HW2

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```r
rm(list = ls())

setwd("C:/Users/Lily/Documents/collegefiles/PLAN 372/plan372_hmks/hw2")

library(tidyverse)

inspection_df = read_csv("restaurant_inspections.csv")
```

The above code sets up the document, changes the working directory, loads tidyverse, and assignes the csv file to the object "inspection_df".

Question 1

```r
ggplot(inspection_df, aes(x = SCORE)) +
  geom_histogram(color = "black", fill = "black", bins = 50) +
  labs(
    x = "Health Inspection Score",
    y = "Count of Restaurants",
    title = "Restaruant Inspection Scores in NC"
  ) +
  theme_bw()
```

This code creates a histogram, showing that the spread of health inspection scores is mostly localized between 80-100 points. The code inside `geom_histogram()` sets the visual appearance of the bars, and `bins = 50` means that each bar represents all values that fall between 2 inspection scores.

Question 2

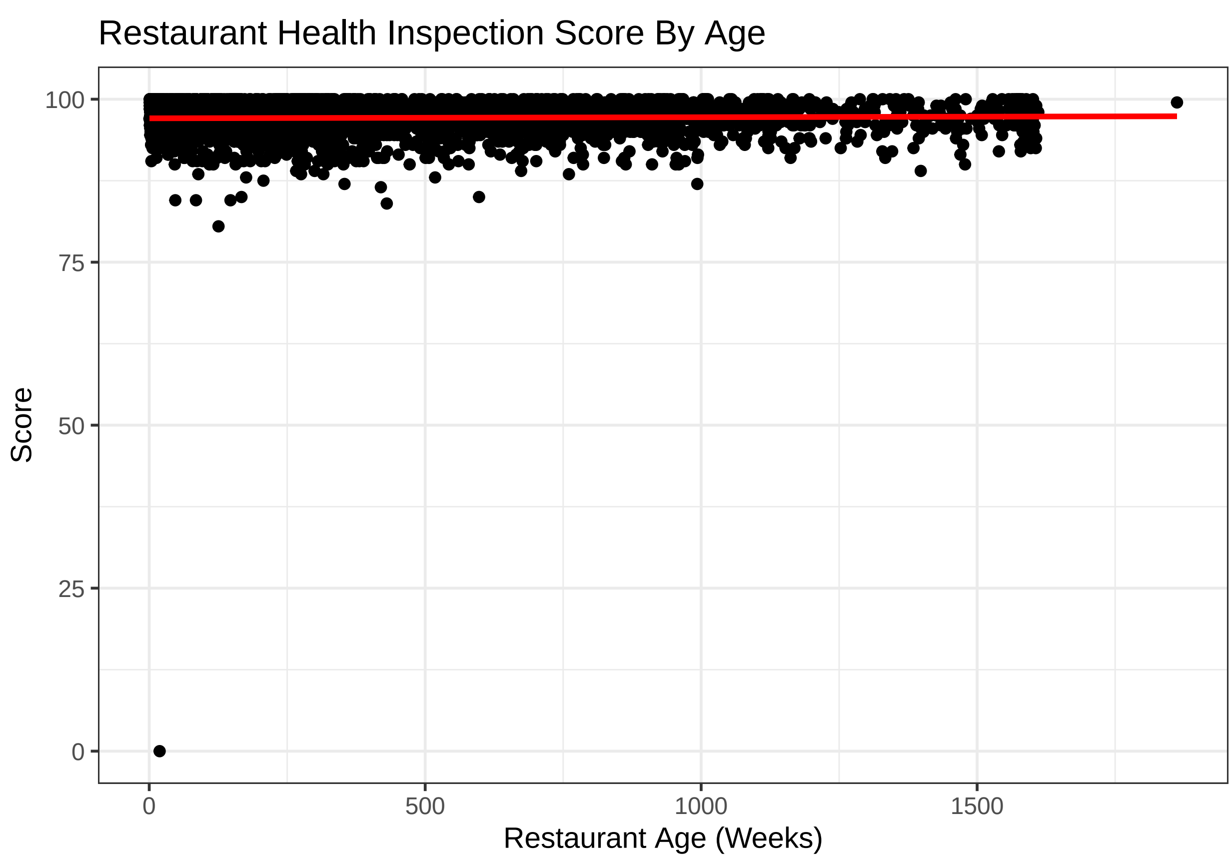
To complete this question I conducted a linear regression to see if inspection scores varied by age of the restaurant, then plotted the relationship on a graph. The use of the difftime function here allows for the subtraction of the two columns and producing the result in "weeks"

```
inspection_df$date_2 = as.Date(inspection_df$DATE_, "%Y/%m/%d")
inspection_df$opendate_2 = as.Date(inspection_df$RESTAURANTOPENDATE, "%Y/%m/%d")
inspection_df$restaurant_age = as.numeric(difftime(inspection_df$date_2, inspection_df$opendate_2, unit

fit1 = lm(SCORE ~ restaurant_age, inspection_df)
summary(fit1)
```

```
##
## Call:
## lm(formula = SCORE ~ restaurant_age, data = inspection_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -97.075  -1.151   0.418   1.763   2.928
##
```

```
## Coefficients:
##                  Estimate Std. Error  t value Pr(>|t|)
## (Intercept)     9.707e+01  7.140e-02 1359.556   <2e-16 ***
## restaurant_age 1.652e-04  1.091e-04    1.515     0.13
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.807 on 3577 degrees of freedom
##   (296 observations deleted due to missingness)
## Multiple R-squared:  0.0006415,  Adjusted R-squared:  0.0003621
## F-statistic: 2.296 on 1 and 3577 DF,  p-value: 0.1298
```

```r
ggplot(inspection_df, aes(x = restaurant_age, y = SCORE)) +
  geom_point() +
  geom_smooth(method = "lm", color = "red") +
  labs(y = "Score", x = "Restaurant Age (Weeks)", title = "Restaurant Health Inspection Score By Age") +
  theme_bw()
```



The incredibly small slope of 0.00017 expected change in score between a brand new restaurant and a dining location one week older translates into about a 0.00884 point yearly increase. In other words, there is little to no relationship between age of a location that serves food and the score it receives. Of note is a single outlier which has a very low age and a score of 0, indicating the data probably needs further cleaning.

Question 3

Because city is not a continuous variable, it will be difficult to perform a regression with it. One possibility is to perform a multivariate regression with dummy variables, but it seems more useful to plot a graph and examine the results visually, as well as numerically. First, though, I utilized base r commands to recode variables because mutate was causing issues that I could not solve.

```
unique(inspection_df$CITY)
```

```
##  [1] "CARY"                    "RALEIGH"                 "KNIGHTDALE"
##  [4] "CLAYTON"                 "FUQUAY VARINA"           NA
##  [7] "GARNER"                  "MORRISVILLE"             "RESEARCH TRIANGLE PARK"
## [10] "RTP"                     "WENDELL"                 "Cary"
## [13] "APEX"                    "Apex"                    "WILLOW SPRING"
## [16] "HOLLY SPRINGS"           "ROLESVILLE"              "ZEBULON"
## [19] "Raleigh"                 "WAKE FOREST"             "NEW HILL"
## [22] "FUQUAY-VARINA"           "Zebulon"                 "Morrisville"
## [25] "Wake Forest"             "Holly Springs"           "ANGIER"
## [28] "Fuquay Varina"           "NORTH CAROLINA"          "MORRISVILE"
## [31] "Fuquay-Varina"           "HOLLY SPRING"            "Garner"
```

```
inspection_df$CITY = toupper(inspection_df$CITY)
unique(inspection_df$CITY)
```

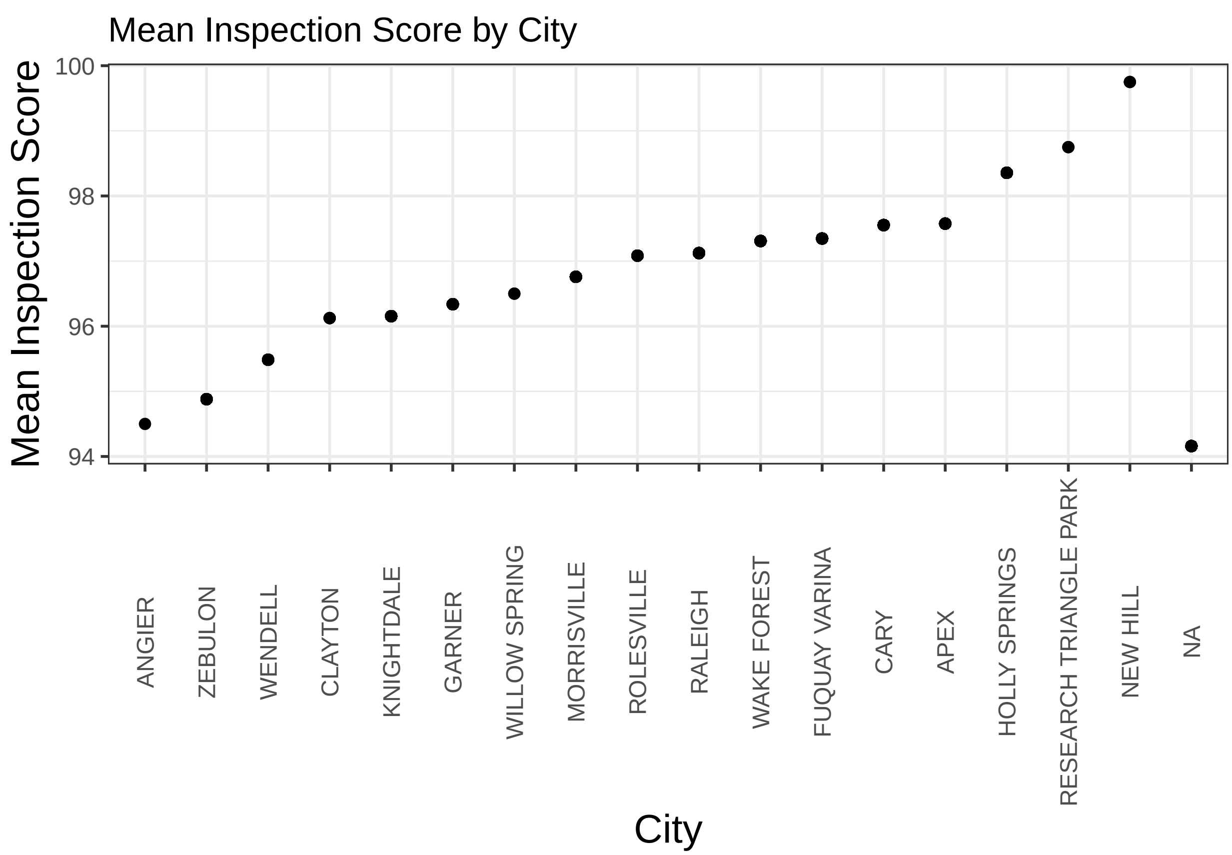
```
##  [1] "CARY"                    "RALEIGH"                 "KNIGHTDALE"
##  [4] "CLAYTON"                 "FUQUAY VARINA"           NA
##  [7] "GARNER"                  "MORRISVILLE"             "RESEARCH TRIANGLE PARK"
## [10] "RTP"                     "WENDELL"                 "APEX"
## [13] "WILLOW SPRING"           "HOLLY SPRINGS"           "ROLESVILLE"
## [16] "ZEBULON"                 "WAKE FOREST"             "NEW HILL"
## [19] "FUQUAY-VARINA"           "ANGIER"                  "NORTH CAROLINA"
## [22] "MORRISVILE"              "HOLLY SPRING"
```

```
inspection_df$CITY[inspection_df$CITY == "RTP"] = "RESEARCH TRIANGLE PARK"
inspection_df$CITY[inspection_df$CITY == "FUQUAY-VARINA"] = "FUQUAY VARINA"
inspection_df$CITY[inspection_df$CITY == "HOLLY SPRING"] = "HOLLY SPRINGS"
inspection_df$CITY[inspection_df$CITY == "MORRISVILE"] = "MORRISVILLE"
inspection_df$CITY[inspection_df$CITY == "NORTH CAROLINA"] = NA


unique(inspection_df$CITY)
```

```
##  [1] "CARY"                    "RALEIGH"                 "KNIGHTDALE"
##  [4] "CLAYTON"                 "FUQUAY VARINA"           NA
##  [7] "GARNER"                  "MORRISVILLE"             "RESEARCH TRIANGLE PARK"
## [10] "WENDELL"                 "APEX"                    "WILLOW SPRING"
## [13] "HOLLY SPRINGS"           "ROLESVILLE"              "ZEBULON"
## [16] "WAKE FOREST"             "NEW HILL"                "ANGIER"
```

```
inspection_df = inspection_df %>%
  group_by(CITY) %>%
```

```
  mutate(inspection_mean = mean(SCORE, na.rm = T)) %>%
  ungroup

ggplot(inspection_df, aes(x = reorder(CITY, inspection_mean), y = inspection_mean)) +
  geom_point() +
  theme_bw() +
  theme(axis.title = element_text(size = 15),
        axis.text.x = element_text(angle = 90, vjust = .5)) +
  labs(x = "City",
       y = "Mean Inspection Score",
       title = "Mean Inspection Score by City")
```



The graph demonstrates that the lowest average scores were in Angier and Zebulon, while Research Triangle Park and New hill had the highest average scores.

Question 4

The following code first groups by the inspector variable and calculates the mean score for each of these groups, giving the mean score for each inspector. The `tibble()` function places the data into a small table-like dataframe, which is then viewed. The summary command allows for the viewing of key summary statistics about the data.

```
inspector_averages = inspection_df %>%
  group_by(INSPECTOR) %>%
  summarize(mean_by_inspector = mean(SCORE, na.rm = T)) %>%
```

```r
  ungroup %>%
  tibble()

inspector_averages
```

```
## # A tibble: 39 x 2
##    INSPECTOR           mean_by_inspector
##    <chr>                           <dbl>
##  1 Angela Myers                     96.9
##  2 Angela Stocks                    96.7
##  3 Brittny Thomas                   98
##  4 Christy Klaus                    96.3
##  5 Cristofer LeClair                97.7
##  6 Daryl Beasley                    95.8
##  7 David Adcock                     97.7
##  8 Dipatrimarki Farkas              97.8
##  9 Elizabeth Jackson                96.6
## 10 Ginger Johnson                   97.6
## # i 29 more rows
```

```r
summary(inspector_averages)
```

```
##   INSPECTOR         mean_by_inspector
##  Length:39          Min.   :89.00
##  Class :character   1st Qu.:96.18
##  Mode  :character   Median :97.02
##                     Mean   :96.78
##                     3rd Qu.:97.73
##                     Max.   :99.00
```

The inspectors all seem to have relatively high average scores, with a minimum of 89, a max of 99, and a median of 97.02. The harshest inspector was Thomas Jumalon, who averaged 89, and the most lenient was James Smith, who averaged 99

Question 5

The following code creates 3 objects, then using the dplyr count function

```r
facilitycount = inspection_df %>%
  count(FACILITYTYPE)
inspectorcount = inspection_df %>%
  count(INSPECTOR)
citycount = inspection_df %>%
  count(CITY)
citycount
```

```
## # A tibble: 18 x 2
##    CITY                      n
##    <chr>                 <int>
##  1 ANGIER                    1
```

```
##  2 APEX                      185
##  3 CARY                      573
##  4 CLAYTON                     4
##  5 FUQUAY VARINA             114
##  6 GARNER                    133
##  7 HOLLY SPRINGS             107
##  8 KNIGHTDALE                 81
##  9 MORRISVILLE               174
## 10 NEW HILL                    2
## 11 RALEIGH                  1895
## 12 RESEARCH TRIANGLE PARK      2
## 13 ROLESVILLE                 24
## 14 WAKE FOREST               196
## 15 WENDELL                    35
## 16 WILLOW SPRING               2
## 17 ZEBULON                    50
## 18 <NA>                      297
```

```
inspectorcount
```

```
## # A tibble: 39 x 2
##    INSPECTOR               n
##    <chr>               <int>
##  1 Angela Myers          138
##  2 Angela Stocks          52
##  3 Brittny Thomas          3
##  4 Christy Klaus         140
##  5 Cristofer LeClair     128
##  6 Daryl Beasley          16
##  7 David Adcock           71
##  8 Dipatrimarki Farkas   155
##  9 Elizabeth Jackson     137
## 10 Ginger Johnson         45
## # i 29 more rows
```

```
facilitycount
```

```
## # A tibble: 11 x 2
##    FACILITYTYPE                         n
##    <chr>                            <int>
##  1 Elderly Nutrition Sites (catered)     8
##  2 Food Stand                         661
##  3 Institutional Food Service          46
##  4 Limited Food Service                 1
##  5 Meat Market                         93
##  6 Mobile Food Units                  181
##  7 Private School Lunchrooms           13
##  8 Public School Lunchrooms           185
##  9 Pushcarts                           39
## 10 Restaurant                        2352
## 11 <NA>                               296
```

It seems as if the sample sizes within all 3 of these groupings are highly varied. For example, only 1 limited food service and 8 elderly nutrition sites are recorded in the dataset, which are sample sizes far to small to draw conclusions about. Furthermore, New Hill, which had particularly high mean scores, only had 2 restaurants in the sample - this indicates that the high scores may not be an accurate aggregate, the same is true for Angier, which had particularly low mean scores - but tested only one For all of these cases, however, it would be important to understand how representative they are of the population; for example, does the distribution of food-service locations in the dataset mirror the distribution of food service in North Carolina at large?

Question 6

The first bit of code in the following block adds a new column to inspection_df, using the `ifelse()` command to create a dummy that shows restaurants and changes all others to "other." The next bit of code creates a new tibble called facilityscores that groups by restaurant & other, then takes the mean of both to find the average health inspector score for each category.

```
inspection_df = inspection_df %>%
  mutate(restaurant_dummy = ifelse(FACILITYTYPE == "Restaurant","Restaurant","Other"))

facilityscores = inspection_df %>%
  group_by(restaurant_dummy) %>%
  summarize(mean(SCORE, na.rm = T))

facilityscores
```

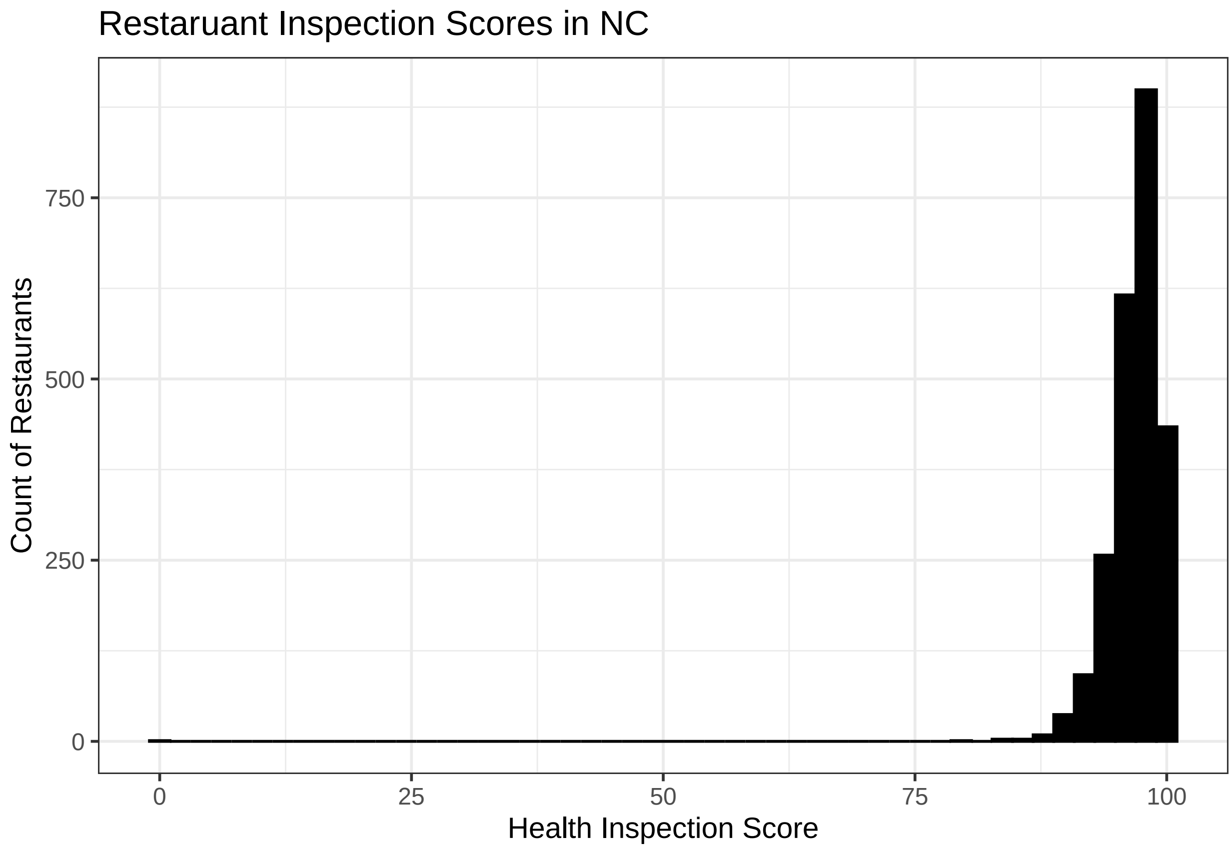
```
## # A tibble: 3 x 2
##   restaurant_dummy `mean(SCORE, na.rm = T)`
##   <chr>                                <dbl>
## 1 Other                                 98.1
## 2 Restaurant                            96.7
## 3 <NA>                                  94.2
```

Restaurants seem to have a lower mean score than other food-service facilities, however only by about 1.5 points on average. This indicates slightly higher scores for non-restaurants, but the smaller sample size for non-restaurants may indicate that it is not representative of the population of non-restaurant food service locations.

Question 7

Essentially, the following codeblock copies the code of the previous question 1, but first filters by restaurant into a new dataframe, restaurant_df.

```
restaurant_df = inspection_df %>%
  filter(FACILITYTYPE == "Restaurant")

#Question 1 analysis with only restaurants
ggplot(restaurant_df, aes(x = SCORE)) +
  geom_histogram(color = "black", fill = "black", bins = 50) +
  labs(
    x = "Health Inspection Score",
    y = "Count of Restaurants",
    title = "Restaruant Inspection Scores in NC"
  ) +
  theme_bw()
```

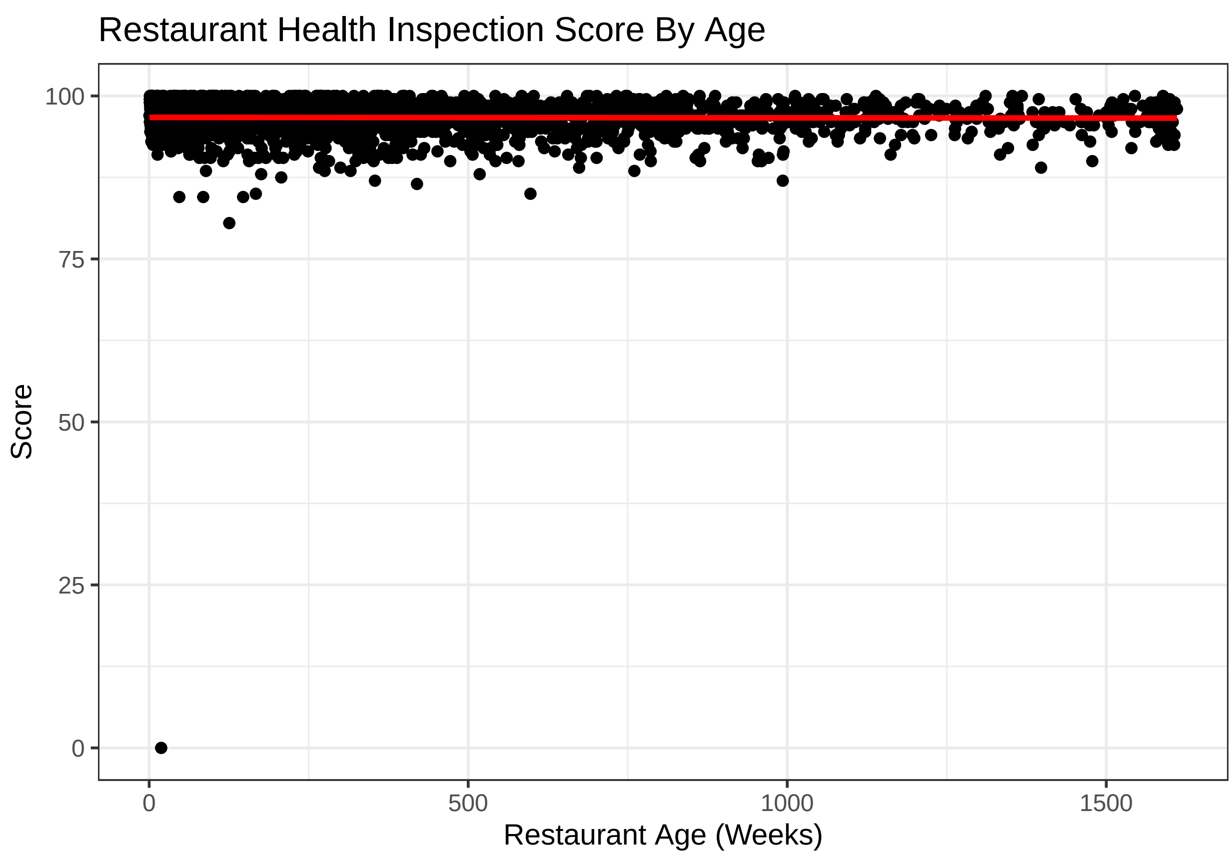


Part 2 of this question changes the outcome only slightly, removing an outlier of a particularly old location, but keeping the distribution mostly the same. The slope of the regression line changed slightly, but both round to 0 at 3 significant figures, so the change is negligible.

```
#Question 2 analysis with only restaurants
fitrestaurant = lm(SCORE ~ restaurant_age, restaurant_df)
summary(fitrestaurant)
```

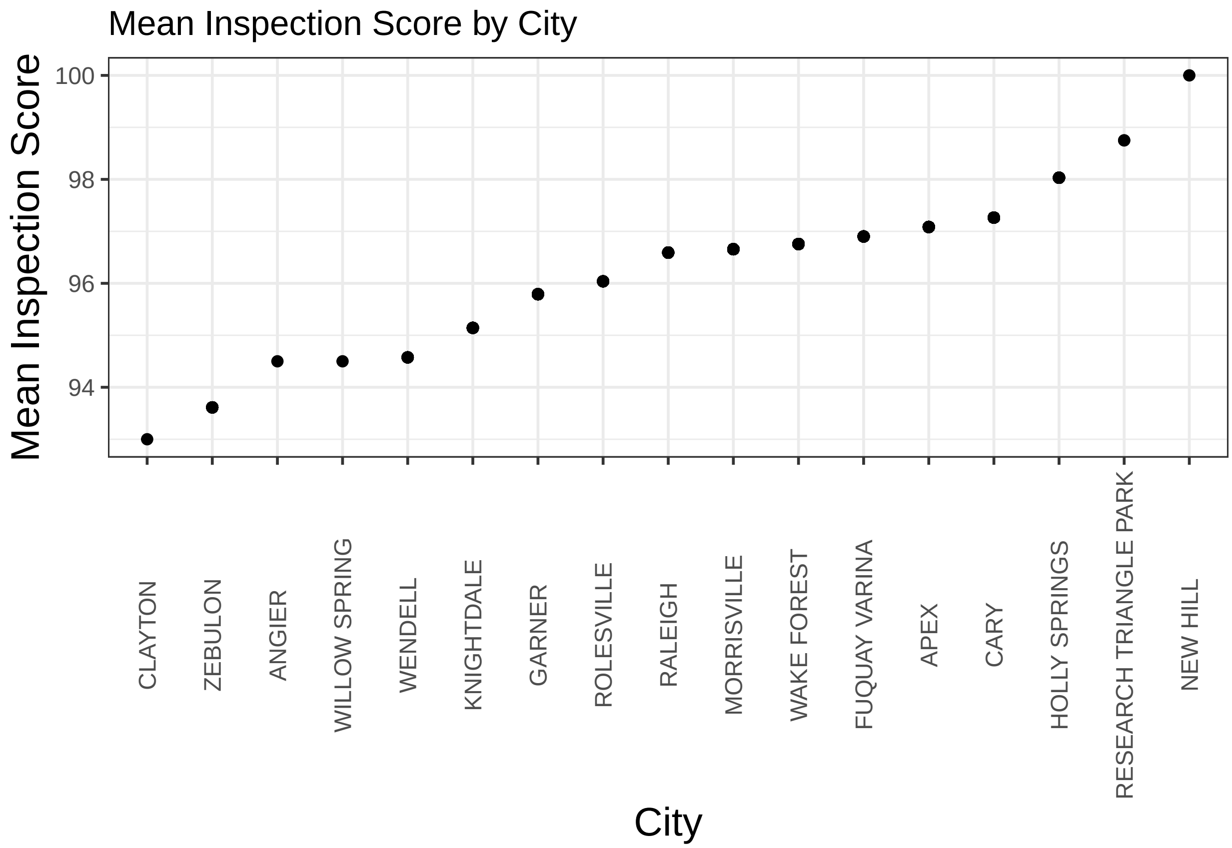
```
##
## Call:
## lm(formula = SCORE ~ restaurant_age, data = restaurant_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -96.710  -1.184   0.325   1.800   3.394
##
## Coefficients:
##                  Estimate Std. Error  t value Pr(>|t|)
## (Intercept)     9.671e+01  9.525e-02 1015.338   <2e-16 ***
## restaurant_age -6.629e-05  1.547e-04   -0.428    0.668
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.08 on 2350 degrees of freedom
## Multiple R-squared:  7.813e-05,  Adjusted R-squared:  -0.0003474
## F-statistic: 0.1836 on 1 and 2350 DF,  p-value: 0.6683
```

```r
ggplot(restaurant_df, aes(x = restaurant_age, y = SCORE)) +
  geom_point() +
  geom_smooth(method = "lm", color = "red") +
  labs(y = "Score", x = "Restaurant Age (Weeks)", title = "Restaurant Health Inspection Score By Age") +
  theme_bw()
```



The code below does mostly the same as the code in question 3, albeit only using the restaurant_df dataframe. The code groups by city and calculates the mean for each city, then plots it on a graph.

```r
#Question 3 analysis with only restaurants
restaurant_df = restaurant_df %>%
  group_by(CITY) %>%
  mutate(inspection_mean = mean(SCORE, na.rm = T)) %>%
  ungroup

ggplot(restaurant_df, aes(x = reorder(CITY, inspection_mean), y = inspection_mean)) +
  geom_point() +
  theme_bw() +
  theme(axis.title = element_text(size = 15),
        axis.text.x = element_text(angle = 90, vjust = .5)) +
  labs(x = "City",
       y = "Mean Inspection Score",
       title = "Mean Inspection Score by City")
```



The code below performs the same code as question 4 but utilizing restaurant_df. The mean's min and max do not change, indicating that utilizing only restaurants does not meaningfully impact average scores per inspector. Of note, however, is the presence of one less row than in question 4, indicating that at least one inspector never inspected a restaurant.

```
# Question 4 with restaurant only
inspector_averages = restaurant_df %>%
  group_by(INSPECTOR) %>%
  summarize(mean_by_inspector = mean(SCORE, na.rm = T)) %>%
  ungroup %>%
  tibble()

inspector_averages
```

```
## # A tibble: 38 x 2
##    INSPECTOR            mean_by_inspector
##    <chr>                            <dbl>
##  1 Angela Myers                      96.7
##  2 Angela Stocks                     96.2
##  3 Brittny Thomas                    98
##  4 Christy Klaus                     95.9
##  5 Cristofer LeClair                 97.1
##  6 Daryl Beasley                     95.4
##  7 David Adcock                      95.9
##  8 Dipatrimarki Farkas               97.7
##  9 Elizabeth Jackson                 95.7
## 10 Ginger Johnson                    97.6
```

```
## # i 28 more rows
```

```r
summary(inspector_averages)
```

```
##   INSPECTOR         mean_by_inspector
##  Length:38          Min.   :88.00
##  Class :character   1st Qu.:95.90
##  Mode  :character   Median :96.75
##                     Mean   :96.37
##                     3rd Qu.:97.59
##                     Max.   :99.00
```

This final code block once again reproduces question 5's code using the restaurant_df dataframe. Naturally, only restaurants are examined so only these locations show up in the table. Overall counts are of course reduced, but seemingly maintain a similar distribution among the two other categories. Overall, the results for only restaurants do not seem particularly different from the total results.

```r
facilitycountrest = restaurant_df %>%
  count(FACILITYTYPE)
inspectorcountrest = restaurant_df %>%
  count(INSPECTOR)
citycountrest = restaurant_df %>%
  count(CITY)
citycountrest
```

```
## # A tibble: 17 x 2
##    CITY                       n
##    <chr>                  <int>
##  1 ANGIER                     1
##  2 APEX                     108
##  3 CARY                     406
##  4 CLAYTON                    1
##  5 FUQUAY VARINA             76
##  6 GARNER                    93
##  7 HOLLY SPRINGS             80
##  8 KNIGHTDALE                49
##  9 MORRISVILLE              144
## 10 NEW HILL                   1
## 11 RALEIGH                 1193
## 12 RESEARCH TRIANGLE PARK     2
## 13 ROLESVILLE                13
## 14 WAKE FOREST              133
## 15 WENDELL                   20
## 16 WILLOW SPRING              1
## 17 ZEBULON                   31
```

```r
inspectorcountrest
```

```
## # A tibble: 38 x 2
##    INSPECTOR               n
##    <chr>               <int>
##  1 Angela Myers          104
```

```
##  2 Angela Stocks          36
##  3 Brittny Thomas          3
##  4 Christy Klaus         100
##  5 Cristofer LeClair      72
##  6 Daryl Beasley          12
##  7 David Adcock            8
##  8 Dipatrimarki Farkas   118
##  9 Elizabeth Jackson      80
## 10 Ginger Johnson         35
## # i 28 more rows
```

```
facilitycountrest
```

```
## # A tibble: 1 x 2
##   FACILITYTYPE     n
##   <chr>        <int>
## 1 Restaurant    2352
```