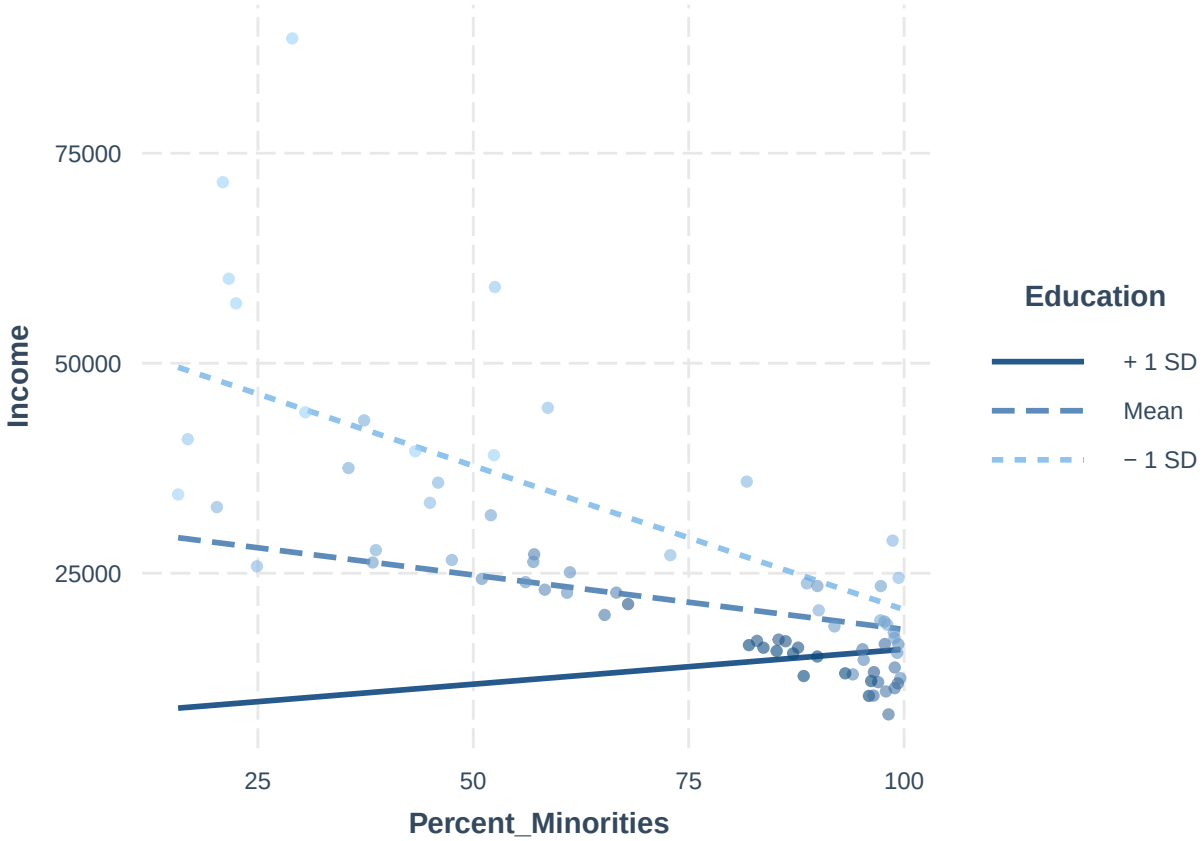
```
## SIMPLE SLOPES ANALYSIS
##
## Slope of Percent_Minorities when Education =  8.61 (- 1 SD):
##
##      Est.    S.E.   t val.      p
## --------- ------- -------- ------
##   -342.46   43.42    -7.89   0.00
##
## Slope of Percent_Minorities when Education = 20.42 (Mean):
##
##      Est.    S.E.   t val.      p
## --------- ------- -------- ------
##   -129.63   57.98    -2.24   0.03
##
## Slope of Percent_Minorities when Education = 32.23 (+ 1 SD):
##
##    Est.     S.E.   t val.      p
## ------- -------- -------- ------
##   83.20   102.11     0.81   0.42
```

```
johnson_neyman(lm_1, pred = Percent_Minorities, modx = Education, alpha = .05)
```

```
## JOHNSON-NEYMAN INTERVAL
##
## When Education is OUTSIDE the interval [20.99, 44.79], the slope of
## Percent_Minorities is p < .05.
##
## Note: The range of observed values of Education is [2.50, 54.80]
```



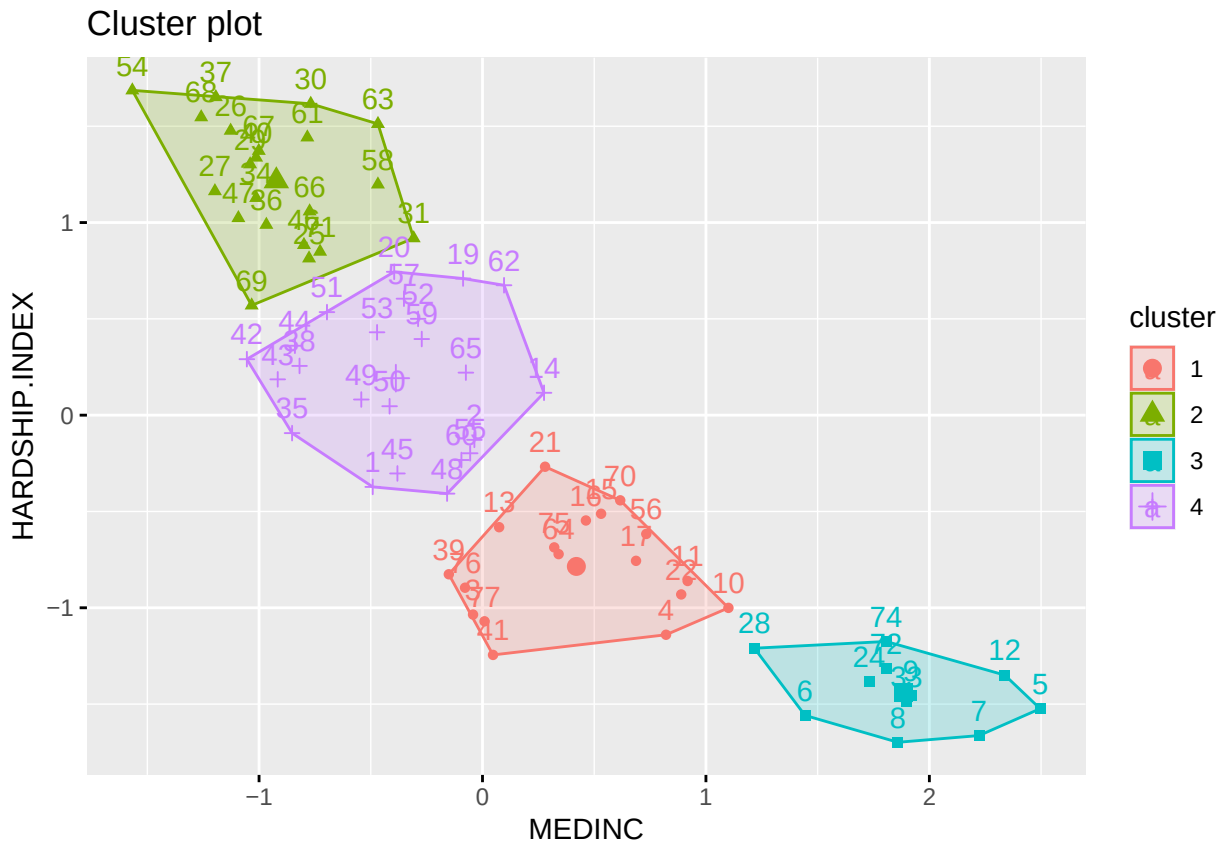

```
interact_plot(lm_1, pred = Percent_Minorities, modx = Education, plot.points = TRUE)
```



(INCLUDE VISUALIZATION) DESCRIBE OUTPUT: There is a statistically significant relationship between the Income and the Percent of Minorities in a Neighborhood + Percent of Education Level in that Neighborhood (% which completed high school). However, the Simple Slopes Analysis shows that the relationship between Education Level and Percent of Minorities in a neighborhood are not statistically significant within +- 1 standard deviation to each other. Additionally, the large range between the Slopes of Percent_Minorities and large Johnoson-Neyman interval indicates a weak/non-statistically significant relation between the education level and the number of minorities in a neighborhood.

Perform Classification or Clustering (e.g., SVM, Decision Tree, K-Means Clustering)

```
# Number on graph is based on the
D <- Chicago_combined %>%
  select(MEDINC, HARDSHIP.INDEX) %>%
  na.omit()

D1 <- scale(D)

D2 <- kmeans(D1, centers = 4, nstart = 50)


fviz_cluster(D2, data = D)
```



(INCLUDE VISUALIZATION) DESCRIBE OUTPUT: There seems to be a strong negative correlation between hardship index and median income. There also seems to be few, if any, outliers that contradict the relationship otherwise, and the observations appear to be clustered closely around 4 centers.