# HW2

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```
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.4.2
```

```
## Warning: package 'ggplot2' was built under R version 4.4.2
```

```
## Warning: package 'lubridate' was built under R version 4.4.2
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ dplyr     1.1.4     ✓ readr     2.1.5
## ✓ forcats   1.0.0     ✓ stringr   1.5.1
## ✓ ggplot2   3.5.1     ✓ tibble    3.2.1
## ✓ lubridate 1.9.4     ✓ tidyr     1.3.1
## ✓ purrr     1.0.2
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
```

```
library(lubridate)
library(kableExtra)
```

```
## Warning: package 'kableExtra' was built under R version 4.4.2
```

```
##
## Attaching package: 'kableExtra'
##
## The following object is masked from 'package:dplyr':
##
##     group_rows
```

```
#loading neccessary libraries

inspections <- read_csv("restaurant_inspections.csv") #loading data set into a df called inspect
ions
```

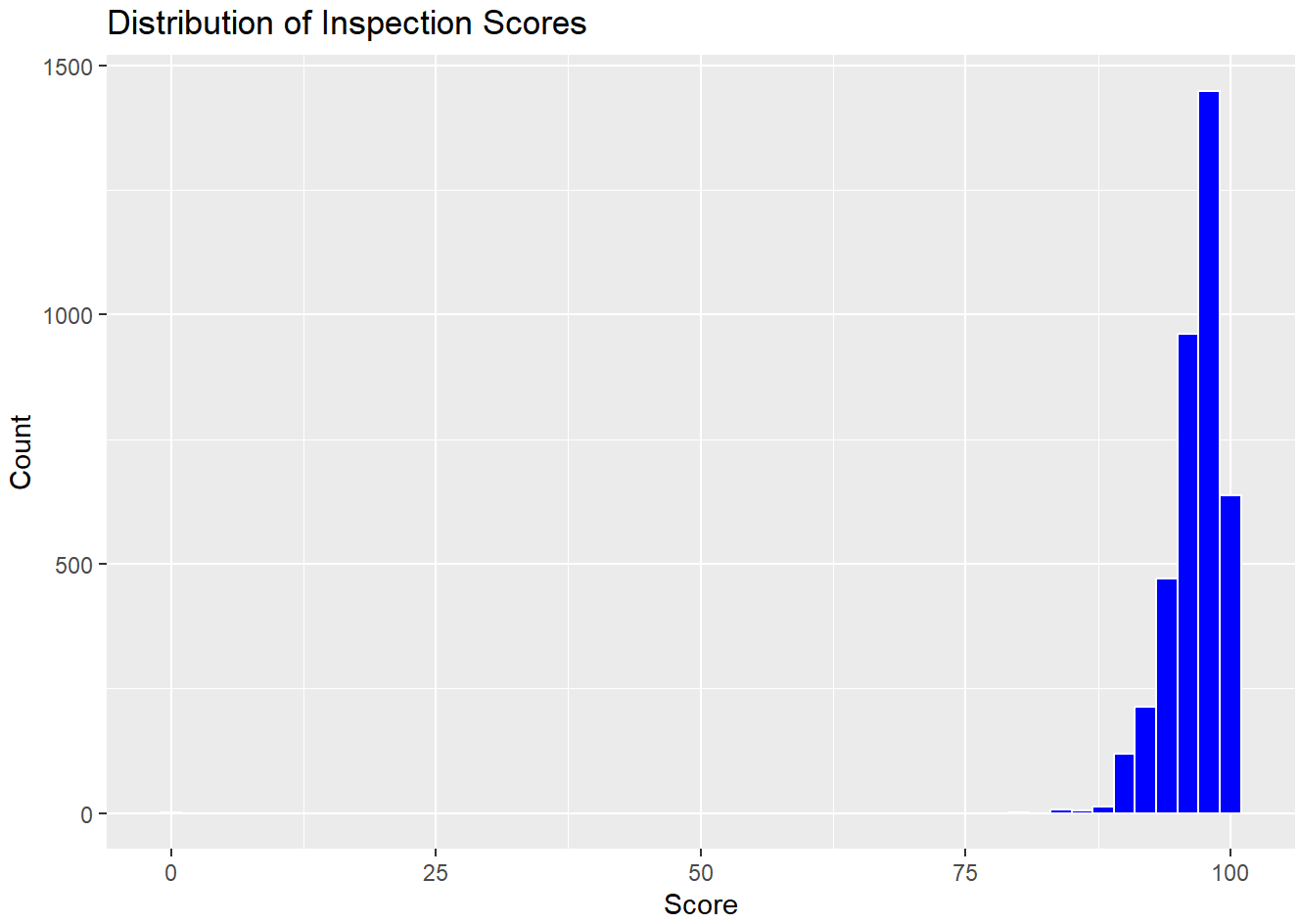
```
## Rows: 3875 Columns: 12
## ── Column specification ────────────────────────────────────────────────────
## Delimiter: ","
## chr  (8): HSISID, DESCRIPTION, TYPE, INSPECTOR, NAME, RESTAURANTOPENDATE, CI...
## dbl  (3): OBJECTID, SCORE, PERMITID
## dttm (1): DATE_
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
inspections <- inspections %>%
  mutate(
    # Convert date columns to proper datetime format
    DATE_ = ymd_hms(DATE_),
    RESTAURANTOPENDATE = ymd_hms(RESTAURANTOPENDATE),

    # Standardize city names for question 3
    CITY = str_to_upper(CITY) %>%
      recode("RTP" = "RESEARCH TRIANGLE PARK",
             "CARY" = "CARY",
             "Apex" = "APEX",
             "RALEIGH" = "RALEIGH",
             "FUQUAY-VARINA" = "FUQUAY VARINA",
             "HOLLY SPRING" = "HOLLY SPRINGS",
             "MORRISVILE" = "MORRISVILLE",
              )
  )
```

# 1) Histogram

```
ggplot(inspections, aes(SCORE)) +
  geom_histogram(binwidth = 2, fill = "blue", color = "white") +
  labs(title = "Distribution of Inspection Scores",
       x = "Score", y = "Count")
```



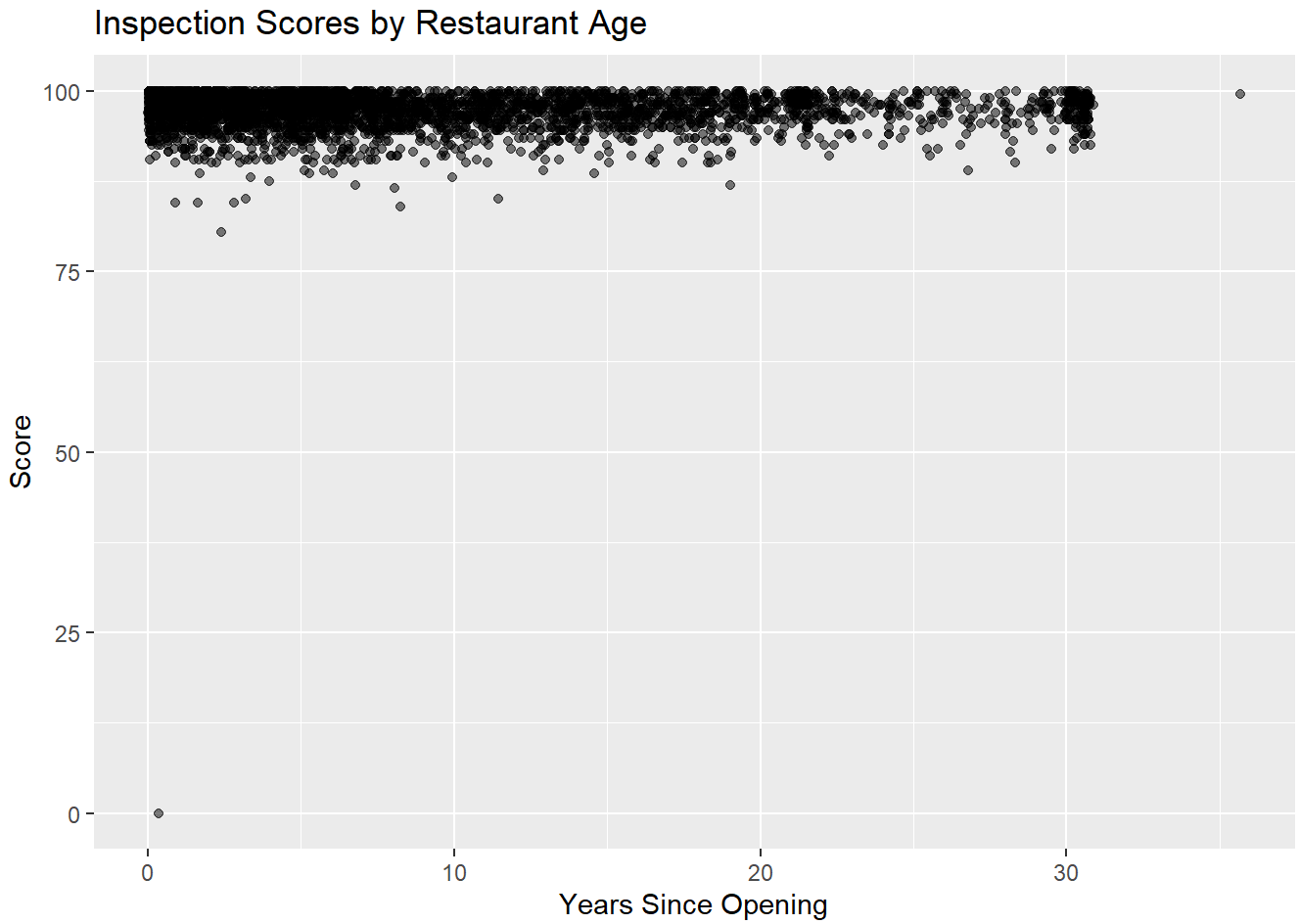

```
#essentially creating a histogram with score as the x axis and count as the y axis, showing the distribution of scores
```

# 2) Trend for New vs Old Facility

We don’t really see any trend visually

```
inspections %>%
  mutate(restaurant_age = time_length(DATE_ - RESTAURANTOPENDATE, "years")) %>% #Essentially what is happening here is calculating how long it's been since they've opened, using the time_length function
  ggplot(aes(restaurant_age, SCORE)) +
  geom_point(alpha = 0.5) +       # Add transparency for overlapping points
  labs(title = "Inspection Scores by Restaurant Age",
       x = "Years Since Opening", y = "Score")
```

```
## Warning: Removed 296 rows containing missing values or values outside the scale range
## (`geom_point()`).
```




```
#We don't really see any trend visually
```

# 3) Vary by City?

Average score seems to have very minimal variation between cities

```
city_scores <- inspections %>%
  group_by(CITY) %>%
  summarise(
    avg_score = mean(SCORE, na.rm = TRUE),
    n_inspections = n(),  # Count number of inspections per city
    .groups = "drop"
  )

# Create formatted table with kableExtra
kable(city_scores, caption = "Average Scores by City") %>%
  kable_styling()
```

Average Scores by City

| CITY | avg_score | n_inspections |
|---|---|---|
| ANGIER | 94.50000 | 1 |

| CITY | avg_score | n_inspections |
|---|---|---|
| APEX | 97.57568 | 185 |
| CARY | 97.55323 | 573 |
| CLAYTON | 96.12500 | 4 |
| FUQUAY VARINA | 97.34649 | 114 |
| GARNER | 96.33835 | 133 |
| HOLLY SPRINGS | 98.35514 | 107 |
| KNIGHTDALE | 96.15432 | 81 |
| MORRISVILLE | 96.75862 | 174 |
| NEW HILL | 99.75000 | 2 |
| NORTH CAROLINA | 97.00000 | 1 |
| RALEIGH | 97.12375 | 1895 |
| RESEARCH TRIANGLE PARK | 98.75000 | 2 |
| ROLESVILLE | 97.08333 | 24 |
| WAKE FOREST | 97.30867 | 196 |
| WENDELL | 95.48571 | 35 |
| WILLOW SPRING | 96.50000 | 2 |
| ZEBULON | 94.88000 | 50 |
| NA | 94.15034 | 296 |

```
#Average score seems to have very minimal variation between cities
```

# 4) Inspector Ratings

Average score does seem to have some variation depending on the inpsector

```
# Calculate inspector performance metrics
inspector_scores <- inspections %>%
  group_by(INSPECTOR) %>%
  summarise(
    avg_score = mean(SCORE, na.rm = TRUE),
    n_inspections = n(),
    .groups = "drop"
  ) %>%
  arrange(desc(avg_score))  # arranging by highest avg score
#Essentially finding highest avg scores by inspector
kable(head(inspector_scores, 200), caption = "Inspectors by Average Score") %>%
  kable_styling()
```

Inspectors by Average Score

| INSPECTOR | avg_score | n_inspections |
|---|---|---|
| James Smith | 99.00000 | 1 |
| Greta Welch | 98.50000 | 2 |
| Kaitlyn Yow | 98.50000 | 1 |
| John Wulffert | 98.39286 | 154 |
| Jamie Phelps | 98.15333 | 150 |
| Nicole Millard | 98.08562 | 146 |
| Zachary Carter | 98.08000 | 150 |
| Brittny Thomas | 98.00000 | 3 |
| Dipatrimarki Farkas | 97.79355 | 155 |
| Sarah Thompson | 97.77899 | 138 |
| David Adcock | 97.69014 | 71 |
| Ursula Gadomski | 97.68976 | 166 |
| Cristofer LeClair | 97.67578 | 128 |
| Melodee Johnson | 97.65549 | 164 |
| Loc Nguyen | 97.63253 | 83 |
| Ginger Johnson | 97.57778 | 45 |
| Laura McNeill | 97.48582 | 141 |

| INSPECTOR | avg_score | n_inspections |
|---|---|---|
| Patricia Sabby | 97.14780 | 159 |
| Joshua Volkan | 97.08333 | 24 |
| Shannon Flynn | 97.02215 | 158 |
| Nikia Lawrence | 96.99029 | 103 |
| Maria Powell | 96.97191 | 89 |
| Samatha Sparano | 96.93066 | 137 |
| Angela Myers | 96.87681 | 138 |
| Naterra McQueen | 96.87413 | 143 |
| Angela Stocks | 96.67308 | 52 |
| Elizabeth Jackson | 96.56569 | 137 |
| Joanne Rutkofske | 96.28611 | 180 |
| Christy Klaus | 96.27143 | 140 |
| Jackson Hooton | 96.09375 | 16 |
| Kendra Wiggins | 96.06000 | 75 |
| Lisa McCoy | 96.01923 | 26 |
| Daryl Beasley | 95.81250 | 16 |
| Karla Crowder | 95.45652 | 23 |
| Jason Dunn | 94.89857 | 350 |
| Lauren Harden | 94.74444 | 45 |
| Lucy Schrum | 94.65476 | 126 |
| Meghan Scott | 94.32432 | 37 |
| Thomas Jumalon | 89.00000 | 3 |

# 5) Small Samples Sizes?

Yes, in both the inspectors and the city tables we see instances where the sample size is less than 5, as you can see in the n_inspections column, which could lead to possible extreme values, skewing the data.

# 6) Restaurants vs Other

As we see in the table, the scores for restaurant (where is_restaurant is TRUE) is slightly less than for non-restaurants

```
inspections %>%
  mutate(is_restaurant = FACILITYTYPE == "Restaurant") %>%
  group_by(is_restaurant) %>%
  summarise(
    avg_score = mean(SCORE, na.rm = TRUE),
    n = n(),  # Total inspections in each group
    .groups = "drop"
  ) %>%
  kable(caption = "Scores by Facility Type") %>%
  kable_styling()
```

Scores by Facility Type

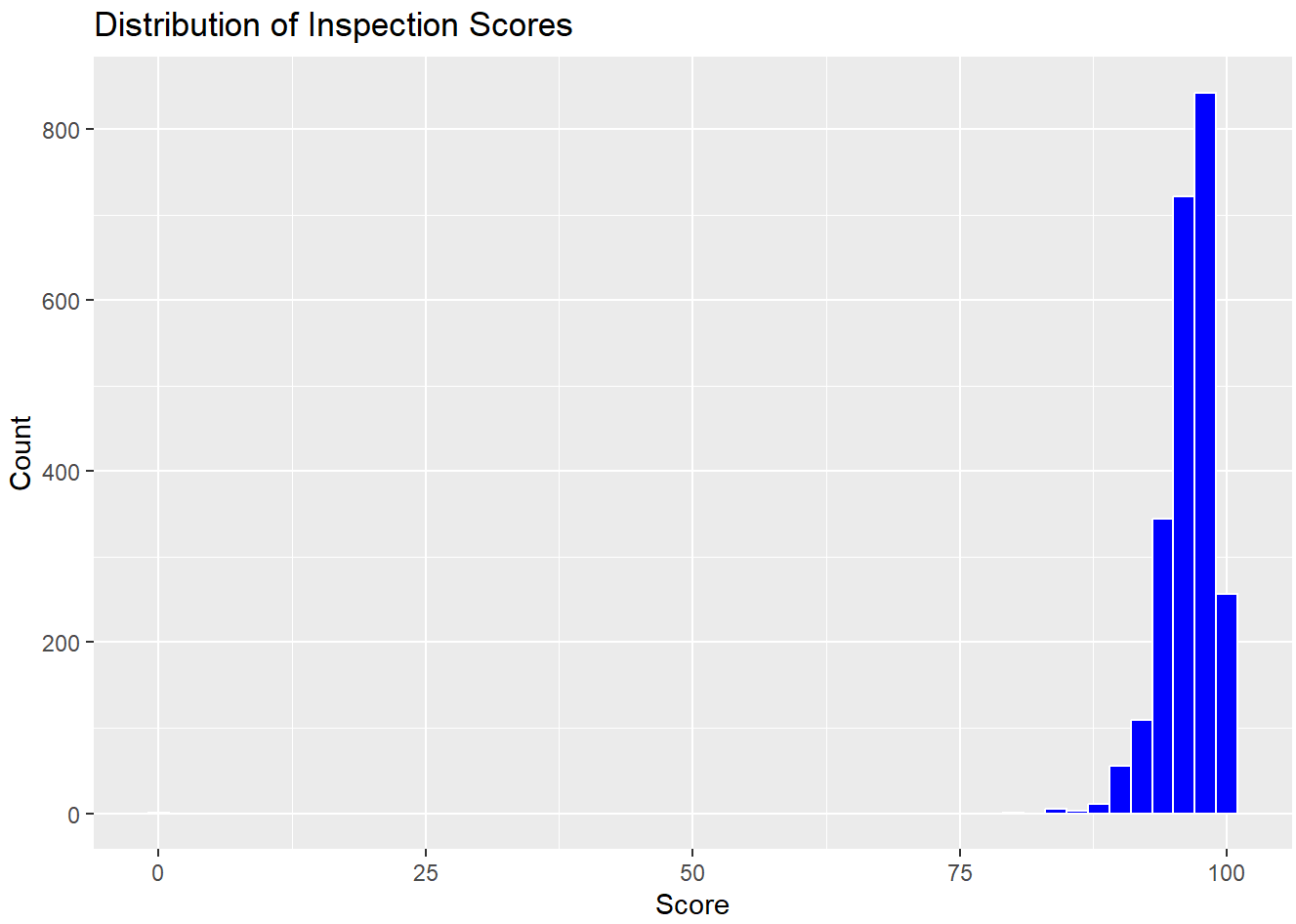
| is_restaurant | avg_score | n |
|---|---|---|
| FALSE | 98.05990 | 1227 |
| TRUE | 96.68070 | 2352 |
| NA | 94.15034 | 296 |

# 7) Restaurant Specific Analysis

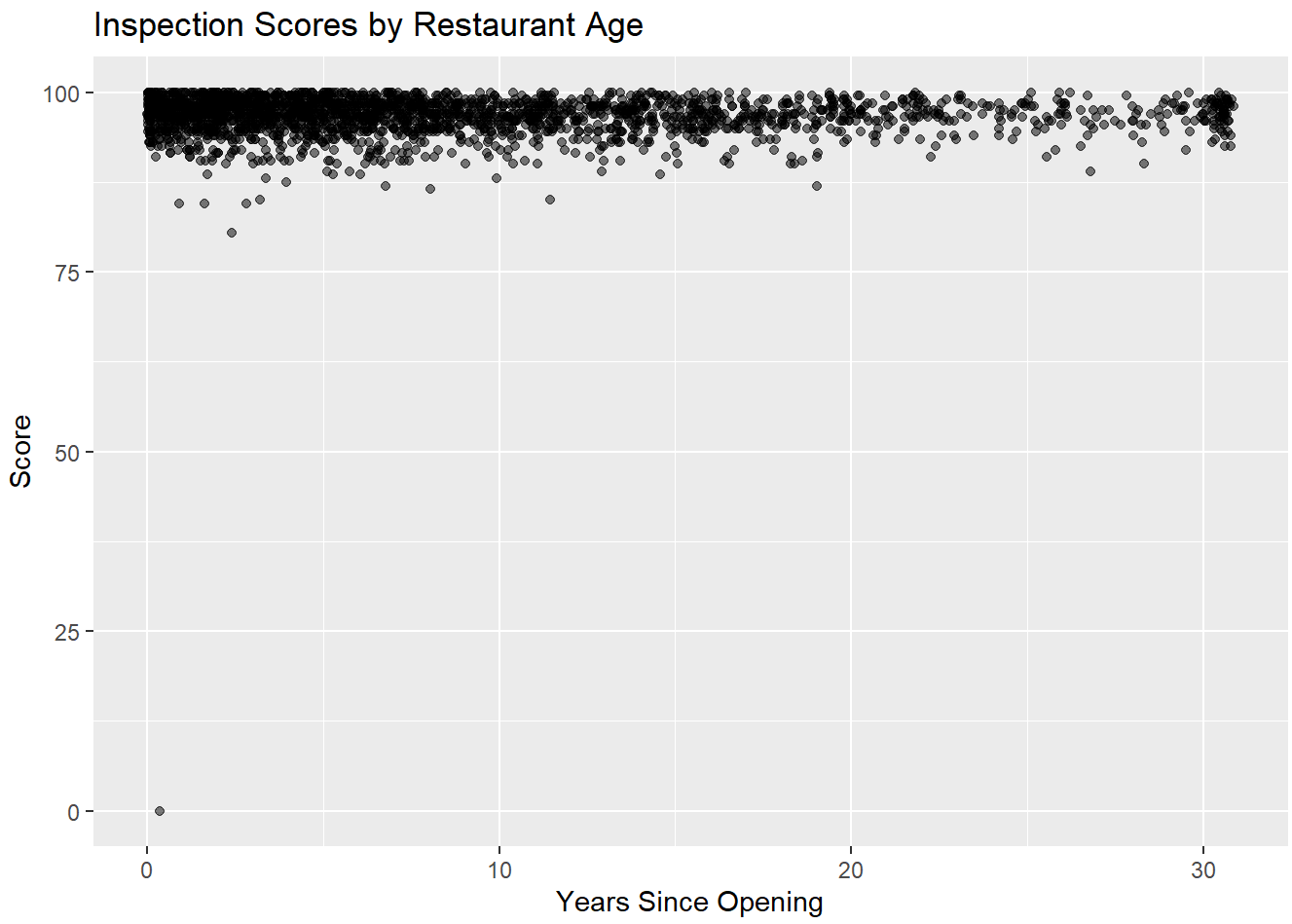
Here we will be redoing all the prior analysis' but with a df that contains only restaurants

```
rest_only <- inspections %>%
  filter(FACILITYTYPE == "Restaurant") #Creates a df with only restaurants

#histogram
ggplot(rest_only, aes(SCORE)) +
  geom_histogram(binwidth = 2, fill = "blue", color = "white") +
  labs(title = "Distribution of Inspection Scores",
       x = "Score", y = "Count")
```




```
#new vs old
rest_only %>%
  mutate(restaurant_age = time_length(DATE_ - RESTAURANTOPENDATE, "years")) %>% #Essentially wha
t is happening here is calculating how long it's been since they've opened, using the time_lengt
h function
  ggplot(aes(restaurant_age, SCORE)) +
  geom_point(alpha = 0.5) +       # Add transparency for overlapping points
  labs(title = "Inspection Scores by Restaurant Age",
       x = "Years Since Opening", y = "Score")
```




```
#by city
rest_city_scores <- rest_only %>%
  group_by(CITY) %>%
  summarise(
    avg_score = mean(SCORE, na.rm = TRUE),
    n_inspections = n(),  # Count number of inspections per city
    .groups = "drop"
  )

# Create formatted table with kableExtra
kable(rest_city_scores, caption = "Average Scores by City") %>%
  kable_styling()
```

Average Scores by City

| CITY | avg_score | n_inspections |
|---|---|---|
| ANGIER | 94.50000 | 1 |
| APEX | 97.08333 | 108 |
| CARY | 97.26355 | 406 |
| CLAYTON | 93.00000 | 1 |

| CITY | avg_score | n_inspections |
|---|---|---|
| FUQUAY VARINA | 96.90132 | 76 |
| GARNER | 95.79032 | 93 |
| HOLLY SPRINGS | 98.03125 | 80 |
| KNIGHTDALE | 95.14286 | 49 |
| MORRISVILLE | 96.65625 | 144 |
| NEW HILL | 100.00000 | 1 |
| RALEIGH | 96.59095 | 1193 |
| RESEARCH TRIANGLE PARK | 98.75000 | 2 |
| ROLESVILLE | 96.03846 | 13 |
| WAKE FOREST | 96.75564 | 133 |
| WENDELL | 94.57500 | 20 |
| WILLOW SPRING | 94.50000 | 1 |
| ZEBULON | 93.61290 | 31 |

```
#inspectors
# Calculate inspector performance metrics
rest_inspector_scores <- rest_only %>%
  group_by(INSPECTOR) %>%
  summarise(
    avg_score = mean(SCORE, na.rm = TRUE),
    n_inspections = n(),
    .groups = "drop"
  ) %>%
  arrange(desc(avg_score))  # arranging by highest avg score
#Essentially finding highest avg scores by inspector
kable(head(rest_inspector_scores, 200), caption = "Inspectors by Average Score") %>%
  kable_styling()
```

Inspectors by Average Score

| INSPECTOR | avg_score | n_inspections |
|---|---|---|
| James Smith | 99.00000 | 1 |
| Greta Welch | 98.50000 | 2 |

| INSPECTOR | avg_score | n_inspections |
|---|---|---|
| John Wulffert | 98.05856 | 111 |
| Brittny Thomas | 98.00000 | 3 |
| Jamie Phelps | 97.91667 | 108 |
| Zachary Carter | 97.81000 | 100 |
| Dipatrimarki Farkas | 97.69492 | 118 |
| Loc Nguyen | 97.64189 | 74 |
| Ginger Johnson | 97.62857 | 35 |
| Nicole Millard | 97.61458 | 48 |
| Sarah Thompson | 97.52551 | 98 |
| Melodee Johnson | 97.26639 | 122 |
| Ursula Gadomski | 97.20673 | 104 |
| Jason Dunn | 97.12500 | 4 |
| Cristofer LeClair | 97.05556 | 72 |
| Joshua Volkan | 96.97727 | 22 |
| Laura McNeill | 96.89674 | 92 |
| Patricia Sabby | 96.83621 | 116 |
| Samatha Sparano | 96.76068 | 117 |
| Angela Myers | 96.74038 | 104 |
| Maria Powell | 96.73333 | 60 |
| Shannon Flynn | 96.60714 | 112 |
| Nikia Lawrence | 96.45312 | 64 |
| Jackson Hooton | 96.29167 | 12 |
| Naterra McQueen | 96.18519 | 81 |
| Angela Stocks | 96.15278 | 36 |
| Lisa McCoy | 96.05556 | 18 |

| INSPECTOR | avg_score | n_inspections |
|---|---|---|
| David Adcock | 95.93750 | 8 |
| Kendra Wiggins | 95.89344 | 61 |
| Christy Klaus | 95.86000 | 100 |
| Elizabeth Jackson | 95.74375 | 80 |
| Daryl Beasley | 95.41667 | 12 |
| Joanne Rutkofske | 94.77174 | 92 |
| Karla Crowder | 94.39286 | 14 |
| Lauren Harden | 94.07353 | 34 |
| Lucy Schrum | 93.84884 | 86 |
| Meghan Scott | 93.31034 | 29 |
| Thomas Jumalon | 88.00000 | 2 |

*#5) Again, sample size where it's less than 5 could yield extreme results where it can skew the overall data*