Lab 5: Comprehensive Exploratory Data Analysis (EDA) Assignment

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Part I: Data Cleaning and Preparation

Import Packages

```r
library(readxl)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(tidyr)
library(ggplot2)
library(knitr)
```

Read-In Data

```r
df = read.csv("Airpollutants.csv")
head(df)
```

```
##         County Ozone Pm2.5   CO   NO2 white.percentage median.income
## 1      alameda 0.106   9.5 0.21 0.014             31.1        92,574
## 2        butte 0.082  11.4 0.24 0.017             71.6        48,443
## 3 contra costa 0.096  10.0   NA 0.020             43.2        93,712
## 4       fresno 0.074  12.5 0.32 0.016               29        51,261
## 5     humboldt    NA   7.4 0.19 0.015            white        45,528
## 6     imperial 0.111  10.2 0.26    NA             10.4        45,834
##   below.povery.level
## 1                9.4
## 2               16.6
## 3                8.8
## 4               19.4
## 5               19.4
## 6               17.3
```

Check & Deal w/ Missing Values

```r
# Apply to each missing value in DataFrame
print(paste("The number of missing values in the df are:", sum(is.na(df))))
```

```
## [1] "The number of missing values in the df are: 4"
```

```r
numeric_columns = sapply(df, is.numeric)

for(col in names(df)[numeric_columns]) {
  df[[col]][is.na(df[[col]])] = mean(df[[col]], na.rm = TRUE)
}

df$Ozone[is.na(df$Ozone)] = mean(df$Ozone, na.rm = TRUE)
print(paste("The number of missing values in the IMPUTED df are:", sum(is.na(df))))
```

```
## [1] "The number of missing values in the IMPUTED df are: 0"
```

```r
df
```

```
##              County     Ozone     Pm2.5        CO        NO2 white.percentage
## 1           alameda  0.1060000  9.500000 0.2100000 0.01400000             31.1
## 2             butte 0.0820000 11.400000 0.2400000 0.01700000             71.6
## 3      contra costa 0.0960000 10.000000 0.2498889 0.02000000             43.2
## 4            fresno 0.0740000 12.500000 0.3200000 0.01600000               29
## 5          humboldt 0.1027222  7.400000 0.1900000 0.01500000            white
## 6          imperial 0.1110000 10.200000 0.2600000 0.01752778             10.4
## 7             inyo  0.0790000  6.400000 0.1700000 0.01300000             61.8
## 8             kern  0.0750000 13.200000 0.2900000 0.01600000             33.5
## 9       los angeles 0.0700000 11.000000 0.3460000 0.01900000             26.1
## 10           marin  0.0820000  7.500000 0.2200000 0.01700000             71.5
## 11        monterey  0.0740000  7.800000 0.2400000 0.01900000             29.5
## 12          orange  0.0680000 11.000000 0.3100000 0.01500000             40.1
## 13       riverside  0.1390000  9.483333 0.3300000 0.01800000             34.7
## 14      sacramento  0.0650000  8.700000 0.2600000 0.01500000             44.2
## 15  san bernandino  0.0850000 11.500000 0.3300000 0.01700000             27.9
## 16       san diego 0.0670000  7.000000 0.2900000 0.01400000             45.2
## 17   san francisco 0.7400000  8.500000 0.2700000 0.01300000             40.3
## 18     san joaquin  0.0720000 12.100000 0.2400000 0.02400000               31
## 19       san mateo  0.0830000  7.600000 0.2700000 0.01200000             38.9
## 20   santa barbara  0.0820000  7.600000 0.2700000 0.01800000             44.1
## 21     santa clara  0.1070000  9.000000 0.2300000 0.02000000               31
## 22          solano  0.0920000  9.700000 0.2500000 0.01500000             37.6
## 23          sonoma  0.0680000  7.300000 0.2100000 0.01600000             63.1
## 24       stanilaus  0.1040000 10.500000 0.3000000 0.01500000             41.1
## 25          ventura 0.0640000  7.900000 0.2800000 0.01900000               45
## 26       santa cruz 0.0700000  7.200000 0.2100000 0.02100000             56.9
## 27           tulare 0.1140000 14.900000 0.2800000 0.01700000             28.1
## 28 San Luis Obispo  0.0800000  8.000000 0.2300000 0.02300000             68.6
## 29      san benito  0.0790000  6.500000 0.1900000 0.01900000             33.5
## 30           nevada 0.1020000  8.800000 0.2000000 0.01600000             84.9
## 31           merced 0.0960000 12.300000 0.2600000 0.02200000             27.1
## 32        mendocino 0.0650000  9.200000 0.2200000 0.01800000             64.7
## 33             lake 0.0630000  6.300000 0.1800000 0.01500000             69.7
## 34            kings 0.0930000 15.900000 0.2500000 0.02500000             31.8
## 35           colusa 0.0720000 10.200000 0.2100000 0.02000000             34.3
```

```
## 36        calaveras 0.0990000  9.000000 0.2000000 0.01900000             80.7
## 37             yolo 0.0800000  7.800000 0.2400000 0.01900000             46.3
##    median.income below.povery.level
## 1         92,574                9.4
## 2         48,443               16.6
## 3         93,712                8.8
## 4         51,261               19.4
## 5         45,528               19.4
## 6         45,834               17.3
## 7         52,874               12.8
## 8         52,479               18.5
## 9         64,251               14.1
## 10       110,217                7.8
## 11        66,676               12.1
## 12        85,398                9.9
## 13        63,948               11.6
## 14        63,902               13.0
## 15        60,164               13.2
## 16        74,855               10.7
## 17       104,552               11.4
## 18        61,145               12.3
## 19       113,776                6.8
## 20        71,657               15.2
## 21       116,178                6.9
## 22        77,609               10.0
## 23        76,753                9.1
## 24        57,387               14.1
## 25        84,017                8.9
## 26        78,041               10.6
## 27        47,518               18.7
## 28        70,699               13.1
## 29        81,977                8.9
## 30        63,240               11.8
## 31        50,129               21.9
## 32        49,233               16.1
## 33        42,475               16.5
## 34        53,865               17.7
## 35        56,704               11.4
## 36        58,151               13.5
## 37        65,923               14.8
```

Ensure Correct Data Types throughout the DataFrame

```r
# Check DTypes
str(df)
```

```
## 'data.frame':    37 obs. of  8 variables:
##  $ County            : chr  "alameda " "butte" "contra costa" "fresno" ...
##  $ Ozone             : num  0.106 0.082 0.096 0.074 0.103 ...
##  $ Pm2.5             : num  9.5 11.4 10 12.5 7.4 10.2 6.4 13.2 11 7.5 ...
##  $ CO                : num  0.21 0.24 0.25 0.32 0.19 ...
##  $ NO2               : num  0.014 0.017 0.02 0.016 0.015 ...
##  $ white.percentage  : chr  "31.1" "71.6" "43.2" "29" ...
##  $ median.income     : chr  "92,574" "48,443" "93,712" "51,261" ...
```

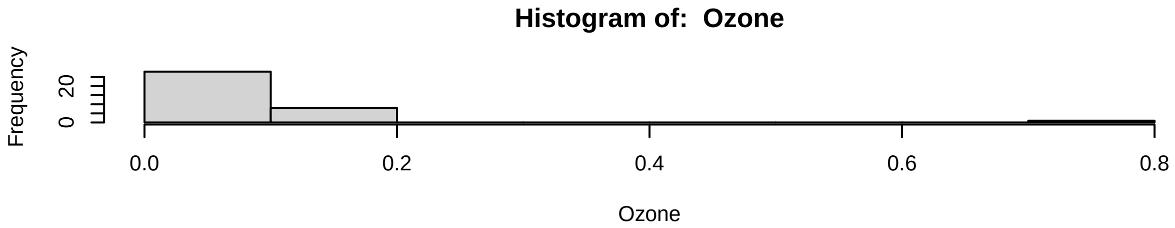
```
##  $ below.povery.level: num  9.4 16.6 8.8 19.4 19.4 17.3 12.8 18.5 14.1 7.8 ...
```

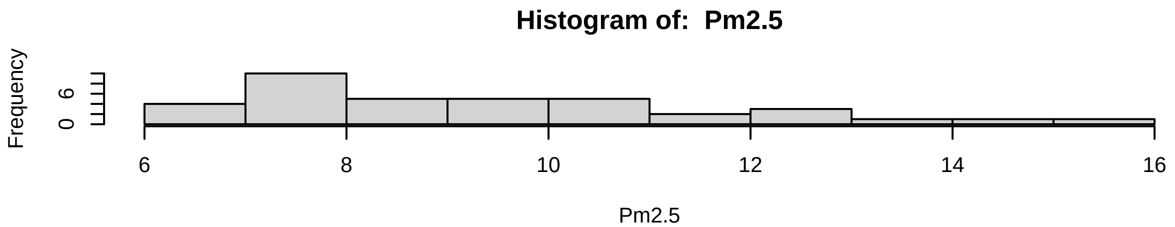
```r
# white.percentage & median.income are affected columns
df$white.percentage[df$white.percentage == "white"] = NA
df$white.percentage = as.numeric(df$white.percentage)
df$white.percentage[is.na(df$white.percentage)] = mean(df$white.percentage, na.rm = TRUE)

df$median.income = gsub(',', '', df$median.income)
df$median.income = as.numeric(df$median.income)

str(df)
```

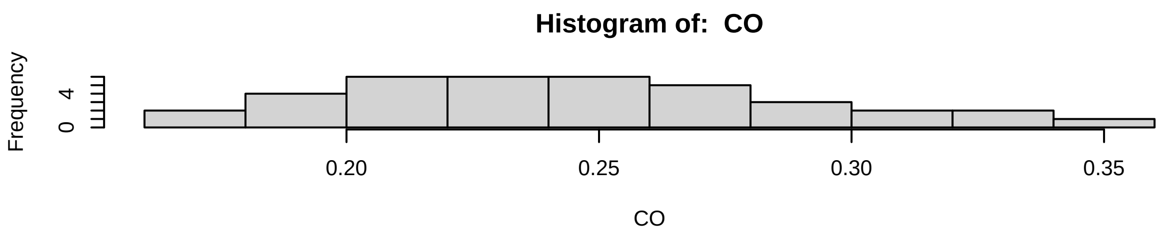
```
## 'data.frame':    37 obs. of  8 variables:
##  $ County            : chr  "alameda " "butte" "contra costa" "fresno" ...
##  $ Ozone             : num  0.106 0.082 0.096 0.074 0.103 ...
##  $ Pm2.5             : num  9.5 11.4 10 12.5 7.4 10.2 6.4 13.2 11 7.5 ...
##  $ CO                : num  0.21 0.24 0.25 0.32 0.19 ...
##  $ NO2               : num  0.014 0.017 0.02 0.016 0.015 ...
##  $ white.percentage  : num  31.1 71.6 43.2 29 44.4 ...
##  $ median.income     : num  92574 48443 93712 51261 45528 ...
##  $ below.povery.level: num  9.4 16.6 8.8 19.4 19.4 17.3 12.8 18.5 14.1 7.8 ...
```

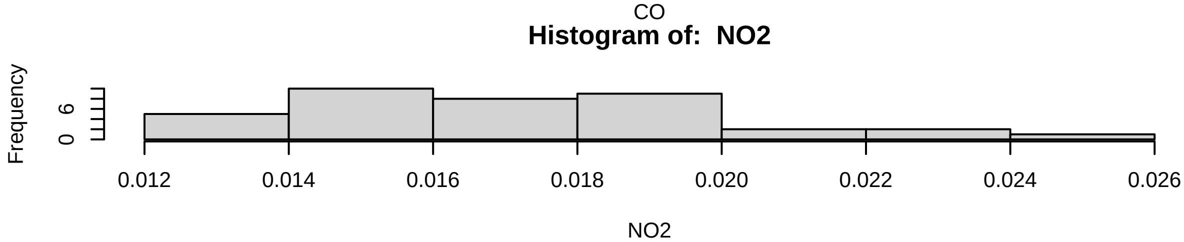
View Data Distribution

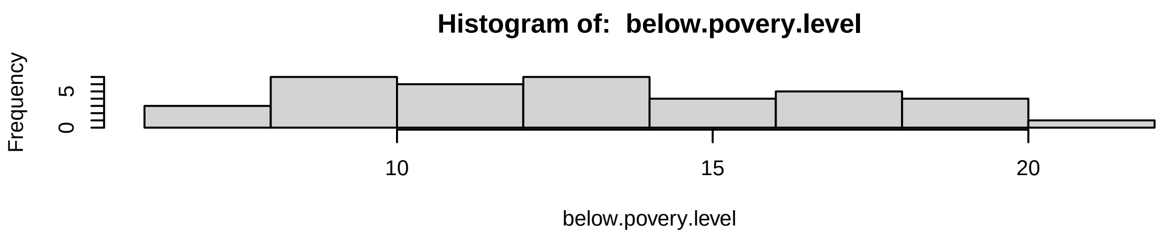
```r
view_dist = function(df) {
  par(mfrow=c(3, 1))

  for (col in names(df)[numeric_columns]) {
    hist(df[[col]], main = paste("Histogram of: ", col), xlab=col)
  }
}

view_dist(df)
```









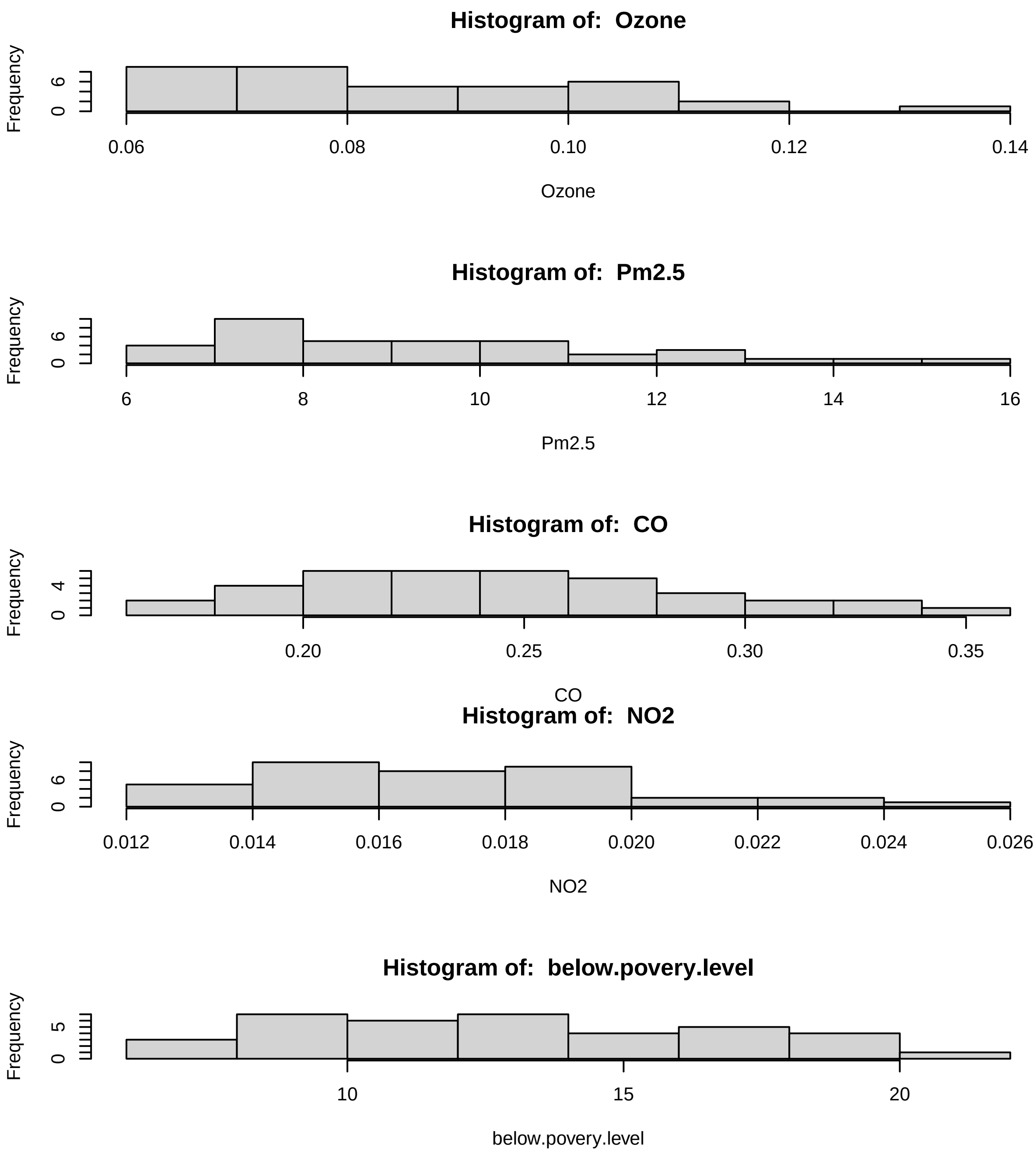


Handling Outliers

We will use the IQR method to detect outliers. To handle these outliers, we will impute them with the median since the dataset is relatively small and the data is slightly skewed.

```
for (col in names(df)[numeric_columns]) {
  q1 = quantile(df[[col]], 0.25, na.rm = TRUE) # Q1
  q3 = quantile(df[[col]], 0.75, na.rm = TRUE) # Q3
  iqr = IQR(df[[col]], na.rm = TRUE)

  lower_bound = q1 - 1.5 * iqr
  upper_bound = q3 + 1.5 * iqr
```

```
  df[[col]] [df[[col]] < lower_bound | df[[col]] > upper_bound] = mean(df[[col]])
}

view_dist(df)
```



Part II: Numerical Summaries and Visualizations

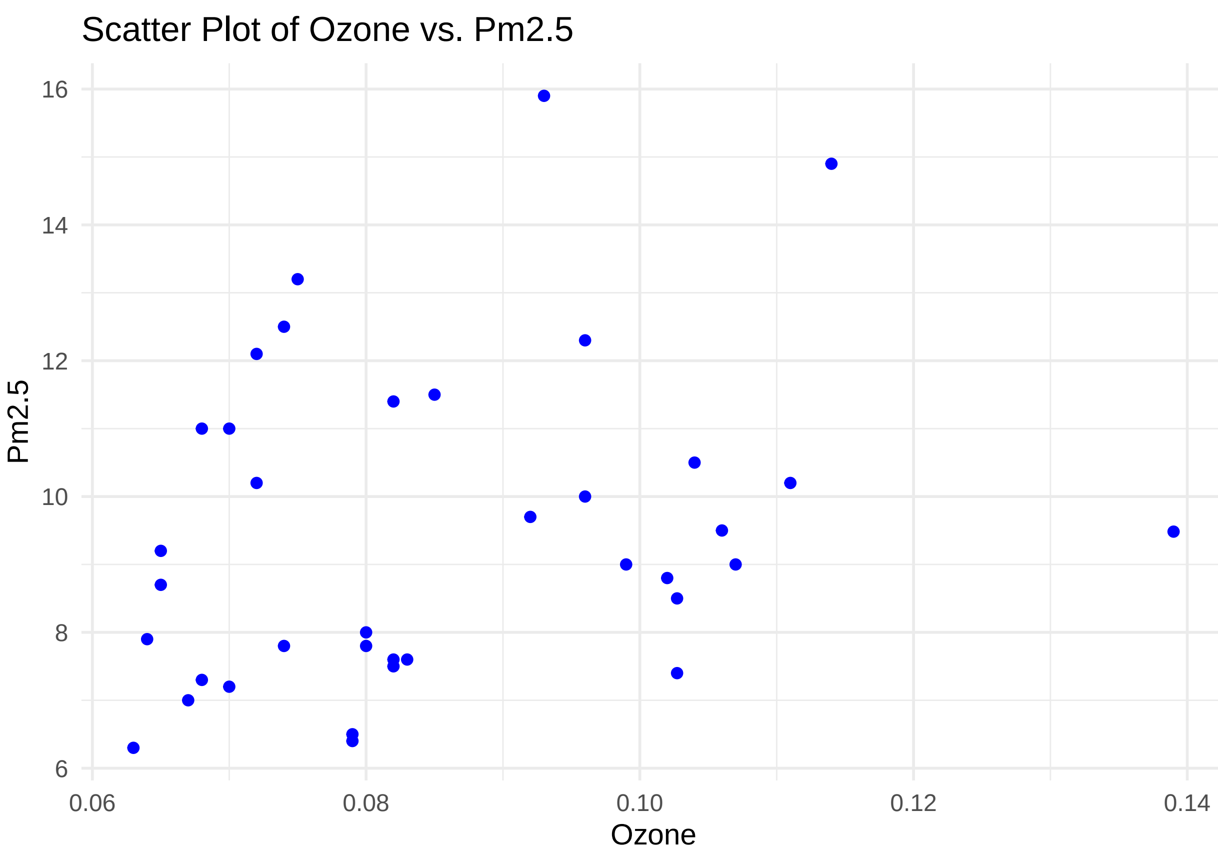
Numerical Summaries

```
kable(summary(df))
```

County	Ozone	Pm2.5	CO	NO2	white.percentage	median.income	below.povery.level
Length:37	Min. :0.0630	Min. : 6.300	Min. :0.1700	Min. :0.01200	Min. :10.4	Min. : 42475	Min. : 6.80
Class :character	1st Qu.:0.0720	1st Qu.: 7.600	1st Qu.:0.2100	1st Qu.:0.01500	1st Qu.:31.1	1st Qu.: 52874	1st Qu.:10.00
Mode :character	Median :0.0820	Median : 9.000	Median :0.2499	Median :0.01700	Median :40.3	Median : 63948	Median :12.80
NA	Mean :0.0855	Mean : 9.483	Mean :0.2499	Mean :0.01753	Mean :44.4	Mean : 69004	Mean :13.09
NA	3rd Qu.:0.0990	3rd Qu.:11.000	3rd Qu.:0.2800	3rd Qu.:0.01900	3rd Qu.:56.9	3rd Qu.: 78041	3rd Qu.:16.10
NA	Max. :0.1390	Max. :15.900	Max. :0.3460	Max. :0.02500	Max. :84.9	Max. :116178	Max. :21.90

Scatterplots & Pairwise Analysis

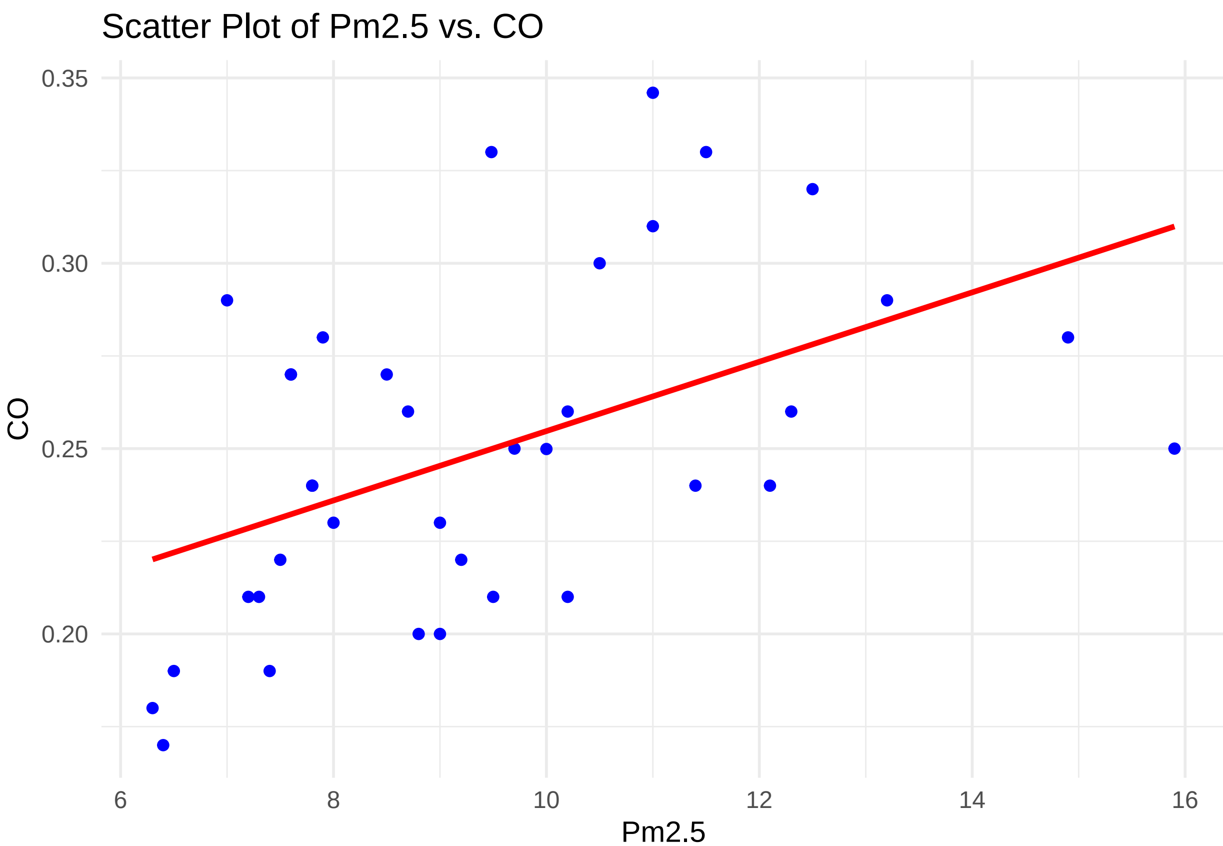
```r
par(mfrow=c(4, 1))

# Ozone V. Pm2.5
ggplot(df, aes(x = Ozone, y = Pm2.5)) +
  geom_point(color = "blue") +
  labs(title = "Scatter Plot of Ozone vs. Pm2.5", x = "Ozone", y = "Pm2.5") +
  theme_minimal()
```




```r
# Pm2.5 vs. CO
ggplot(df, aes(x = Pm2.5, y = CO)) +
```

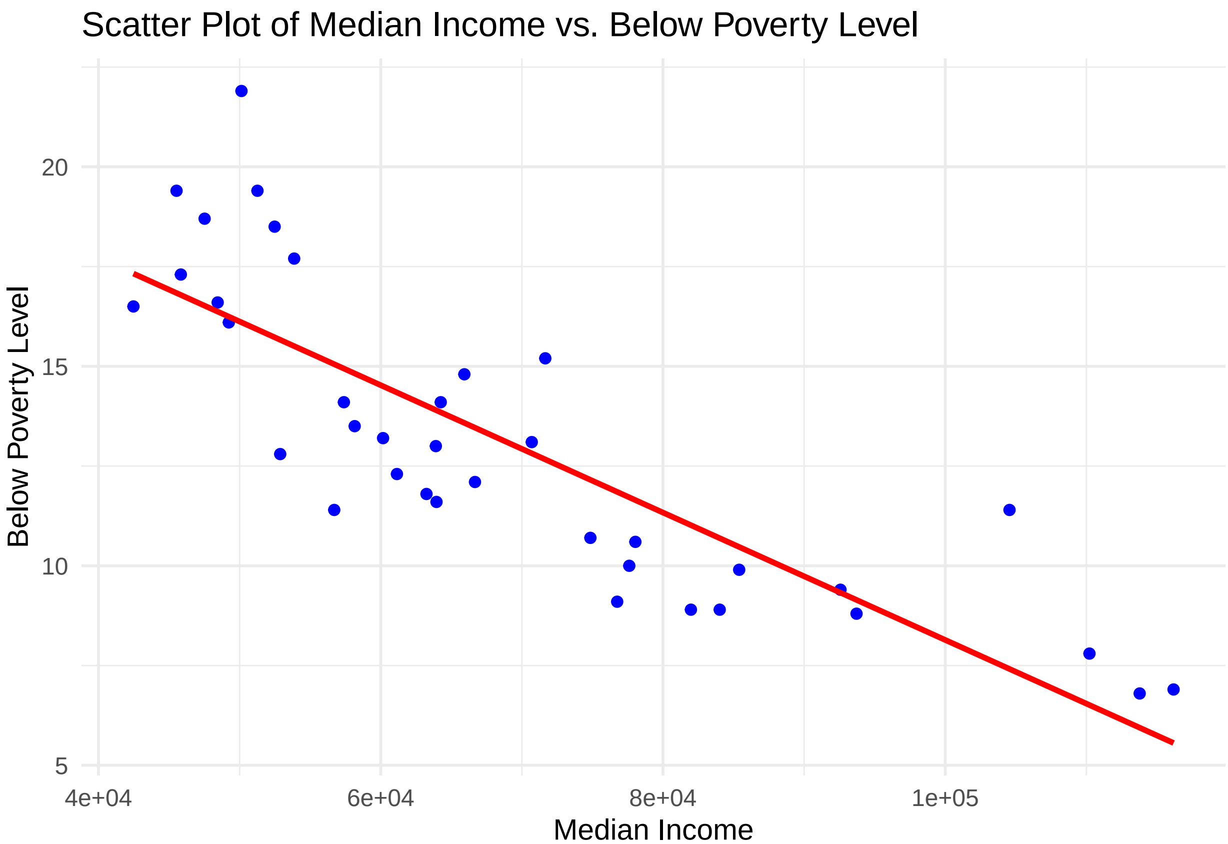
```
  geom_point(color = "blue") +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Scatter Plot of Pm2.5 vs. CO", x = "Pm2.5", y = "CO") +
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

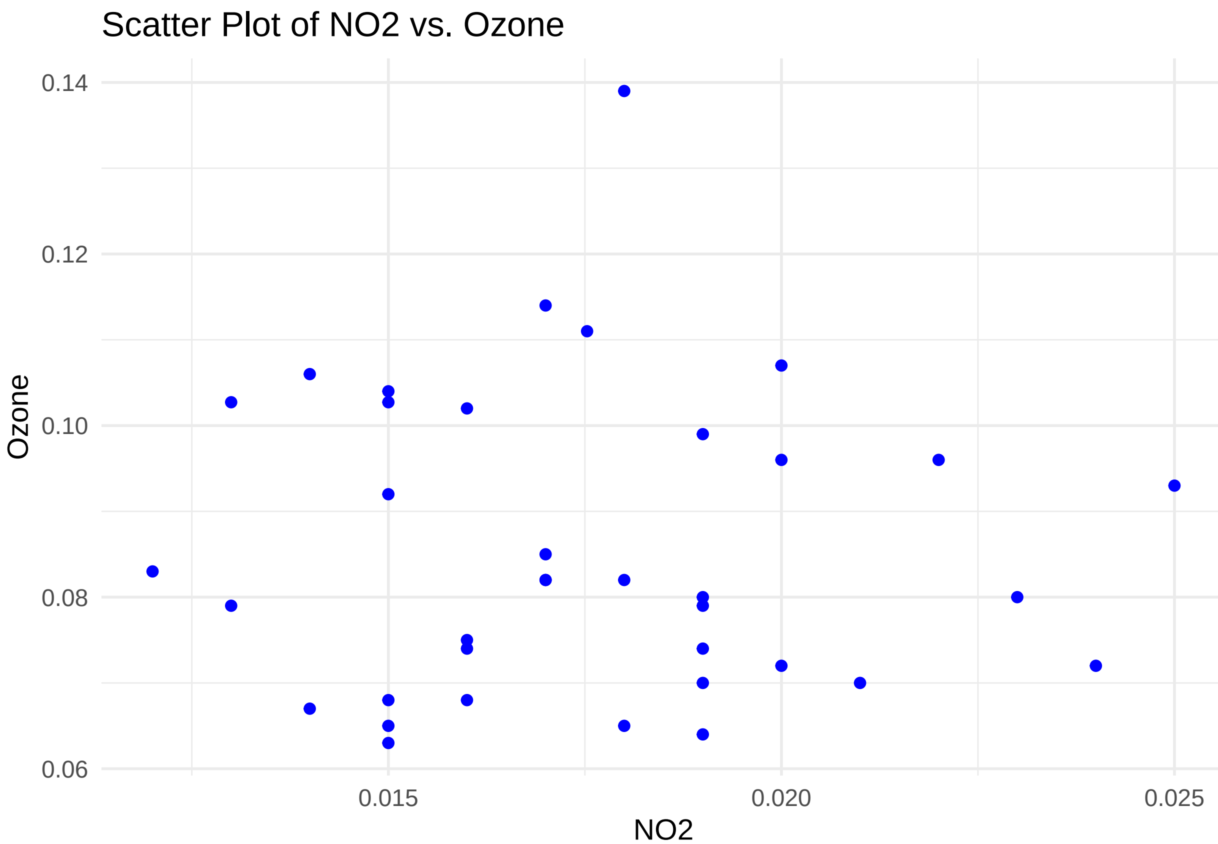



```
# Median Income V. Below Poverty Level
ggplot(df, aes(x = median.income, y = below.povery.level)) +
  geom_point(color = "blue") +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Scatter Plot of Median Income vs. Below Poverty Level", x = "Median Income", y = "Below
  theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```




```r
# NO2 V. Ozone
ggplot(df, aes(x = NO2, y = Ozone)) +
  geom_point(color = "blue") +
  labs(title = "Scatter Plot of NO2 vs. Ozone", x = "NO2", y = "Ozone") +
  theme_minimal()
```



Correlation

```
# Calculate Pearson's Correlation
corr_Pm2_Ozone = cor(df$Ozone, df$Pm2.5, method = 'pearson')
corr_Pm2_CO = cor(df$Pm2.5, df$CO, method = 'pearson')
corr_Income_Poverty = cor(df$median.income, df$below.povery.level, method = 'pearson')
corr_NO2_Ozone = cor(df$NO2, df$Ozone, method = 'pearson')

cat("Correlation between Ozone and Pm2.5:", corr_Pm2_Ozone, "\n")
```

```
## Correlation between Ozone and Pm2.5: 0.2444828
```

```
cat("Correlation between Pm2.5 and CO:", corr_Pm2_CO, "\n")
```

```
## Correlation between Pm2.5 and CO: 0.486746
```

```
cat("Correlation between Median Income and Below Poverty Level:", corr_Income_Poverty, "\n")
```

```
## Correlation between Median Income and Below Poverty Level: -0.8323263
```

```
cat("Correlation between NO2 and Ozone:", corr_NO2_Ozone, "\n")
```

```
## Correlation between NO2 and Ozone: -0.02552856
```

1. Correlation between Ozone and Pm2.5: 0.244: - The correlation is weakly positive. This suggests that there is a slight tendency for higher Ozone levels to be associated with higher Pm2.5 levels, but the relationship is not strong. Factors other than Pm2.5 are likely influencing Ozone levels.

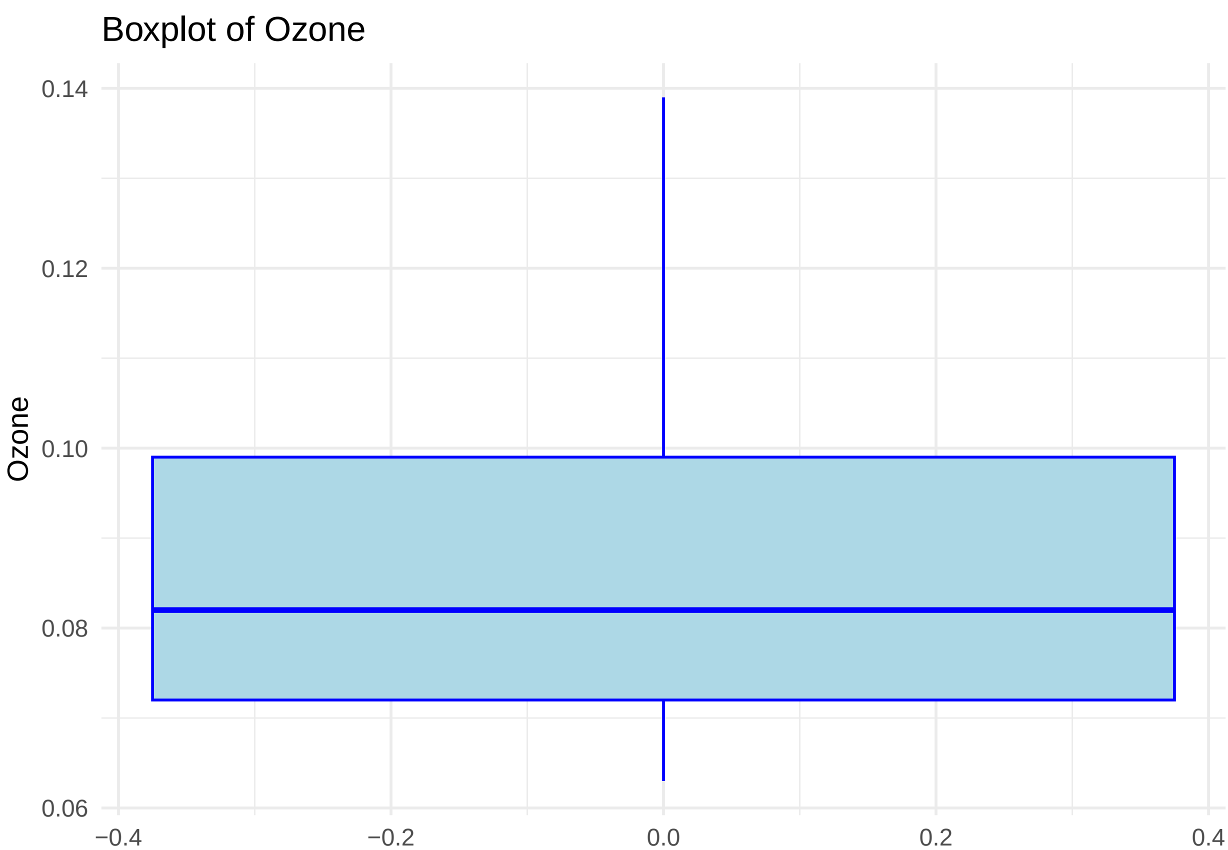
2. Correlation between Pm2.5 and CO: 0.487: - This is a moderate positive correlation. It indicates that as Pm2.5 levels increase, CO levels also tend to increase. This suggests that these two pollutants may be related, potentially coming from similar sources such as vehicle emissions or industrial activities.

3. Correlation between Median Income and Below Poverty Level: -0.832: - This is a strong negative correlation, which is expected. As median income increases, the percentage of people below the poverty level decreases significantly. This suggests a strong inverse relationship, where areas with higher income levels have fewer people living below the poverty line.

4. Correlation between NO2 and Ozone: -0.026: - This is a very weak negative correlation. The near-zero value indicates that there is no significant linear relationship between NO2 and Ozone in the dataset. These two pollutants do not seem to be directly related, or their relationship is influenced by other factors not captured in this simple correlation.

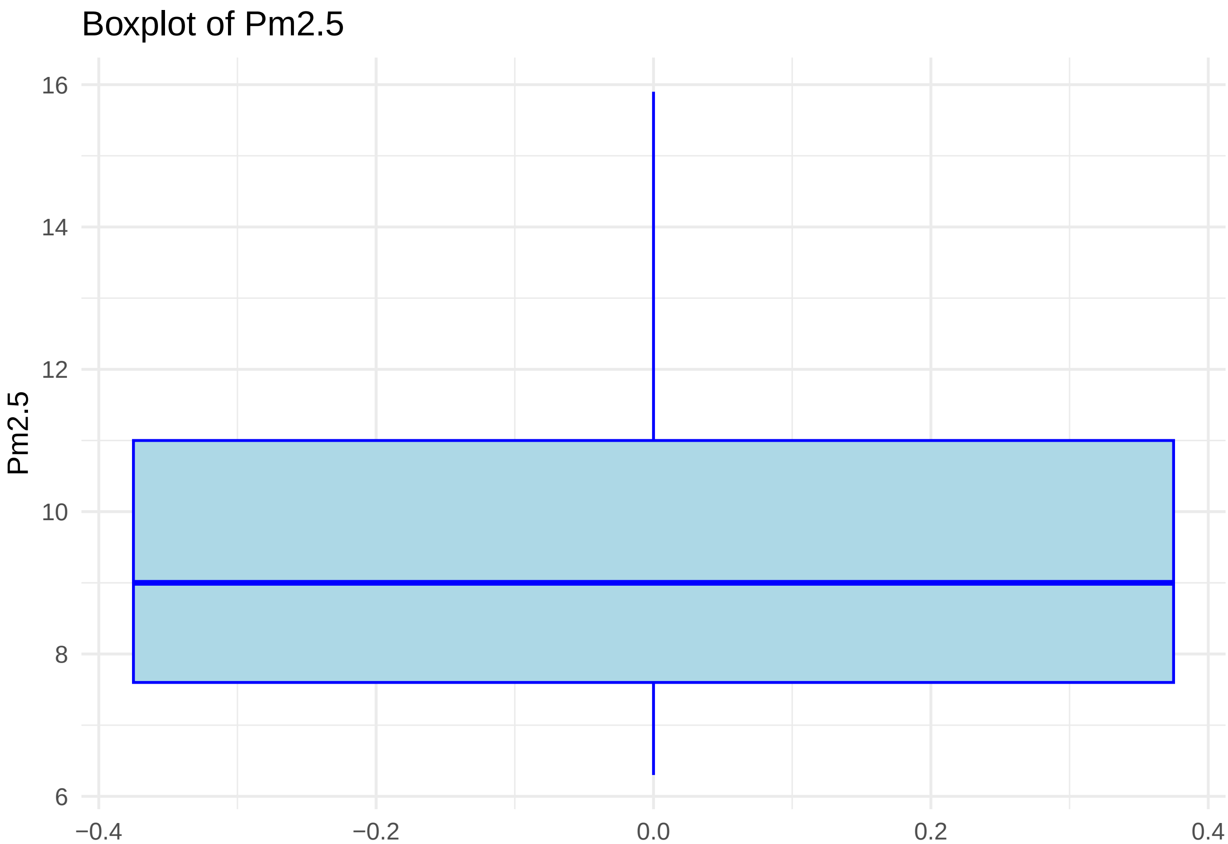
Histograms & Boxplots

```
# Histograms Already Completed in Prior Step **

par(mfrow=c(3, 1))

# Create Box Plots
# Ozone
ggplot(df, aes(y = Ozone)) +
  geom_boxplot(fill = "lightblue", color = "blue") +
  labs(title = "Boxplot of Ozone", y = "Ozone") +
  theme_minimal()
```

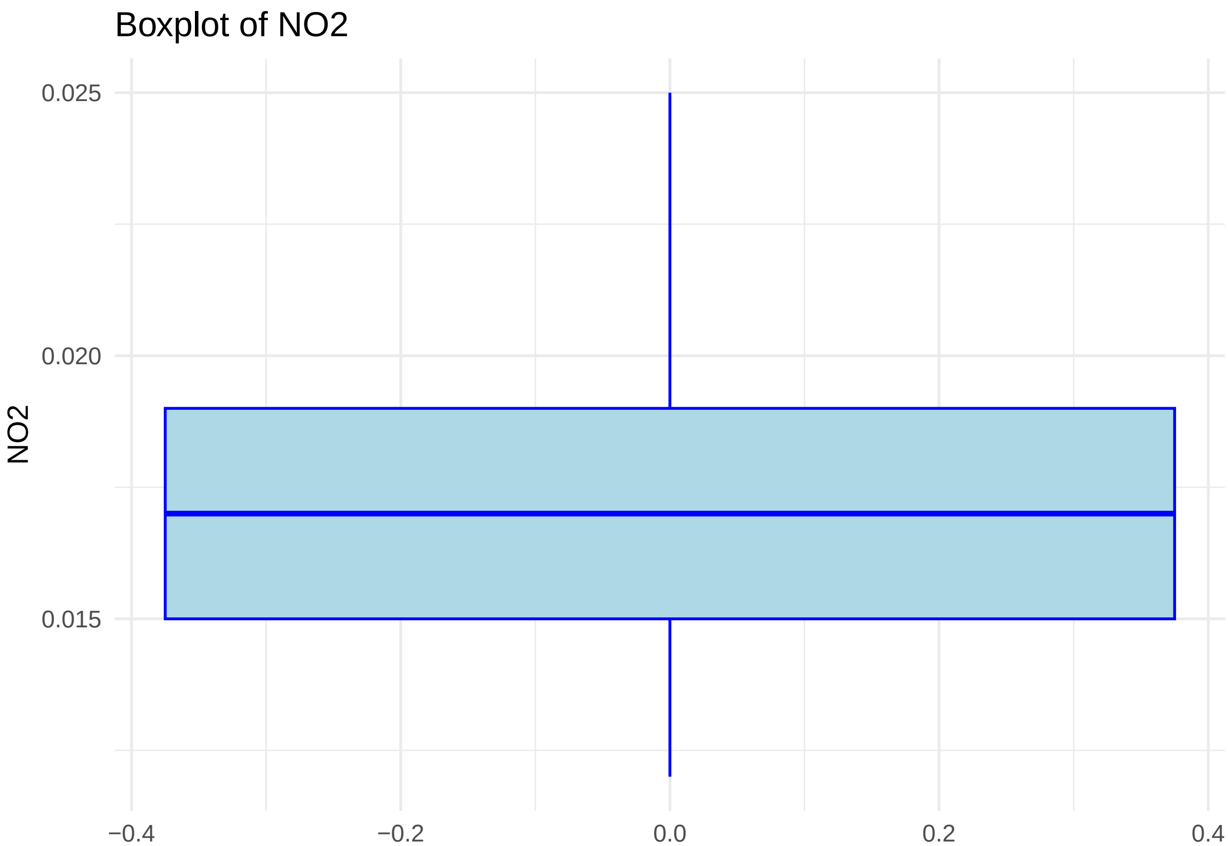



```
# Pm2.5
ggplot(df, aes(y = Pm2.5)) +
  geom_boxplot(fill = "lightblue", color = "blue") +
```

```r
  labs(title = "Boxplot of Pm2.5", y = "Pm2.5") +
  theme_minimal()
```



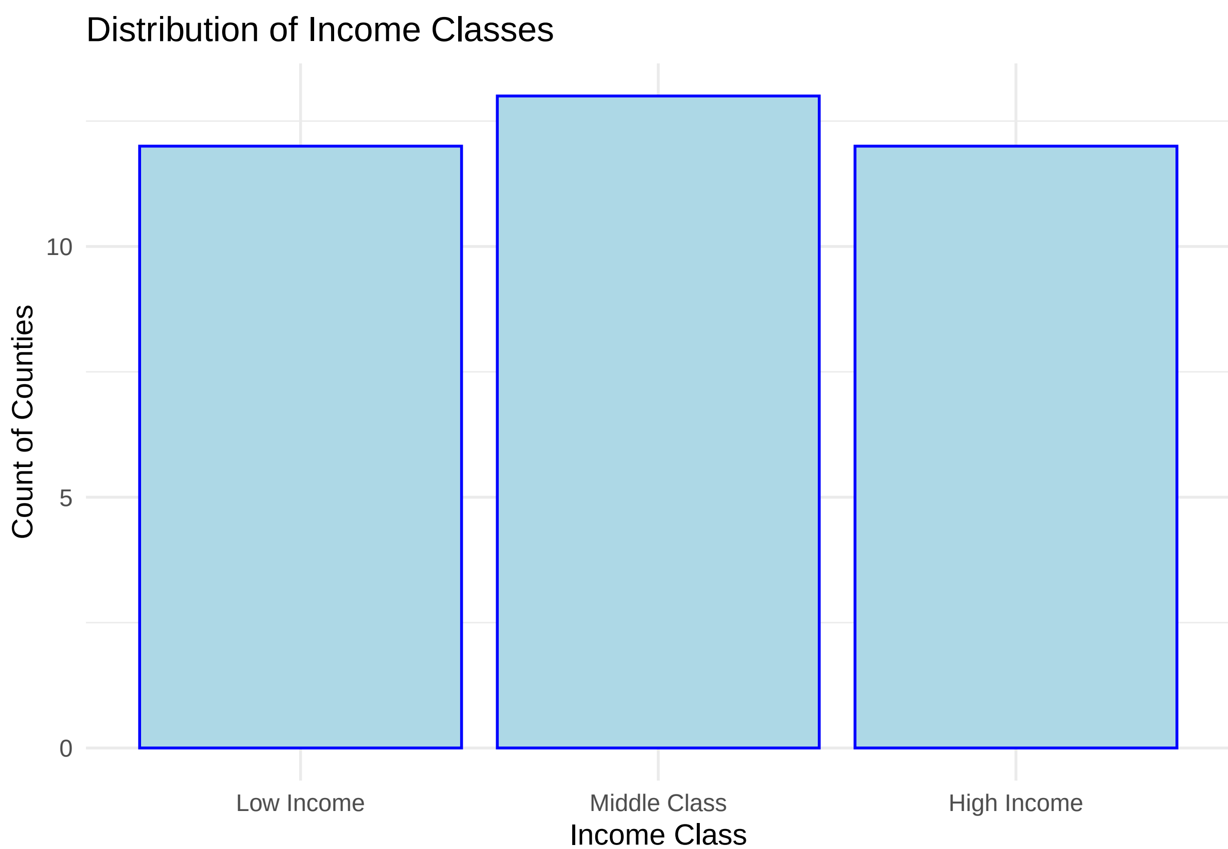

```r
# NO2
ggplot(df, aes(y = NO2)) +
  geom_boxplot(fill = "lightblue", color = "blue") +
  labs(title = "Boxplot of NO2", y = "NO2") +
  theme_minimal()
```



Part III: Creating and Analyzing New Categorical Variables

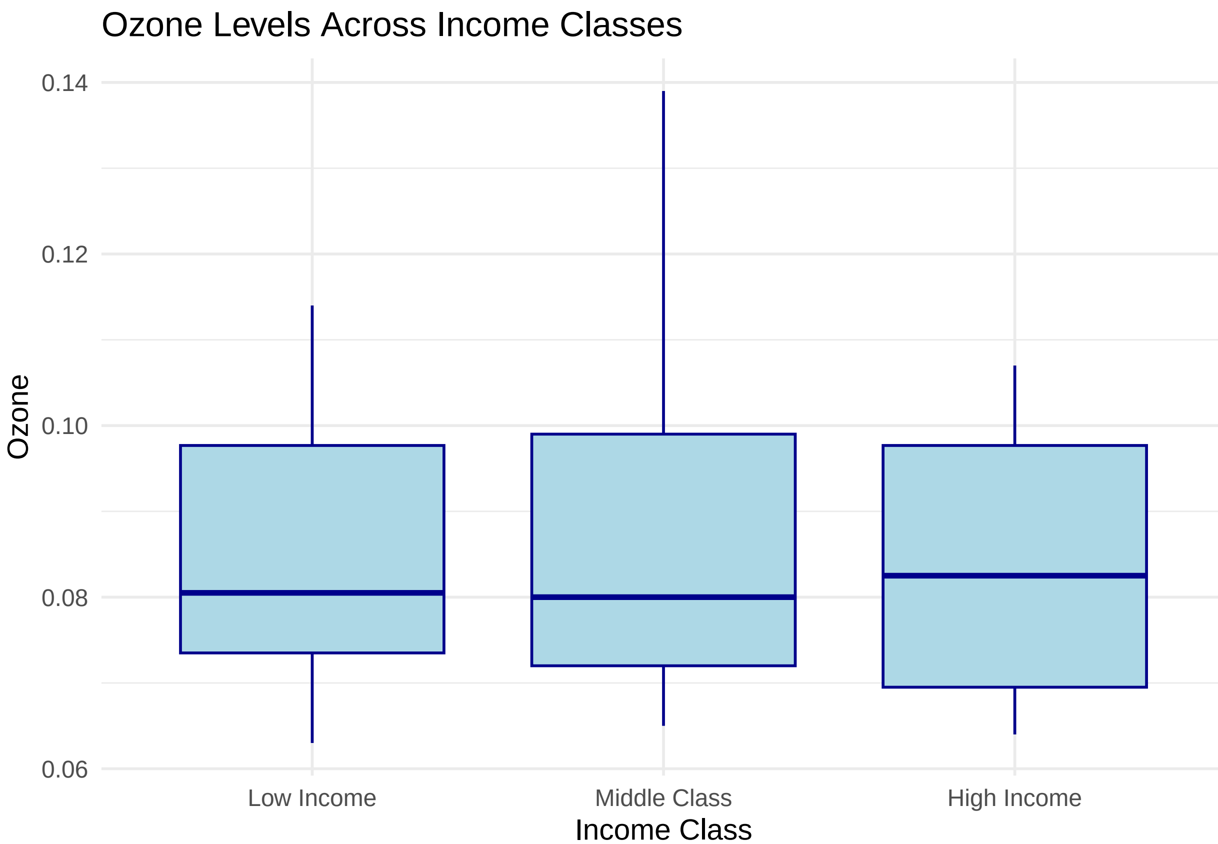
Creating Income Classes

```r
income_33rd = quantile(df$median.income, 0.33)
income_67th = quantile(df$median.income, 0.67)

df$income_class = cut(df$median.income,
  breaks = c(-Inf, income_33rd, income_67th, Inf),
  labels = c("Low Income", "Middle Class", "High Income")
)

ggplot(df, aes(x = income_class)) +
      geom_bar(fill = "lightblue", color = "blue") +
      labs(title = "Distribution of Income Classes", x = "Income Class", y = "Count of Counties") +
      theme_minimal()
```



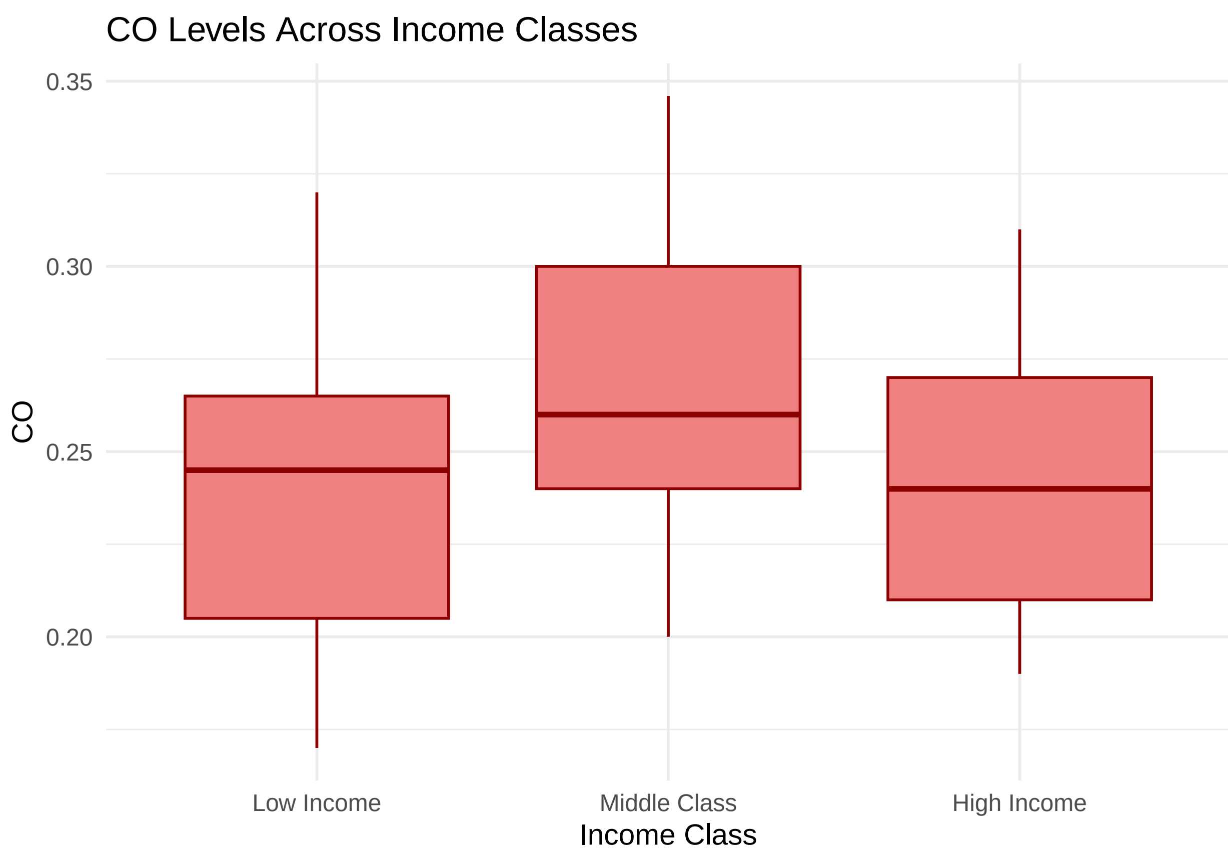
Analysis By Income Classes

```r
# Ozone boxplot by income class
ggplot(df, aes(x = income_class, y = Ozone)) +
  geom_boxplot(fill = "lightblue", color = "darkblue") +
  labs(title = "Ozone Levels Across Income Classes", x = "Income Class", y = "Ozone") +
  theme_minimal()
```

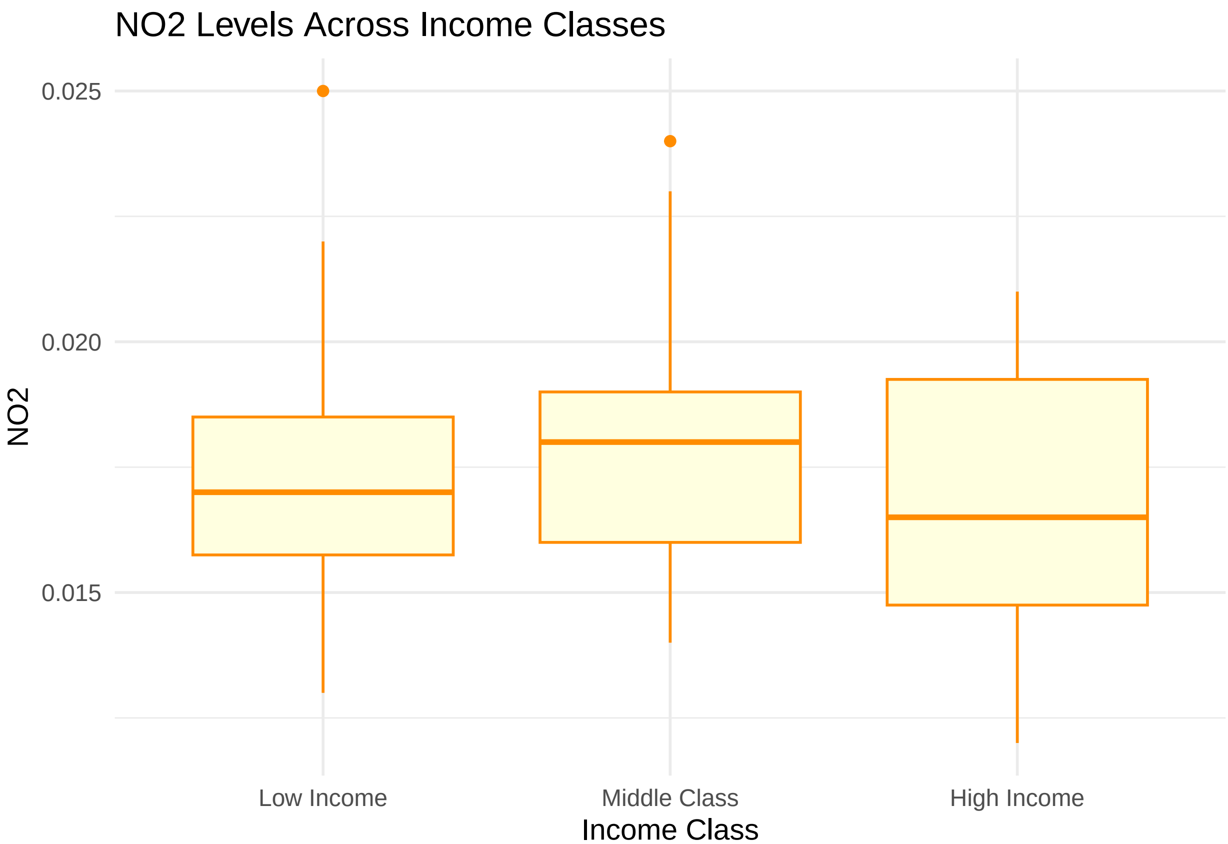



```r
# Pm2.5 boxplot by income class
ggplot(df, aes(x = income_class, y = Pm2.5)) +
  geom_boxplot(fill = "lightgreen", color = "darkgreen") +
  labs(title = "Pm2.5 Levels Across Income Classes", x = "Income Class", y = "Pm2.5") +
  theme_minimal()
```


```r
# CO boxplot by income class
ggplot(df, aes(x = income_class, y = CO)) +
  geom_boxplot(fill = "lightcoral", color = "darkred") +
  labs(title = "CO Levels Across Income Classes", x = "Income Class", y = "CO") +
  theme_minimal()
```




```r
# NO2 boxplot by income class
ggplot(df, aes(x = income_class, y = NO2)) +
  geom_boxplot(fill = "lightyellow", color = "darkorange") +
  labs(title = "NO2 Levels Across Income Classes", x = "Income Class", y = "NO2") +
  theme_minimal()
```



Ozone: No significant differences in Ozone levels across income classes; median and IQR are similar for all groups.

Pm2.5: Higher levels and greater variability in low-income counties, suggesting particulate pollution is more prevalent in these areas. High-income counties have the lowest Pm2.5 levels.

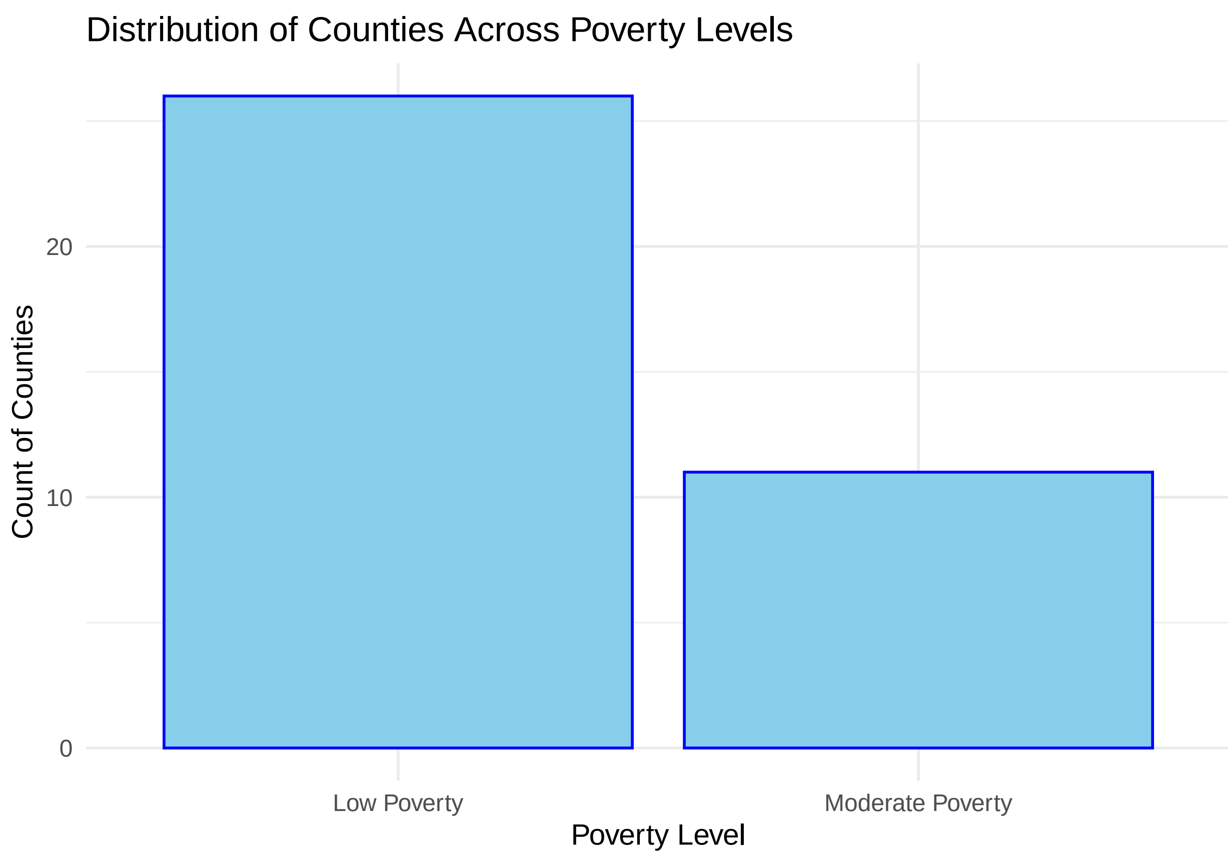
CO: Slightly higher CO levels in middle-income counties, but overall CO distributions are similar across all income classes.

NO2: Minimal differences across income classes, with consistent distributions and a couple of outliers in middle and high-income groups.

In general, Pm2.5 shows the clearest disparity, with higher levels in lower-income counties, while Ozone, CO, and NO2 remain relatively stable across income classes.

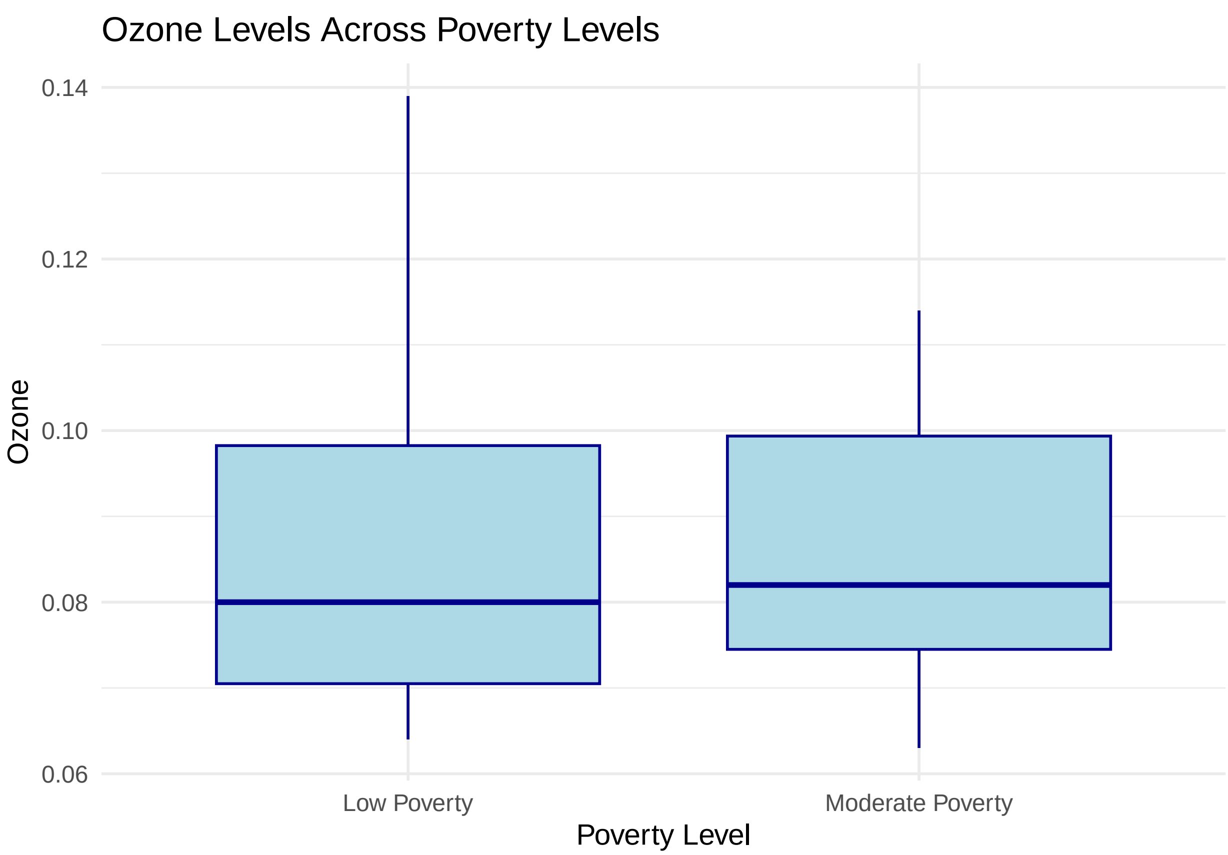
Analyzing By Poverty Levels

```
df$poverty_class = cut(df$below.povery.level,
                        breaks = c(-Inf, 15, 30, Inf),
                        labels = c("Low Poverty", "Moderate Poverty", "High Poverty"))

ggplot(df, aes(x = poverty_class)) +
  geom_bar(fill = "skyblue", color = "blue") +
  labs(title = "Distribution of Counties Across Poverty Levels", x = "Poverty Level", y = "Count of Cou
  theme_minimal()
```

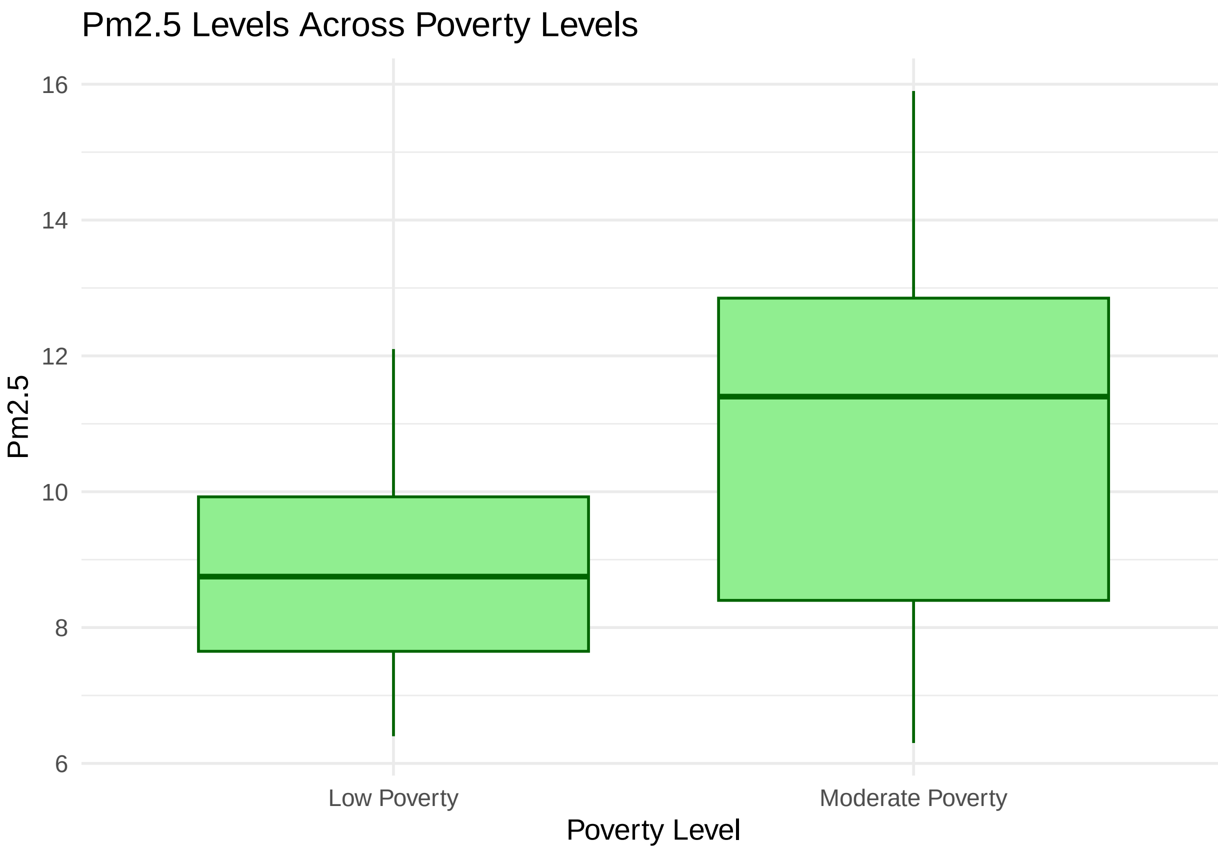


Analysis By Poverty Levels

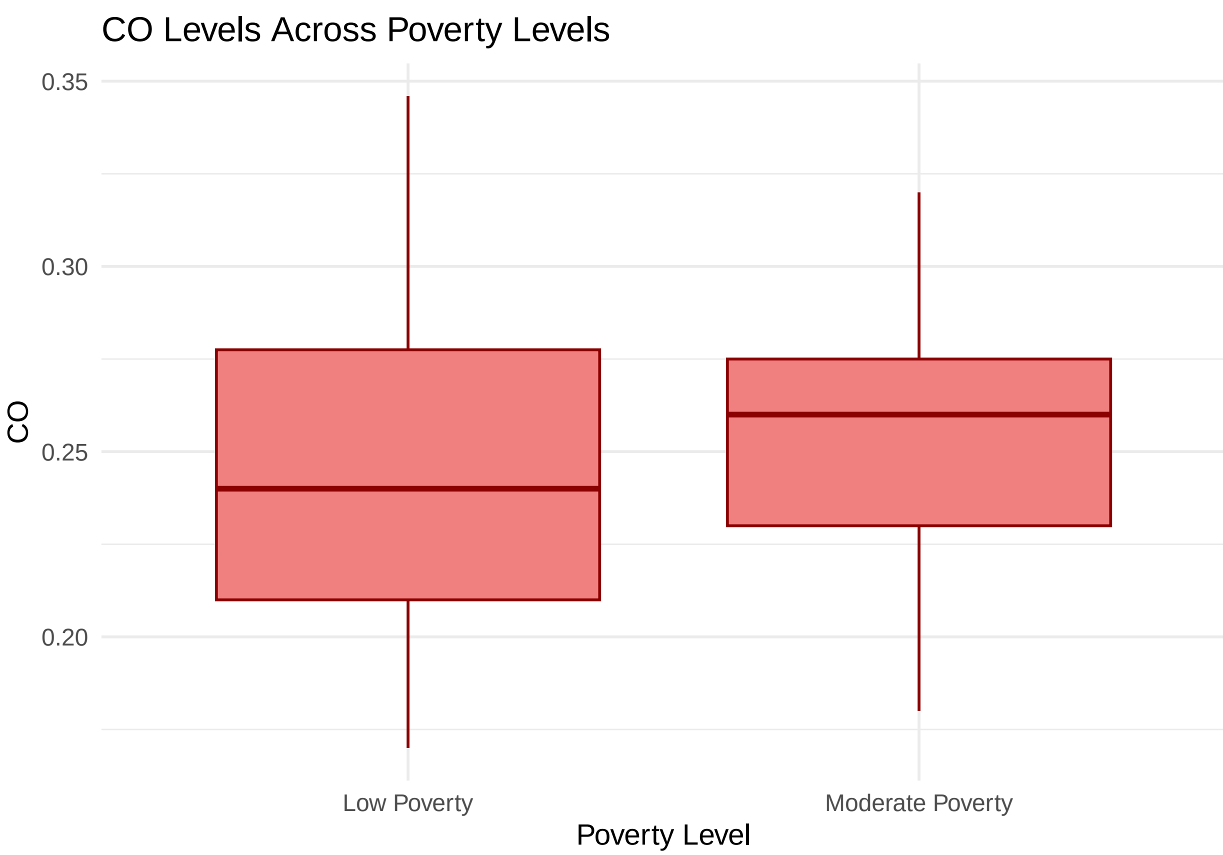
```
# Ozone boxplot by poverty class
ggplot(df, aes(x = poverty_class, y = Ozone)) +
  geom_boxplot(fill = "lightblue", color = "darkblue") +
  labs(title = "Ozone Levels Across Poverty Levels", x = "Poverty Level", y = "Ozone") +
  theme_minimal()
```



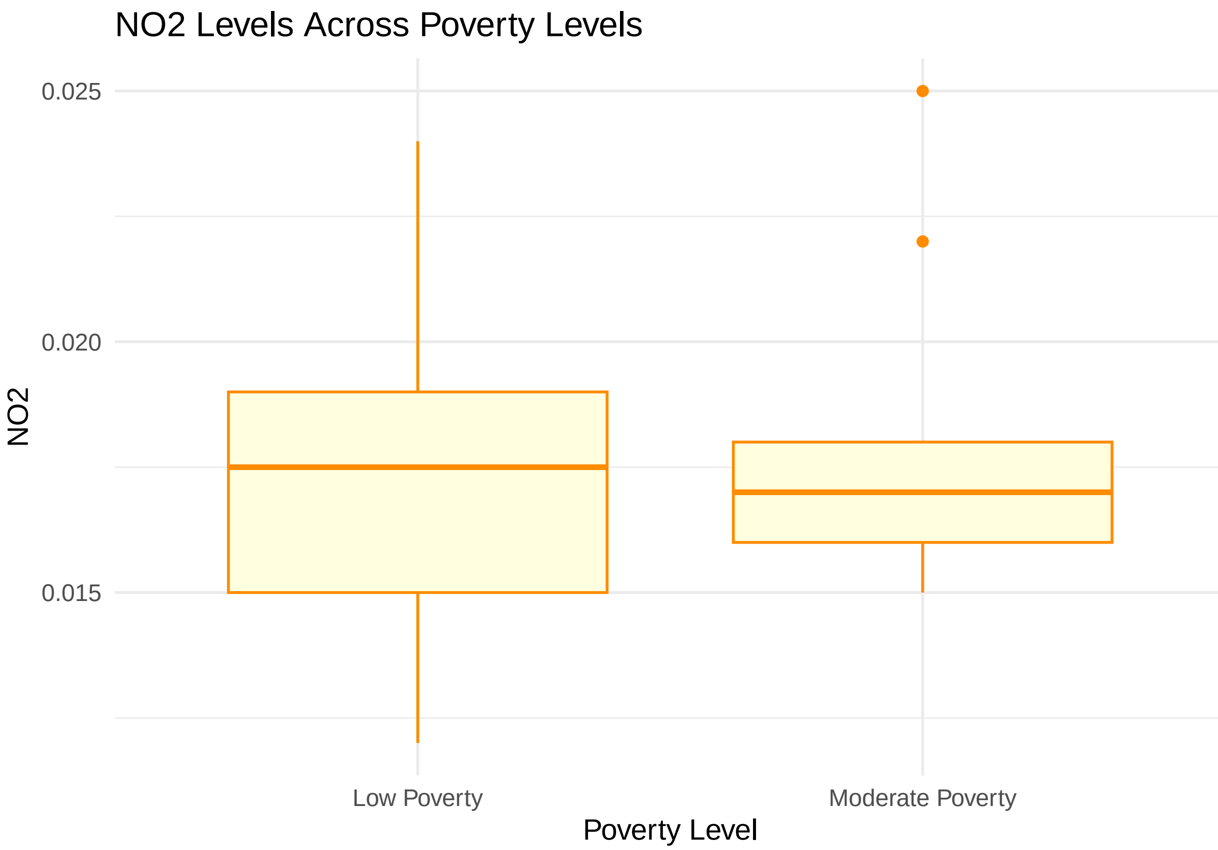

```r
# Pm2.5 boxplot by poverty class
ggplot(df, aes(x = poverty_class, y = Pm2.5)) +
  geom_boxplot(fill = "lightgreen", color = "darkgreen") +
  labs(title = "Pm2.5 Levels Across Poverty Levels", x = "Poverty Level", y = "Pm2.5") +
  theme_minimal()
```




```r
# CO boxplot by poverty class
ggplot(df, aes(x = poverty_class, y = CO)) +
  geom_boxplot(fill = "lightcoral", color = "darkred") +
  labs(title = "CO Levels Across Poverty Levels", x = "Poverty Level", y = "CO") +
  theme_minimal()
```




```
# NO2 boxplot by poverty class
ggplot(df, aes(x = poverty_class, y = NO2)) +
  geom_boxplot(fill = "lightyellow", color = "darkorange") +
  labs(title = "NO2 Levels Across Poverty Levels", x = "Poverty Level", y = "NO2") +
  theme_minimal()
```



Metrics that I measured did not indicate much change between Low and Moderate Poverty classes. *However*, Moderate poverty counties appear to have higher Pm2.5 levels and more variability compared to low-poverty counties. This suggests that moderate poverty areas may experience worse air quality in terms of particulate matter pollution. There are also no High Poverty counties to compare to in our dataset as shown below.

```r
# Check the unique values and the distribution of poverty levels
summary(df$below.povery.level)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    6.80   10.00   12.80   13.09   16.10   21.90
```

```r
table(df$poverty_class)
```

```
##
##      Low Poverty Moderate Poverty     High Poverty
##               26               11                0
```

Part IV: Conclusions & Insights

- **What relationships did you observe between air quality metrics and socioeconomic factors (income and poverty levels)?**
  - CO2, Ozone, and NO2 did not show much variability when compared against socioeconomic factors. However, higher Pm2.5 levels were more prevalent in low-income counties compared to middle and high-income counties.
- **Did removing outliers affect your results or lead to more accurate insights?**

- Outliers were handled during the analysis, but the air quality metrics didn't exhibit many extreme values, so removing outliers had minimal impact on the results.
- In cases where outliers were present (like for CO and NO2), removing them did help slightly reduce skewness and provided a clearer picture of the overall trend, making the insights more consistent and reflective of the general population.

- **Were any air quality variables particularly associated with higher poverty levels or lower income levels?**
  - Pm2.5 was the air quality metric most strongly associated with higher poverty and lower income levels. Both moderate poverty and low-income counties exhibited higher levels of Pm2.5.
- **What additional analyses would you recommend if you had more data?**
  - **High Poverty Data -** Since there is no current data for high-poverty counties, this would truly help us understand the relationship between pollutants and low-income areas.
  - **Geographic Data -** Data that shows us the proximity to areas that could have higher pollutants or not (highways, farms, forests, etc.) could help uncover more specific factors driving the differences in air quality.