

ISYE 6414B Project

Yuanting Fan XXXX

2024-11-30

Contents

Clean the data: handle missing values	1
Exploratory Data Analysis	2
Stepwise MLR	74
BoxCox MLR	100
Ridge MLR (considering the dataset has high multicollinearity)	130
Poisson: not suitable (fail the goodness-of-fit test)	133
Model Comparison - Prediction accuracy	137

Clean the data: handle missing values

- (1) Data collection: 29 variables (monthly or quarterly frequency), 157 data points in total
 - Time data: Month, Date(the last day of each month of each year)
 - LDV (light duty vehicle) sales unit: NEV car sales, Gasoline car sales
 - Macro economy data GDP, Durable consumption, Non durable consumption, Residential fixed investment, Nonresidential fixed investment, unemployment rate, federal effective rate, M1, M2 (we remove the M3 variable due to the data incompleteness), Per capita disposable income
 - Demographically data: Population, Percentage of employees who are middle-aged (25-55), Percentage of employees with a bachelor's degree or higher education
 - Industry specific data: Tesla model S price, Gasoline price, Electric retail price
 - Number of government new energy vehicles policies: these figures represent the incentive from the US government
 - Covid 19 period: categorical data "1" for from Jan 2020 - May 2023 (the end of the federal COVID-19 PHE declaration) , otherwise "0"
- (2) handling missing values
 - transform quarterly data into monthly data by linear interpolation

- fill the missing values of Tesla model S price by using the previous valid price (It also makes sense because only when the company decides to change their price, the price floats)

(3) we do not scale data as it will stop doing boxcox transformation

```
data <- read.csv("D:/GT Master/1. Academic/Semester 1/ISYE6414/6414 Project/us market data.csv",
                sep=",")

data$Year <- NULL

data$GDP[which(is.na(data$GDP))] <- approx(data$Date, data$GDP, xout = data$Date[which(is.na(data$GDP))])

data$Durable.goods.consumption[which(is.na(data$Durable.goods.consumption))] <- approx(data$Date, data$Durable.goods.consumption, xout = data$Date[which(is.na(data$Durable.goods.consumption))])

data$Nondurable.goods.consumption[which(is.na(data$Nondurable.goods.consumption))] <- approx(data$Date, data$Nondurable.goods.consumption, xout = data$Date[which(is.na(data$Nondurable.goods.consumption))])

data$Residential.fixed.Investment[which(is.na(data$Residential.fixed.Investment))] <- approx(data$Date, data$Residential.fixed.Investment, xout = data$Date[which(is.na(data$Residential.fixed.Investment))])

data$Nonresidential.fixed.Investment[which(is.na(data$Nonresidential.fixed.Investment))] <- approx(data$Date, data$Nonresidential.fixed.Investment, xout = data$Date[which(is.na(data$Nonresidential.fixed.Investment))])

data$Population[which(is.na(data$Population))] <- approx(data$Date, data$Population, xout = data$Date[which(is.na(data$Population))])

data$Per.capita.disposable.income[which(is.na(data$Per.capita.disposable.income))] <- approx(data$Date, data$Per.capita.disposable.income, xout = data$Date[which(is.na(data$Per.capita.disposable.income))])

library(tidyr)
data <- data %>% fill(Tesla.model.S.price, .direction = "down")
data <- data %>% fill(Electric.retail.price, .direction = "down")
data <- data %>% fill(Population, .direction = "down")
data <- data %>% fill(Per.capita.disposable.income, .direction = "down")
```

Exploratory Data Analysis

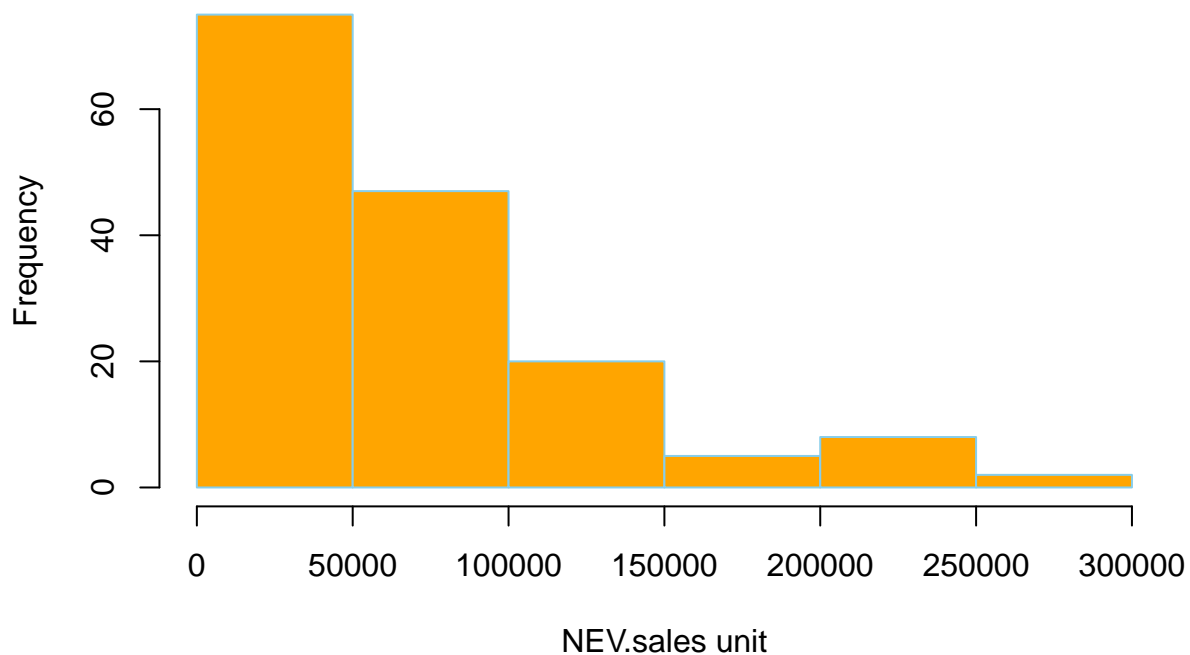
```
install.packages("plotly")

## 'plotly' MD5
##
##
## C:\Users\yuanting\AppData\Local\Temp\RtmpWUhATB\downloaded_packages

library(plotly)

## Warning: 'plotly' R 4.4.2
## ggplot2
##
```

```
## 'plotly'
## The following object is masked from 'package:ggplot2':
##
## last_plot
## The following object is masked from 'package:stats':
##
## filter
## The following object is masked from 'package:graphics':
##
## layout
hist(data$Total.NEV.Sales,main="",xlab="NEV.sales unit",border = "skyblue",col="orange")
```



```
data$formateddate <- as.Date(data$Date, origin = "1970-01-01")
data$formateddate <- format(data$formateddate, "%Y%m")

plot_ly(data = data, x = ~formateddate) %>%
  add_lines(y = ~data$Total.NEV.Sales, name = "NEV.Sales", line = list(color = "blue"))
  add_lines(y = ~data$Gasoline.LDV.sales, name = "Gasoline.sales", line = list(color = "red"))
  layout(
    title = "LDV sales unit in US",
```

```

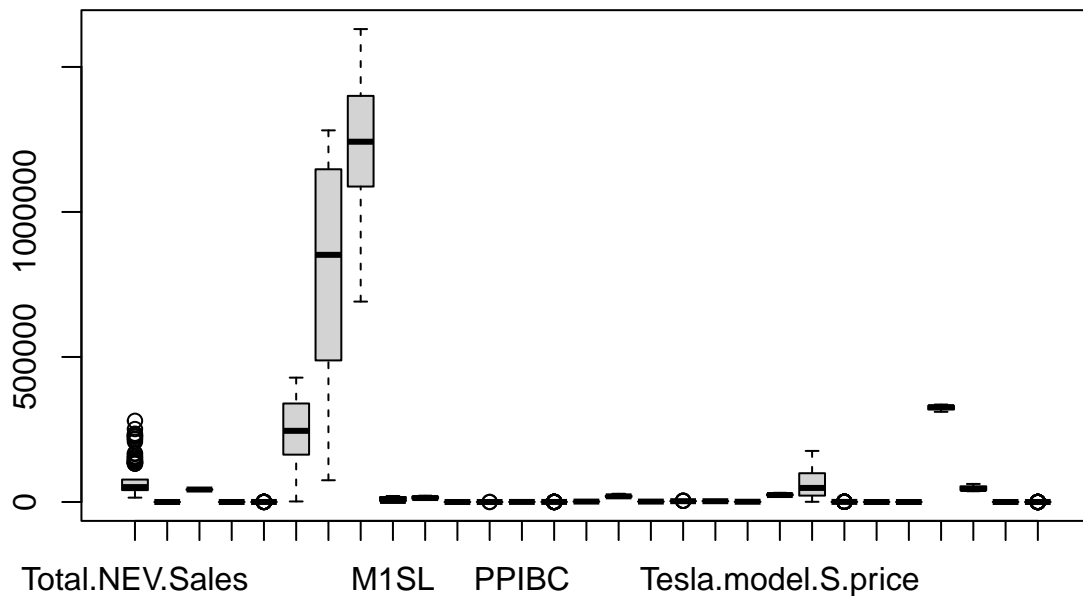
    yaxis = list(title = "NEV.Sales", side = "left"),
    yaxis2 = list(title = "Gasoline.sales", side = "right", overlaying = "y"),
    xaxis = list(title = "Date")
  )

plot_ly(data = data, x = ~formattedate) %>%
  add_lines(y = ~log(data$Total.NEV.Sales), name = "log NEV.Sales", line = list(color =
  layout(
    title = "log NEV.Sales unit in US",
    xaxis = list(title = "Date")
  )

data$formattedate <- NULL

boxplot(data)

```

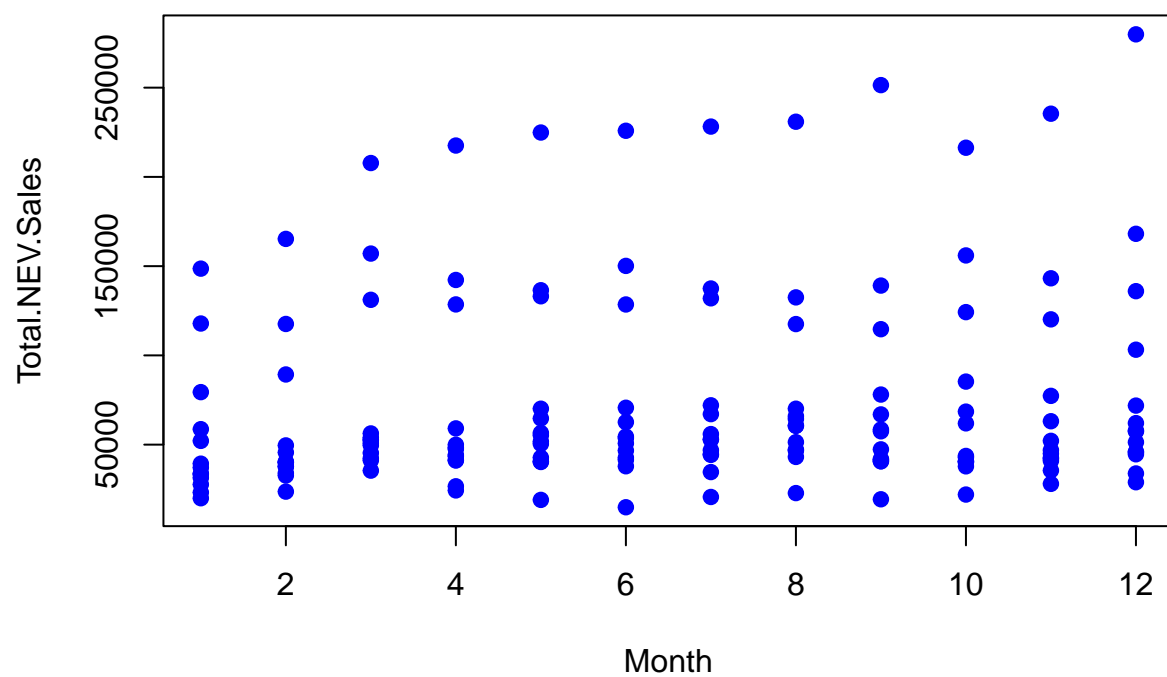


```

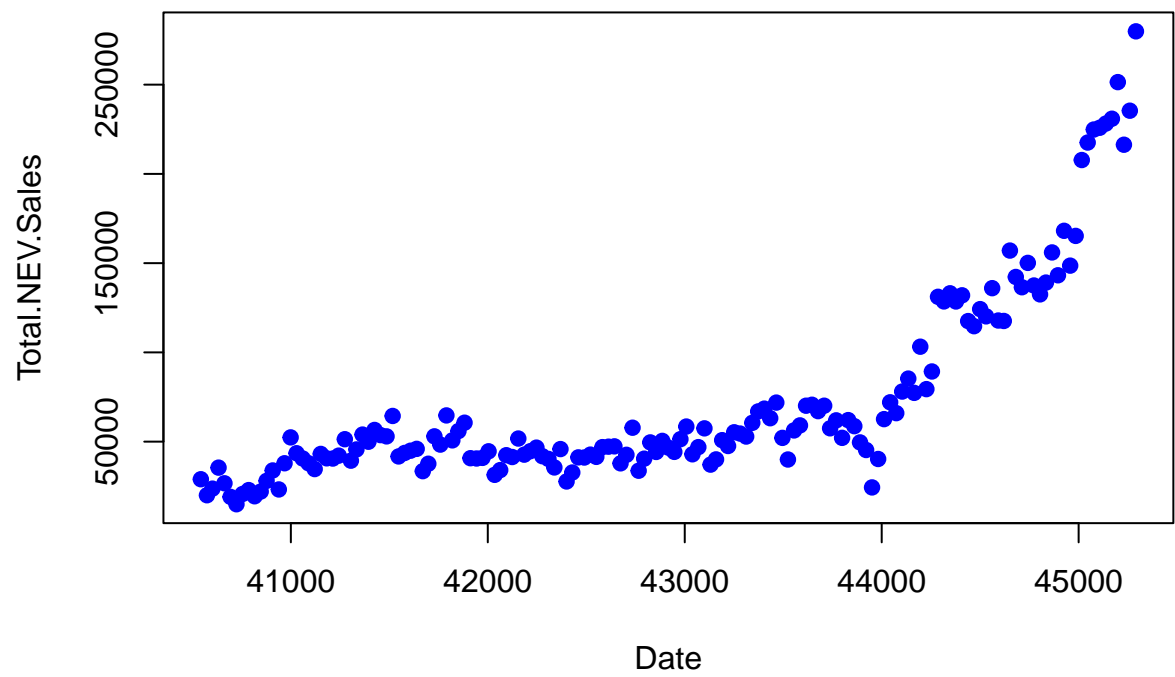
for (i in 2:29) { # Looping through the other 10 variables
  plot(data[[i]], data$Total.NEV.Sales,
    main = paste("Plot of Total.NEV.Sales vs ", colnames(data)[i]),
    xlab = colnames(data)[i], ylab = "Total.NEV.Sales",
    col = "blue", pch = 19)
}

```

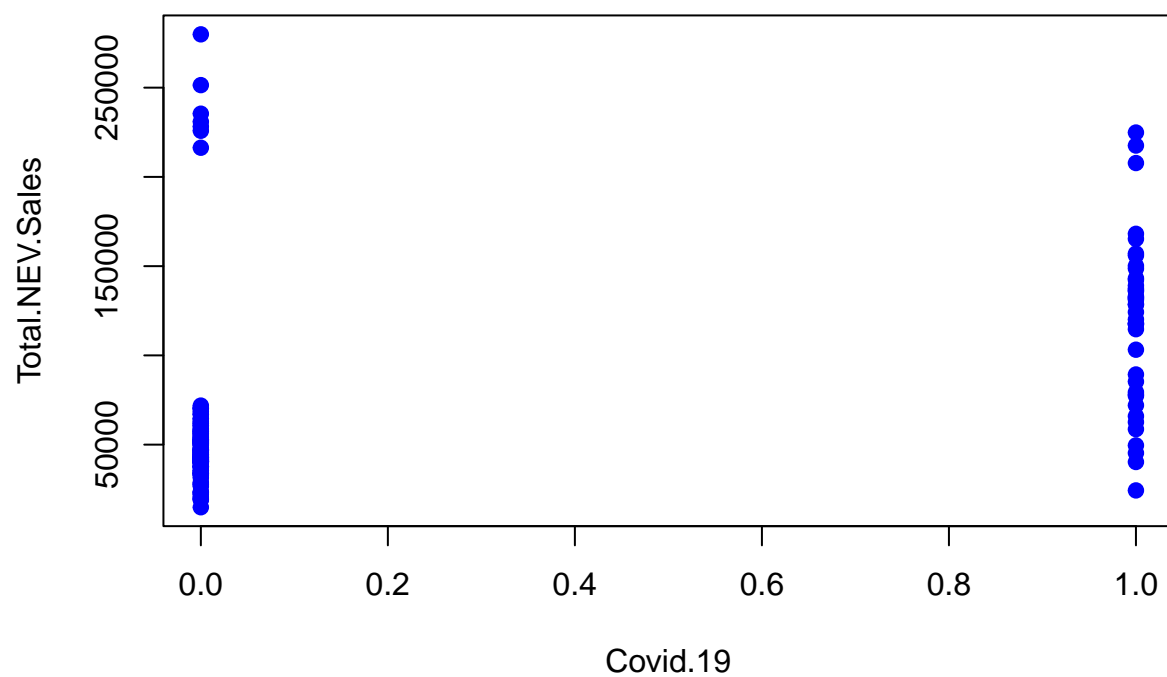
Plot of Total.NEV.Sales vs Month



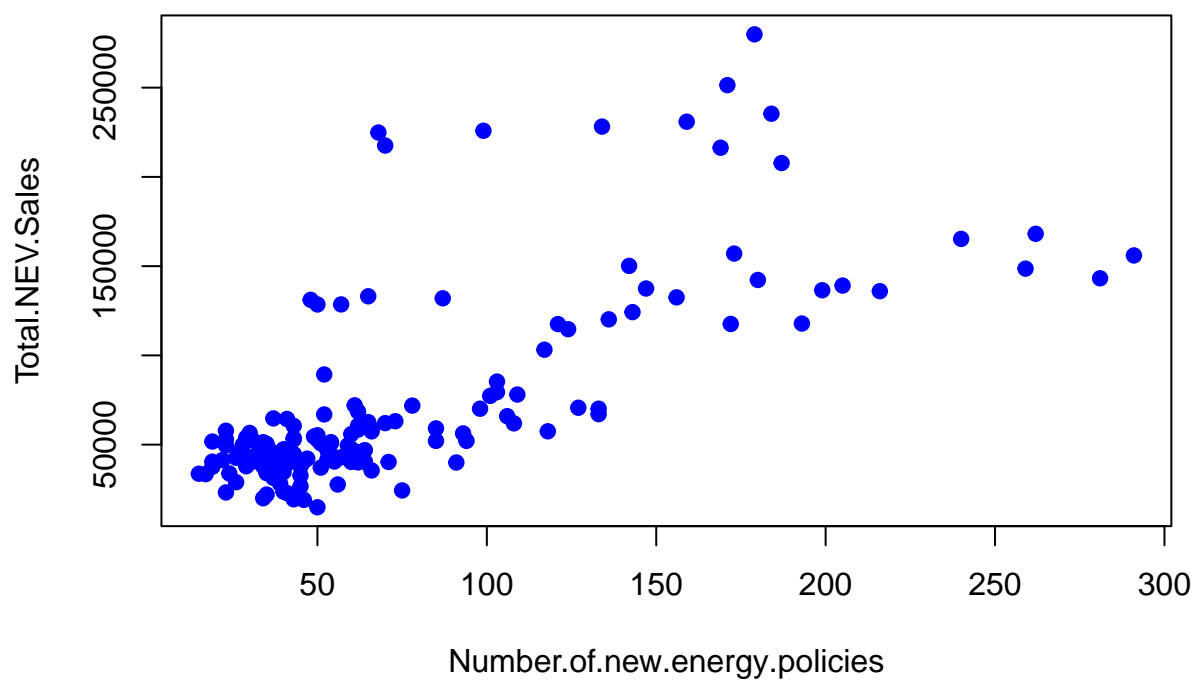
Plot of Total.NEV.Sales vs Date



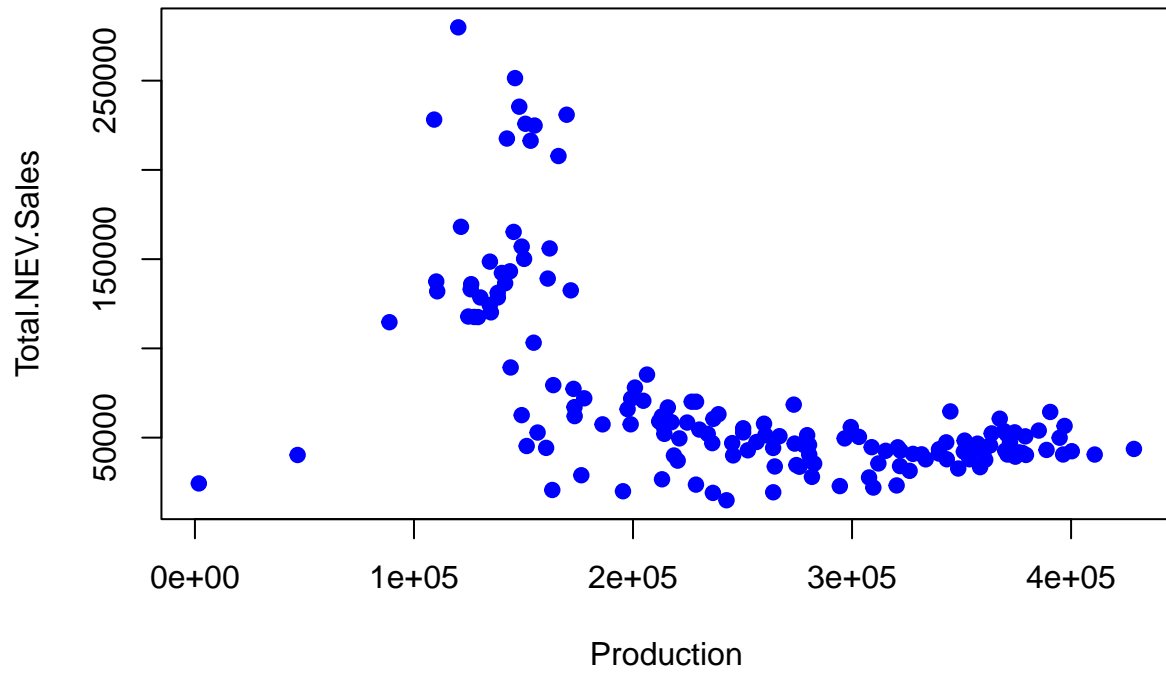
Plot of Total.NEV.Sales vs Covid.19



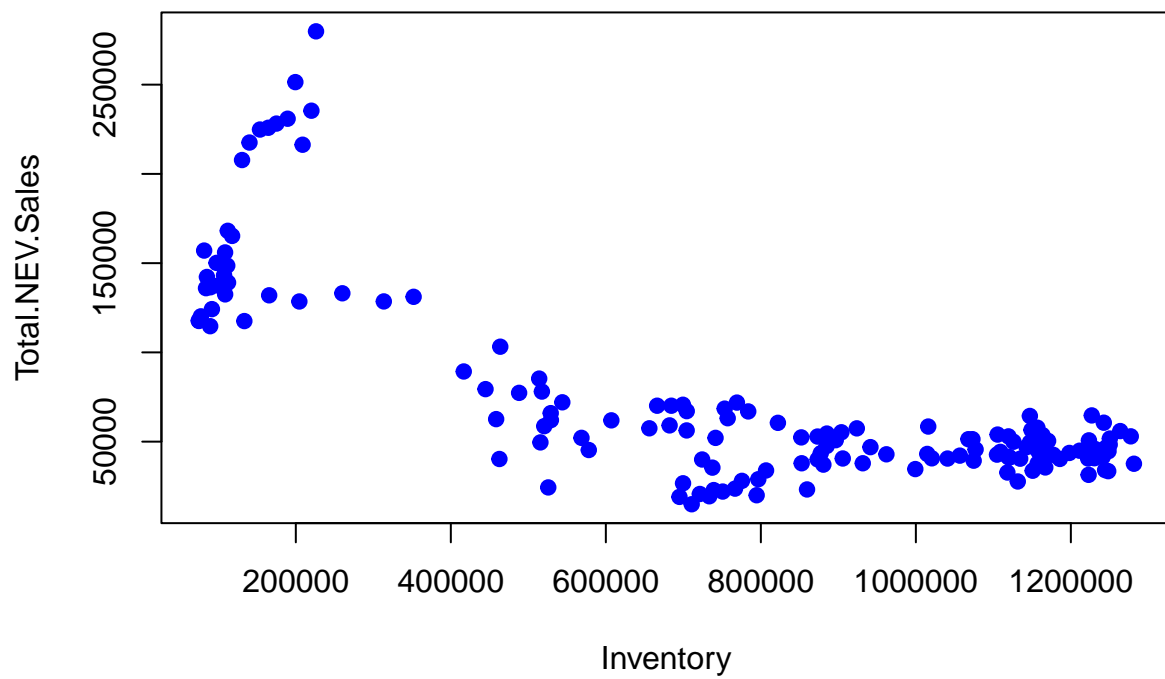
Plot of Total.NEV.Sales vs Number.of.new.energy.policies



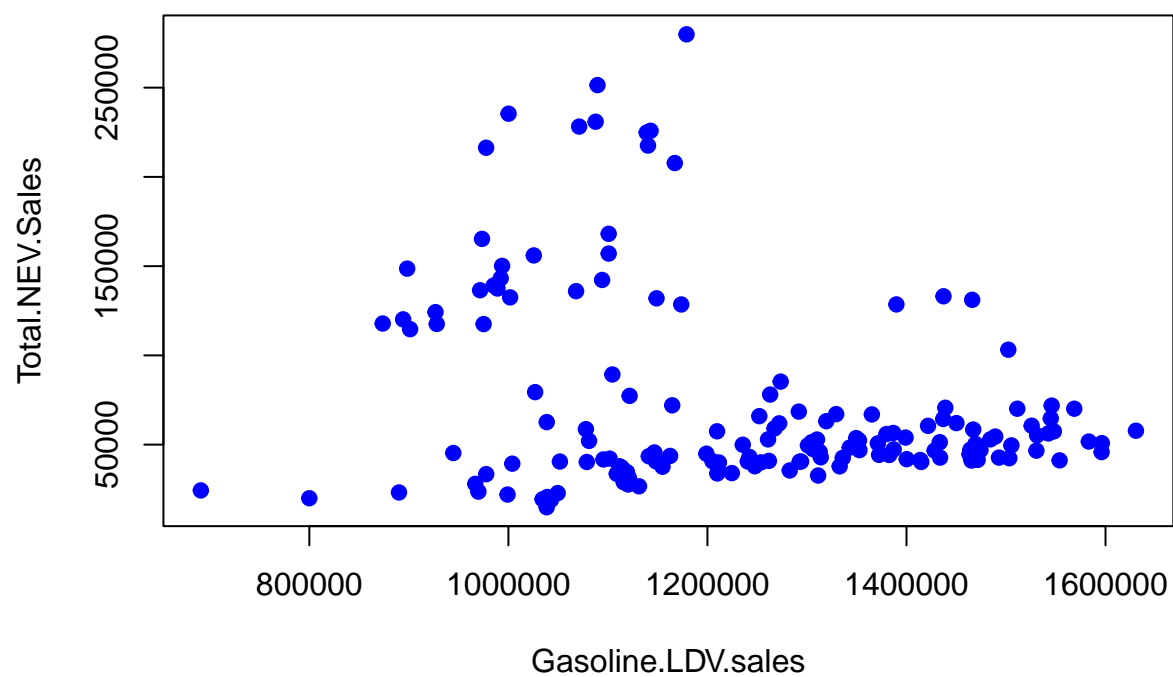
Plot of Total.NEV.Sales vs Production



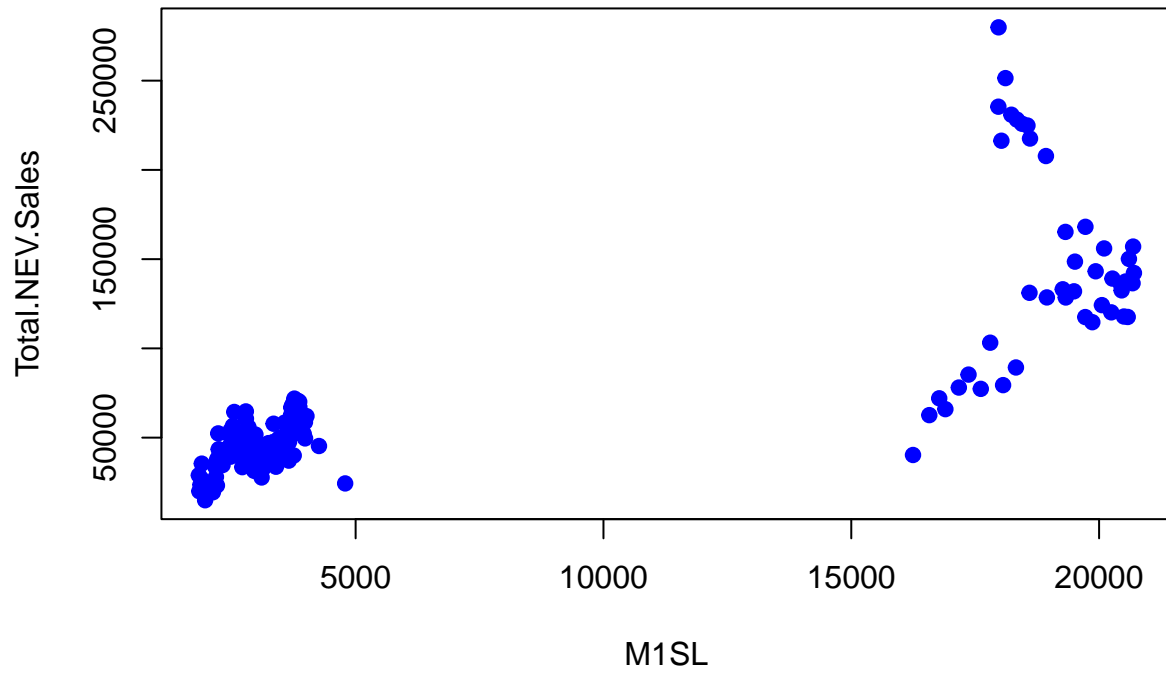
Plot of Total.NEV.Sales vs Inventory



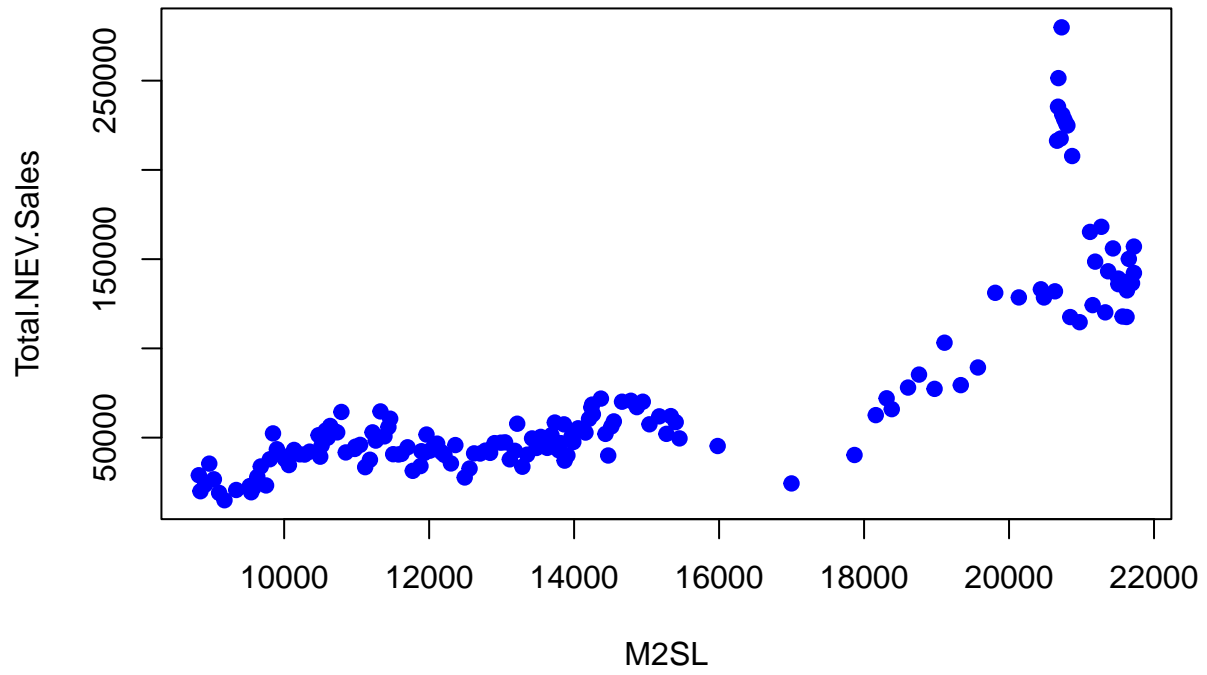
Plot of Total.NEV.Sales vs Gasoline.LDV.sales



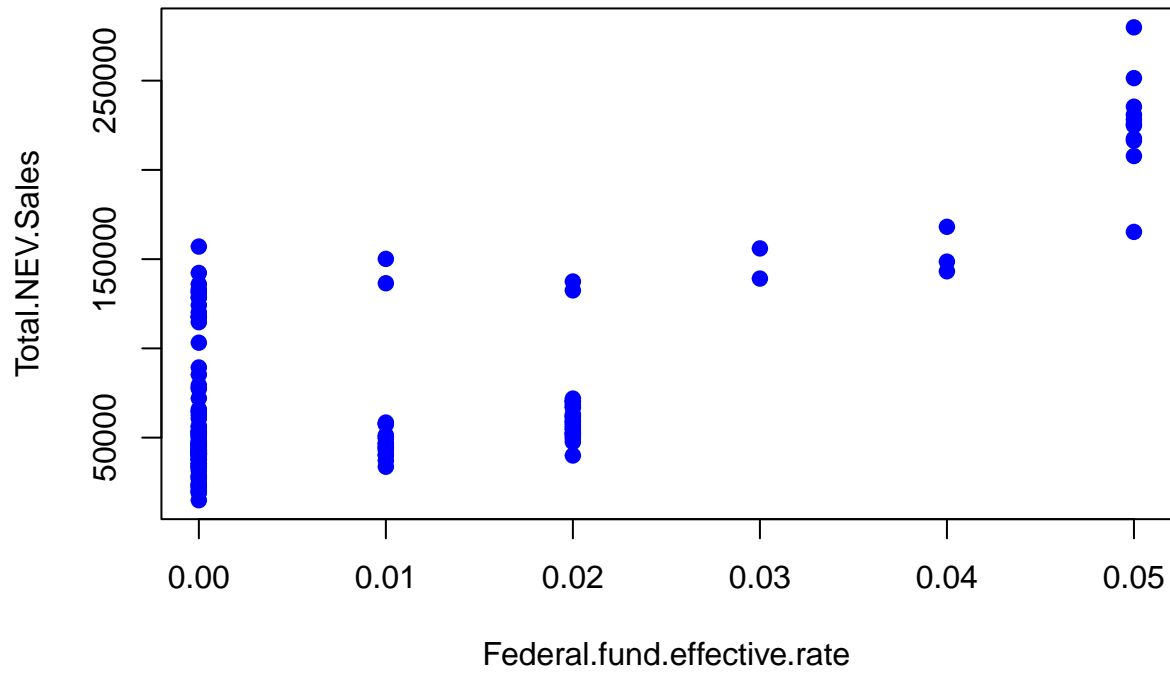
Plot of Total.NEV.Sales vs M1SL



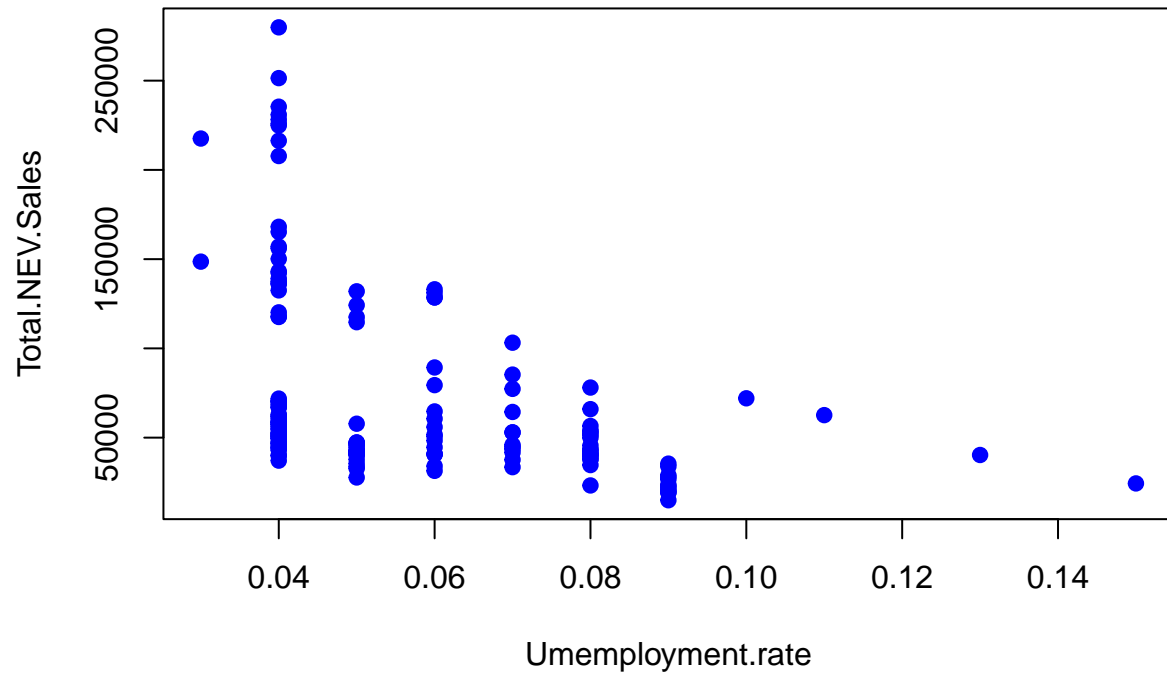
Plot of Total.NEV.Sales vs M2SL



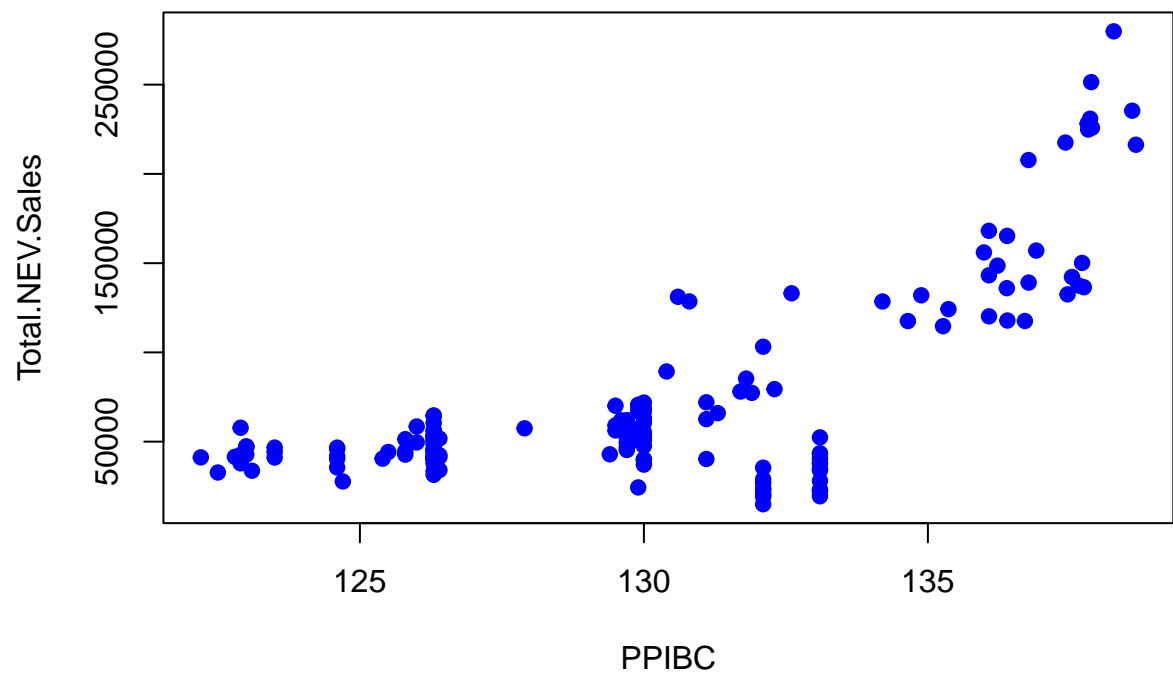
Plot of Total.NEV.Sales vs Federal.fund.effective.rate



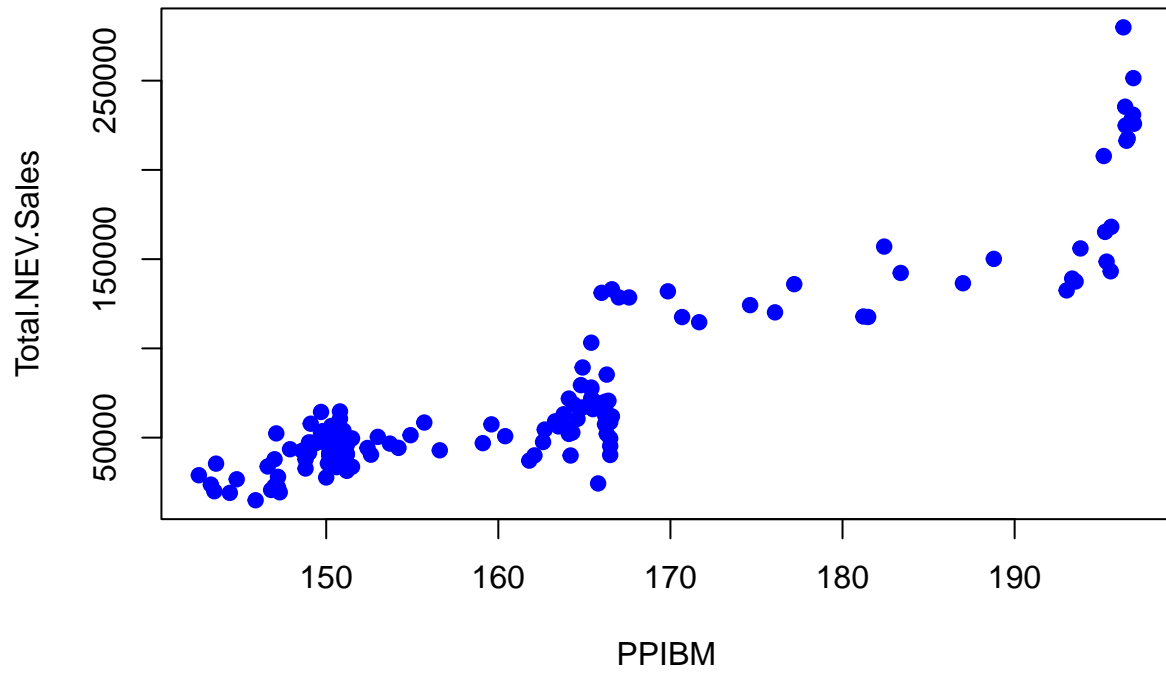
Plot of Total.NEV.Sales vs Umemployment.rate



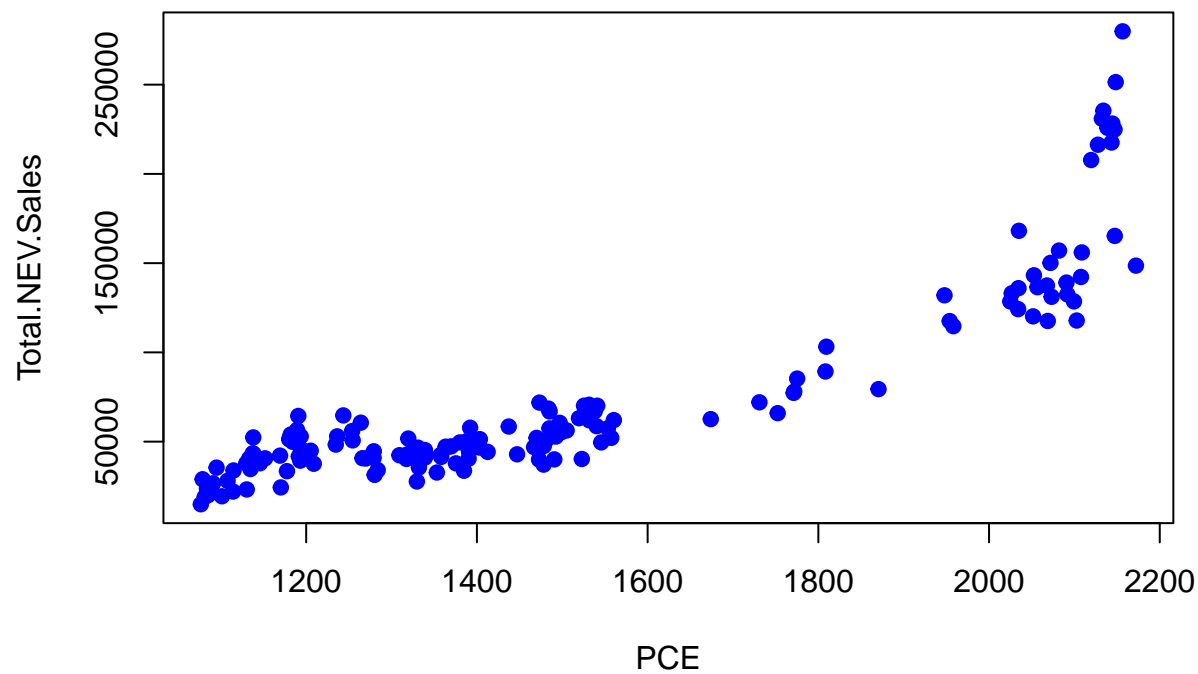
Plot of Total.NEV.Sales vs PPIBC



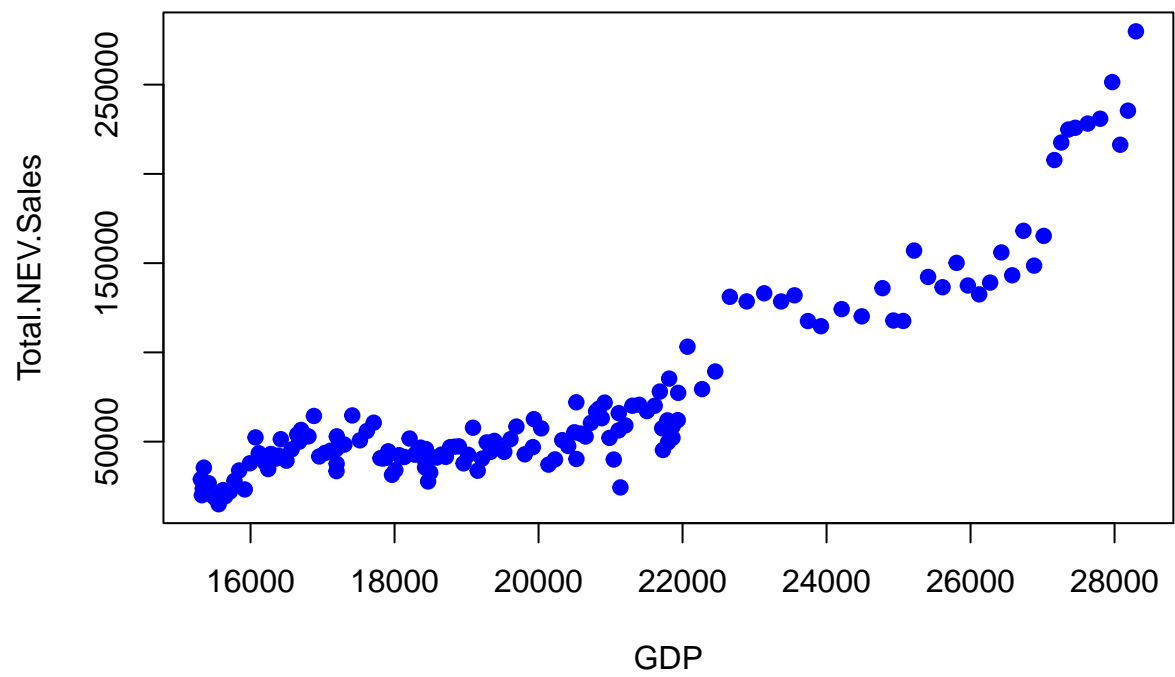
Plot of Total.NEV.Sales vs PPIBM



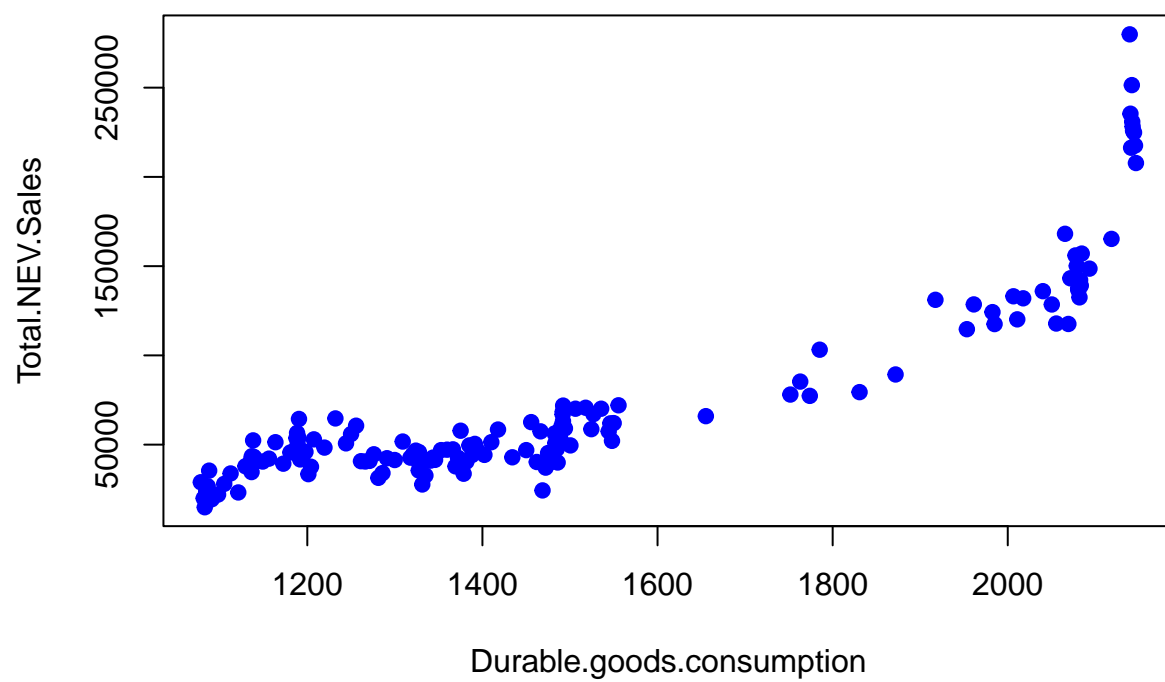
Plot of Total.NEV.Sales vs PCE



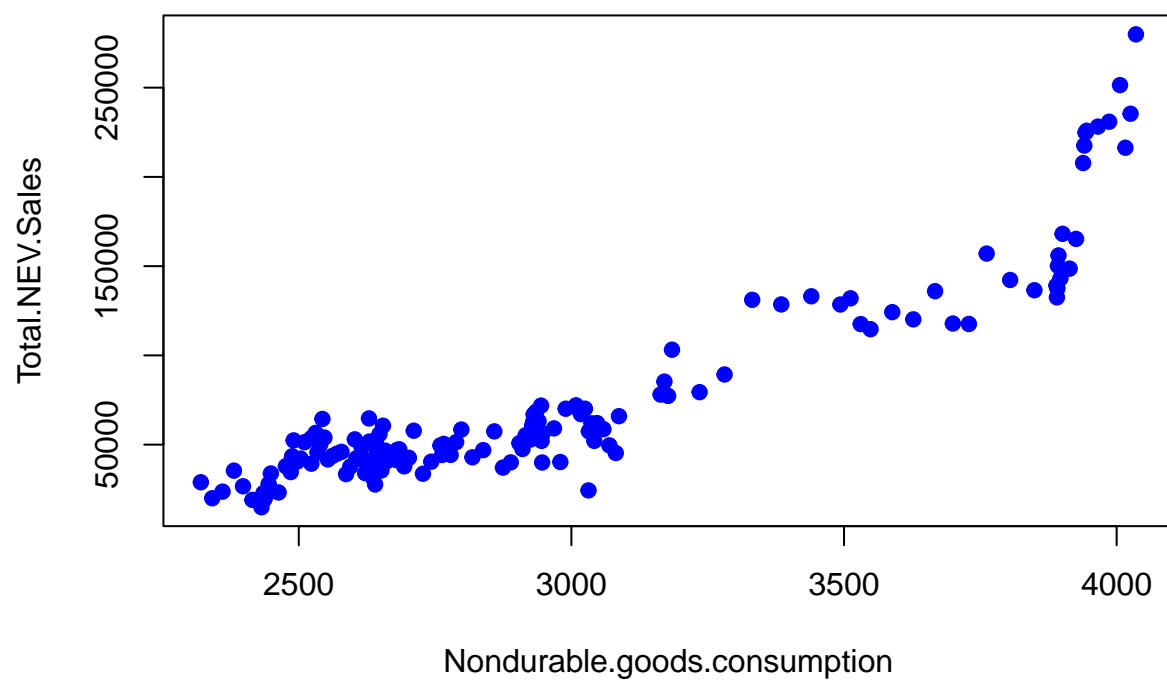
Plot of Total.NEV.Sales vs GDP



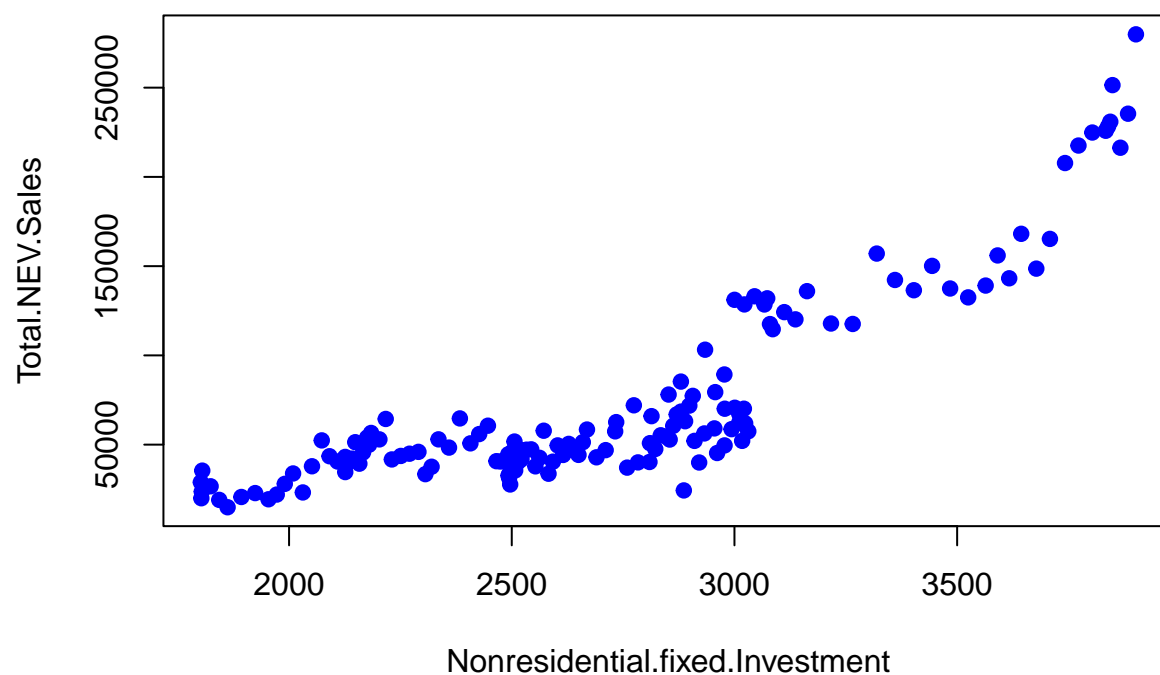
Plot of Total.NEV.Sales vs Durable.goods.consumption



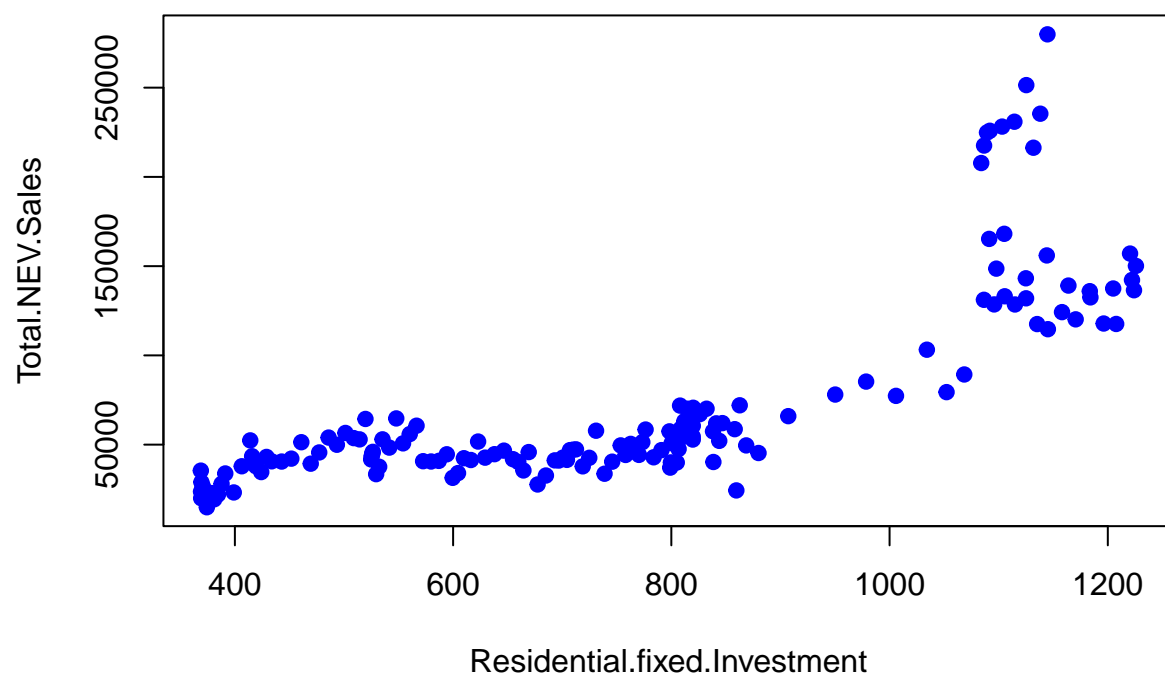
Plot of Total.NEV.Sales vs Nondurable.goods.consumption



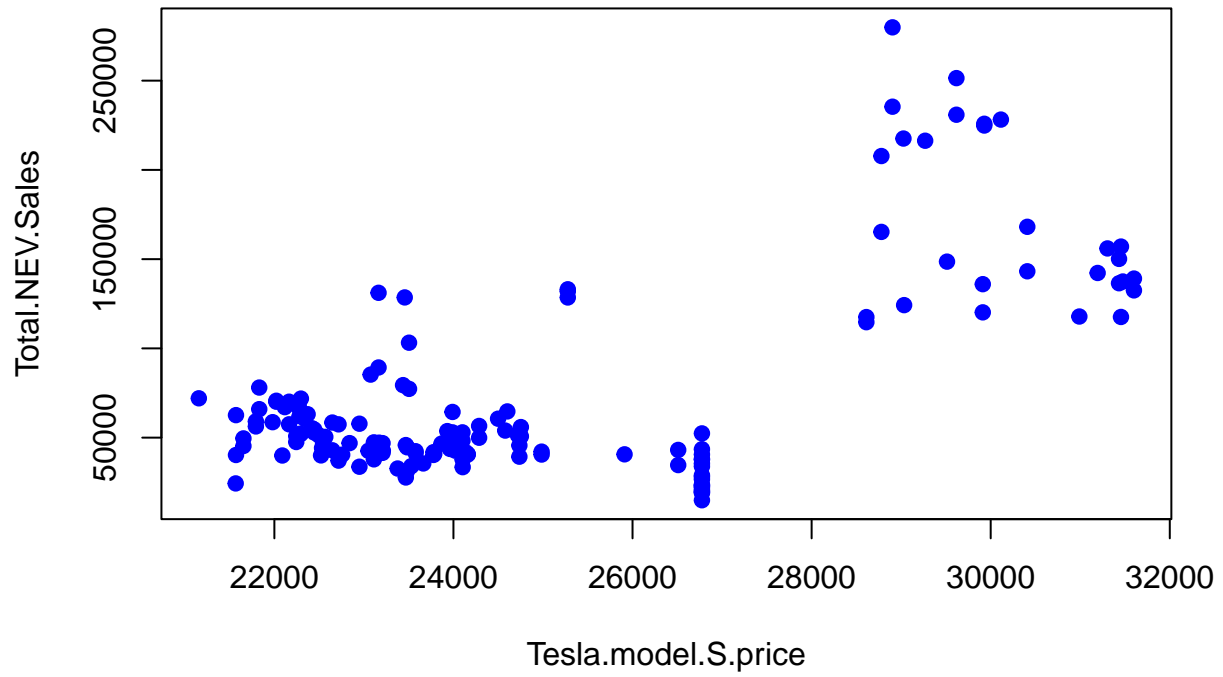
Plot of Total.NEV.Sales vs Nonresidential.fixed.Investment



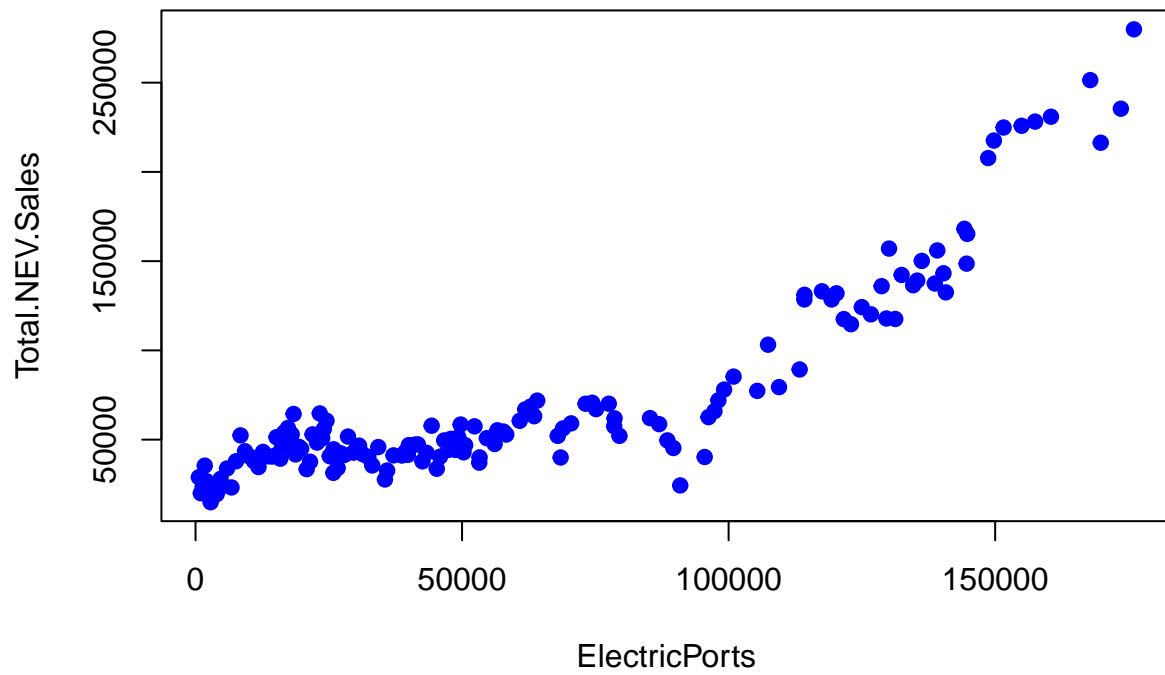
Plot of Total.NEV.Sales vs Residential.fixed.Investment



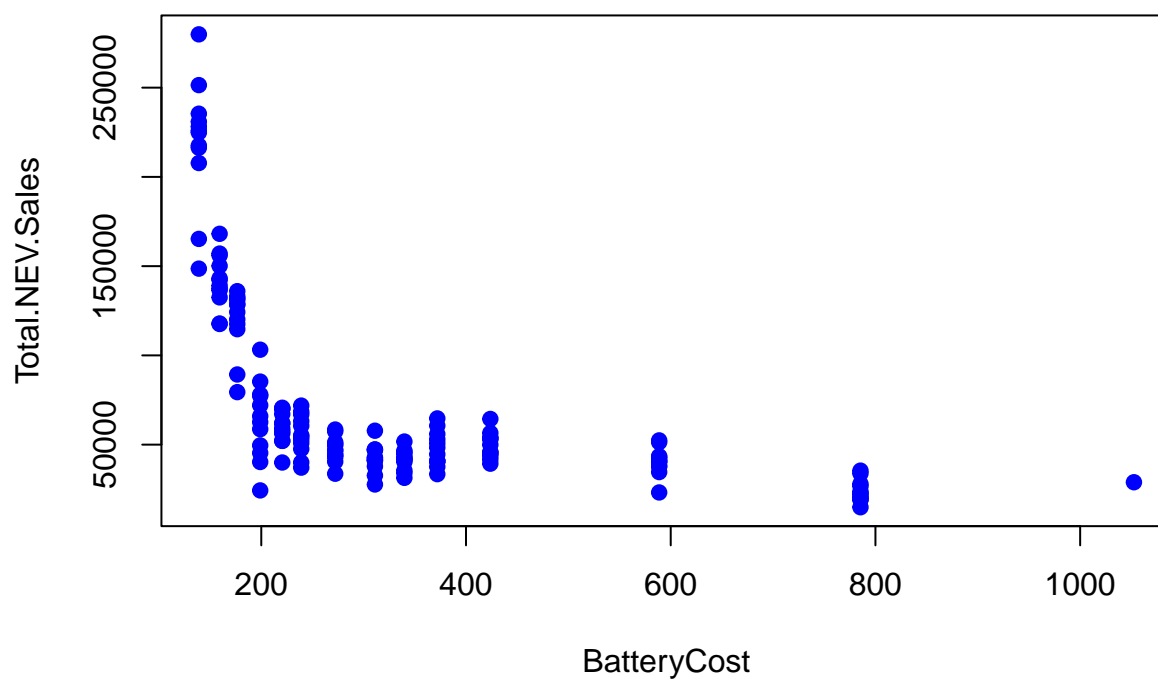
Plot of Total.NEV.Sales vs Tesla.model.S.price



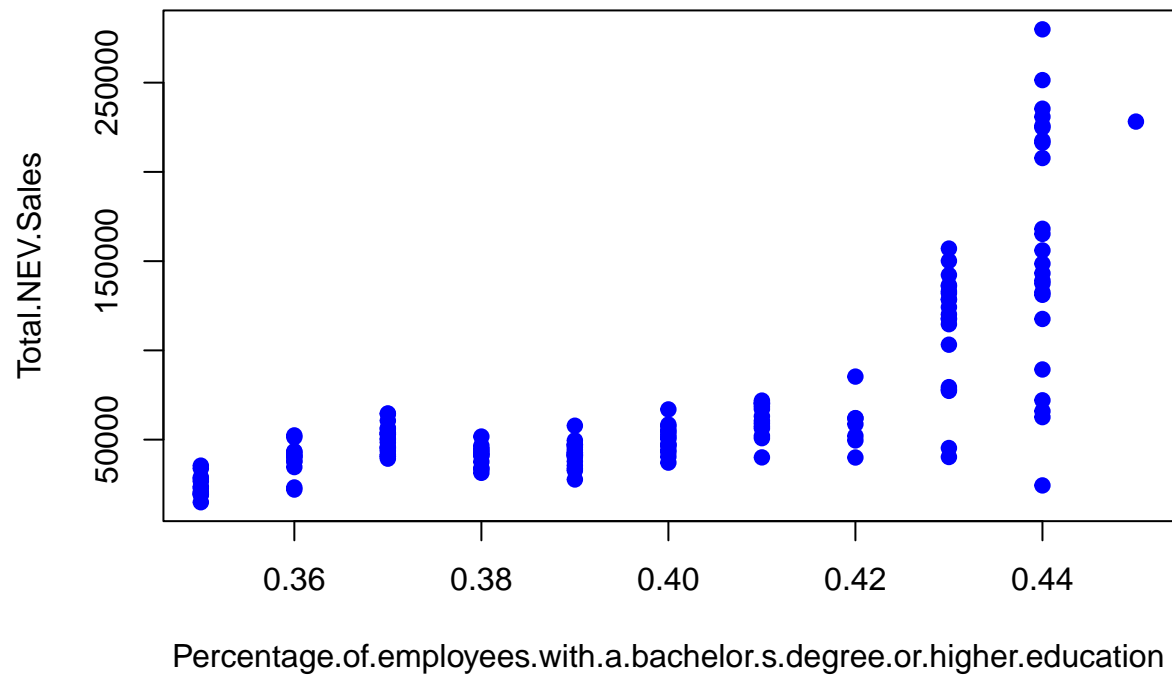
Plot of Total.NEV.Sales vs ElectricPorts



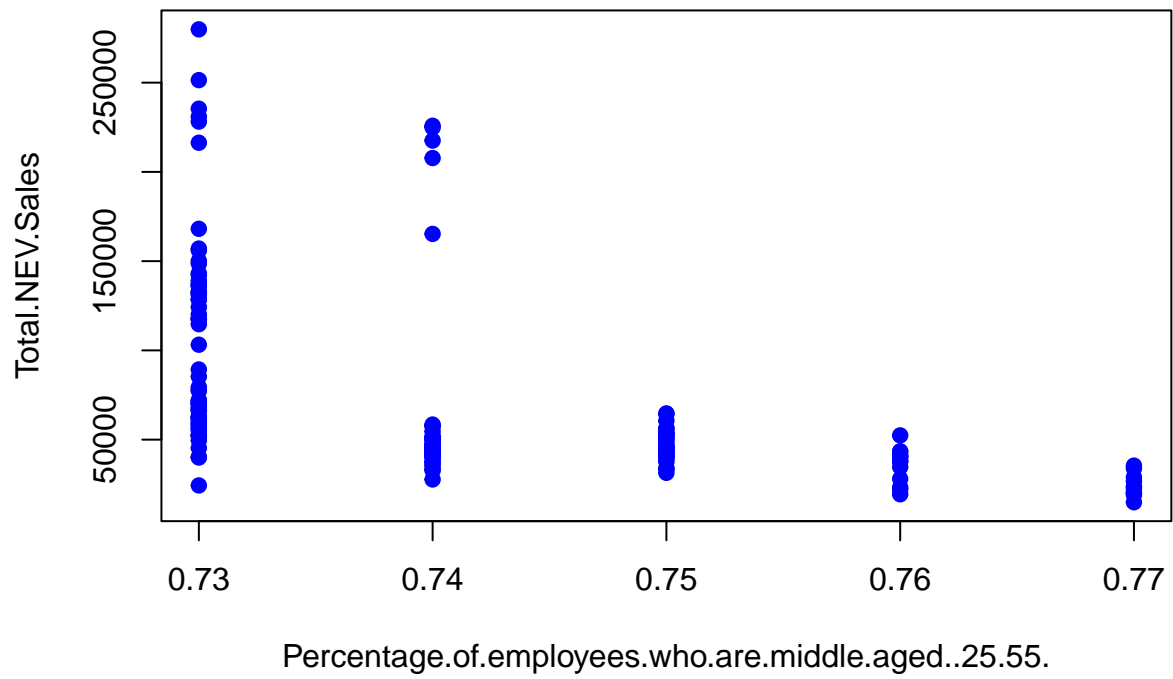
Plot of Total.NEV.Sales vs BatteryCost



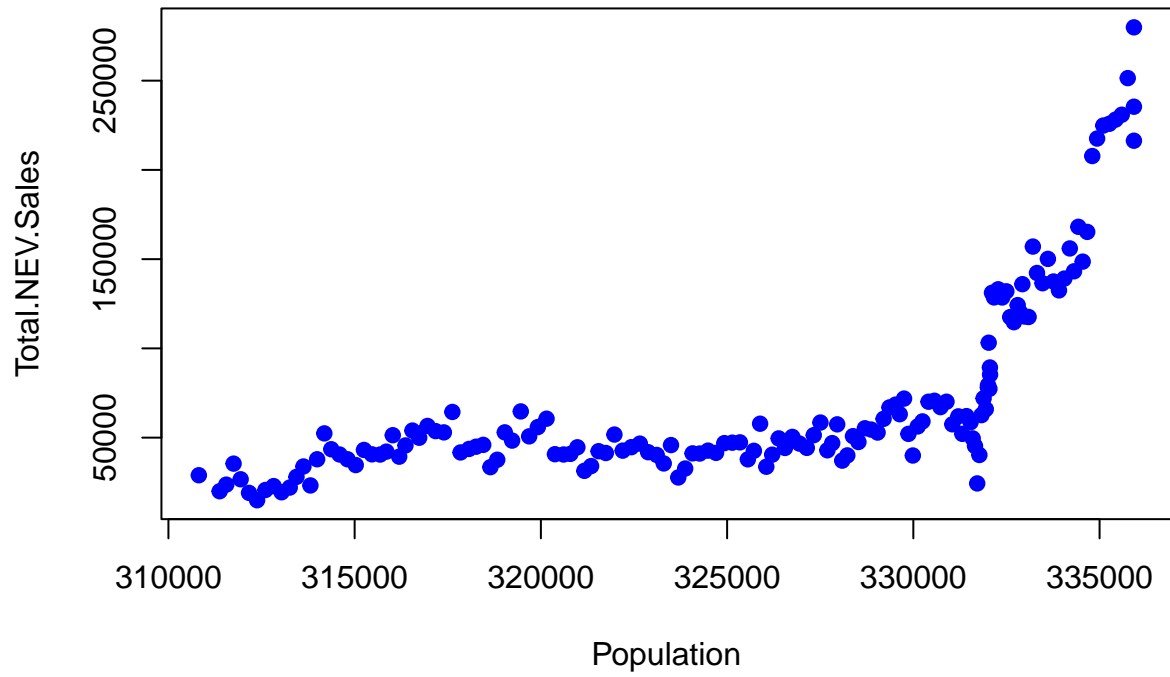
I.NEV.Sales vs Percentage.of.employees.with.a.bachelor.s.degree.or.h



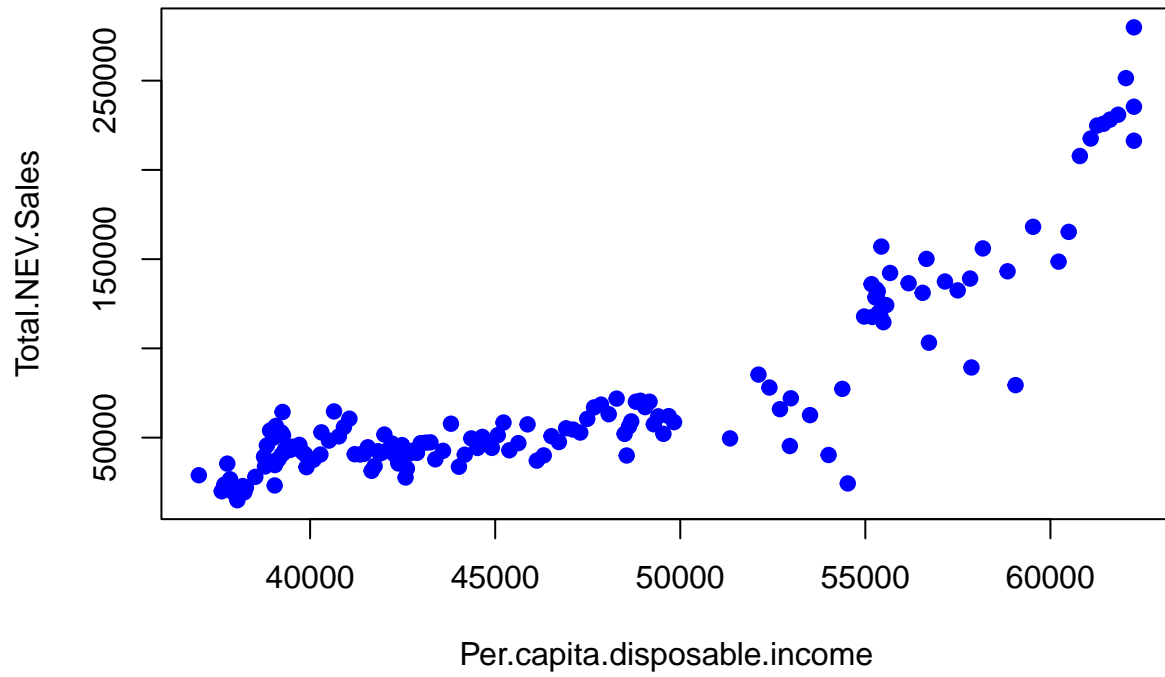
Plot of Total.NEV.Sales vs Percentage.of.employees.who.are.middle.aged



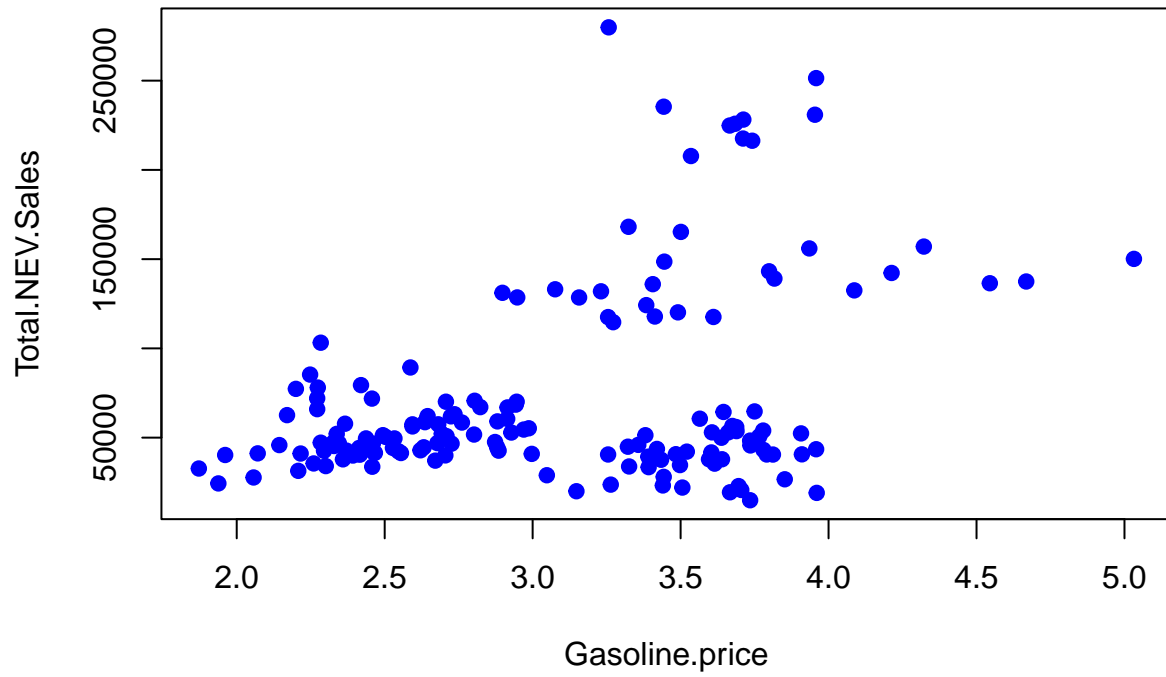
Plot of Total.NEV.Sales vs Population



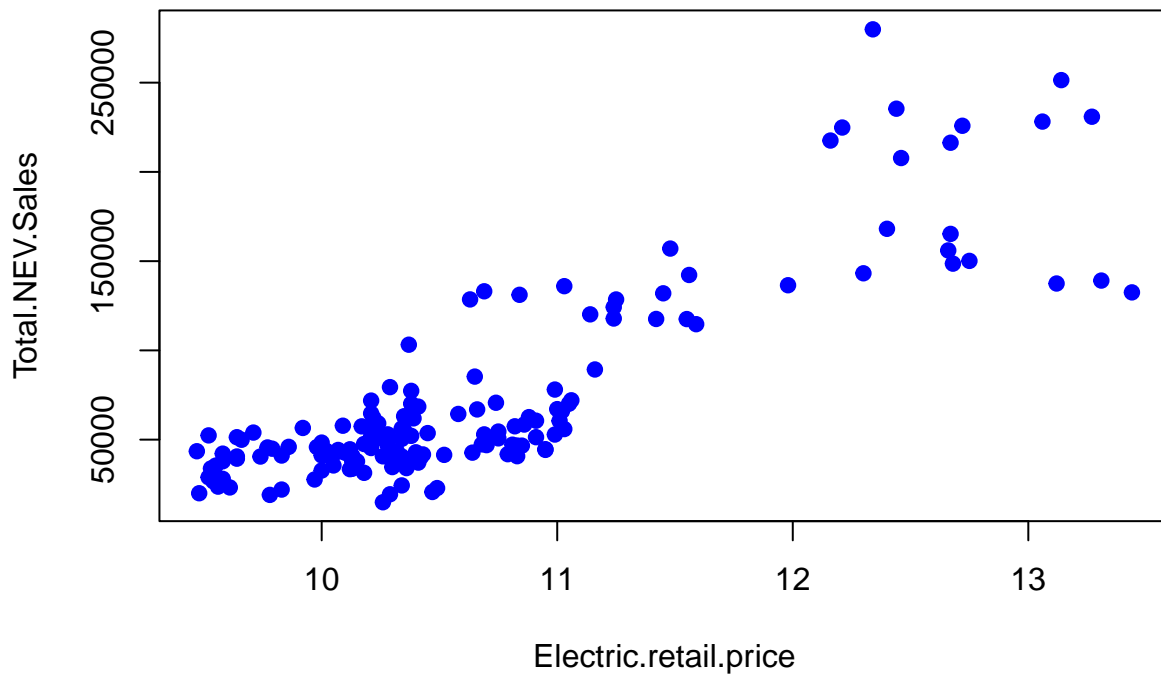
Plot of Total.NEV.Sales vs Per.capita.disposable.income



Plot of Total.NEV.Sales vs Gasoline.price



Plot of Total.NEV.Sales vs Electric.retail.price



```
# cor_matrix <- cor(data[5:22])
# print(cor_matrix)
```

Trend and Seasonlity

```
trend <- lm(data$Total.NEV.Sales~data$Date+as.factor(data$Month))
summary(trend)
```

```
##
## Call:
## lm(formula = data$Total.NEV.Sales ~ data$Date + as.factor(data$Month))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -79738 -25424  -1119   18530 122044
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.262e+06  8.664e+04 -14.565  <2e-16 ***
## data$Date       3.077e+01  2.013e+00  15.284  <2e-16 ***
## as.factor(data$Month)2    3.076e+03  1.362e+04   0.226   0.8217
```



```
## as.factor(data$Month)3    1.923e+04    1.362e+04    1.412    0.1601
## as.factor(data$Month)4    1.356e+04    1.362e+04    0.996    0.3211
## as.factor(data$Month)5    1.809e+04    1.362e+04    1.328    0.1862
## as.factor(data$Month)6    1.675e+04    1.362e+04    1.229    0.2209
## as.factor(data$Month)7    1.651e+04    1.362e+04    1.212    0.2276
## as.factor(data$Month)8    1.741e+04    1.363e+04    1.278    0.2034
## as.factor(data$Month)9    1.526e+04    1.363e+04    1.120    0.2647
## as.factor(data$Month)10   1.295e+04    1.363e+04    0.950    0.3437
## as.factor(data$Month)11   1.143e+04    1.363e+04    0.838    0.4032
## as.factor(data$Month)12   2.607e+04    1.338e+04    1.949    0.0533 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 34720 on 144 degrees of freedom
## Multiple R-squared:  0.6273, Adjusted R-squared:  0.5963
## F-statistic: 20.2 on 12 and 144 DF,  p-value: < 2.2e-16
```

Outlier Detection

```
detect_multiple_outliers <- function(data, start_col = 2, end_col = 29) {
  # Store original options
  original_options <- options()

  # Set options for better display
  options(tibble.width = Inf)
  options(tibble.print_max = Inf)
  options(width = 150)

  all_results <- list()

  for (i in start_col:end_col) {
    if (!is.numeric(data[[i]])) {
      cat("Skipping column", names(data)[i], "as it's not numeric\n")
      next
    }

    x <- data[[i]]
    var_name <- names(data)[i]

    results <- list()

    # Z-score method
    z_scores <- scale(x)
    results$zscore_indices <- which(abs(z_scores) > 3)
```

```

results$zscore_values <- x[results$zscore_indices]

# IQR method
Q1 <- quantile(x, 0.25, na.rm = TRUE)
Q3 <- quantile(x, 0.75, na.rm = TRUE)
IQR <- Q3 - Q1
lower_bound <- Q1 - 1.5 * IQR
upper_bound <- Q3 + 1.5 * IQR
results$iqr_indices <- which(x < lower_bound | x > upper_bound)
results$iqr_values <- x[results$iqr_indices]
results$iqr_bounds <- c(lower_bound = lower_bound, upper_bound = upper_bound)

# Modified Z-score method
median_x <- median(x, na.rm = TRUE)
mad_x <- mad(x, na.rm = TRUE)
modified_z_scores <- 0.6745 * (x - median_x) / mad_x
results$modified_zscore_indices <- which(abs(modified_z_scores) > 3.5)
results$modified_zscore_values <- x[results$modified_zscore_indices]

# Create visualization
df_plot <- data.frame(
  value = x,
  y = 1
)

p <- ggplot2::ggplot(df_plot, ggplot2::aes(y = factor(y), x = value)) +
  ggplot2::geom_boxplot(outlier.color = "red", width = 0.5) +
  ggplot2::geom_jitter(height = 0.1, alpha = 0.5, color = "blue") +
  ggplot2::labs(title = paste("Outlier Detection for", var_name),
    x = var_name,
    y = "") +
  ggplot2::theme_minimal() +
  ggplot2::theme(axis.text.y = ggplot2::element_blank(),
    axis.ticks.y = ggplot2::element_blank())

results$plot <- p

# Store results for this variable
all_results[[var_name]] <- results

# Print section header
cat("\n=====\n")
cat("=== Variable:", var_name, "===\n")
cat("=====\n")

```

```

# Function to print outlier values
print_outliers <- function(values, method_name) {
  if (length(values) > 0) {
    cat("\n", method_name, "\n")
    cat("Number of outliers:", length(values), "\n")
    cat("Outlier values:", paste(round(values, 3), collapse = ", "), "\n")
  }
}

# Print results for each method
cat("\nOutlier Detection Results:\n")

# Z-score outliers
print_outliers(results$zscore_values, "Z-score method ( $|z| > 3$ )")

# IQR outliers
cat("\nIQR method\n")
cat("IQR bounds: Lower =", round(lower_bound, 3), ", Upper =", round(upper_bound, 3))
print_outliers(results$iqr_values, "IQR outliers")

# Modified Z-score outliers
print_outliers(results$modified_zscore_values, "Modified Z-score method ( $|modified z| > 3$ )")

# Print summary statistics
cat("\nSummary Statistics:\n")
summary_stats <- list(
  mean = mean(x, na.rm = TRUE),
  median = median(x, na.rm = TRUE),
  sd = sd(x, na.rm = TRUE),
  Q1 = Q1,
  Q3 = Q3
)
print(lapply(summary_stats, round, 3))

# Display plot
print(results$plot)
cat("\n-----\n")
}

options(original_options)

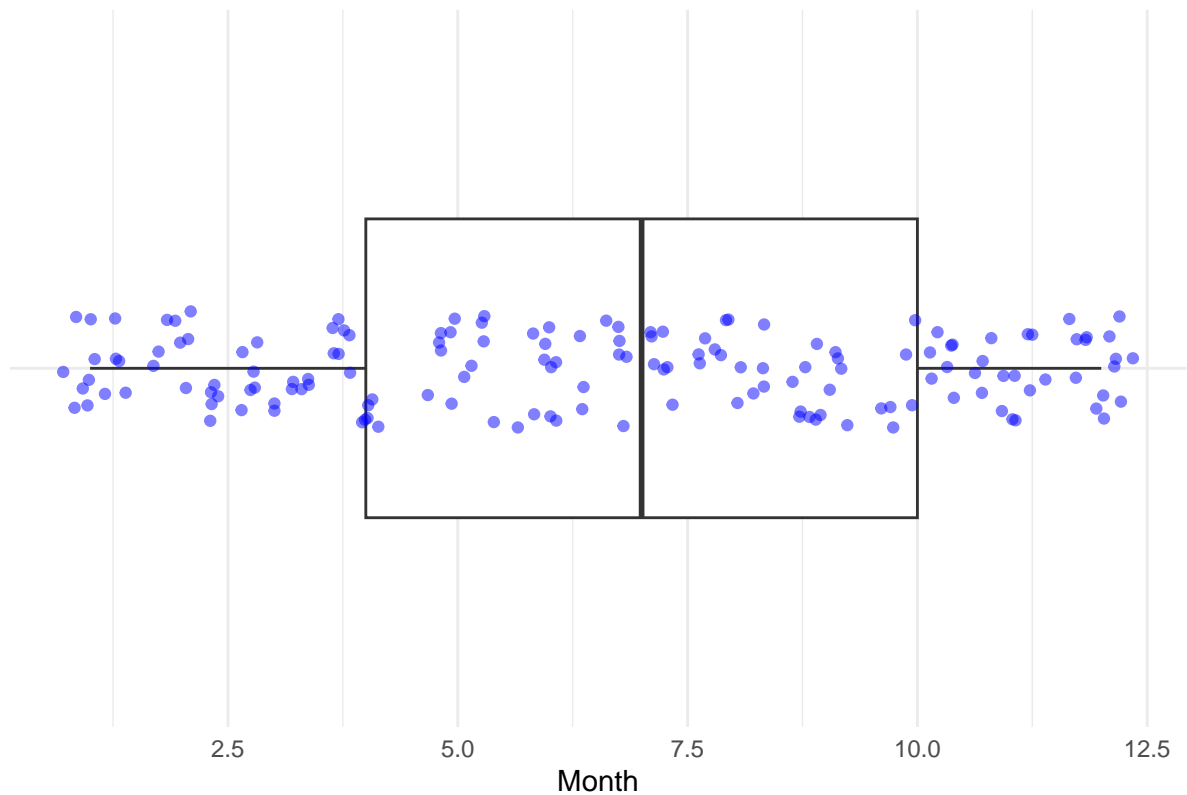
return(all_results)
}

```

```
results <- detect_multiple_outliers(data)
```

```
##  
## =====  
## === Variable: Month ===  
## =====  
##  
## Outlier Detection Results:  
##  
## IQR method  
## IQR bounds: Lower = -5 , Upper = 19  
##  
## Summary Statistics:  
## $mean  
## [1] 6.535  
##  
## $median  
## [1] 7  
##  
## $sd  
## [1] 3.48  
##  
## $Q1  
## 25%  
## 4  
##  
## $Q3  
## 75%  
## 10
```

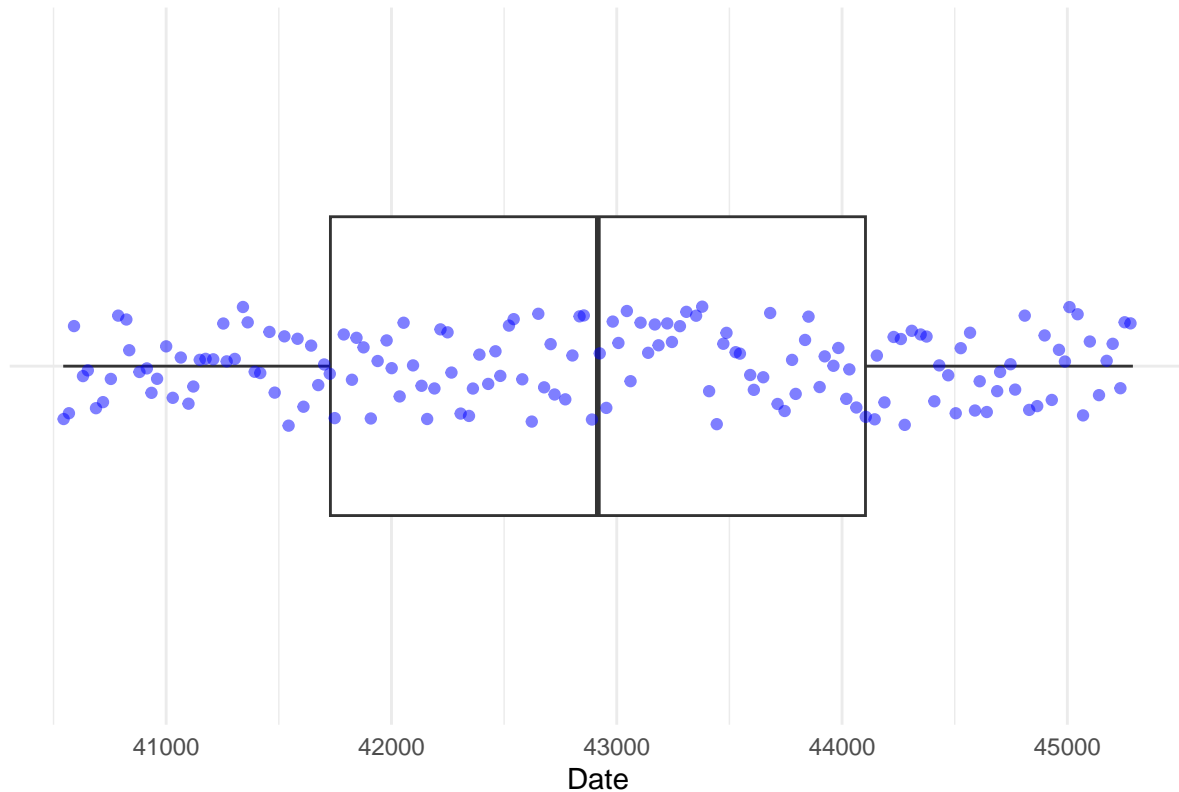
Outlier Detection for Month



```
##
## -----
##
## =====
## === Variable: Date ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 38166.5 , Upper = 47666.5
##
## Summary Statistics:
## $mean
## [1] 42916.53
##
## $median
## [1] 42916
##
## $sd
## [1] 1383.858
```

```
##
## $Q1
## 25%
## 41729
##
## $Q3
## 75%
## 44104
```

Outlier Detection for Date



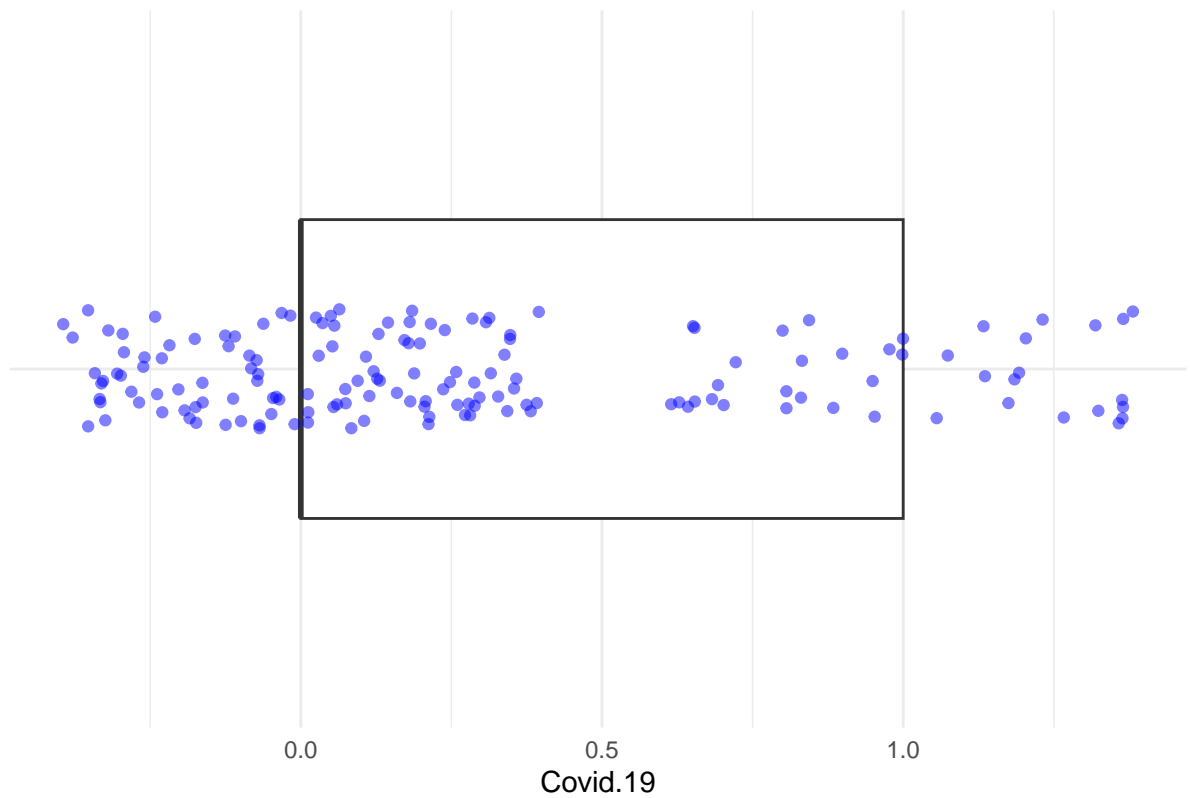
```
##
## -----
##
## =====
## === Variable: Covid.19 ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = -1.5 , Upper = 2.5
##
## Modified Z-score method (|modified z| > 3.5)
```

```

## Number of outliers: 41
## Outlier values: 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
##
## Summary Statistics:
## $mean
## [1] 0.261
##
## $median
## [1] 0
##
## $sd
## [1] 0.441
##
## $Q1
## 25%
## 0
##
## $Q3
## 75%
## 1

```

Outlier Detection for Covid.19



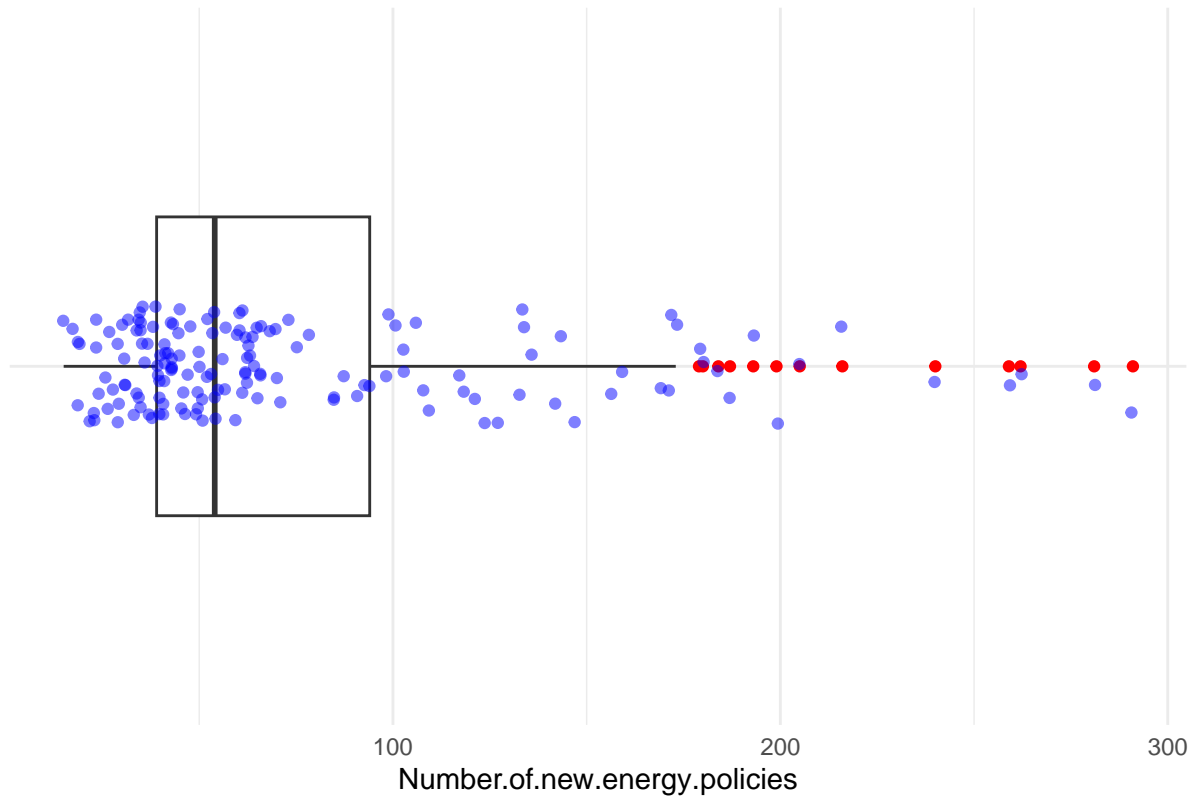
```
##
```

```

## -----
##
## =====
## === Variable: Number.of.new.energy.policies ===
## =====
##
## Outlier Detection Results:
##
## Z-score method ( $|z| > 3$ )
## Number of outliers: 4
## Outlier values: 291, 281, 262, 259
##
## IQR method
## IQR bounds: Lower = -43.5 , Upper = 176.5
##
## IQR outliers
## Number of outliers: 13
## Outlier values: 216, 193, 180, 199, 205, 291, 281, 262, 259, 240, 187, 184, 179
##
## Modified Z-score method ( $|\text{modified } z| > 3.5$ )
## Number of outliers: 7
## Outlier values: 216, 205, 291, 281, 262, 259, 240
##
## Summary Statistics:
## $mean
## [1] 75.478
##
## $median
## [1] 54
##
## $sd
## [1] 57.753
##
## $Q1
## 25%
## 39
##
## $Q3
## 75%
## 94

```

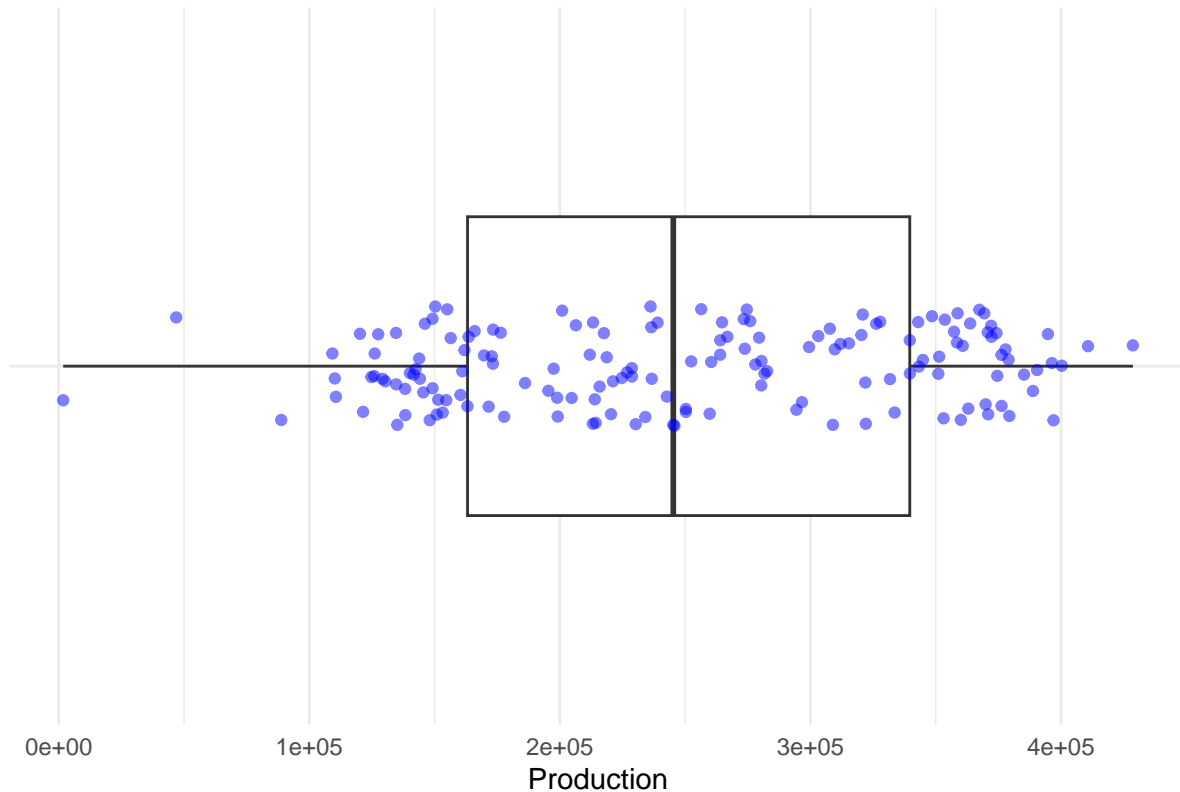

Outlier Detection for Number.of.new.energy.policies



```
##
## -----
##
## =====
## === Variable: Production ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = -101620 , Upper = 604412
##
## Summary Statistics:
## $mean
## [1] 249727.2
##
## $median
## [1] 245279
##
## $sd
## [1] 93137.35
```

```
##
## $Q1
##      25%
## 163142
##
## $Q3
##      75%
## 339650
```

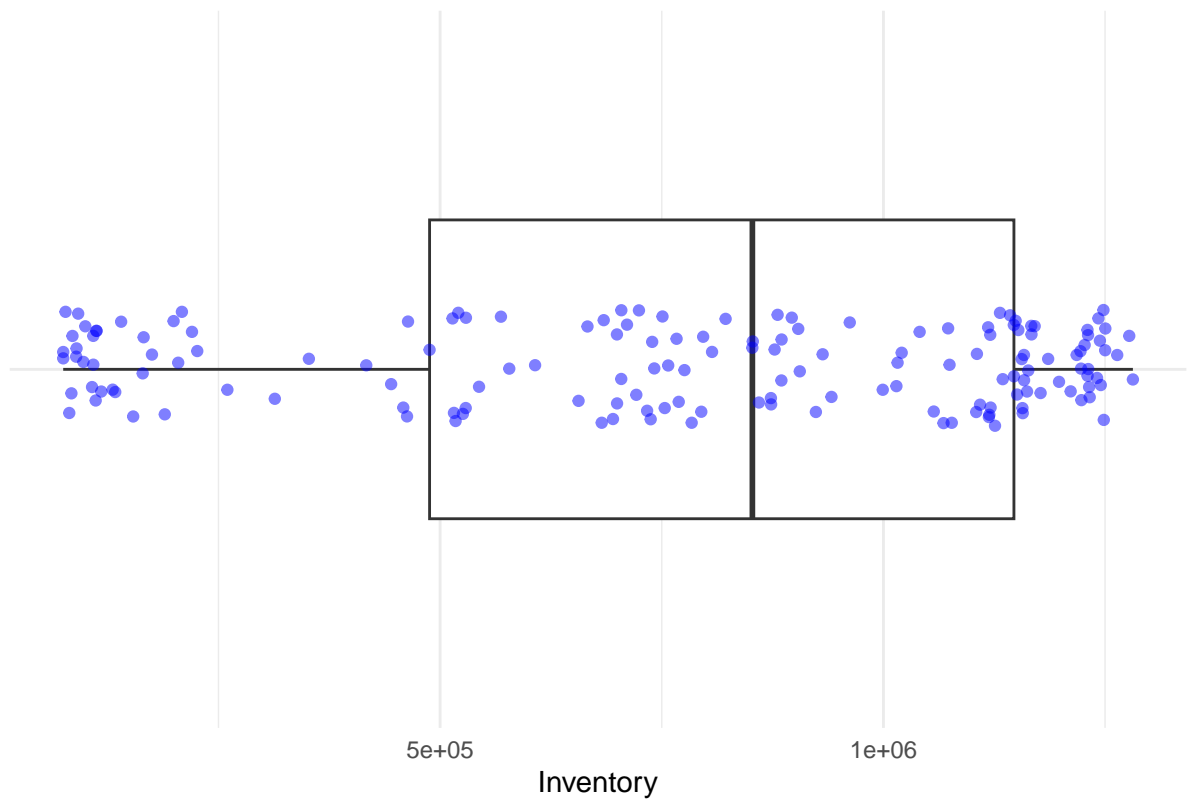
Outlier Detection for Production



```
##
## -----
##
## =====
## === Variable: Inventory ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = -500591 , Upper = 2135921
##
## Summary Statistics:
```

```
## $mean
## [1] 771654.7
##
## $median
## [1] 852200
##
## $sd
## [1] 400402.5
##
## $Q1
## 25%
## 488101
##
## $Q3
## 75%
## 1147229
```

Outlier Detection for Inventory



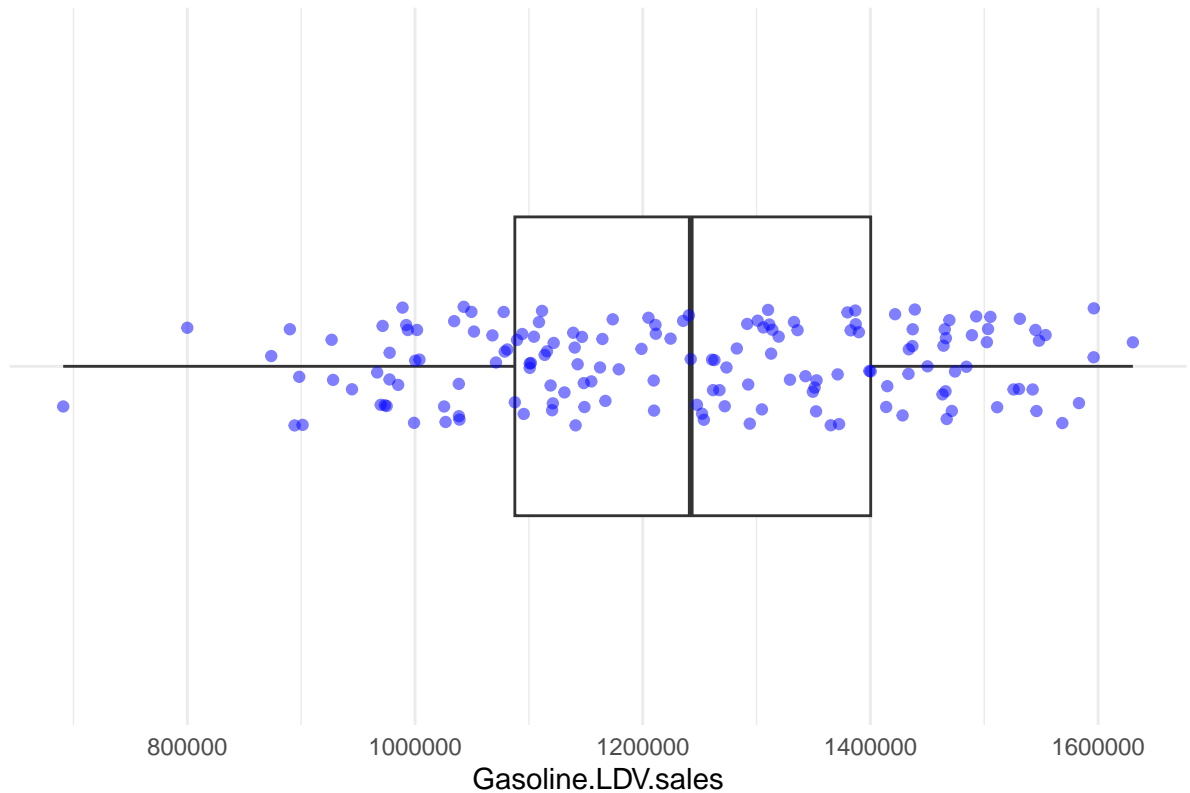
```
##
## -----
##
## =====
## === Variable: Gasoline.LDV.sales ===
```

```

## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 618790 , Upper = 1869150
##
## Summary Statistics:
## $mean
## [1] 1236707
##
## $median
## [1] 1242179
##
## $sd
## [1] 200399.2
##
## $Q1
##      25%
## 1087675
##
## $Q3
##      75%
## 1400265

```

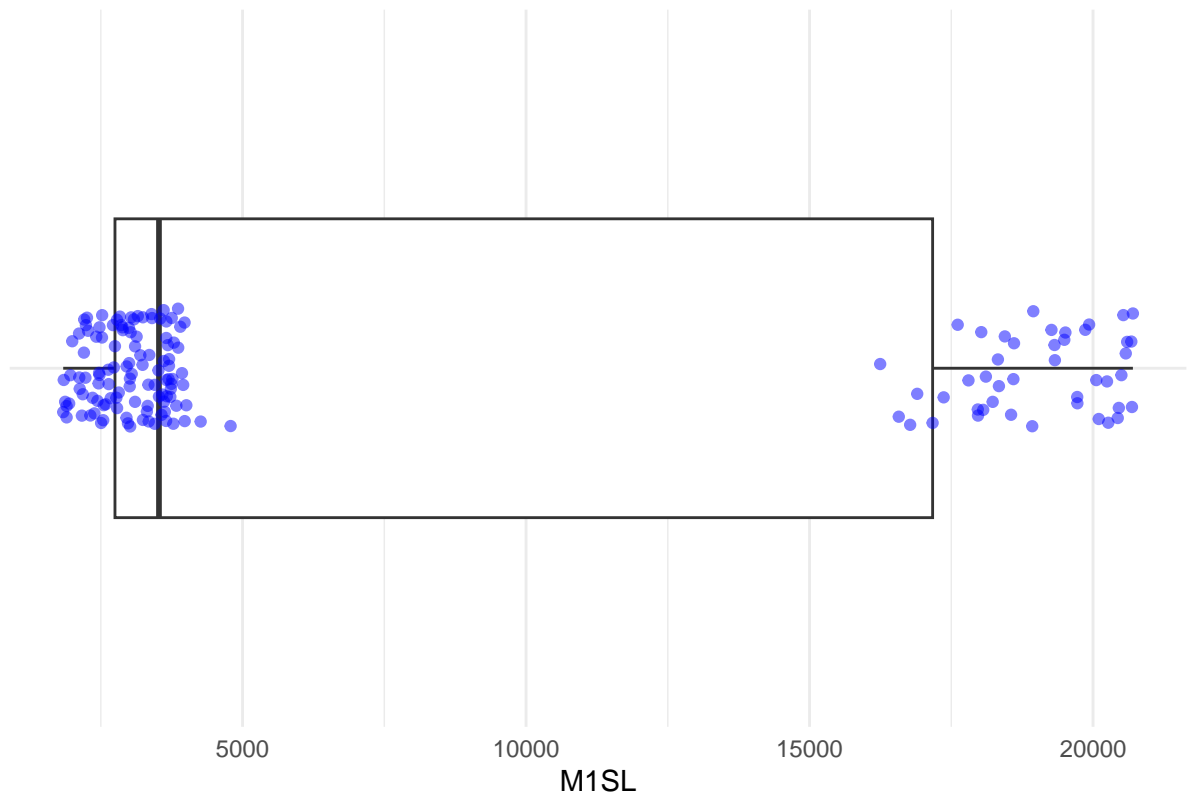
Outlier Detection for Gasoline.LDV.sales



```
##
## -----
##
## =====
## === Variable: M1SL ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = -18882.5 , Upper = 38802.3
##
## Modified Z-score method (|modified z| > 3.5)
## Number of outliers: 44
## Outlier values: 16245.5, 16574.1, 16774.5, 16898.8, 17170.5, 17365.7, 17612.9, 17803,
##
## Summary Statistics:
## $mean
## [1] 7506.645
##
## $median
```

```
## [1] 3525.3
##
## $sd
## [1] 7240.829
##
## $Q1
##      25%
## 2749.3
##
## $Q3
##      75%
## 17170.5
```

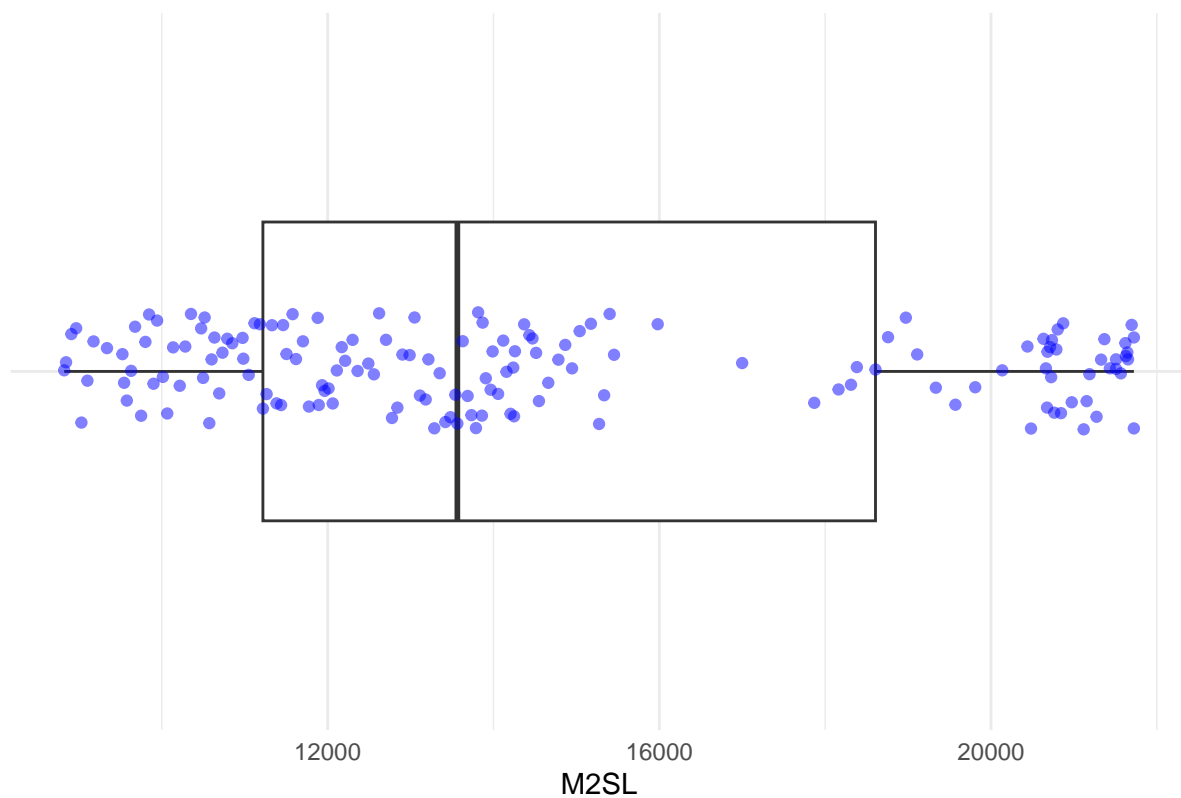
Outlier Detection for M1SL



```
##
## -----
##
## =====
## === Variable: M2SL ===
## =====
##
## Outlier Detection Results:
##
```

```
## IQR method
## IQR bounds: Lower = 137.55 , Upper = 29688.35
##
## Summary Statistics:
## $mean
## [1] 14541.98
##
## $median
## [1] 13564.1
##
## $sd
## [1] 4129.859
##
## $Q1
##      25%
## 11219.1
##
## $Q3
##      75%
## 18606.8
```

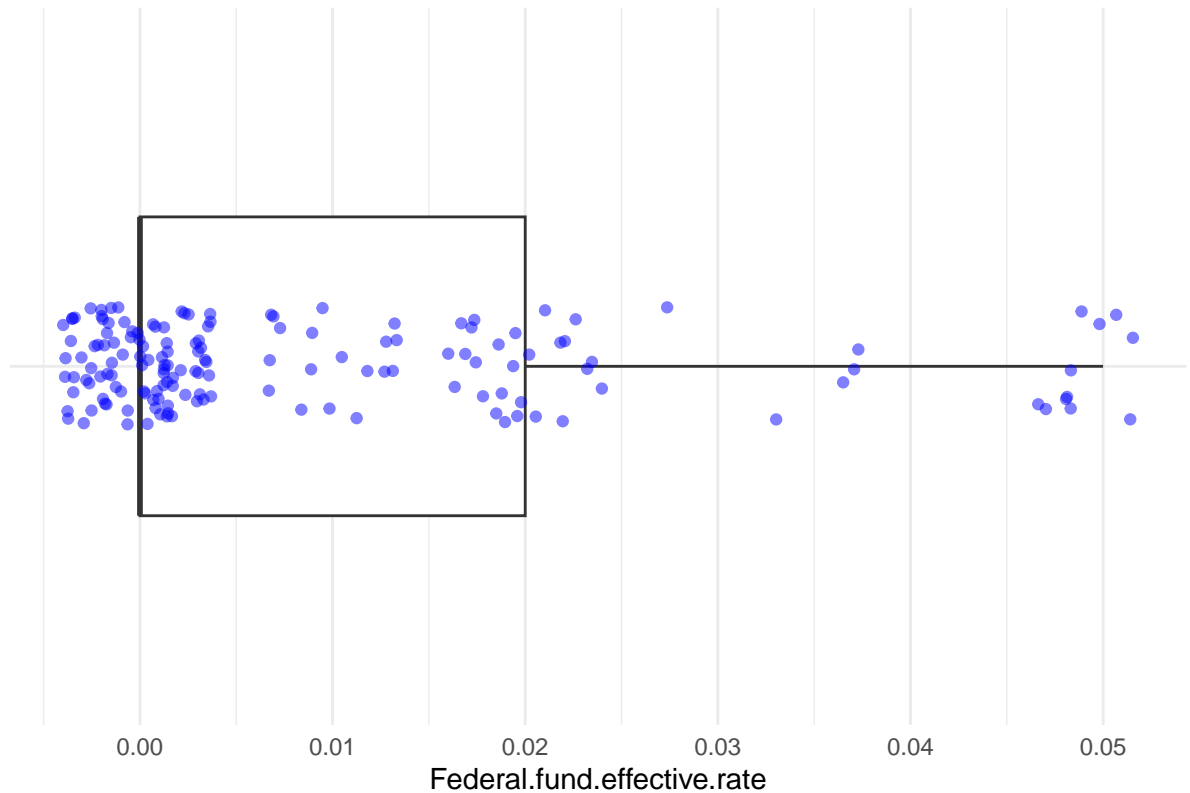
Outlier Detection for M2SL



```
##
```

[illegible]

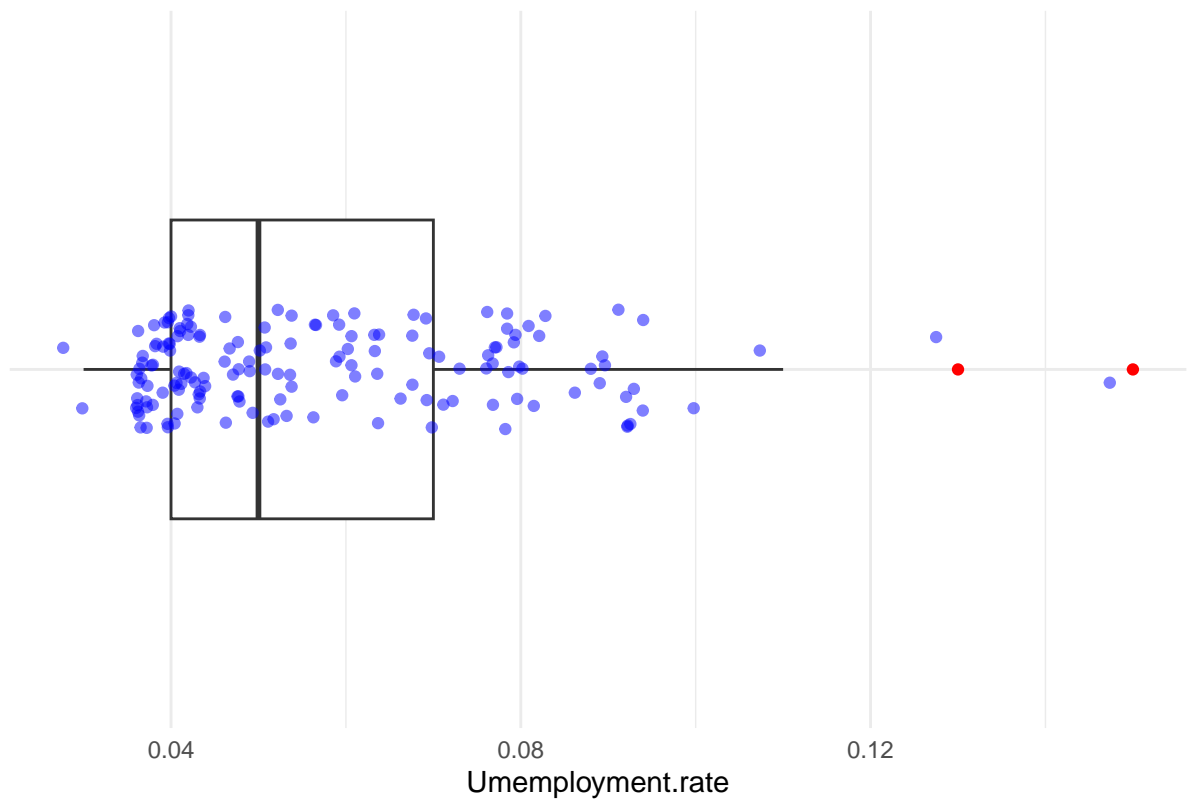
Outlier Detection for Federal.fund.effective.rate



```
##
## -----
##
## =====
## === Variable: Umemployment.rate ===
## =====
##
## Outlier Detection Results:
##
## Z-score method ( $|z| > 3$ )
## Number of outliers: 2
## Outlier values: 0.15, 0.13
##
## IQR method
## IQR bounds: Lower = -0.005 , Upper = 0.115
##
## IQR outliers
## Number of outliers: 2
## Outlier values: 0.15, 0.13
##
## Modified Z-score method ( $|\text{modified } z| > 3.5$ )
```

```
## Number of outliers: 2
## Outlier values: 0.15, 0.13
##
## Summary Statistics:
## $mean
## [1] 0.058
##
## $median
## [1] 0.05
##
## $sd
## [1] 0.021
##
## $Q1
## 25%
## 0.04
##
## $Q3
## 75%
## 0.07
```

Outlier Detection for Umemployment.rate



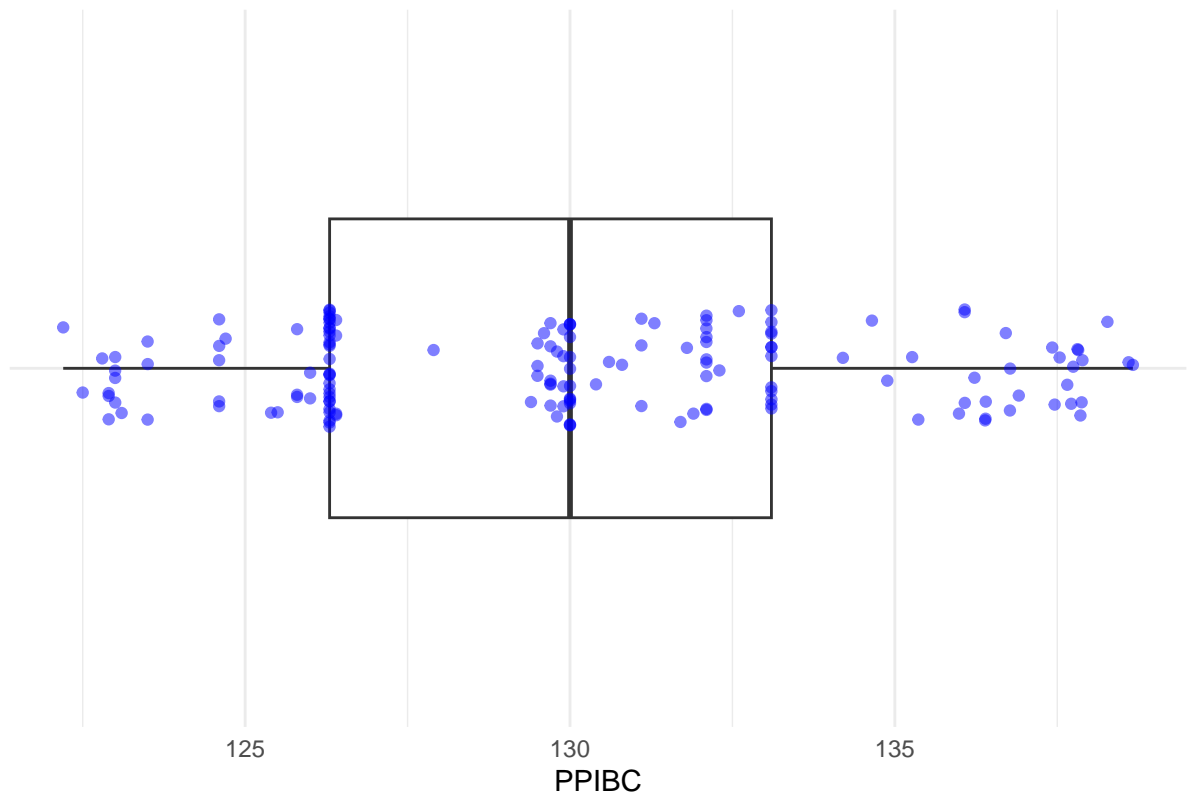
```
##
```

```

## -----
##
## =====
## === Variable: PPIBC ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 116.1 , Upper = 143.3
##
## Summary Statistics:
## $mean
## [1] 129.983
##
## $median
## [1] 130
##
## $sd
## [1] 4.47
##
## $Q1
## 25%
## 126.3
##
## $Q3
## 75%
## 133.1

```

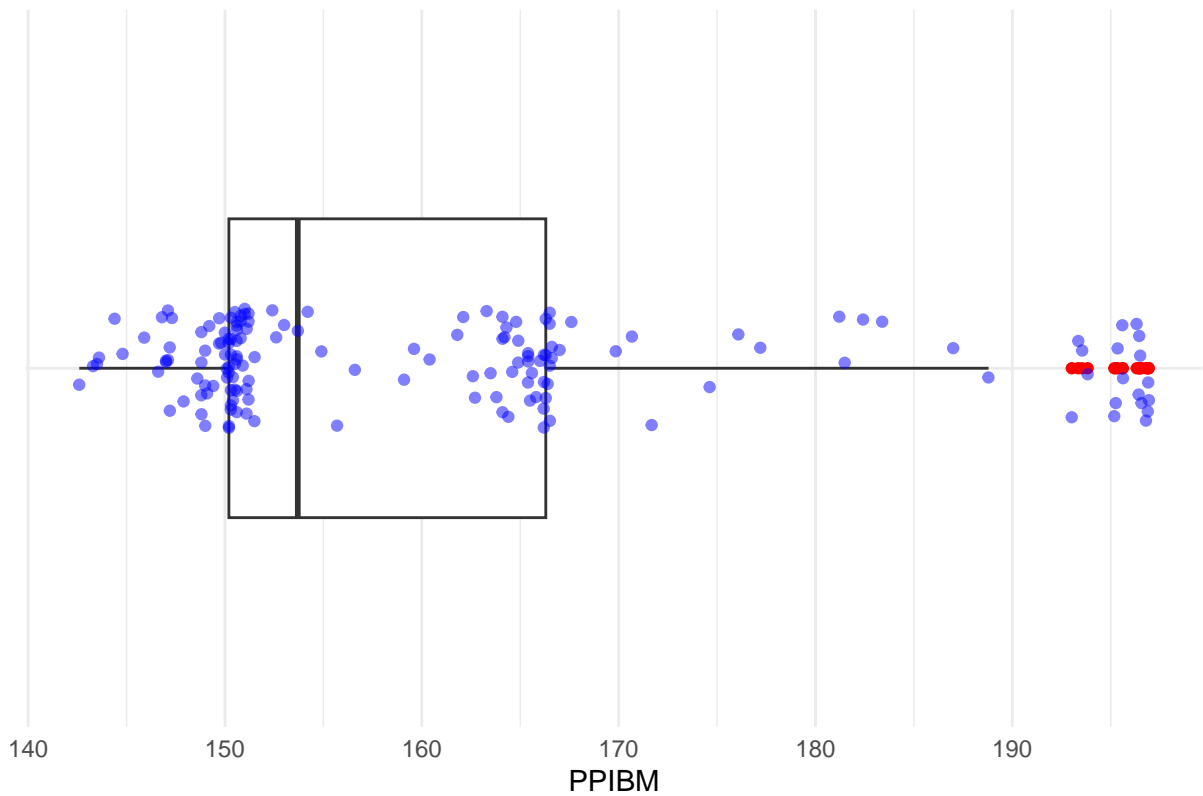
Outlier Detection for PPIBC



```
##
## -----
##
## =====
## === Variable: PPIBM ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 126.05 , Upper = 190.45
##
## IQR outliers
## Number of outliers: 18
## Outlier values: 193.543, 193.021, 193.345, 193.825, 195.581, 195.614, 195.345, 195.25
##
## Summary Statistics:
## $mean
## [1] 161.423
##
## $median
```

```
## [1] 153.7
##
## $sd
## [1] 15.528
##
## $Q1
## 25%
## 150.2
##
## $Q3
## 75%
## 166.3
```

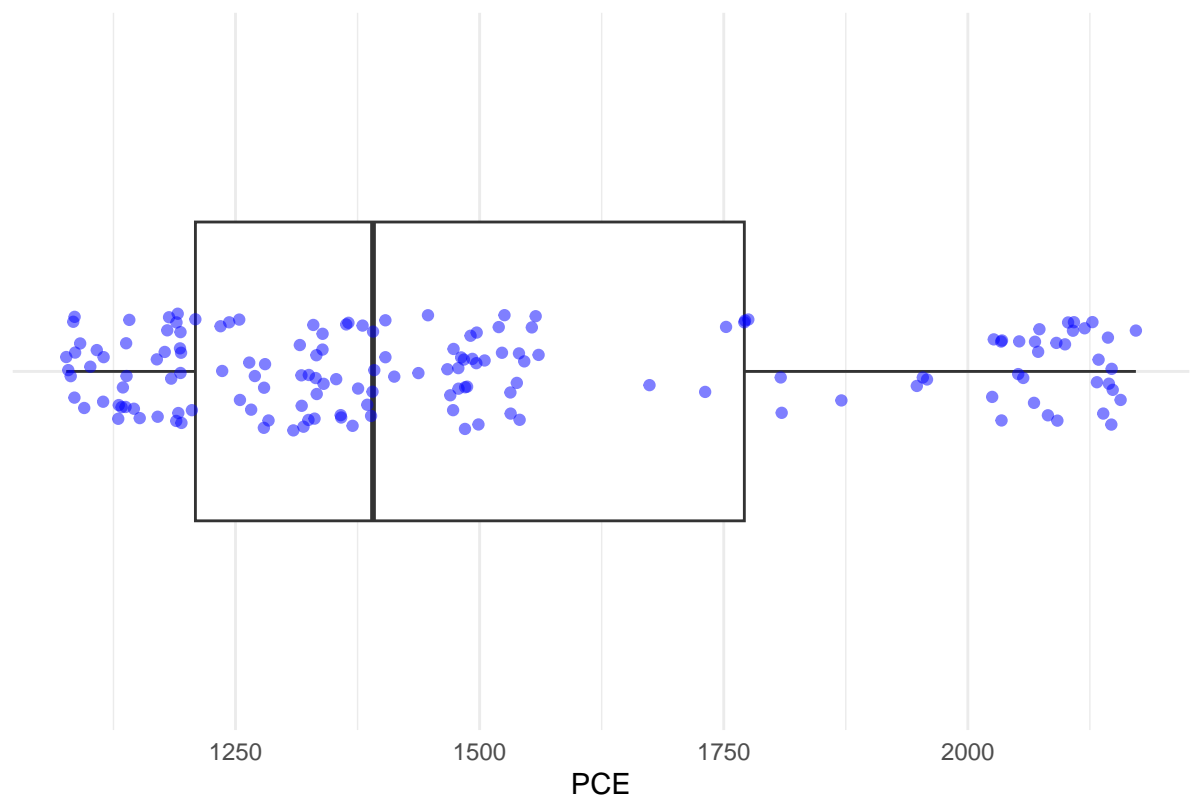
Outlier Detection for PPIBM



```
##
## -----
##
## =====
## === Variable: PCE ===
## =====
##
## Outlier Detection Results:
##
```

```
## IQR method
## IQR bounds: Lower = 365.6 , Upper = 2614.4
##
## Summary Statistics:
## $mean
## [1] 1505.364
##
## $median
## [1] 1390.8
##
## $sd
## [1] 348.248
##
## $Q1
## 25%
## 1208.9
##
## $Q3
## 75%
## 1771.1
```

Outlier Detection for PCE



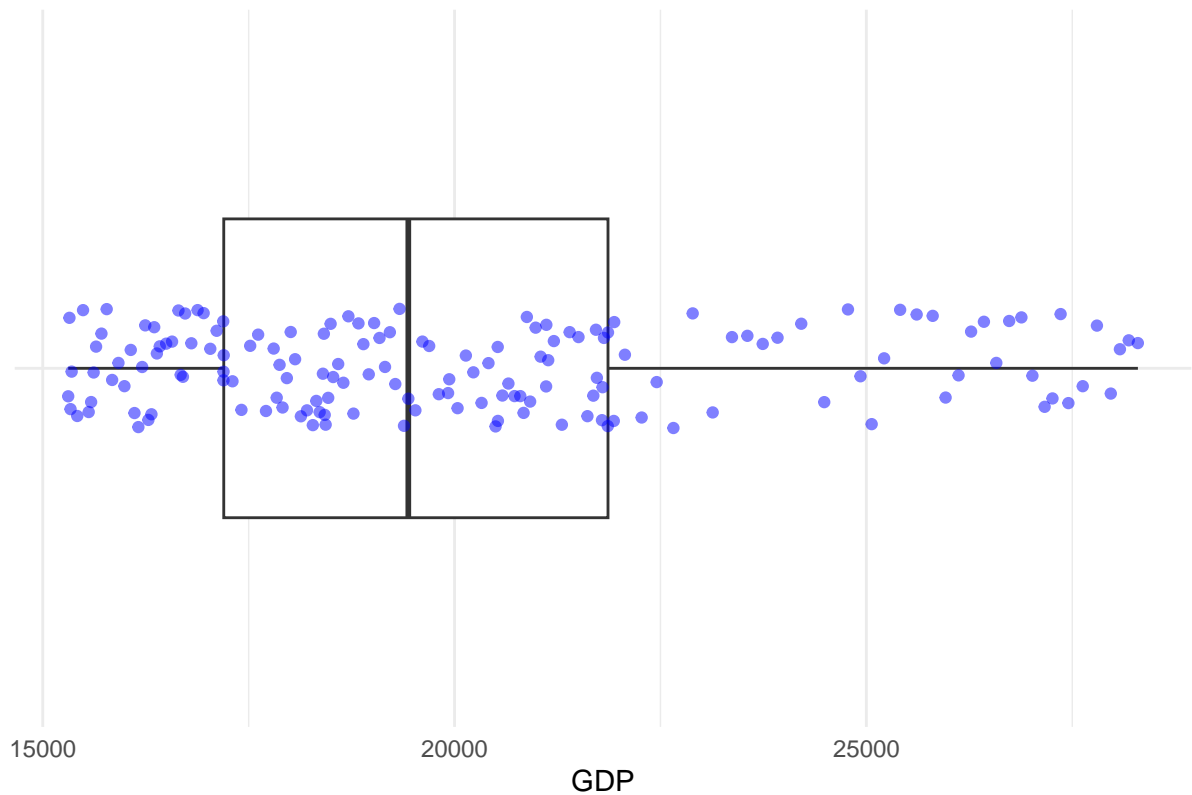
```
##
```

```

## -----
##
## =====
## === Variable: GDP ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 10199.46 , Upper = 28861.44
##
## Summary Statistics:
## $mean
## [1] 20194.55
##
## $median
## [1] 19438.6
##
## $sd
## [1] 3578.868
##
## $Q1
##      25%
## 17197.7
##
## $Q3
##      75%
## 21863.19

```

Outlier Detection for GDP

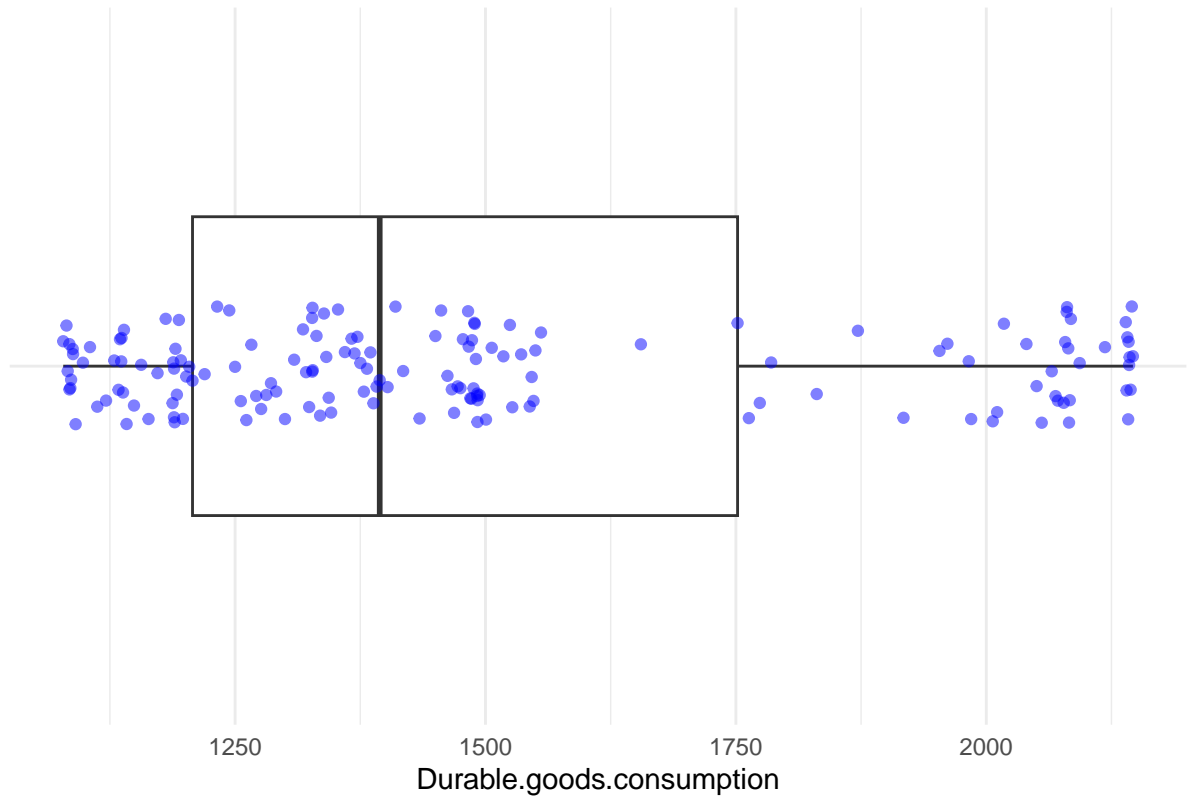


```
##
## -----
##
## =====
## === Variable: Durable.goods.consumption ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 391.2 , Upper = 2568
##
## Summary Statistics:
## $mean
## [1] 1498.626
##
## $median
## [1] 1394.4
##
## $sd
## [1] 343.381
```



```
##
## $Q1
##      25%
## 1207.5
##
## $Q3
##      75%
## 1751.7
```

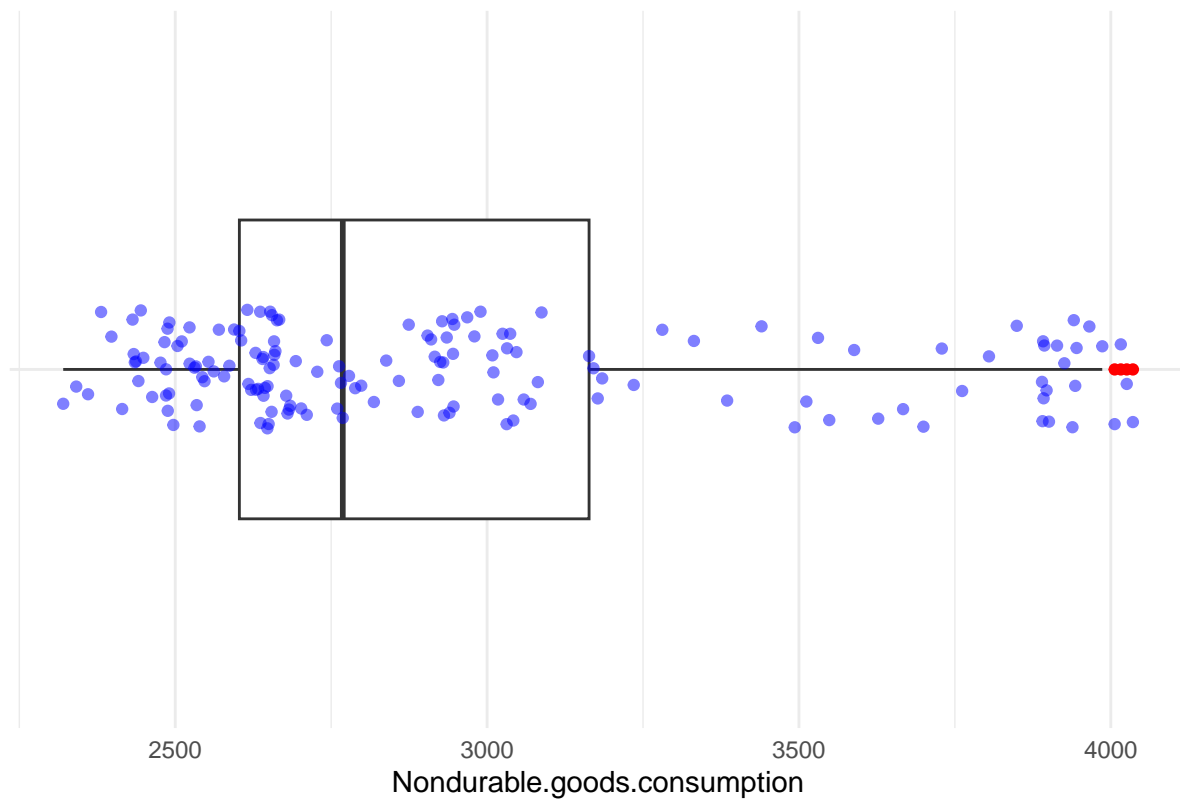
Outlier Detection for Durable.goods.consumption



```
##
## -----
##
## =====
## === Variable: Nondurable.goods.consumption ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 1761.75 , Upper = 4004.55
##
## IQR outliers
```

```
## Number of outliers: 4
## Outlier values: 4006.2, 4016.039, 4025.561, 4035.4
##
## Summary Statistics:
## $mean
## [1] 2953.967
##
## $median
## [1] 2768.6
##
## $sd
## [1] 493.195
##
## $Q1
## 25%
## 2602.8
##
## $Q3
## 75%
## 3163.5
```

Outlier Detection for Nondurable.goods.consumption



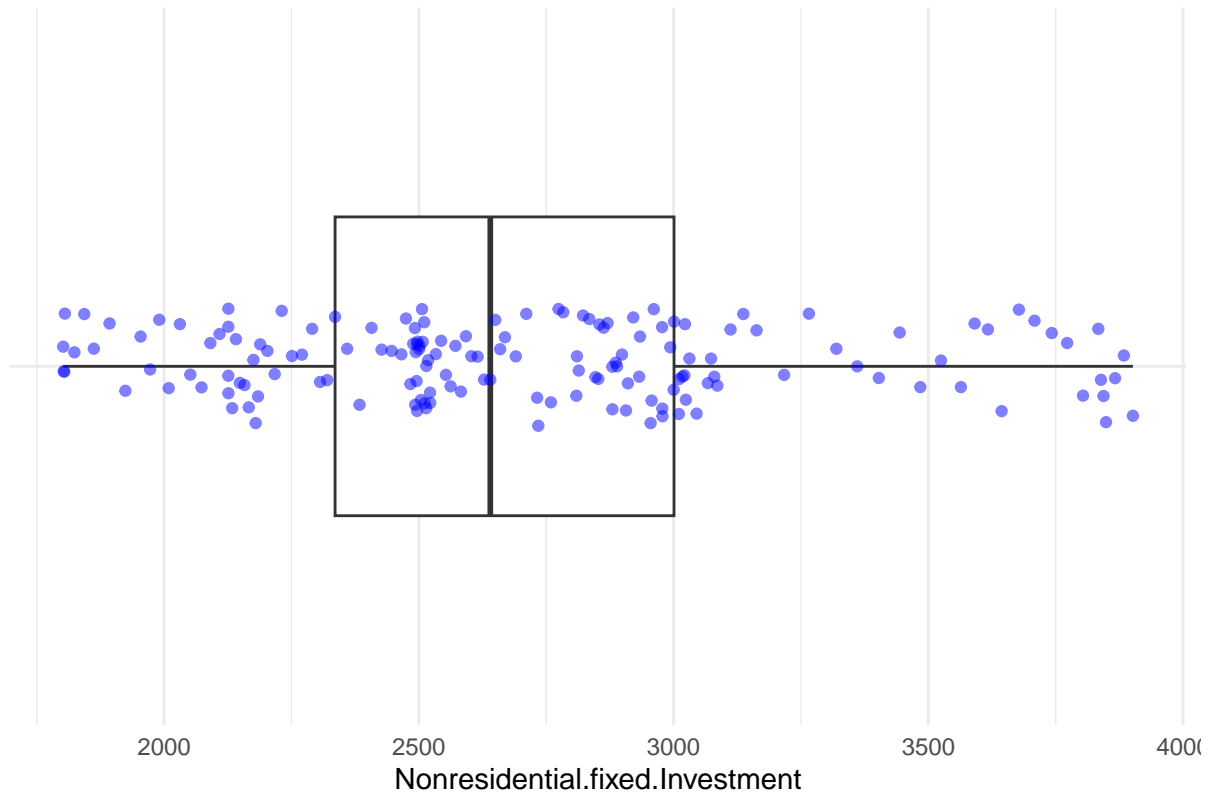
```
##
```

```

## -----
##
## =====
## === Variable: Nonresidential.fixed.Investment ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 1337.55 , Upper = 3998.75
##
## Summary Statistics:
## $mean
## [1] 2711.07
##
## $median
## [1] 2640.2
##
## $sd
## [1] 524.978
##
## $Q1
##      25%
## 2335.5
##
## $Q3
##      75%
## 3000.8

```

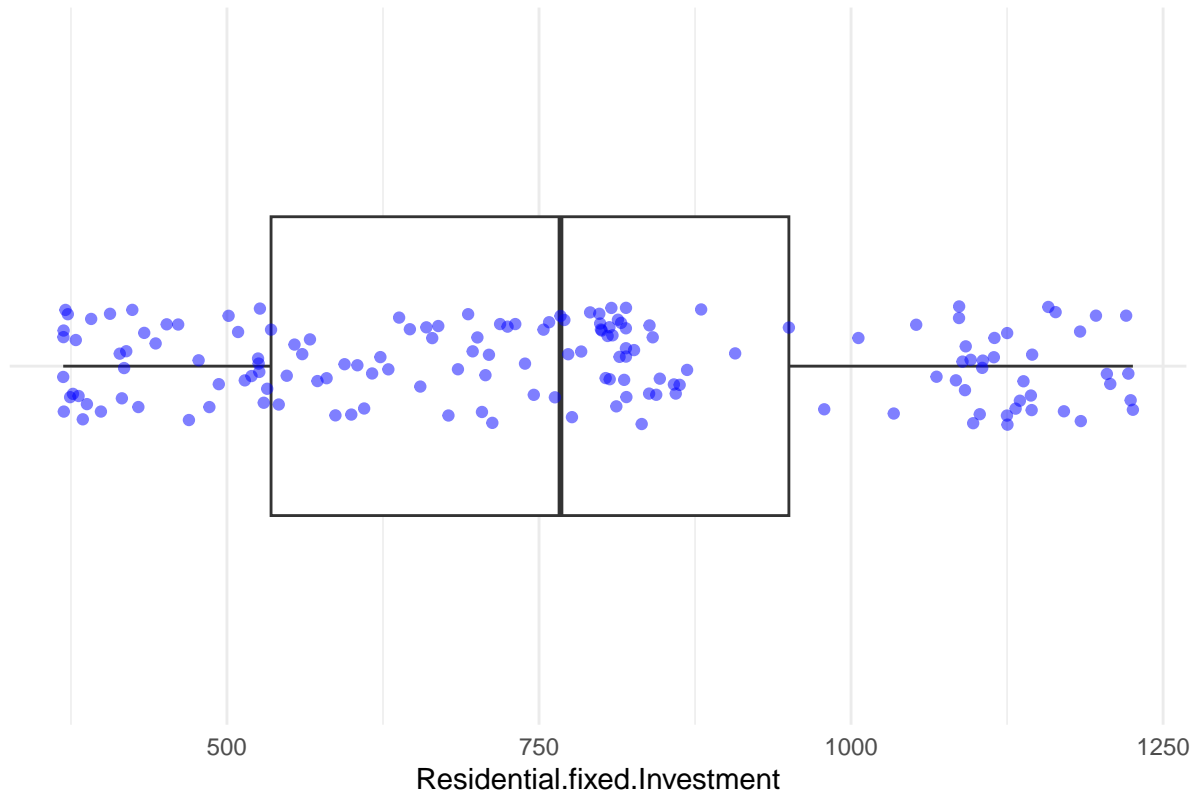
Outlier Detection for Nonresidential.fixed.Investment



```
##
## -----
##
## =====
## === Variable: Residential.fixed.Investment ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = -87.05 , Upper = 1572.55
##
## Summary Statistics:
## $mean
## [1] 761.288
##
## $median
## [1] 767.2
##
## $sd
## [1] 257.924
```

```
##
## $Q1
## 25%
## 535.3
##
## $Q3
## 75%
## 950.2
```

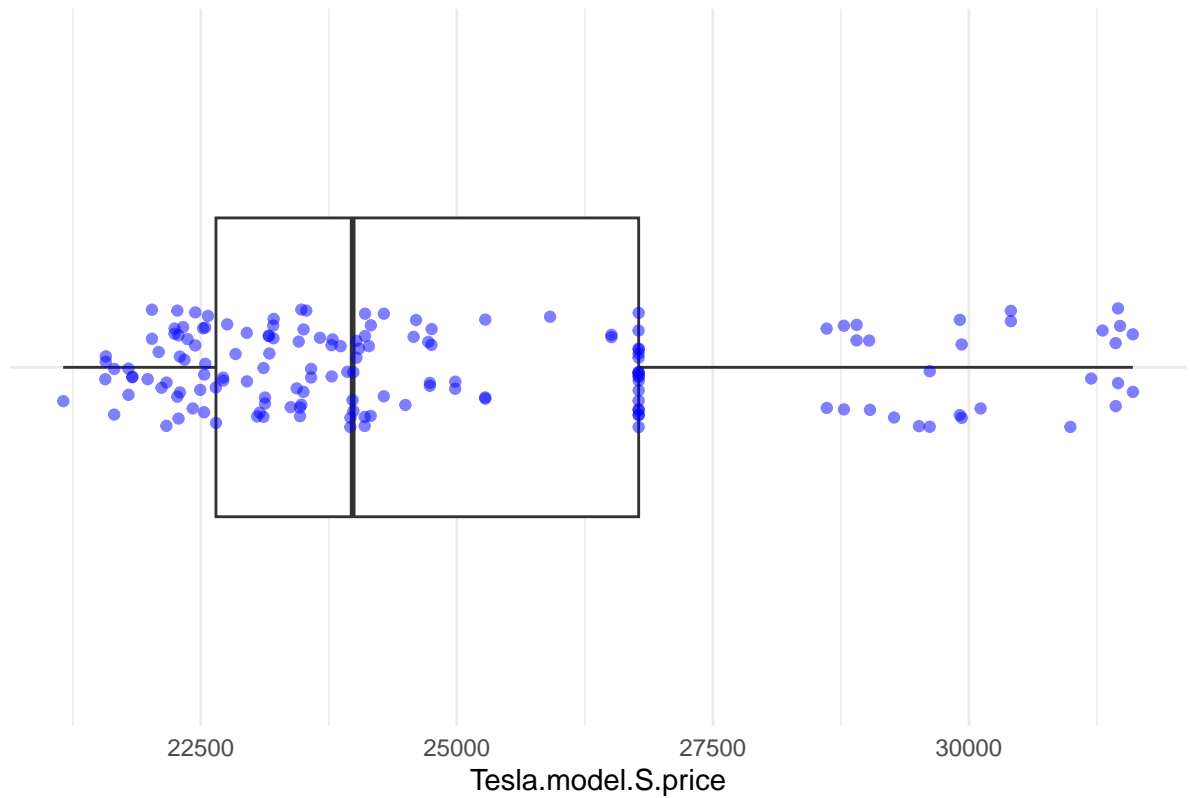
Outlier Detection for Residential.fixed.Investment



```
##
## -----
##
## =====
## === Variable: Tesla.model.S.price ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 16456.83 , Upper = 32966.32
##
## Summary Statistics:
```

```
## $mean
## [1] 24964.04
##
## $median
## [1] 23982.49
##
## $sd
## [1] 2889.943
##
## $Q1
##      25%
## 22647.89
##
## $Q3
##      75%
## 26775.26
```

Outlier Detection for Tesla.model.S.price



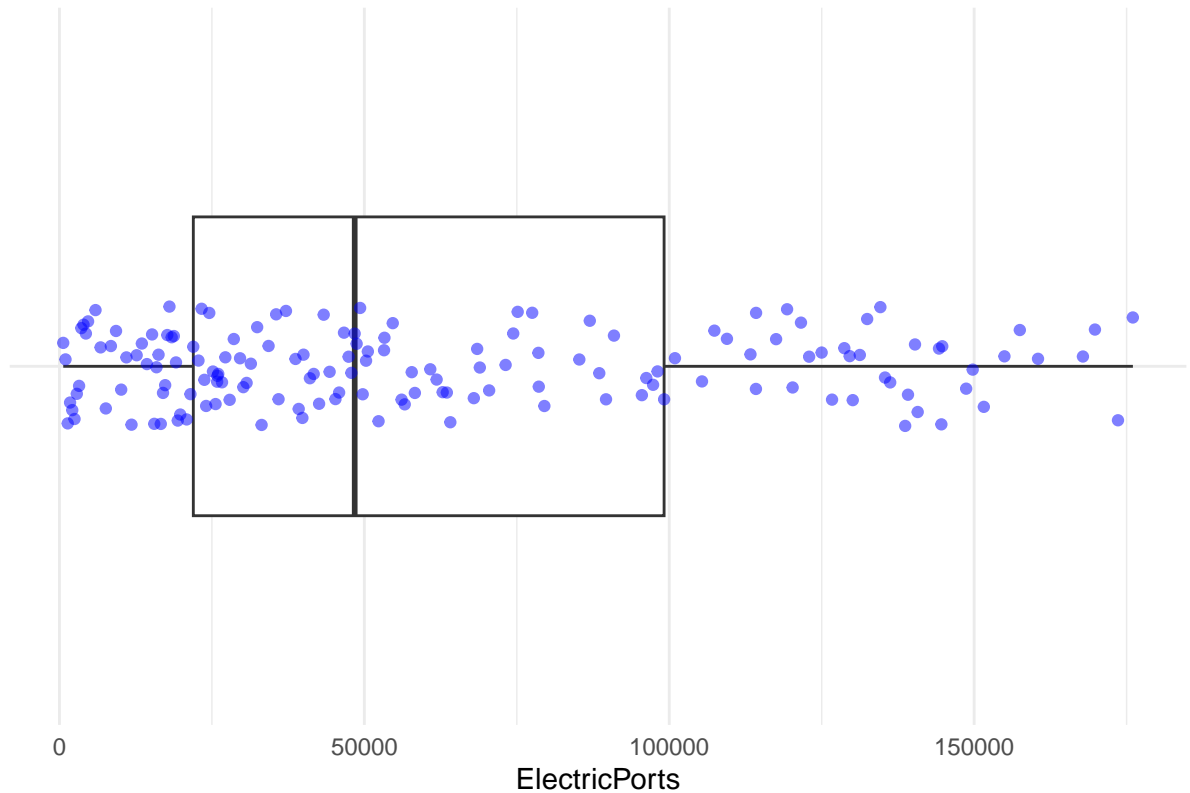
```
##
## -----
##
## =====
## === Variable: ElectricPorts ===
```

```

## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = -93844.5 , Upper = 214951.5
##
## Summary Statistics:
## $mean
## [1] 62525.83
##
## $median
## [1] 48416
##
## $sd
## [1] 48945.74
##
## $Q1
## 25%
## 21954
##
## $Q3
## 75%
## 99153

```

Outlier Detection for ElectricPorts

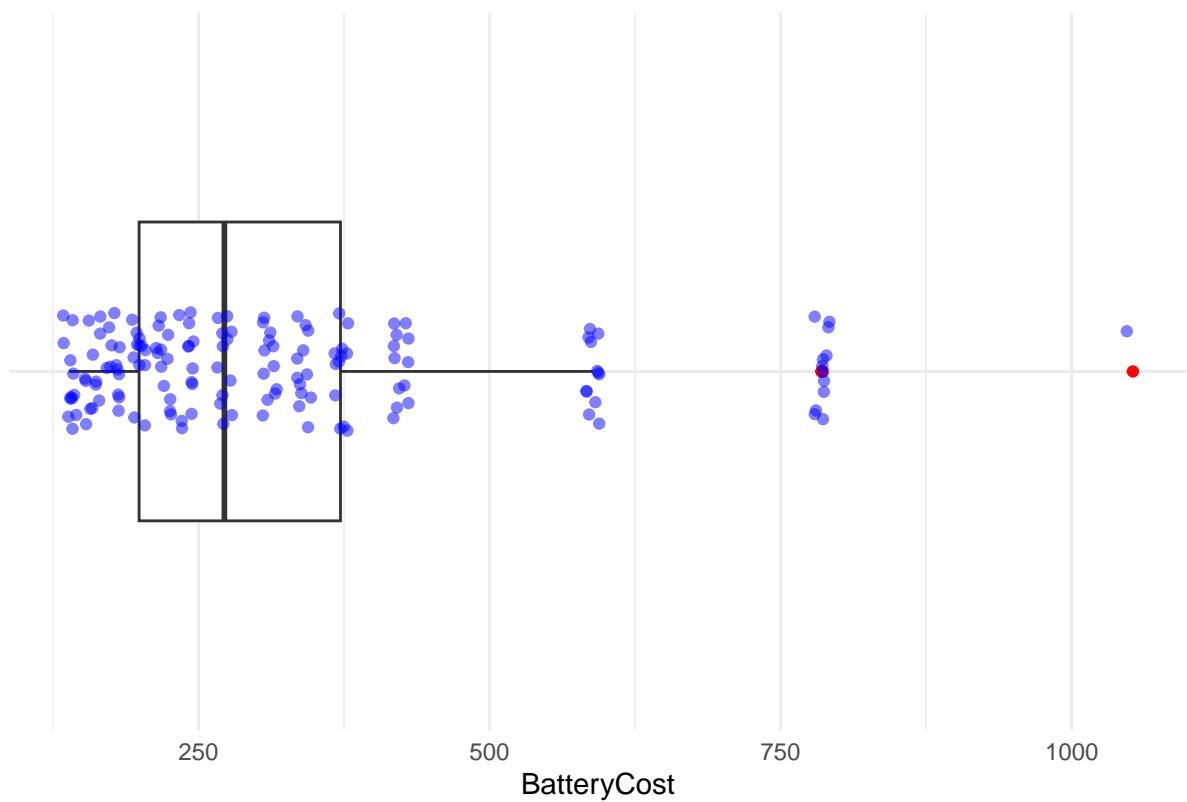


```
##
## -----
##
## =====
## === Variable: BatteryCost ===
## =====
##
## Outlier Detection Results:
##
## Z-score method ( $|z| > 3$ )
## Number of outliers: 1
## Outlier values: 1052.559
##
## IQR method
## IQR bounds: Lower = -60.541 , Upper = 631.478
##
## IQR outliers
## Number of outliers: 13
## Outlier values: 1052.559, 785.396, 785.396, 785.396, 785.396, 785.396, 785.396, 785.396, 785.396, 785.396, 785.396, 785.396, 785.396
##
## Modified Z-score method ( $|\text{modified } z| > 3.5$ )
```



```
## Number of outliers: 1
## Outlier values: 1052.559
##
## Summary Statistics:
## $mean
## [1] 329.734
##
## $median
## [1] 272.233
##
## $sd
## [1] 187.858
##
## $Q1
##      25%
## 198.966
##
## $Q3
##      75%
## 371.971
```

Outlier Detection for BatteryCost



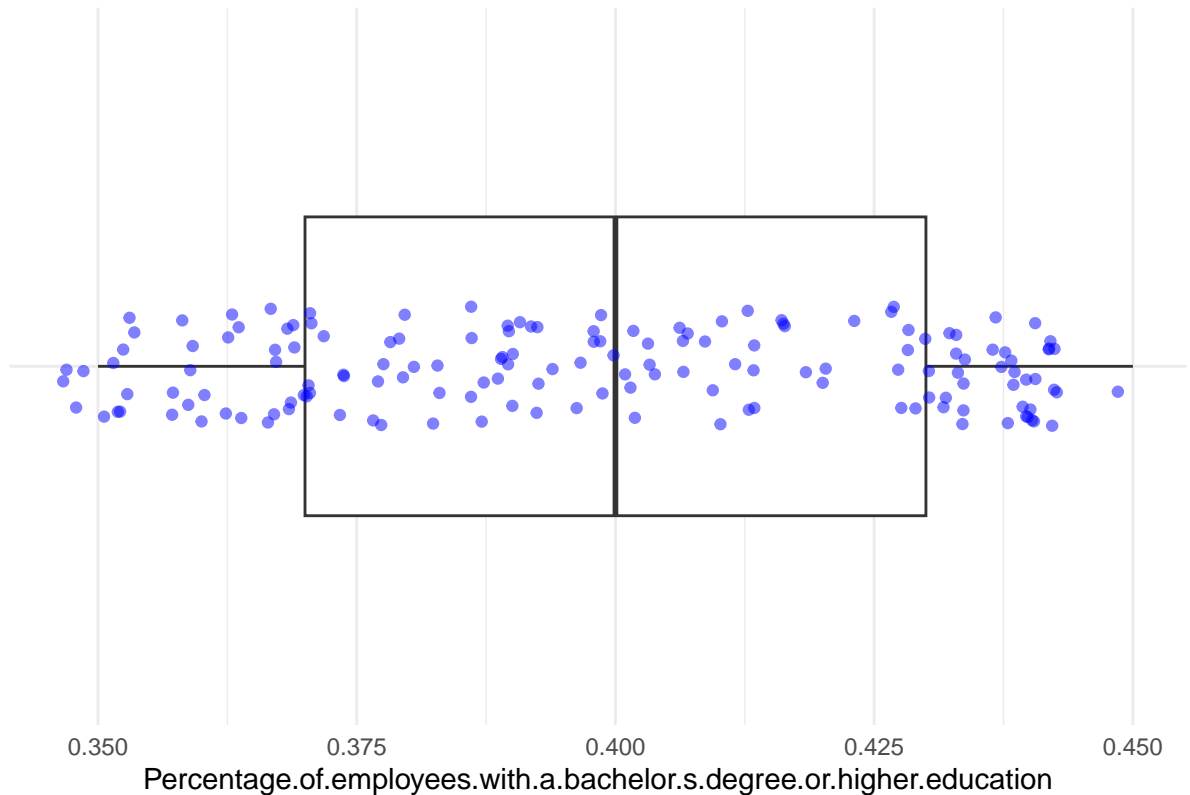
```
##
```

```

## -----
##
## =====
## === Variable: Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 0.28 , Upper = 0.52
##
## Summary Statistics:
## $mean
## [1] 0.398
##
## $median
## [1] 0.4
##
## $sd
## [1] 0.03
##
## $Q1
## 25%
## 0.37
##
## $Q3
## 75%
## 0.43

```

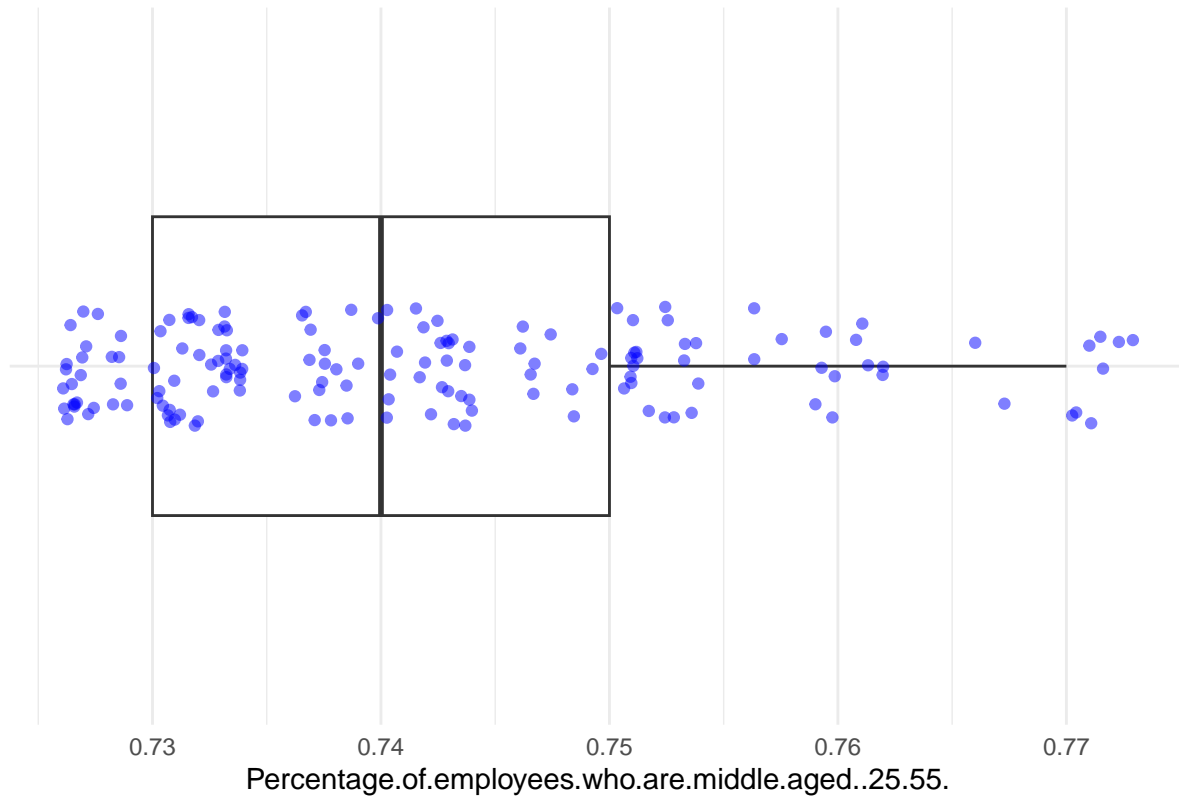
Outlier Detection for Percentage.of.employees.with.a.bachelor.s.degree.or.higl



```
##
## -----
##
## =====
## === Variable: Percentage.of.employees.who.are.middle.aged..25.55. ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 0.7 , Upper = 0.78
##
## Summary Statistics:
## $mean
## [1] 0.742
##
## $median
## [1] 0.74
##
## $sd
## [1] 0.012
```

```
##
## $Q1
## 25%
## 0.73
##
## $Q3
## 75%
## 0.75
```

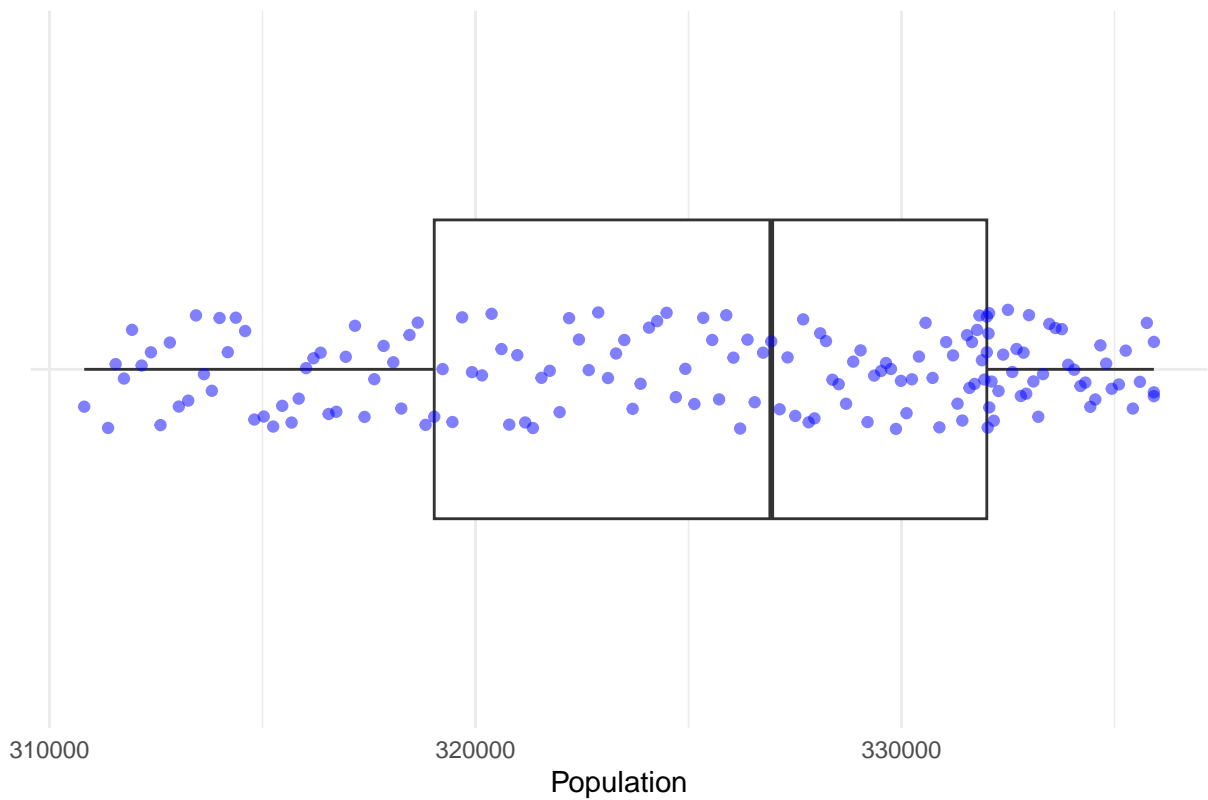
Outlier Detection for Percentage.of.employees.who.are.middle.aged..25.55.



```
##
## -----
##
## =====
## === Variable: Population ===
## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 299576.1 , Upper = 351457
##
## Summary Statistics:
```

```
## $mean
## [1] 325413
##
## $median
## [1] 326942.5
##
## $sd
## [1] 7372.479
##
## $Q1
##      25%
## 319031.5
##
## $Q3
##      75%
## 332001.7
```

Outlier Detection for Population



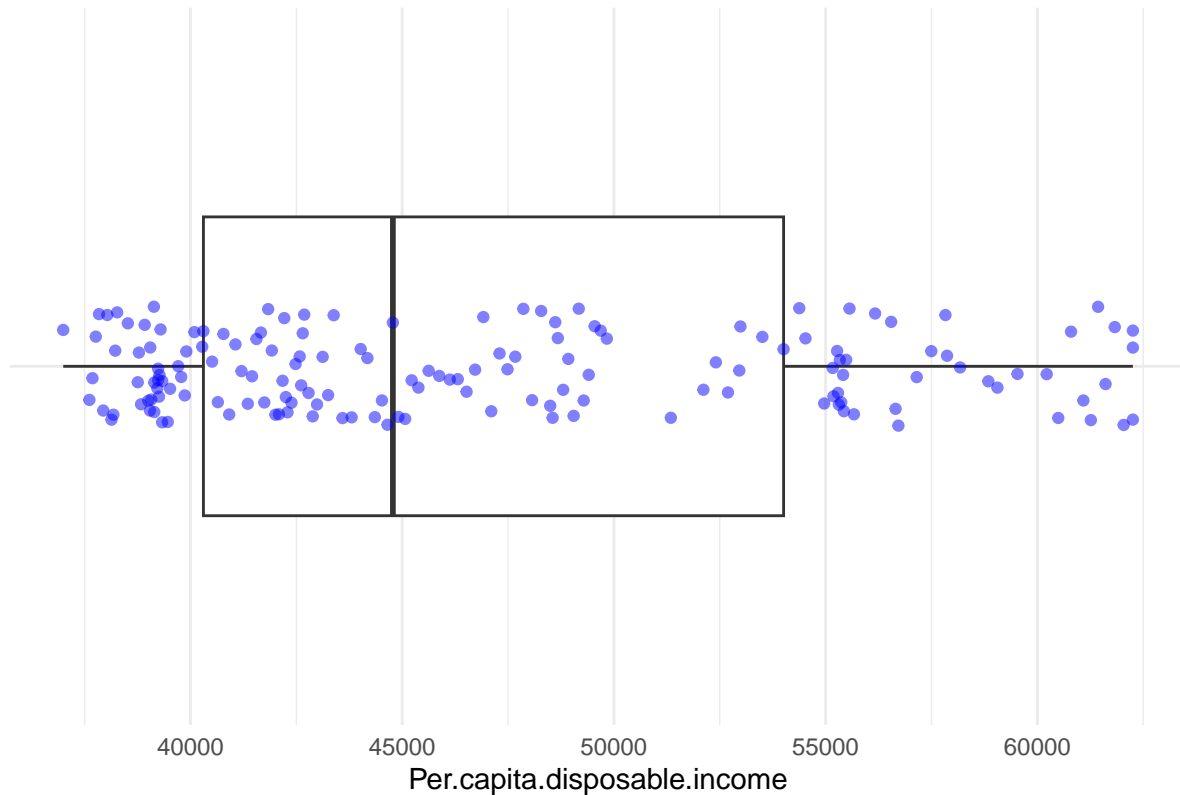
```
##
## -----
##
## =====
## === Variable: Per.capita.disposable.income ===
```

```

## =====
##
## Outlier Detection Results:
##
## IQR method
## IQR bounds: Lower = 19751.03 , Upper = 74561.13
##
## Summary Statistics:
## $mean
## [1] 46949.09
##
## $median
## [1] 44779.71
##
## $sd
## [1] 7481.783
##
## $Q1
##      25%
## 40304.82
##
## $Q3
##      75%
## 54007.35

```

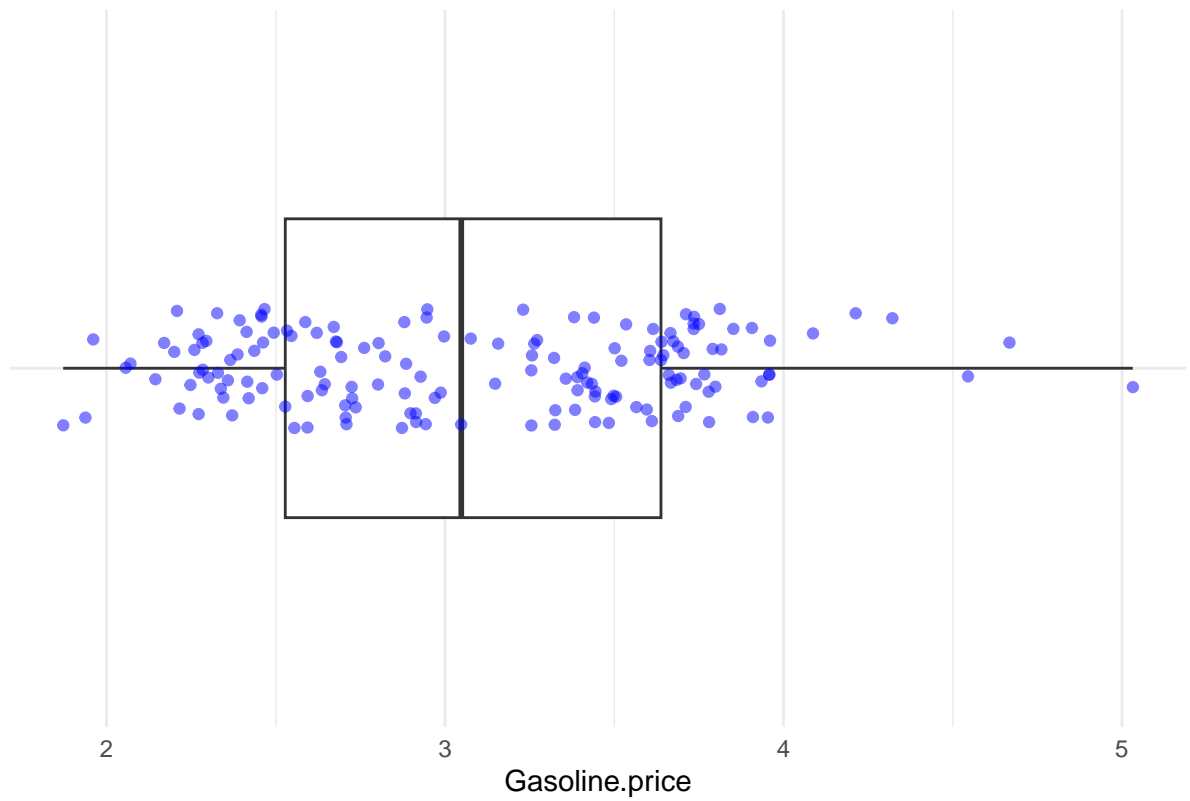
Outlier Detection for Per.capita.disposable.income



```
##
## -----
##
## =====
## === Variable: Gasoline.price ===
## =====
##
## Outlier Detection Results:
##
## Z-score method ( $|z| > 3$ )
## Number of outliers: 1
## Outlier values: 5.032
##
## IQR method
## IQR bounds: Lower = 0.863 , Upper = 5.303
##
## Summary Statistics:
## $mean
## [1] 3.087
##
## $median
```

```
## [1] 3.048
##
## $sd
## [1] 0.637
##
## $Q1
## 25%
## 2.528
##
## $Q3
## 75%
## 3.638
```

Outlier Detection for Gasoline.price



```
##
## -----
##
## =====
## === Variable: Electric.retail.price ===
## =====
##
## Outlier Detection Results:
##
```

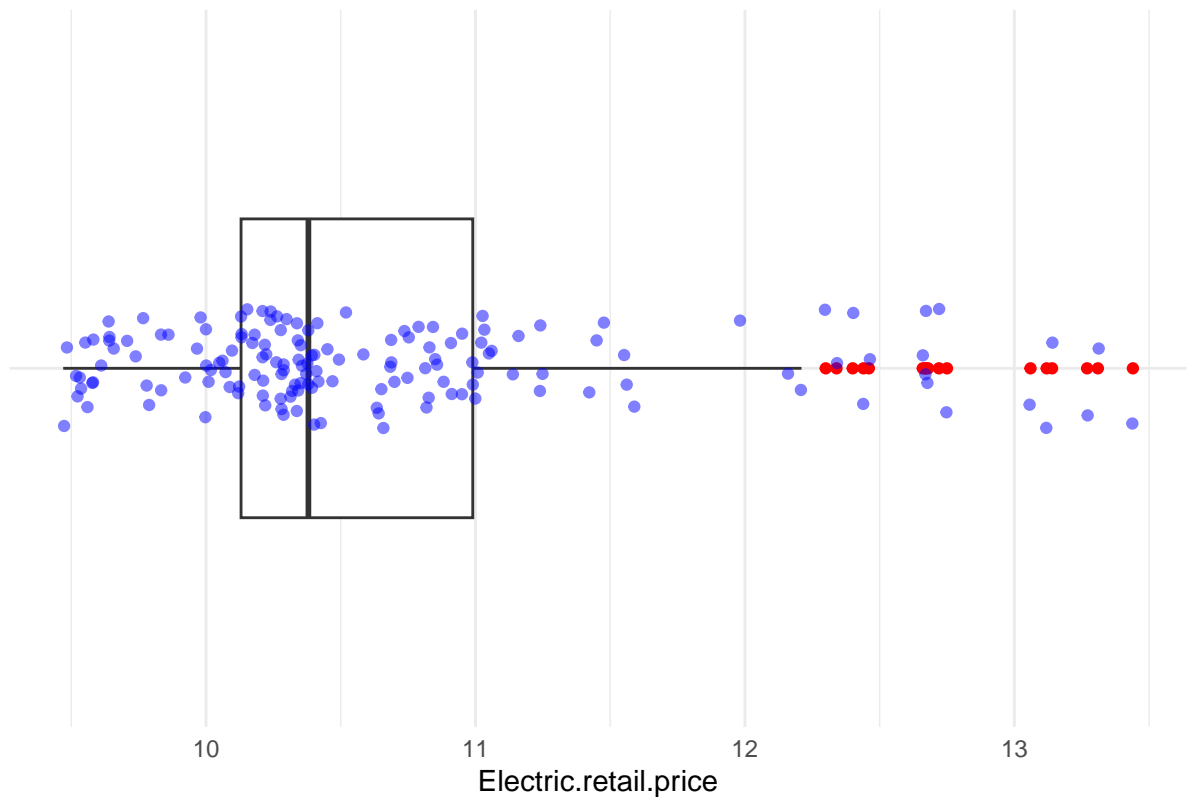


```

## Z-score method ( $|z| > 3$ )
## Number of outliers: 1
## Outlier values: 13.44
##
## IQR method
## IQR bounds: Lower = 8.84 , Upper = 12.28
##
## IQR outliers
## Number of outliers: 17
## Outlier values: 12.75, 13.12, 13.44, 13.31, 12.66, 12.3, 12.4, 12.68, 12.67, 12.46, 1
##
## Summary Statistics:
## $mean
## [1] 10.673
##
## $median
## [1] 10.38
##
## $sd
## [1] 0.918
##
## $Q1
## 25%
## 10.13
##
## $Q3
## 75%
## 10.99

```

Outlier Detection for Electric.retail.price



```
##
```

```
## -----
```

Stepwise MLR

```
install.packages("leaps")
```

```
## 'leaps' MD5
```

```
## Warning: 'leaps'
```

```
## Warning in file.copy(savedcopy, lib, recursive = TRUE):
```

```
## D:\Software\R-4.4.1\library\00LOCK\leaps\libs\x64\leaps.dll D:\Software\R-4.4.1\libr
```

```
## denied
```

```
## Warning: 'leaps'
```

```
##
```

```
##
```

```
## C:\Users\yuanting\AppData\Local\Temp\RtmpWUhATB\downloaded_packages
```

```
library("leaps")
```

```
## Warning: 'leaps' R 4.4.2
```

```

full_model <- lm(data$Total.NEV.Sales~., data = data)
stepwise_model <- step(full_model, direction = "both", trace = 0)
summary(stepwise_model)

##
## Call:
## lm(formula = data$Total.NEV.Sales ~ Month + Date + Covid.19 +
##      Number.of.new.energy.policies + Inventory + Gasoline.LDV.sales +
##      M2SL + Umemployment.rate + PCE + Durable.goods.consumption +
##      Nondurable.goods.consumption + Nonresidential.fixed.Investment +
##      Residential.fixed.Investment + Tesla.model.S.price + ElectricPorts +
##      BatteryCost + Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education +
##      Population, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -23665.1  -3936.7   146.7   3616.7  22207.9
##
## Coefficients:
##                                     Estimate
## (Intercept)                      -2.260e+05
## Month                                7.202e+02
## Date                                1.657e+02
## Covid.19                          -1.253e+04
## Number.of.new.energy.policies      -1.265e+02
## Inventory                           3.758e-02
## Gasoline.LDV.sales                  3.695e-02
## M2SL                               -1.769e+01
## Umemployment.rate                   1.598e+05
## PCE                                 4.052e+01
## Durable.goods.consumption           9.803e+01
## Nondurable.goods.consumption         6.942e+01
## Nonresidential.fixed.Investment      -7.402e+01
## Residential.fixed.Investment         -1.212e+02
## Tesla.model.S.price                  2.816e+00
## ElectricPorts                       9.869e-01
## BatteryCost                         -6.182e+01
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education -3.573e+05
## Population                          -2.065e+01
##                                     Std. Error
## (Intercept)                      6.211e+05
## Month                            2.193e+02
## Date                             5.764e+01
## Covid.19                         4.596e+03

```

## Number.of.new.energy.policies	2.333e+01
## Inventory	8.642e-03
## Gasoline.LDV.sales	5.178e-03
## M2SL	4.651e+00
## Unemployment.rate	1.024e+05
## PCE	1.881e+01
## Durable.goods.consumption	3.106e+01
## Nondurable.goods.consumption	2.902e+01
## Nonresidential.fixed.Investment	2.564e+01
## Residential.fixed.Investment	4.047e+01
## Tesla.model.S.price	1.150e+00
## ElectricPorts	3.611e-01
## BatteryCost	1.802e+01
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	1.670e+05
## Population	6.372e+00
##	t value
## (Intercept)	-0.364
## Month	3.283
## Date	2.874
## Covid.19	-2.727
## Number.of.new.energy.policies	-5.423
## Inventory	4.349
## Gasoline.LDV.sales	7.135
## M2SL	-3.803
## Unemployment.rate	1.560
## PCE	2.154
## Durable.goods.consumption	3.156
## Nondurable.goods.consumption	2.393
## Nonresidential.fixed.Investment	-2.886
## Residential.fixed.Investment	-2.994
## Tesla.model.S.price	2.449
## ElectricPorts	2.733
## BatteryCost	-3.432
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	-2.140
## Population	-3.241
##	Pr(> t)
## (Intercept)	0.716547
## Month	0.001300
## Date	0.004689
## Covid.19	0.007226
## Number.of.new.energy.policies	2.55e-07
## Inventory	2.64e-05
## Gasoline.LDV.sales	4.98e-11
## M2SL	0.000214
## Unemployment.rate	0.121025

```
## PCE 0.032941
## Durable.goods.consumption 0.001961
## Nondurable.goods.consumption 0.018078
## Nonresidential.fixed.Investment 0.004525
## Residential.fixed.Investment 0.003263
## Tesla.model.S.price 0.015569
## ElectricPorts 0.007104
## BatteryCost 0.000792
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education 0.034152
## Population 0.001495
##
## (Intercept)
## Month **
## Date **
## Covid.19 **
## Number.of.new.energy.policies ***
## Inventory ***
## Gasoline.LDV.sales ***
## M2SL ***
## Unemployment.rate
## PCE *
## Durable.goods.consumption **
## Nondurable.goods.consumption *
## Nonresidential.fixed.Investment **
## Residential.fixed.Investment **
## Tesla.model.S.price *
## ElectricPorts **
## BatteryCost ***
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education *
## Population **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7405 on 138 degrees of freedom
## Multiple R-squared:  0.9838, Adjusted R-squared:  0.9816
## F-statistic: 464.3 on 18 and 138 DF,  p-value: < 2.2e-16
```

```
library(car)
```

```
##      carData
```

```
vif(stepwise_model)
```

```
##      Month
##      1.657330
##      Date
```

```
##                                18101.439629
##                                Covid.19
##                                11.668300
##                                Number.of.new.energy.policies
##                                5.166106
##                                Inventory
##                                34.059699
##                                Gasoline.LDV.sales
##                                3.063568
##                                M2SL
##                                1049.702132
##                                Unemployment.rate
##                                12.613786
##                                PCE
##                                122.058974
##                                Durable.goods.consumption
##                                323.540754
##                                Nondurable.goods.consumption
##                                582.539717
##                                Nonresidential.fixed.Investment
##                                515.587131
##                                Residential.fixed.Investment
##                                309.945416
##                                Tesla.model.S.price
##                                31.408739
##                                ElectricPorts
##                                888.792974
##                                BatteryCost
##                                32.582692
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education
##                                70.251108
##                                Population
##                                6278.272065
```

there is problem with multi colinearity, we should not use all of these predictors

```
data_stepwise <- subset(data, select = -c(M2SL,GDP,Durable.goods.consumption,Nondurable.
data_stepwise0<-data_stepwise
full_model2 <- lm(Total.NEV.Sales~., data = data_stepwise)
stepwise_model2 <- step(full_model2, direction = "both", trace = 0)
summary(stepwise_model2)
```

```
##
## Call:
## lm(formula = Total.NEV.Sales ~ Date + Covid.19 + Number.of.new.energy.policies +
##      Production + Gasoline.LDV.sales + M1SL + Federal.fund.effective.rate +
```

```
##      Umemployment.rate + PPIBC + Tesla.model.S.price + Gasoline.price +
##      Electric.retail.price, data = data_stepwise)
##
## Residuals:
##      Min        1Q    Median        3Q        Max
## -37728  -5242   -588    5908   62345
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -6.345e+05  2.016e+05  -3.148  0.00200 **
## Date          1.634e+01  3.988e+00   4.097  6.97e-05 ***
## Covid.19      -3.250e+04  5.516e+03  -5.892  2.59e-08 ***
## Number.of.new.energy.policies -1.605e+02  3.586e+01  -4.475  1.54e-05 ***
## Production     3.810e-02  2.370e-02   1.608  0.11011
## Gasoline.LDV.sales 3.391e-02  8.076e-03   4.199  4.67e-05 ***
## M1SL           5.750e+00  6.435e-01   8.936  1.76e-15 ***
## Federal.fund.effective.rate  1.627e+06  1.532e+05  10.615 < 2e-16 ***
## Umemployment.rate 3.008e+05  1.023e+05   2.942  0.00380 **
## PPIBC          -1.553e+03  6.110e+02  -2.542  0.01208 *
## Tesla.model.S.price 5.712e+00  1.105e+00   5.168  7.77e-07 ***
## Gasoline.price   1.262e+04  3.191e+03   3.955  0.00012 ***
## Electric.retail.price -7.435e+03  2.963e+03  -2.509  0.01320 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12910 on 144 degrees of freedom
## Multiple R-squared:  0.9485, Adjusted R-squared:  0.9442
## F-statistic: 221 on 12 and 144 DF, p-value: < 2.2e-16
```

```
library(car)
vif(stepwise_model2)
```

```
##              Date              Covid.19
##      28.509174          5.532017
## Number.of.new.energy.policies Production
##      4.016289          4.561375
##      Gasoline.LDV.sales          M1SL
##      2.451947          20.328002
##      Federal.fund.effective.rate Umemployment.rate
##      4.689438          4.137900
##      PPIBC          Tesla.model.S.price
##      6.983916          9.551348
##      Gasoline.price          Electric.retail.price
##      3.862100          6.924861
```

Autocorrelation—adding lagged values

```
library(lmtest)

##      zoo
## Warning:   'zoo' R 4.4.2
##
##      'zoo'
## The following objects are masked from 'package:base':
##
##      as.Date, as.Date.numeric

dwtest(stepwise_model2)

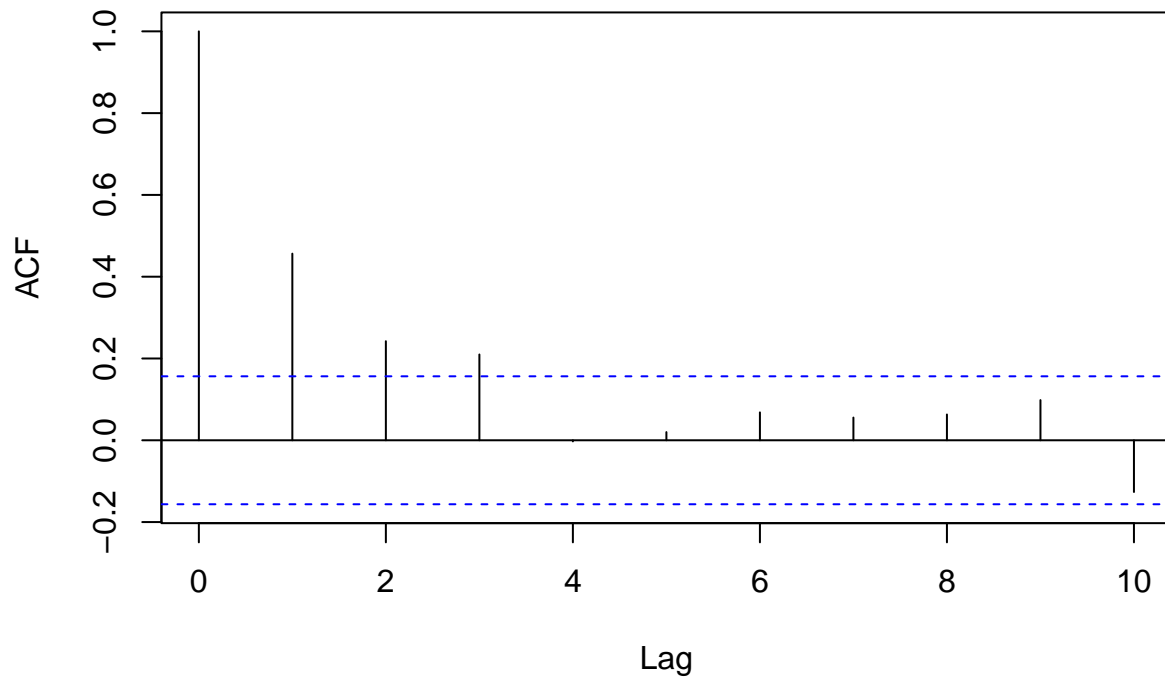
##
## Durbin-Watson test
##
## data:  stepwise_model2
## DW = 0.92266, p-value = 1.541e-14
## alternative hypothesis: true autocorrelation is greater than 0

library(dplyr)

## Warning:   'dplyr' R 4.4.2
##
##      'dplyr'
## The following object is masked from 'package:car':
##
##      recode
## The following objects are masked from 'package:stats':
##
##      filter, lag
## The following objects are masked from 'package:base':
##
##      intersect, setdiff, setequal, union

residuals_lagged <- residuals(stepwise_model2)
acf(residuals_lagged, main = "ACF of Residuals", lag.max = 10)
```


ACF of Residuals



From the ACF of Residuals, the residual autocorrelation at lag orders 1, 7 and 10 is
data_stepwise <- data_stepwise %>%

mutate(lagged_value1 = lag(data_stepwise\$Total.NEV.Sales, n = 1),lagged_value2 = lag(c

data_stepwise <- subset(data_stepwise, select = -c(PPIBM,Date))

test if lagged variables solve the autocorrelation problem

lagged_model <- lm(data_stepwise\$Total.NEV.Sales~., data = data_stepwise)
dwtest(lagged_model)

##

Durbin-Watson test

##

data: lagged_model

DW = 1.8647, p-value = 0.033

alternative hypothesis: true autocorrelation is greater than 0

summary(lagged_model)

##

Call:

```
## lm(formula = data_stepwise$Total.NEV.Sales ~ ., data = data_stepwise)
##
## Residuals:
##      Min        1Q    Median        3Q        Max
## -24667.1  -3802.9   107.8   3869.5  28580.9
##
## Coefficients:
##                                     Estimate Std. Error
## (Intercept)                      -2.247e+04  1.606e+05
## Month                          5.767e+01  2.266e+02
## Covid.19                        3.153e+03  4.305e+03
## Number.of.new.energy.policies  -4.584e+01  2.495e+01
## Production                       9.140e-04  1.693e-02
## Inventory                       2.104e-03  8.814e-03
## Gasoline.LDV.sales              4.820e-02  5.220e-03
## M1SL                           2.272e+00  4.520e-01
## Federal.fund.effective.rate     7.529e+05  1.161e+05
## Unemployment.rate              1.444e+05  6.064e+04
## PPIBC                          -3.979e+02  4.507e+02
## Tesla.model.S.price             1.264e+00  7.506e-01
## BatteryCost                    9.801e+00  1.860e+01
## Percentage.of.employees.who.are.middle.aged..25.55.  2.290e+04  2.257e+05
## Gasoline.price                 4.228e+03  2.004e+03
## Electric.retail.price          -6.482e+03  1.872e+03
## lagged_value1                  3.965e-01  6.398e-02
## lagged_value2                  8.182e-02  6.849e-02
## lagged_value3                  3.786e-01  6.157e-02
##
##                                     t value Pr(>|t|)
## (Intercept)                      -0.140 0.888974
## Month                          0.255 0.799488
## Covid.19                        0.732 0.465159
## Number.of.new.energy.policies  -1.837 0.068433 .
## Production                       0.054 0.957037
## Inventory                       0.239 0.811668
## Gasoline.LDV.sales              9.233 4.88e-16 ***
## M1SL                           5.026 1.56e-06 ***
## Federal.fund.effective.rate     6.485 1.55e-09 ***
## Unemployment.rate              2.381 0.018677 *
## PPIBC                          -0.883 0.378872
## Tesla.model.S.price             1.684 0.094463 .
## BatteryCost                    0.527 0.599018
## Percentage.of.employees.who.are.middle.aged..25.55.  0.101 0.919359
## Gasoline.price                 2.110 0.036715 *
## Electric.retail.price          -3.462 0.000717 ***
## lagged_value1                  6.197 6.52e-09 ***
```

```
## lagged_value2                1.195 0.234324
## lagged_value3                6.148 8.29e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7767 on 135 degrees of freedom
## ( 3 )
## Multiple R-squared:  0.9822, Adjusted R-squared:  0.9799
## F-statistic: 414.9 on 18 and 135 DF,  p-value: < 2.2e-16
```

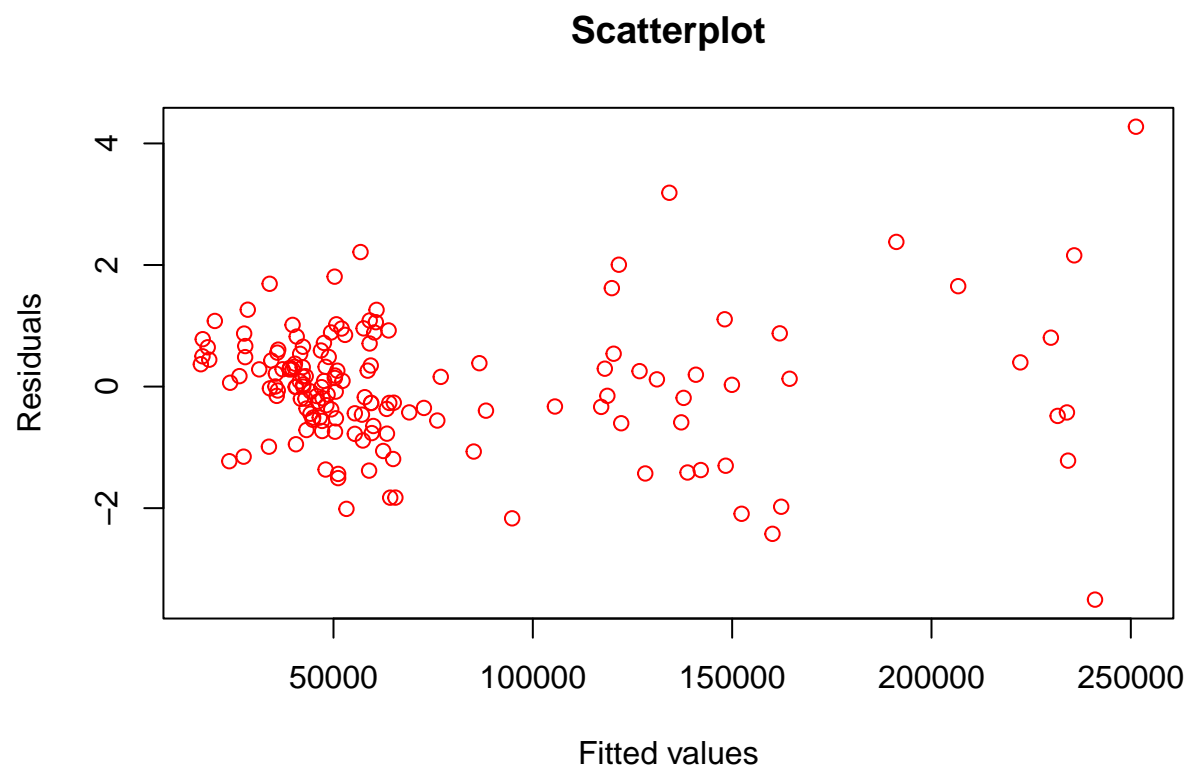
```
library(car)
vif(lagged_model)
```

```
##                               Month
##                               1.538686
##                               Covid.19
##                               9.244310
##                               Number.of.new.energy.policies
##                               5.314122
##                               Production
##                               6.390757
##                               Inventory
##                               32.206621
##                               Gasoline.LDV.sales
##                               2.703344
##                               M1SL
##                               27.374849
##                               Federal.fund.effective.rate
##                               7.380239
##                               Unemployment.rate
##                               3.822012
##                               PPIBC
##                               10.448824
##                               Tesla.model.S.price
##                               12.076718
##                               BatteryCost
##                               26.087605
## Percentage.of.employees.who.are.middle.aged..25.55.
##                               17.365337
##                               Gasoline.price
##                               4.205110
##                               Electric.retail.price
##                               7.400783
##                               lagged_value1
##                               28.389926
```

```
## lagged_value2
## 30.645384
## lagged_value3
## 23.536047
```

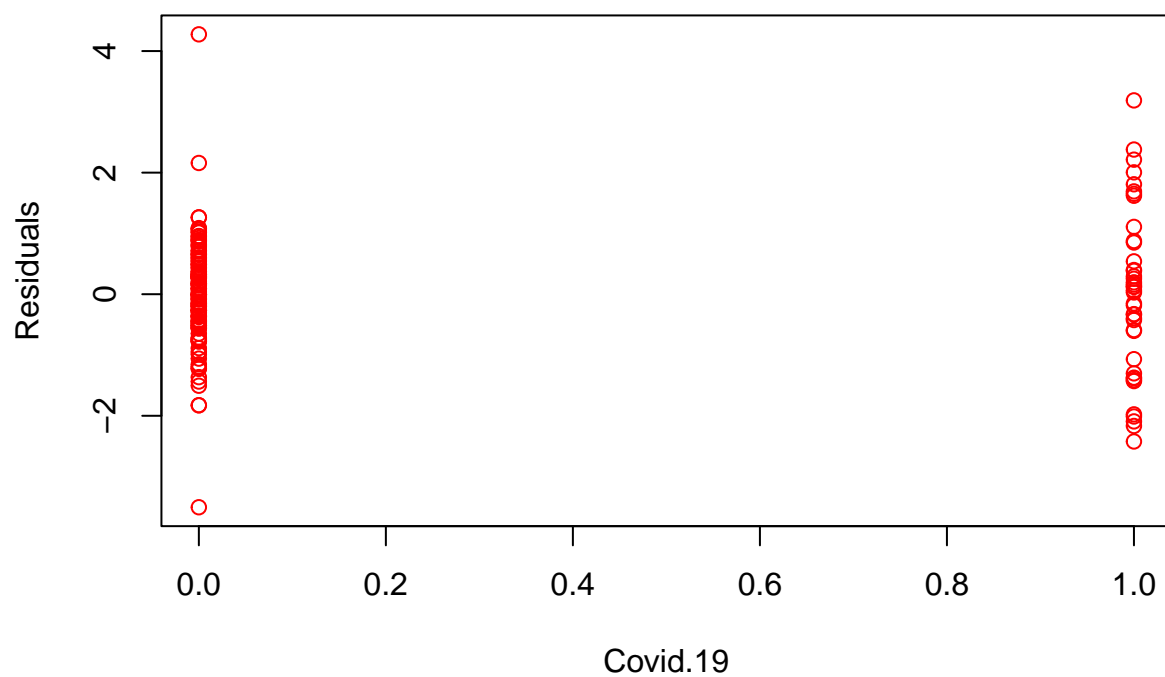
Goodness of fit

```
# Constant Variance Assumption: hold
resids=rstandard(lagged_model)
fits=lagged_model$fitted
plot(fits,resids,xlab="Fitted values",ylab="Residuals",main="Scatterplot",col="red")
```



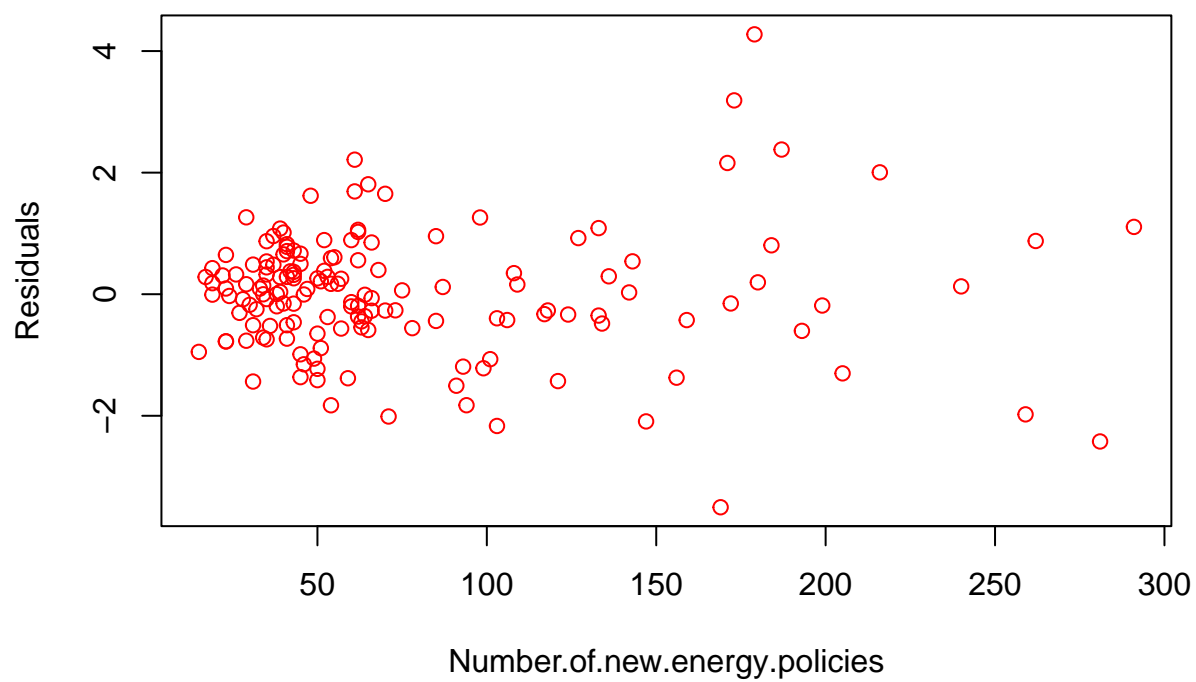
```
# Linearity Assumption: hold
# following codes should be checked according to the variable selection results in cas
plot(data$Covid.19[4:nrow(data)],resids,xlab="Covid.19",ylab="Residuals",main="Scatterpl
```

Scatterplot

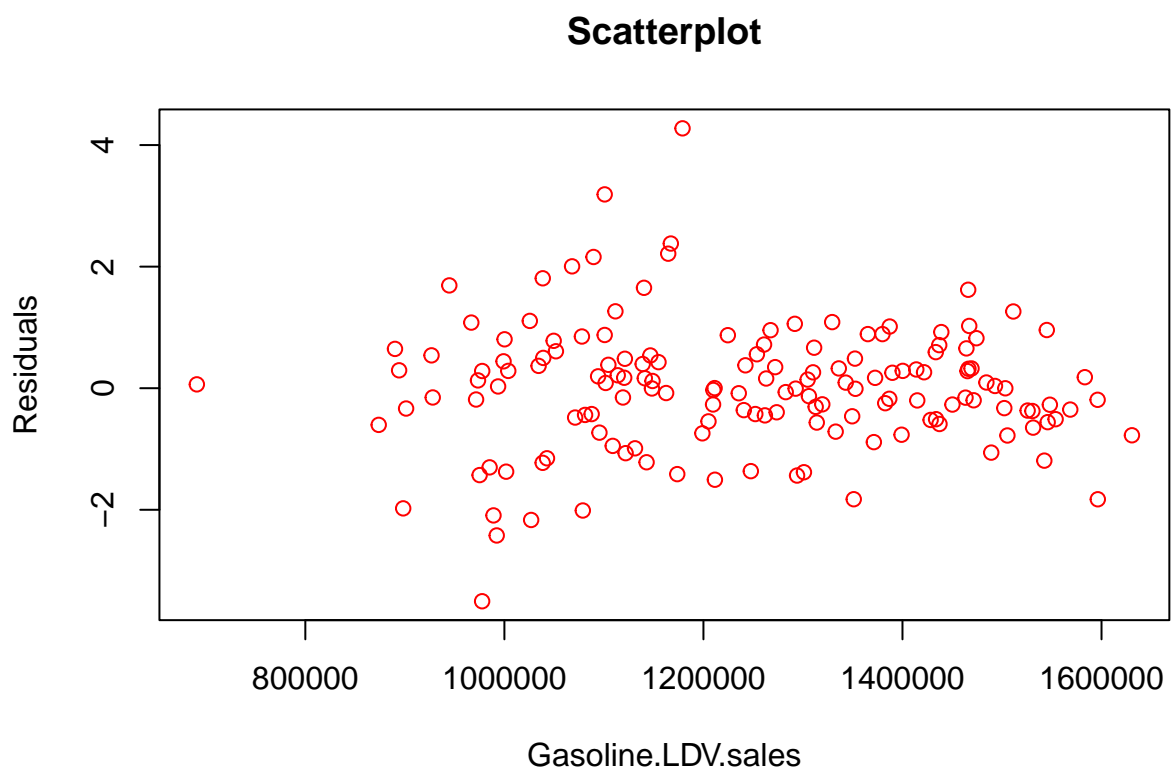


```
plot(data$Number.of.new.energy.policies[4:nrow(data)],resids,xlab="Number.of.new.energy.policies",yresids)
```

Scatterplot

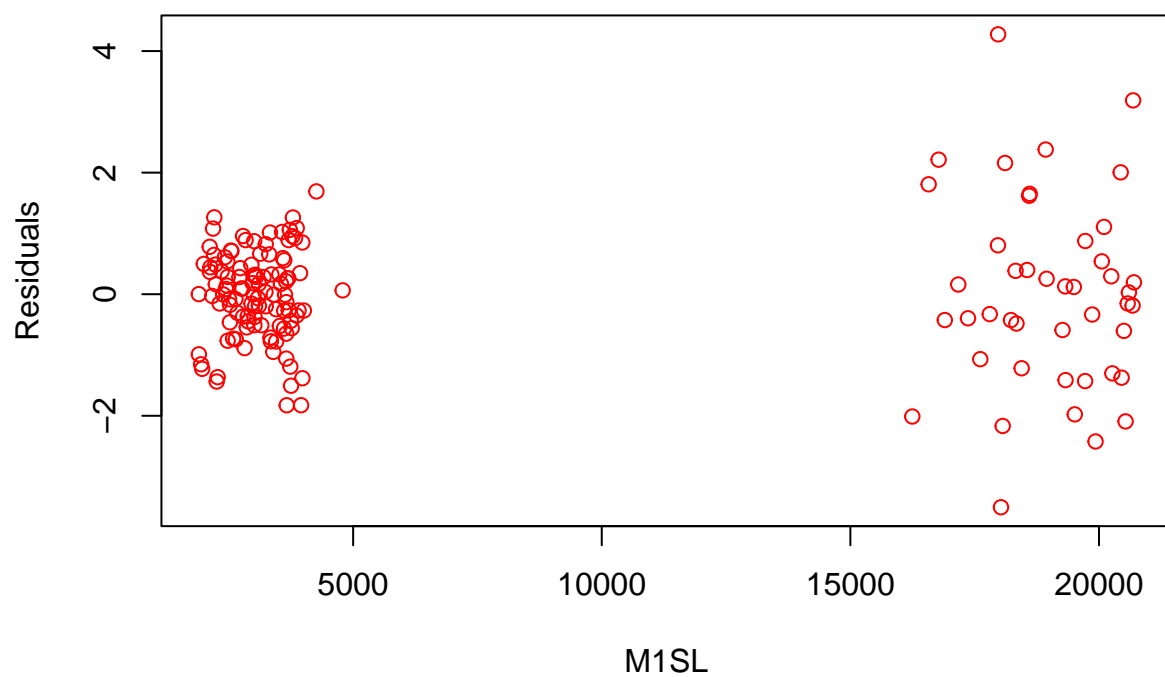


```
plot(data$Gasoline.LDV.sales[4:nrow(data)],resids,xlab="Gasoline.LDV.sales",ylab="Residuals")
```



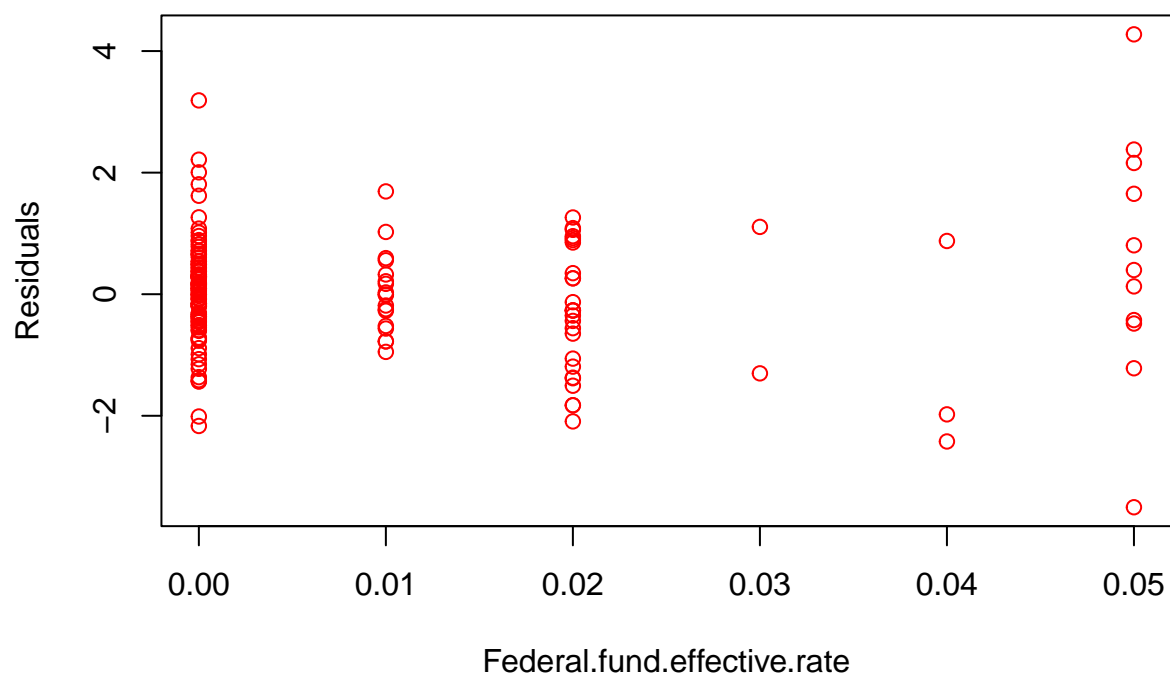
```
plot(data$M1SL[4:nrow(data)],resids,xlab="M1SL",ylab="Residuals",main="Scatterplot",col=
```

Scatterplot



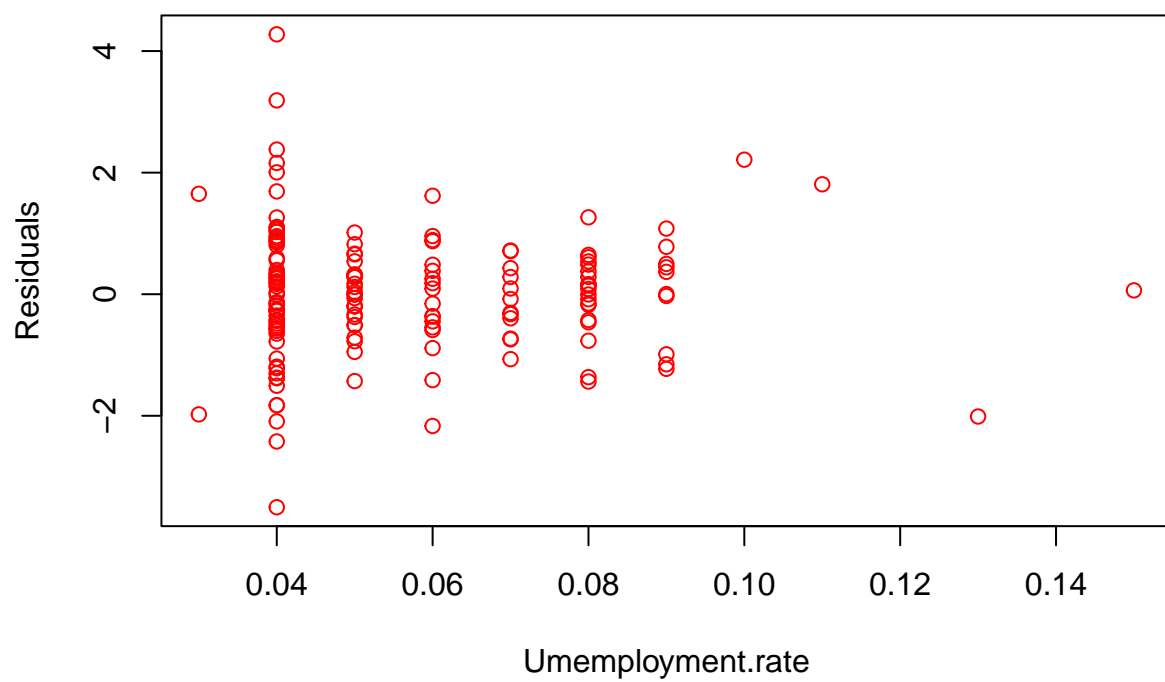
```
plot(data$Federal.fund.effective.rate[4:nrow(data)],resids,xlab="Federal.fund.effective.rate",yresids)
```


Scatterplot

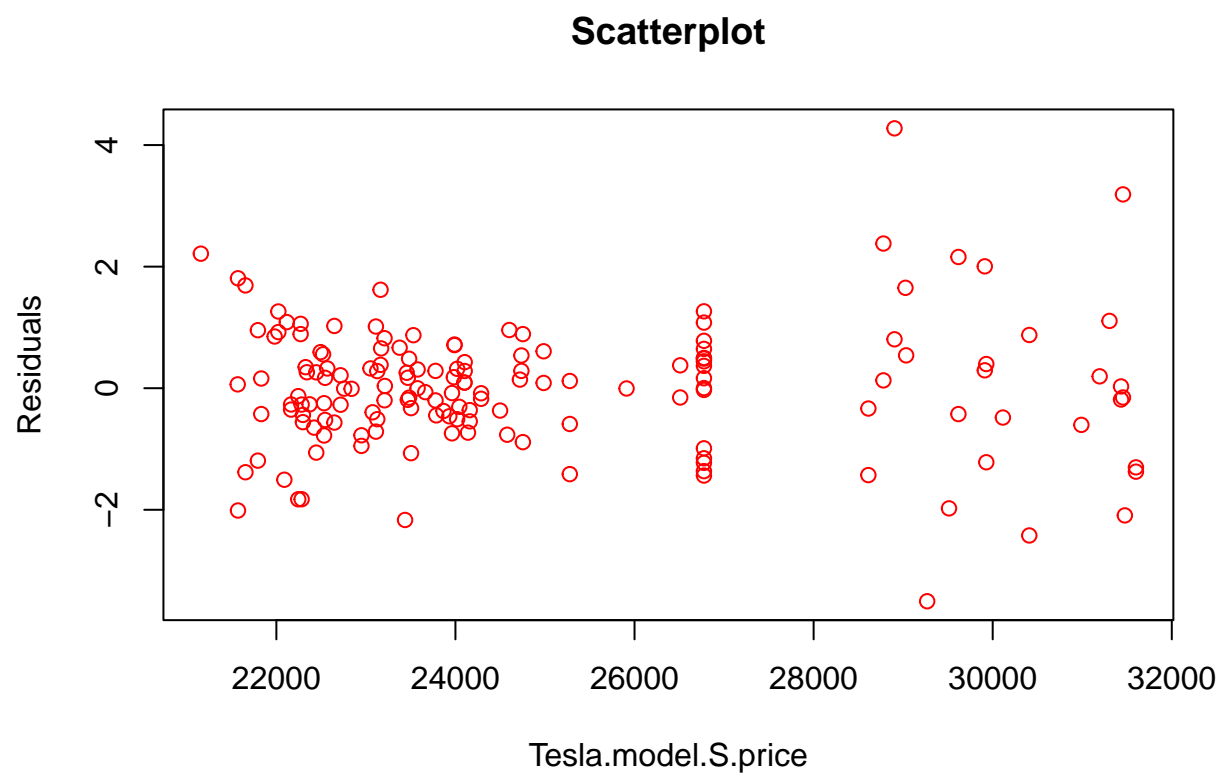


```
plot(data$Unemployment.rate[4:nrow(data)],resids,xlab="Unemployment.rate",ylab="Residuals")
```

Scatterplot

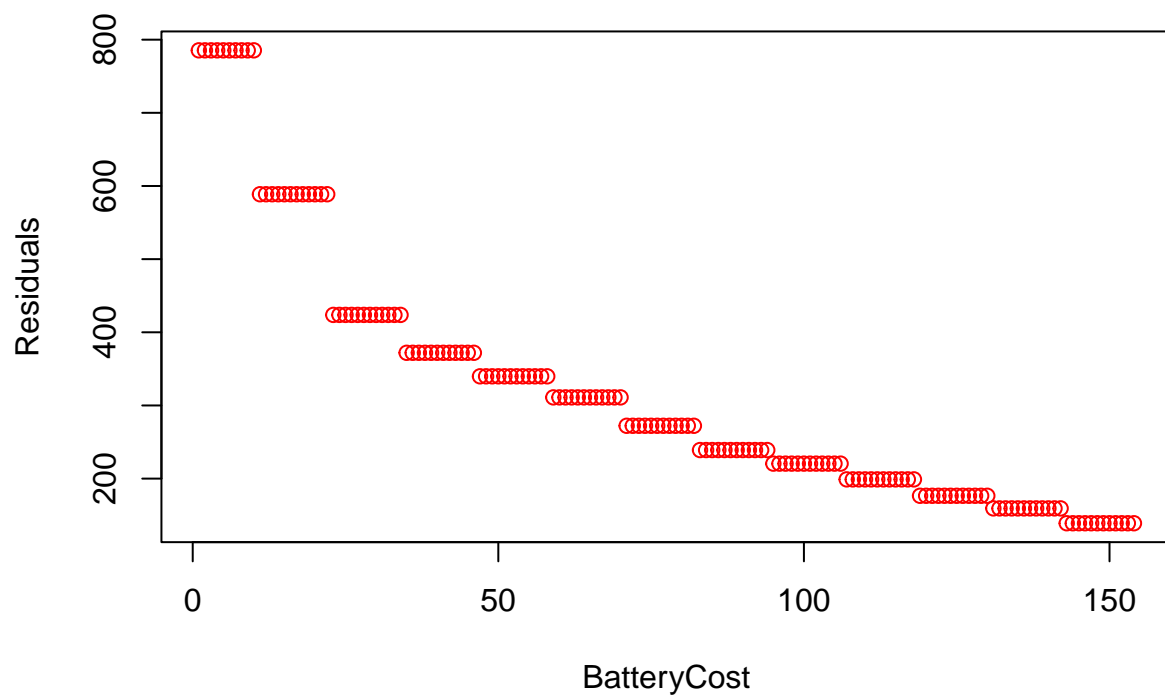


```
plot(data$Tesla.model.S.price[4:nrow(data)],resids,xlab="Tesla.model.S.price",ylab="Resi
```



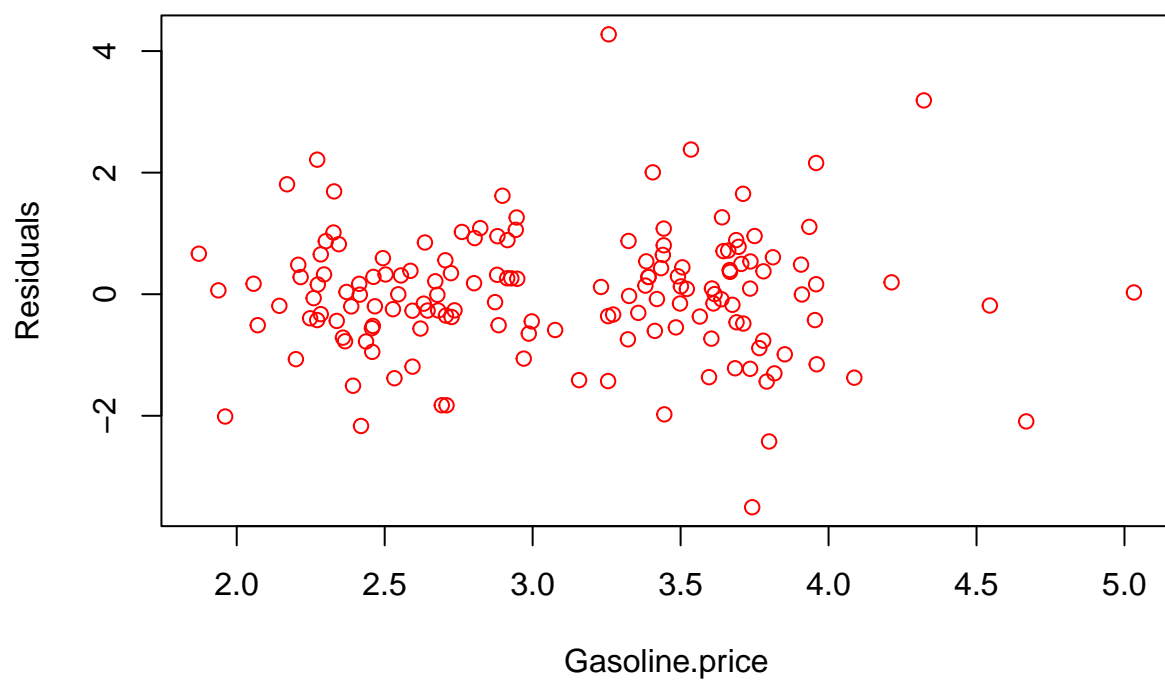
```
plot(data$BatteryCost[4:nrow(data)],xlab="BatteryCost",ylab="Residuals",main="Scatterplot")
```

Scatterplot

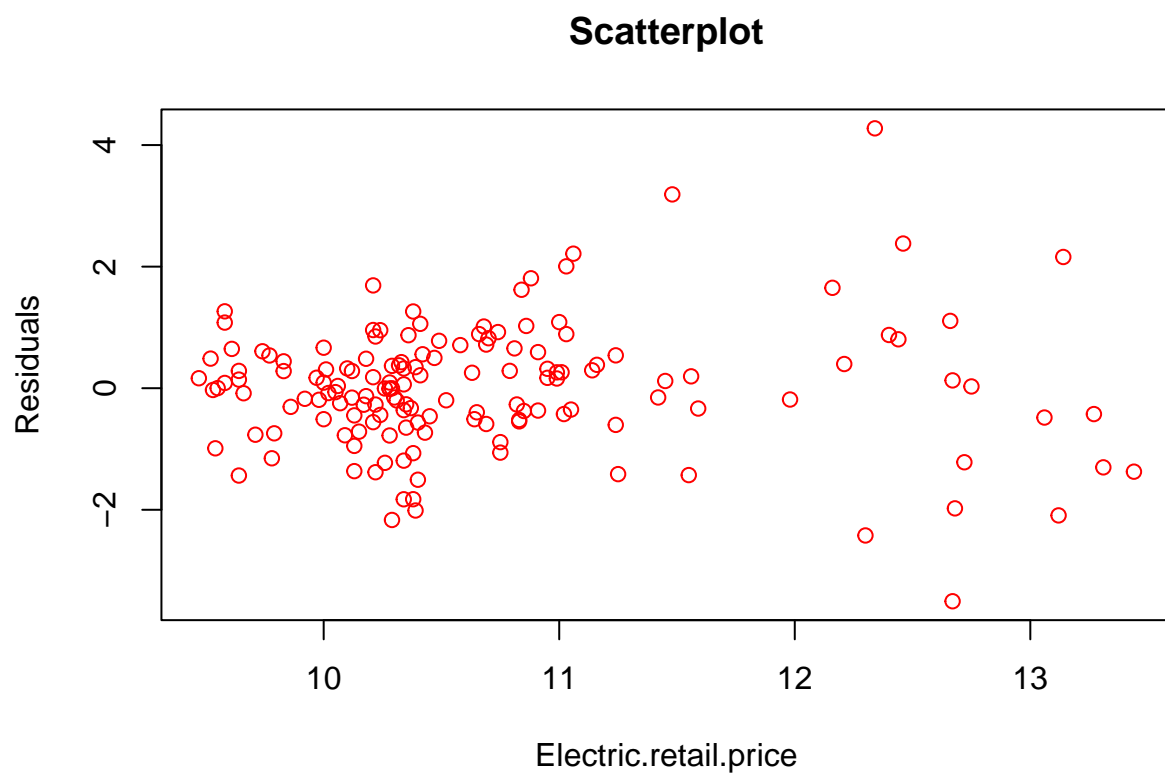


```
plot(data$Gasoline.price[4:nrow(data)],resids,xlab="Gasoline.price",ylab="Residuals",mai
```

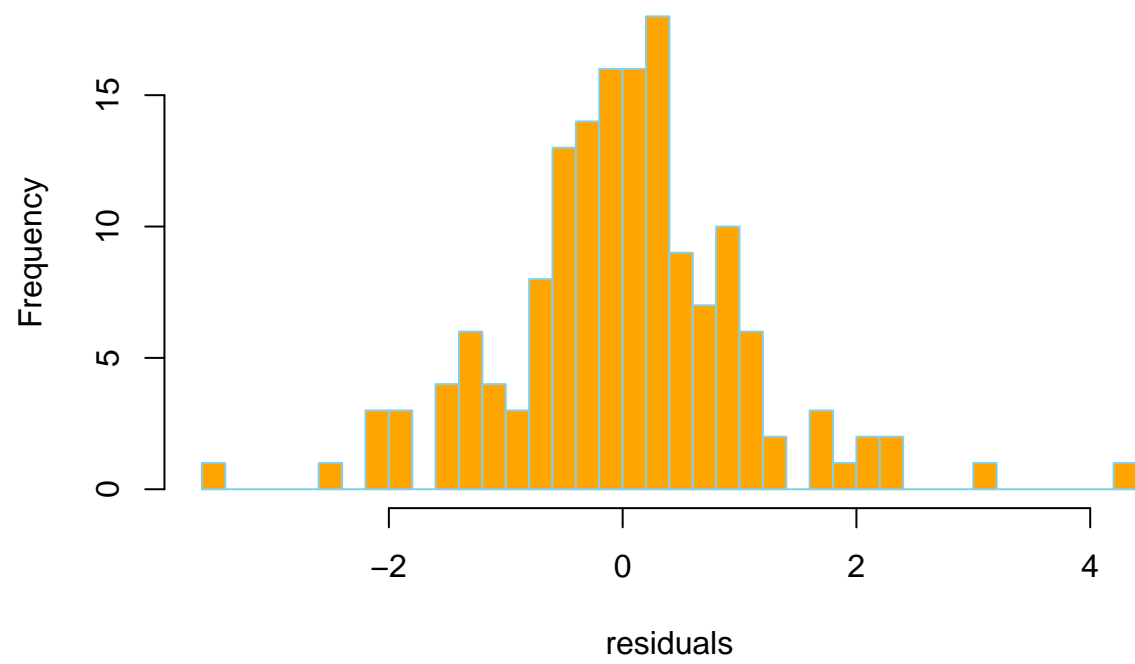
Scatterplot



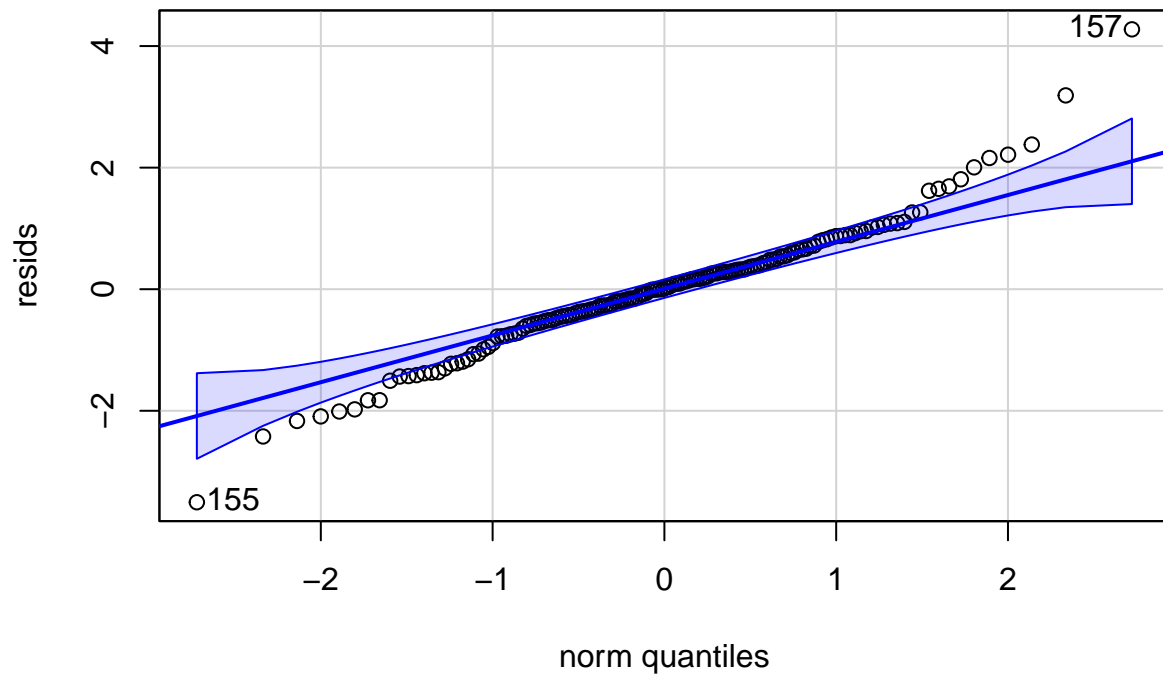
```
plot(data$Electric.retail.price[4:nrow(data)],resids,xlab="Electric.retail.price",ylab="
```



```
# Normality Assumption: hold  
hist(resids,breaks = 30,main="",xlab="residuals",border = "skyblue",col="orange")
```



```
qqPlot(resids)
```



```
## 157 155
## 154 152
```

Goodness of fit: Some Outliers

```
cook=cooks.distance(lagged_model)
outlier_table <- data.frame(Standardized_Residuals=resids,Cooks_Distance = cook)
print(outlier_table)
```

##	Standardized_Residuals	Cooks_Distance
## 4	0.001730881	2.078387e-08
## 5	-0.988794916	8.098317e-03
## 6	-1.152720975	9.388277e-03
## 7	-1.227472874	1.082723e-02
## 8	0.498604927	2.554984e-03
## 9	0.779782974	4.863038e-03
## 10	0.367627509	1.119733e-03
## 11	0.442222028	1.563929e-03
## 12	1.079963505	9.834924e-03
## 13	-0.029014095	6.186683e-06
## 14	0.646659129	2.591857e-03
## 15	1.264789428	8.031495e-03

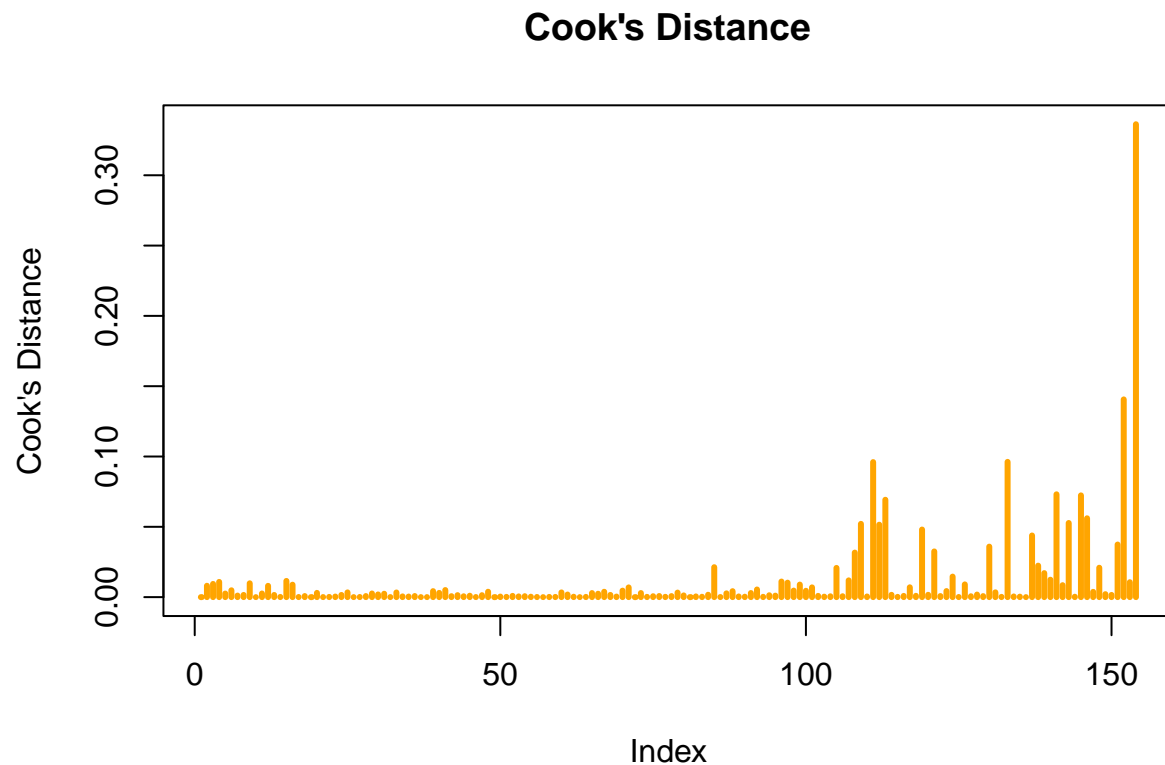
## 16	0.486908040	1.554683e-03
## 17	0.164212787	1.452780e-04
## 18	-1.436425682	1.152518e-02
## 19	-1.364028509	8.850997e-03
## 20	-0.152742905	1.161564e-04
## 21	0.376688155	7.668700e-04
## 22	-0.004370129	8.398940e-08
## 23	0.607671067	3.031759e-03
## 24	0.086397823	6.033840e-05
## 25	0.141823658	1.889679e-04
## 26	0.284957596	4.309222e-04
## 27	0.538863856	1.545594e-03
## 28	-0.764833835	3.368316e-03
## 29	-0.082806564	2.860297e-05
## 30	-0.174052199	1.237197e-04
## 31	-0.461695011	7.671713e-04
## 32	0.718436603	2.589570e-03
## 33	0.708920466	1.901912e-03
## 34	-0.730868790	2.416304e-03
## 35	-0.079493133	4.231583e-05
## 36	-0.742264829	3.307188e-03
## 37	-0.306557416	5.220389e-04
## 38	0.282885903	4.308713e-04
## 39	0.428900293	7.825739e-04
## 40	0.093843481	3.738577e-05
## 41	0.092311530	3.522389e-05
## 42	0.957261300	4.267924e-03
## 43	-0.886726820	3.029302e-03
## 44	0.890141036	5.028655e-03
## 45	-0.367328026	6.896800e-04
## 46	-0.545624435	1.407357e-03
## 47	-0.360386554	6.246327e-04
## 48	-0.446840526	1.015872e-03
## 49	-0.155125003	9.398998e-05
## 50	0.484438916	1.387810e-03
## 51	0.872473485	3.838758e-03
## 52	-0.001354384	1.123750e-08
## 53	0.308352260	4.196920e-04
## 54	0.181449116	1.928938e-04
## 55	-0.509499071	9.100296e-04
## 56	0.319434635	5.302491e-04
## 57	-0.374979504	6.827613e-04
## 58	0.285181395	3.170995e-04
## 59	-0.200785072	1.336213e-04
## 60	-0.064390725	1.342047e-05

## 61	-0.190575072	1.823678e-04
## 62	0.172297886	1.670319e-04
## 63	0.666545256	3.358143e-03
## 64	-0.509857222	1.845323e-03
## 65	0.281769356	3.016884e-04
## 66	0.037033392	4.893632e-06
## 67	-0.198610615	1.828594e-04
## 68	0.822549219	2.887697e-03
## 69	0.655250711	2.420904e-03
## 70	1.014777807	3.821256e-03
## 71	-0.714439962	1.573952e-03
## 72	0.325632911	4.041038e-04
## 73	-0.774041586	4.630368e-03
## 74	-0.948832227	6.907983e-03
## 75	-0.006682400	2.289971e-07
## 76	-0.777664601	2.908098e-03
## 77	-0.246253707	2.227533e-04
## 78	0.324726042	6.517159e-04
## 79	-0.521932153	8.180493e-04
## 80	0.170626077	2.383742e-04
## 81	0.593661818	7.594255e-04
## 82	1.024380769	3.237978e-03
## 83	-0.564791622	1.224030e-03
## 84	-0.009656212	4.042819e-07
## 85	-0.271617973	5.118950e-04
## 86	0.212883482	2.716805e-04
## 87	0.558551420	1.703413e-03
## 88	-1.827223384	2.129067e-02
## 89	-0.130457740	8.453493e-05
## 90	-0.648279888	2.693851e-03
## 91	-1.059419054	4.235291e-03
## 92	0.261056297	4.891802e-04
## 93	0.262423367	3.123203e-04
## 94	0.890054683	2.920306e-03
## 95	1.058998818	5.432728e-03
## 96	-0.265153025	2.335382e-04
## 97	-0.558360992	1.342547e-03
## 98	-0.439355042	1.066517e-03
## 99	-1.505484460	1.109104e-02
## 100	-1.191594441	1.029366e-02
## 101	0.954571097	4.656965e-03
## 102	1.262311792	8.918235e-03
## 103	0.923623075	4.527929e-03
## 104	1.087547626	6.931653e-03
## 105	-0.351197818	9.102641e-04

## 106	-0.267442607	3.541310e-04
## 107	0.346615790	5.918072e-04
## 108	-1.826001853	2.077991e-02
## 109	-0.268598586	6.425773e-04
## 110	0.850753126	1.191653e-02
## 111	-1.382078525	3.168898e-02
## 112	1.691401460	5.211264e-02
## 113	0.063124638	4.706428e-04
## 114	-2.011986010	9.602353e-02
## 115	1.808319140	5.151643e-02
## 116	2.213475582	6.924829e-02
## 117	-0.424873329	1.650048e-03
## 118	0.159754295	1.997854e-04
## 119	-0.395996383	8.932357e-04
## 120	-1.068671880	6.988187e-03
## 121	-0.327605476	9.401444e-04
## 122	-2.167391254	4.806715e-02
## 123	0.384696828	1.657604e-03
## 124	1.619764738	3.250021e-02
## 125	0.253985673	7.794773e-04
## 126	-0.588788879	4.320743e-03
## 127	-1.413304928	1.459515e-02
## 128	0.118963014	1.158233e-04
## 129	-1.428957434	9.058827e-03
## 130	-0.334052172	6.400536e-04
## 131	0.540737403	1.830320e-03
## 132	0.294574737	7.321892e-04
## 133	2.004860513	3.590477e-02
## 134	-0.602924137	3.399034e-03
## 135	-0.152270562	2.017406e-04
## 136	3.188569181	9.619568e-02
## 137	0.195182398	4.784648e-04
## 138	-0.185713020	3.504129e-04
## 139	0.029054829	1.051316e-05
## 140	-2.092431920	4.384706e-02
## 141	-1.373131728	2.238077e-02
## 142	-1.302037155	1.707928e-02
## 143	1.107292372	1.240538e-02
## 144	-2.422540248	7.312728e-02
## 145	0.875715966	8.503295e-03
## 146	-1.976694108	5.272610e-02
## 147	0.128723708	2.985956e-04
## 148	2.379898536	7.235181e-02
## 149	1.651648506	5.606962e-02
## 150	0.397926013	3.759211e-03

```
## 151      -1.218306004    2.091852e-02
## 152      -0.482418688    2.111637e-03
## 153      -0.425270620    1.572610e-03
## 154       2.158928322    3.740619e-02
## 155      -3.504525836    1.406168e-01
## 156       0.804657134    1.061166e-02
## 157       4.275133388    3.362954e-01
```

```
plot(cook,type="h",lwd=3,col="orange",ylab="Cook's Distance",main="Cook's Distance")
```



```
condition <- (abs(resids) > 2) & (cook > 4 / 157)
count_rows <- sum(condition)
count_rows/157
```

```
## [1] 0.07006369
```

BoxCox MLR

```
# Box-Cox transformation
library(MASS)
```

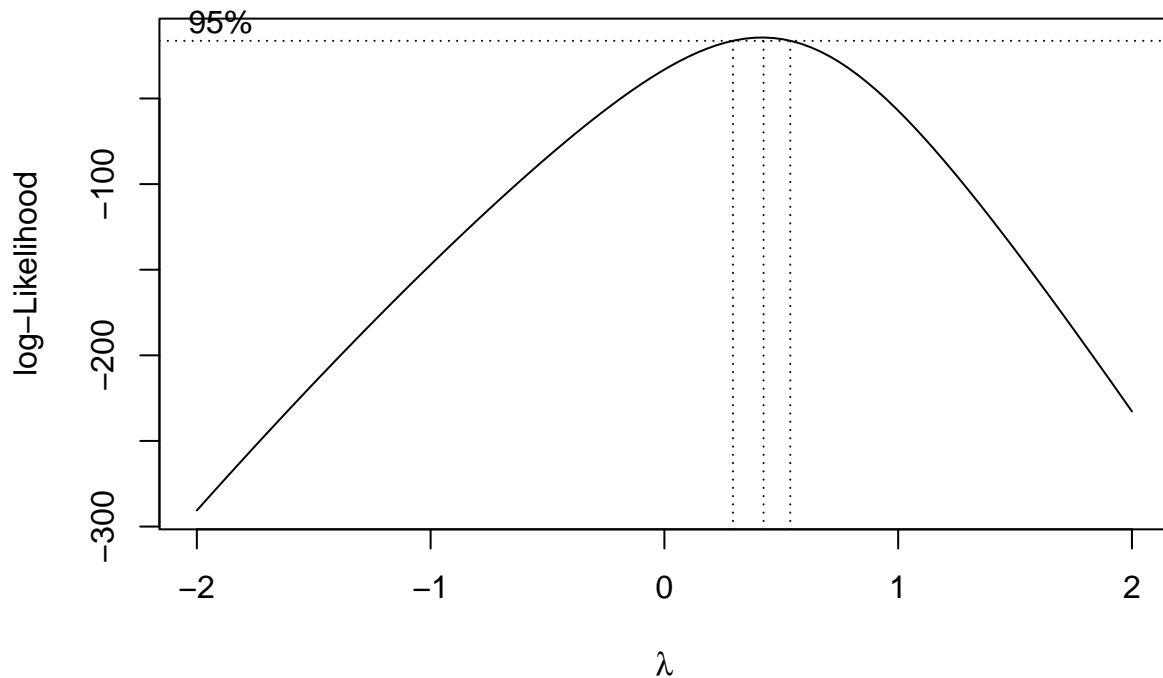
```
##
```

```
##      'MASS'

## The following object is masked from 'package:dplyr':
##
##      select

## The following object is masked from 'package:plotly':
##
##      select

boxcox_result <- boxcox(full_model, plotit = TRUE)
```



```
best_lambda <- boxcox_result$x[which.max(boxcox_result$y)]
print(best_lambda)

## [1] 0.4242424

# If lambda = 0, use log transformation, otherwise use (y^lambda - 1) / lambda
model_boxcox <- lm(((Total.NEV.Sales^best_lambda) - 1) / best_lambda ~ ., data = data)
summary(model_boxcox)

##
## Call:
## lm(formula = ((Total.NEV.Sales^best_lambda) - 1)/best_lambda ~
```

```

##      ., data = data)
##
## Residuals:
##      Min        1Q      Median        3Q        Max
## -28.1193  -4.9063  -0.0071   5.9883  25.3090
##
## Coefficients:
##                                     Estimate
## (Intercept)                      1.298e+03
## Month                          1.531e+00
## Date                          2.772e-01
## Covid.19                       -6.494e+00
## Number.of.new.energy.policies  -6.342e-02
## Production                      -9.753e-06
## Inventory                       6.016e-05
## Gasoline.LDV.sales              6.175e-05
## M1SL                          -3.752e-03
## M2SL                          -1.266e-03
## Federal.fund.effective.rate      9.869e+02
## Unemployment.rate               -1.455e+02
## PPIBC                          4.446e-01
## PPIBM                          1.397e-01
## PCE                            4.624e-02
## GDP                           -2.351e-02
## Durable.goods.consumption        2.024e-01
## Nondurable.goods.consumption     -6.756e-02
## Nonresidential.fixed.Investment  -4.324e-02
## Residential.fixed.Investment     -1.340e-01
## Tesla.model.S.price              5.022e-03
## ElectricPorts                   1.536e-03
## BatteryCost                     -1.192e-01
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education -4.502e+02
## Percentage.of.employees.who.are.middle.aged..25.55. -3.308e+02
## Population                      -3.780e-02
## Per.capita.disposable.income     -8.256e-04
## Gasoline.price                   1.602e+01
## Electric.retail.price            -4.115e+00
##
##                                     Std. Error
## (Intercept)                      1.272e+03
## Month                          3.270e-01
## Date                          1.019e-01
## Covid.19                       7.125e+00
## Number.of.new.energy.policies   3.699e-02
## Production                      2.634e-05
## Inventory                      1.812e-05

```

## Gasoline.LDV.sales	7.729e-06
## M1SL	1.907e-03
## M2SL	1.045e-02
## Federal.fund.effective.rate	3.762e+02
## Umemployment.rate	1.545e+02
## PPIBC	7.196e-01
## PPIBM	7.528e-01
## PCE	3.277e-02
## GDP	1.650e-02
## Durable.goods.consumption	6.194e-02
## Nondurable.goods.consumption	8.059e-02
## Nonresidential.fixed.Investment	4.954e-02
## Residential.fixed.Investment	8.153e-02
## Tesla.model.S.price	2.269e-03
## ElectricPorts	6.151e-04
## BatteryCost	3.249e-02
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	2.641e+02
## Percentage.of.employees.who.are.middle.aged..25.55.	3.347e+02
## Population	1.073e-02
## Per.capita.disposable.income	1.634e-03
## Gasoline.price	5.386e+00
## Electric.retail.price	2.776e+00
##	t value
## (Intercept)	1.020
## Month	4.682
## Date	2.720
## Covid.19	-0.911
## Number.of.new.energy.policies	-1.714
## Production	-0.370
## Inventory	3.320
## Gasoline.LDV.sales	7.990
## M1SL	-1.967
## M2SL	-0.121
## Federal.fund.effective.rate	2.623
## Umemployment.rate	-0.942
## PPIBC	0.618
## PPIBM	0.186
## PCE	1.411
## GDP	-1.424
## Durable.goods.consumption	3.268
## Nondurable.goods.consumption	-0.838
## Nonresidential.fixed.Investment	-0.873
## Residential.fixed.Investment	-1.644
## Tesla.model.S.price	2.214
## ElectricPorts	2.497

## BatteryCost	-3.670
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	-1.705
## Percentage.of.employees.who.are.middle.aged..25.55.	-0.988
## Population	-3.522
## Per.capita.disposable.income	-0.505
## Gasoline.price	2.974
## Electric.retail.price	-1.482
##	Pr(> t)
## (Intercept)	0.309459
## Month	7.14e-06
## Date	0.007435
## Covid.19	0.363789
## Number.of.new.energy.policies	0.088880
## Production	0.711829
## Inventory	0.001172
## Gasoline.LDV.sales	6.82e-13
## M1SL	0.051320
## M2SL	0.903708
## Federal.fund.effective.rate	0.009761
## Unemployment.rate	0.348104
## PPIBC	0.537778
## PPIBM	0.853059
## PCE	0.160723
## GDP	0.156780
## Durable.goods.consumption	0.001391
## Nondurable.goods.consumption	0.403425
## Nonresidential.fixed.Investment	0.384383
## Residential.fixed.Investment	0.102630
## Tesla.model.S.price	0.028631
## ElectricPorts	0.013786
## BatteryCost	0.000355
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	0.090668
## Percentage.of.employees.who.are.middle.aged..25.55.	0.324973
## Population	0.000595
## Per.capita.disposable.income	0.614190
## Gasoline.price	0.003514
## Electric.retail.price	0.140758
##	
## (Intercept)	
## Month	***
## Date	**
## Covid.19	
## Number.of.new.energy.policies	.
## Production	
## Inventory	**


```
## Gasoline.LDV.sales ***
## M1SL .
## M2SL
## Federal.fund.effective.rate **
## Umemployment.rate
## PPIBC
## PPIBM
## PCE
## GDP
## Durable.goods.consumption **
## Nondurable.goods.consumption
## Nonresidential.fixed.Investment
## Residential.fixed.Investment
## Tesla.model.S.price *
## ElectricPorts *
## BatteryCost ***
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education .
## Percentage.of.employees.who.are.middle.aged..25.55.
## Population ***
## Per.capita.disposable.income
## Gasoline.price **
## Electric.retail.price
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.26 on 128 degrees of freedom
## Multiple R-squared:  0.984, Adjusted R-squared:  0.9805
## F-statistic: 280.9 on 28 and 128 DF,  p-value: < 2.2e-16
```

```
library(car)
vif(model_boxcox)
```

```
## Month
## 1.920368
## Date
## 29501.153805
## Covid.19
## 14.618061
## Number.of.new.energy.policies
## 6.767884
## Production
## 8.927369
## Inventory
## 78.038416
## Gasoline.LDV.sales
```

##	3.557467
##	M1SL
##	282.814081
##	M2SL
##	2759.810876
##	Federal.fund.effective.rate
##	44.756856
##	Unemployment.rate
##	14.968166
##	PPIBC
##	15.339518
##	PPIBM
##	202.623852
##	PCE
##	193.148413
##	GDP
##	5172.768085
##	Durable.goods.consumption
##	670.782082
##	Nondurable.goods.consumption
##	2342.557766
##	Nonresidential.fixed.Investment
##	1002.806743
##	Residential.fixed.Investment
##	655.749898
##	Tesla.model.S.price
##	63.749847
##	ElectricPorts
##	1344.055530
##	BatteryCost
##	55.226187
##	Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education
##	91.605819
##	Percentage.of.employees.who.are.middle.aged..25.55.
##	24.533040
##	Population
##	9287.203160
##	Per.capita.disposable.income
##	221.534172
##	Gasoline.price
##	17.426933
##	Electric.retail.price
##	9.631857

```
data_boxcox <- subset(data, select = -c(Date,M1SL,M2SL,GDP,Nondurable.goods.consumption,
data_boxcox0<-data_boxcox
model_boxcox2 <- lm(((Total.NEV.Sales^best_lambda) - 1) / best_lambda ~ ., data = data_b
summary(model_boxcox2)
```

```
##
## Call:
## lm(formula = ((Total.NEV.Sales^best_lambda) - 1)/best_lambda ~
##     ., data = data_boxcox)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-33.628	-8.070	0.667	7.233	61.779

```
##
## Coefficients:
```

	Estimate	Std. Error
(Intercept)	-2.115e+02	3.036e+02
Month	1.577e+00	4.301e-01
Covid.19	-7.225e+00	6.970e+00
Number.of.new.energy.policies	-1.184e-01	4.739e-02
Production	4.312e-05	3.262e-05
Inventory	1.688e-05	1.815e-05
Gasoline.LDV.sales	4.868e-05	1.051e-05
Federal.fund.effective.rate	1.424e+03	1.796e+02
Unemployment.rate	7.793e+02	1.116e+02
PPIBC	-5.618e-01	8.978e-01
PCE	2.052e-01	1.865e-02
Tesla.model.S.price	5.312e-03	1.384e-03
BatteryCost	-7.419e-02	3.127e-02
Percentage.of.employees.who.are.middle.aged..25.55.	2.466e+01	4.317e+02
Gasoline.price	2.206e+01	3.880e+00
Electric.retail.price	-9.746e+00	3.667e+00

```
##
## t value Pr(>|t|)
```

	t value	Pr(> t)
(Intercept)	-0.697	0.487176
Month	3.666	0.000348 ***
Covid.19	-1.037	0.301642
Number.of.new.energy.policies	-2.498	0.013639 *
Production	1.322	0.188309
Inventory	0.930	0.354127
Gasoline.LDV.sales	4.630	8.22e-06 ***
Federal.fund.effective.rate	7.925	6.25e-13 ***
Unemployment.rate	6.983	1.05e-10 ***
PPIBC	-0.626	0.532499
PCE	11.003	< 2e-16 ***

```
## Tesla.model.S.price          3.839 0.000186 ***
## BatteryCost                  -2.373 0.018997 *
## Percentage.of.employees.who.are.middle.aged..25.55. 0.057 0.954524
## Gasoline.price               5.685 7.24e-08 ***
## Electric.retail.price        -2.657 0.008783 **
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Residual standard error: 15.72 on 141 degrees of freedom
```

```
## Multiple R-squared:  0.9586, Adjusted R-squared:  0.9542
```

```
## F-statistic: 217.5 on 15 and 141 DF,  p-value: < 2.2e-16
```

```
Date <- data$Date
```

```
model_date_included <- lm(((Total.NEV.Sales^best_lambda) - 1) / best_lambda ~ . + I(Date
```

```
anova_result <- anova(model_boxcox2,model_date_included)
```

```
print(anova_result)
```

```
## Analysis of Variance Table
```

```
##
```

```
## Model 1: ((Total.NEV.Sales^best_lambda) - 1)/best_lambda ~ Month + Covid.19 +
```

```
##   Number.of.new.energy.policies + Production + Inventory +
```

```
##   Gasoline.LDV.sales + Federal.fund.effective.rate + Unemployment.rate +
```

```
##   PPIBC + PCE + Tesla.model.S.price + BatteryCost + Percentage.of.employees.who.are
```

```
##   Gasoline.price + Electric.retail.price
```

```
## Model 2: ((Total.NEV.Sales^best_lambda) - 1)/best_lambda ~ Month + Covid.19 +
```

```
##   Number.of.new.energy.policies + Production + Inventory +
```

```
##   Gasoline.LDV.sales + Federal.fund.effective.rate + Unemployment.rate +
```

```
##   PPIBC + PCE + Tesla.model.S.price + BatteryCost + Percentage.of.employees.who.are
```

```
##   Gasoline.price + Electric.retail.price + I(Date)
```

```
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
```

```
## 1      141 34847
```

```
## 2      140 34837  1      9.2838 0.0373 0.8471
```

```
## Reject the null hypothesis, which means we shouldn't keep date in the boxcox transf
```

```
library(car)
```

```
vif(model_boxcox2)
```

```
##                               Month
```

```
##                               1.413901
```

```
##                               Covid.19
```

```
##                               5.954011
```

```
##   Number.of.new.energy.policies
```

```
##                               4.727917
```

```
##   Production
```

```
##                               5.825524
```

```
##                               Inventory
##                               33.351361
##                               Gasoline.LDV.sales
##                               2.802633
##                               Federal.fund.effective.rate
##                               4.345362
##                               Unemployment.rate
##                               3.322561
##                               PPIBC
##                               10.165497
##                               PCE
##                               26.632445
##                               Tesla.model.S.price
##                               10.094932
##                               BatteryCost
##                               21.775594
## Percentage.of.employees.who.are.middle.aged..25.55.
##                               17.370260
##                               Gasoline.price
##                               3.849206
##                               Electric.retail.price
##                               7.153222
```

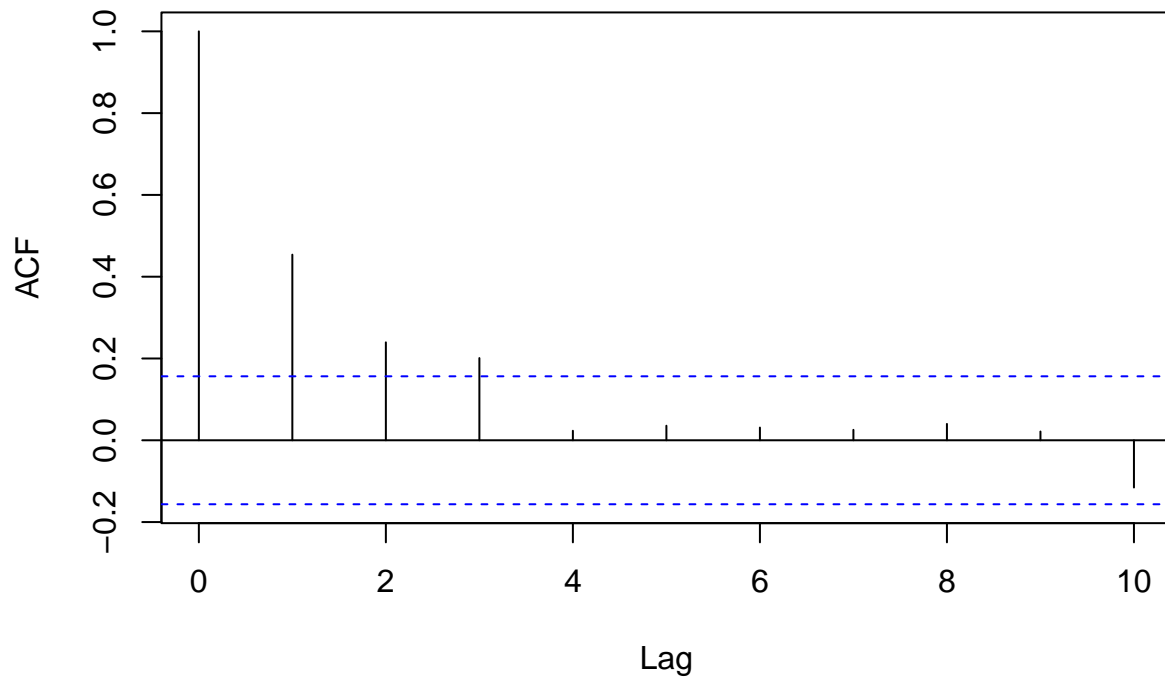
Autocorrelation

```
library(lmtest)
dwtest(model_boxcox2)

##
## Durbin-Watson test
##
## data:  model_boxcox2
## DW = 1.0071, p-value = 2.163e-13
## alternative hypothesis: true autocorrelation is greater than 0

residuals_lagged <- residuals(model_boxcox2)
acf(residuals_lagged, main = "ACF of Residuals", lag.max = 10)
```

ACF of Residuals



```
# From the ACF of Residuals, the residual autocorrelation at lag orders 1, 2 and 3 is
library(dplyr)

data_boxcox <- data_boxcox %>%
  mutate(
    lagged_value1 = ((lag(Total.NEV.Sales, n = 1))^best_lambda - 1) / best_lambda,
    lagged_value2 = ((lag(Total.NEV.Sales, n = 2))^best_lambda - 1) / best_lambda,
    lagged_value3 = ((lag(Total.NEV.Sales, n = 3))^best_lambda - 1) / best_lambda
  )
# test if lagged variables solve the autocorrelation problem
lagged_model2 <- lm(((Total.NEV.Sales^best_lambda) - 1) / best_lambda ~ ., data = data_boxcox)
dwtest(lagged_model2)

##
## Durbin-Watson test
##
## data: lagged_model2
## DW = 1.8235, p-value = 0.01811
## alternative hypothesis: true autocorrelation is greater than 0
```

```
summary(lagged_model2)
```

```
##
## Call:
## lm(formula = ((Total.NEV.Sales^best_lambda) - 1)/best_lambda ~
##     ., data = data_boxcox)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -28.368  -6.616   0.174   6.915  33.049
##
## Coefficients:
##                                     Estimate Std. Error
## (Intercept)                      -3.651e+01  2.255e+02
## Month                          5.022e-01  3.306e-01
## Covid.19                        7.873e+00  5.324e+00
## Number.of.new.energy.policies  -5.218e-02  3.433e-02
## Production                      2.938e-05  2.433e-05
## Inventory                      1.436e-05  1.375e-05
## Gasoline.LDV.sales              7.343e-05  7.841e-06
## Federal.fund.effective.rate     8.083e+02  1.389e+02
## Unemployment.rate              5.483e+02  8.258e+01
## PPIBC                          1.285e-01  6.419e-01
## PCE                            1.038e-01  1.637e-02
## Tesla.model.S.price            2.477e-03  1.026e-03
## BatteryCost                   1.405e-02  2.869e-02
## Percentage.of.employees.who.are.middle.aged..25.55. -2.839e+02  3.260e+02
## Gasoline.price                 1.093e+01  3.005e+00
## Electric.retail.price          -8.083e+00  2.646e+00
## lagged_value1                  3.494e-01  5.892e-02
## lagged_value2                  7.277e-02  5.991e-02
## lagged_value3                  2.369e-01  5.316e-02
##                                     t value Pr(>|t|)
## (Intercept)                      -0.162 0.871612
## Month                          1.519 0.131028
## Covid.19                        1.479 0.141530
## Number.of.new.energy.policies  -1.520 0.130872
## Production                      1.208 0.229268
## Inventory                      1.044 0.298196
## Gasoline.LDV.sales              9.365 2.29e-16 ***
## Federal.fund.effective.rate     5.821 4.05e-08 ***
## Unemployment.rate              6.640 7.03e-10 ***
## PPIBC                          0.200 0.841607
## PCE                            6.342 3.17e-09 ***
```

```
## Tesla.model.S.price          2.414 0.017113 *
## BatteryCost                  0.490 0.625175
## Percentage.of.employees.who.are.middle.aged..25.55. -0.871 0.385327
## Gasoline.price               3.639 0.000389 ***
## Electric.retail.price        -3.055 0.002710 **
## lagged_value1                5.929 2.41e-08 ***
## lagged_value2                1.215 0.226641
## lagged_value3                4.457 1.73e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.15 on 135 degrees of freedom
## ( 3 )
## Multiple R-squared:  0.9794, Adjusted R-squared:  0.9767
## F-statistic: 357.4 on 18 and 135 DF,  p-value: < 2.2e-16
```

```
library(car)
vif(lagged_model2)
```

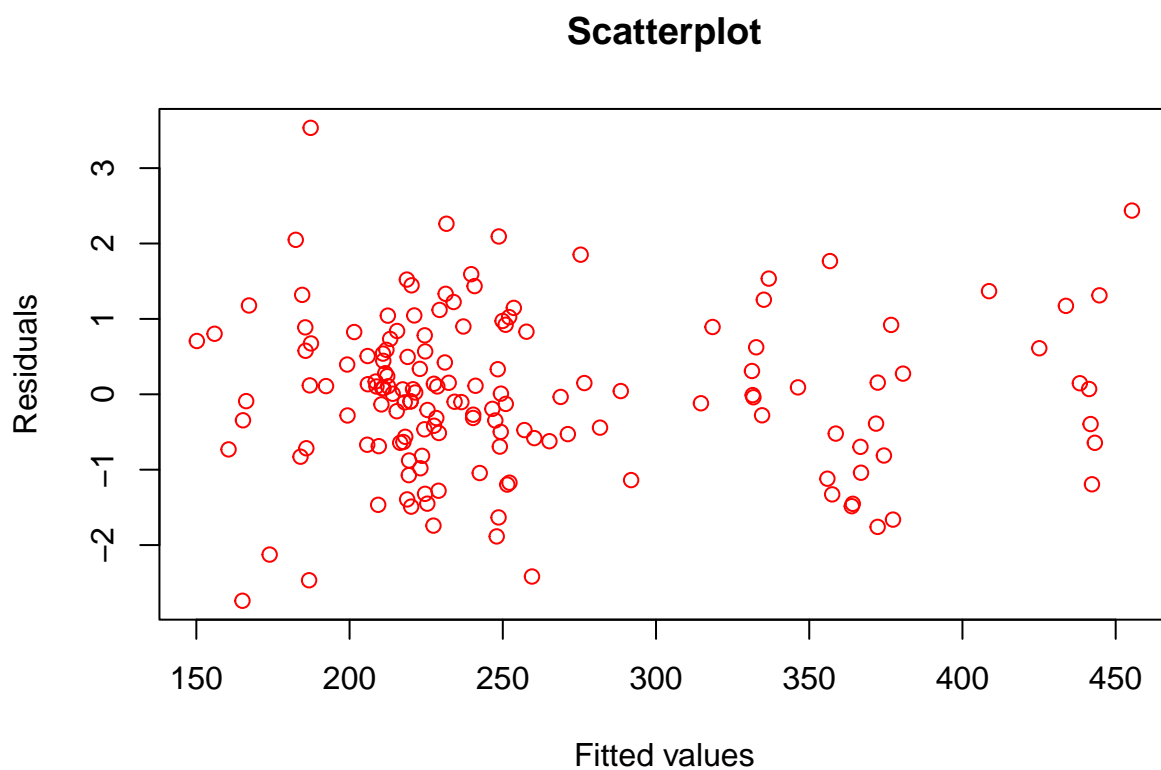
```
##                               Month
##                               1.588687
##                               Covid.19
##                               6.857932
##                               Number.of.new.energy.policies
##                               4.879246
##                               Production
##                               6.398033
##                               Inventory
##                               38.037019
##                               Gasoline.LDV.sales
##                               2.958084
##                               Federal.fund.effective.rate
##                               5.119534
##                               Unemployment.rate
##                               3.438718
##                               PPIBC
##                               10.281360
##                               PCE
##                               39.598421
##                               Tesla.model.S.price
##                               10.946846
##                               BatteryCost
##                               30.114201
## Percentage.of.employees.who.are.middle.aged..25.55.
##                               17.564326
```



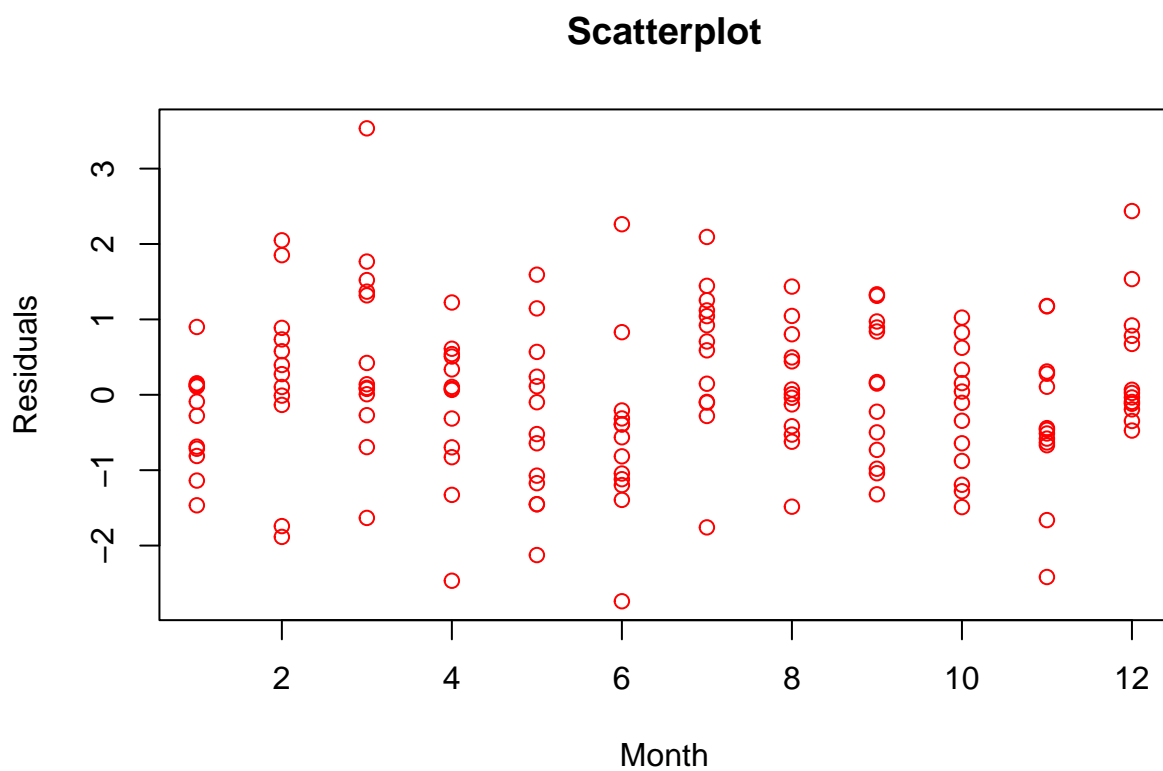
```
## Gasoline.price
## 4.585222
## Electric.retail.price
## 7.169106
## lagged_value1
## 21.643336
## lagged_value2
## 21.612604
## lagged_value3
## 16.424033
```

Goodness of fit

```
# Constant Variance Assumption: hold
resids=rstandard(lagged_model2)
fits=lagged_model2$fitted
plot(fits,resids,xlab="Fitted values",ylab="Residuals",main="Scatterplot",col="red")
```

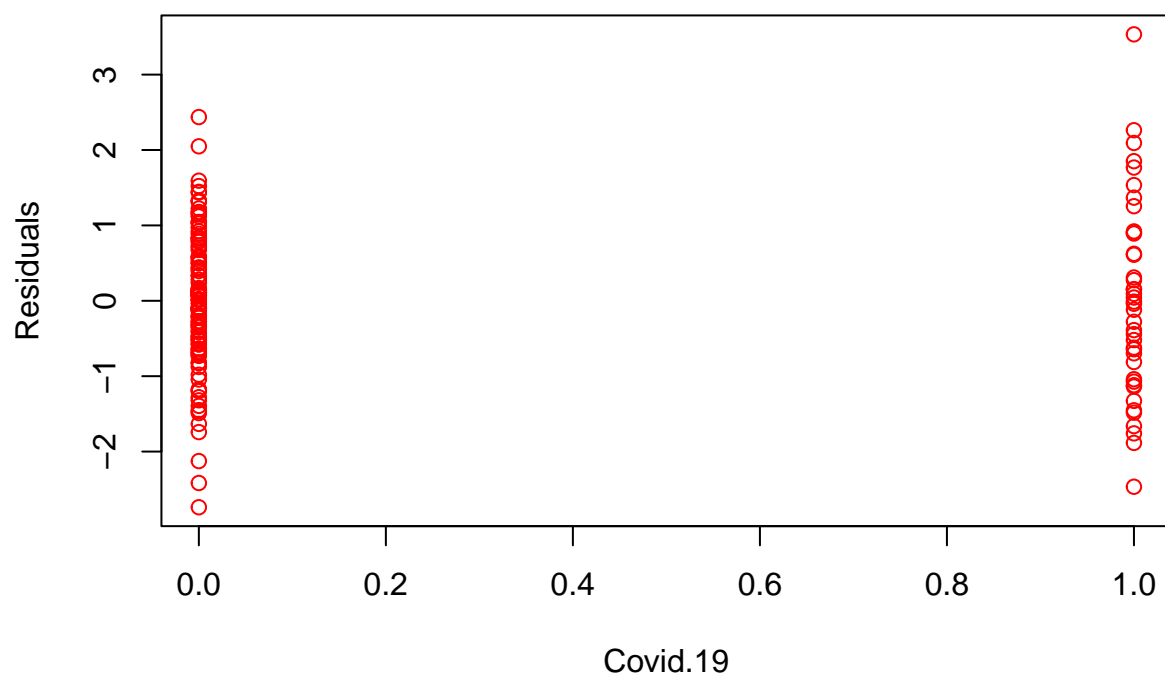


```
# Linearity Assumption: hold
# following codes should be checked according to the variable selection results in case
plot(data$Month[4:nrow(data)],resids,xlab="Month",ylab="Residuals",main="Scatterplot",col="red")
```



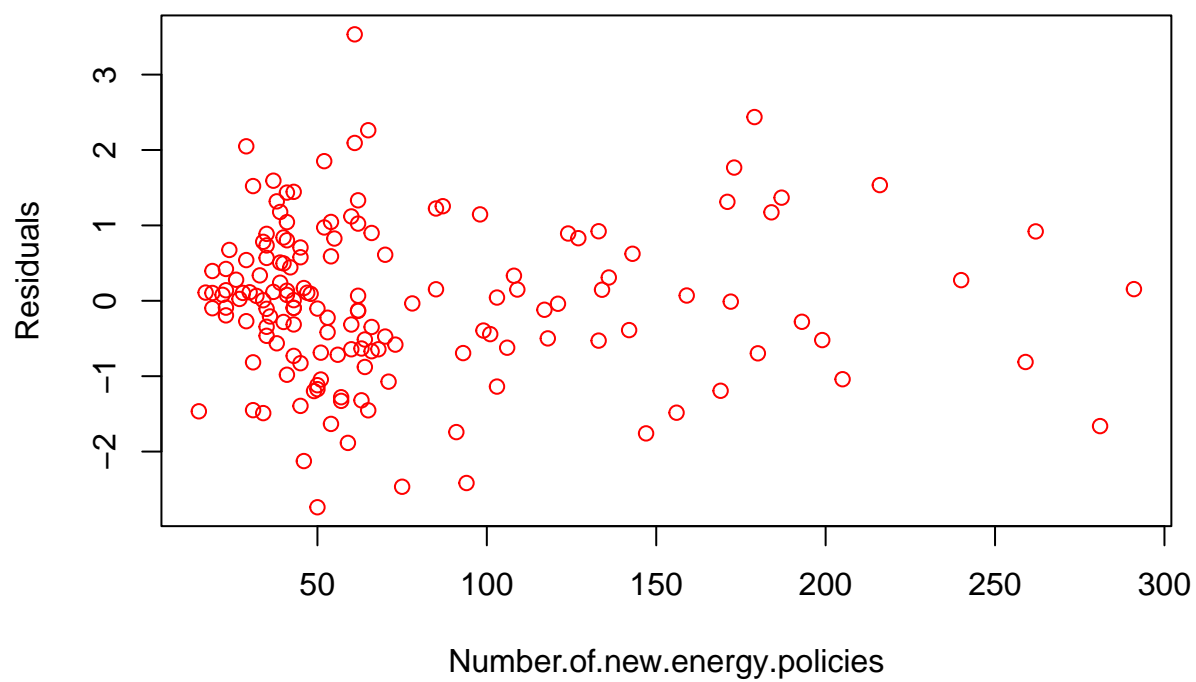
```
plot(data$Covid.19[4:nrow(data)],resids,xlab="Covid.19",ylab="Residuals",main="Scatterplot")
```

Scatterplot



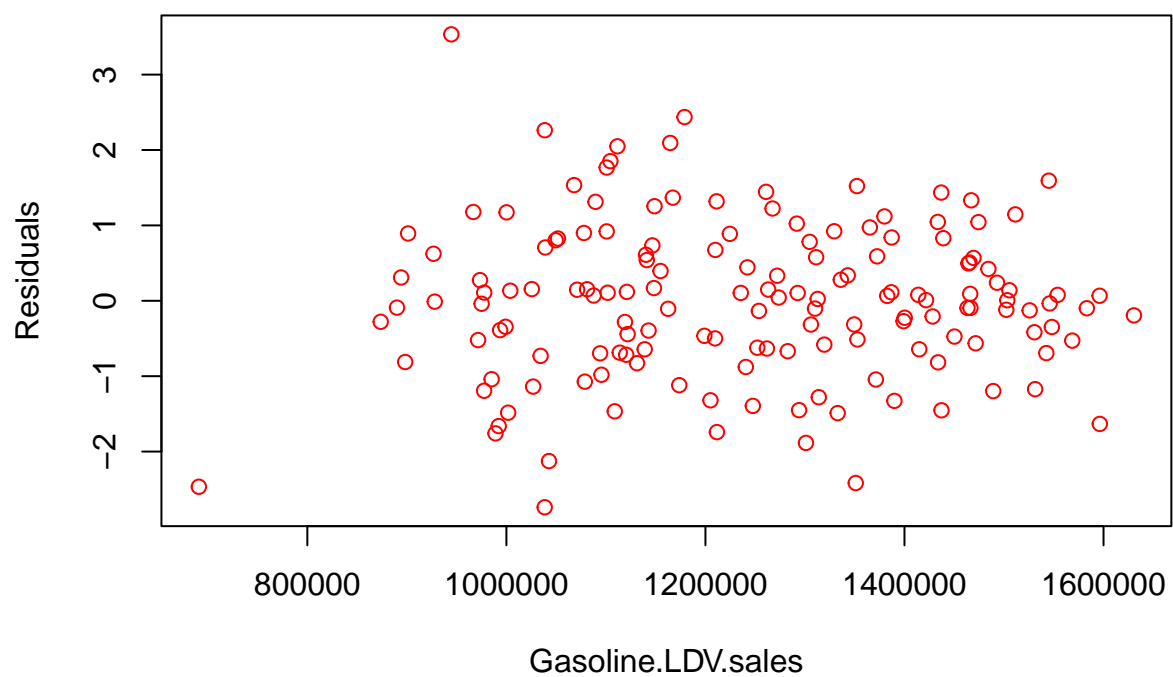
```
plot(data$Number.of.new.energy.policies[4:nrow(data)],resids,xlab="Number.of.new.energy.policies")
```

Scatterplot



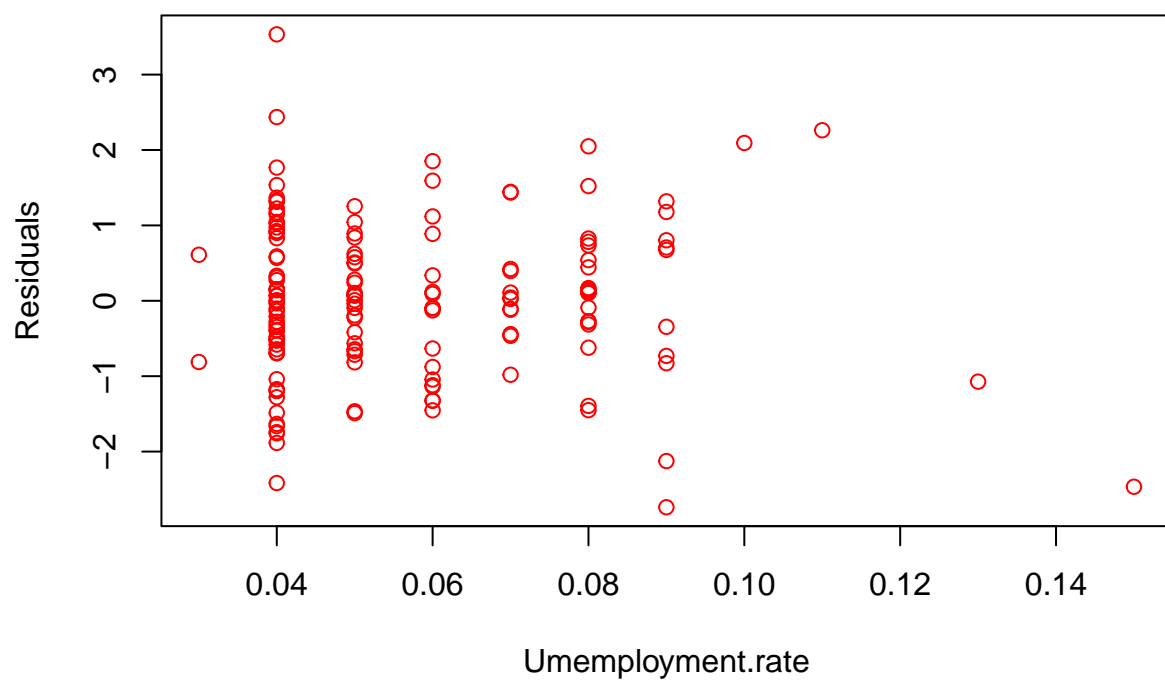
```
plot(data$Gasoline.LDV.sales[4:nrow(data)],resids,xlab="Gasoline.LDV.sales",ylab="Residu
```

Scatterplot



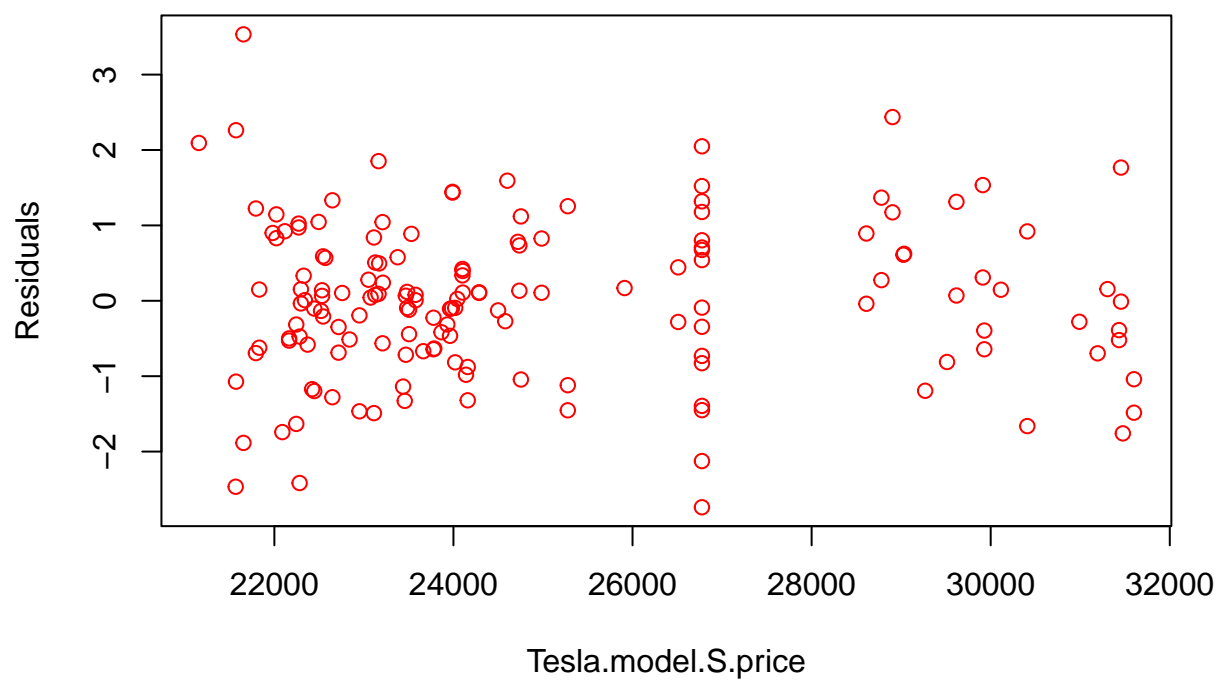
```
plot(data$Unemployment.rate[4:nrow(data)],resids,xlab="Unemployment.rate",ylab="Residuals")
```

Scatterplot



```
plot(data$Tesla.model.S.price[4:nrow(data)],resids,xlab="Tesla.model.S.price",ylab="Resi
```

Scatterplot



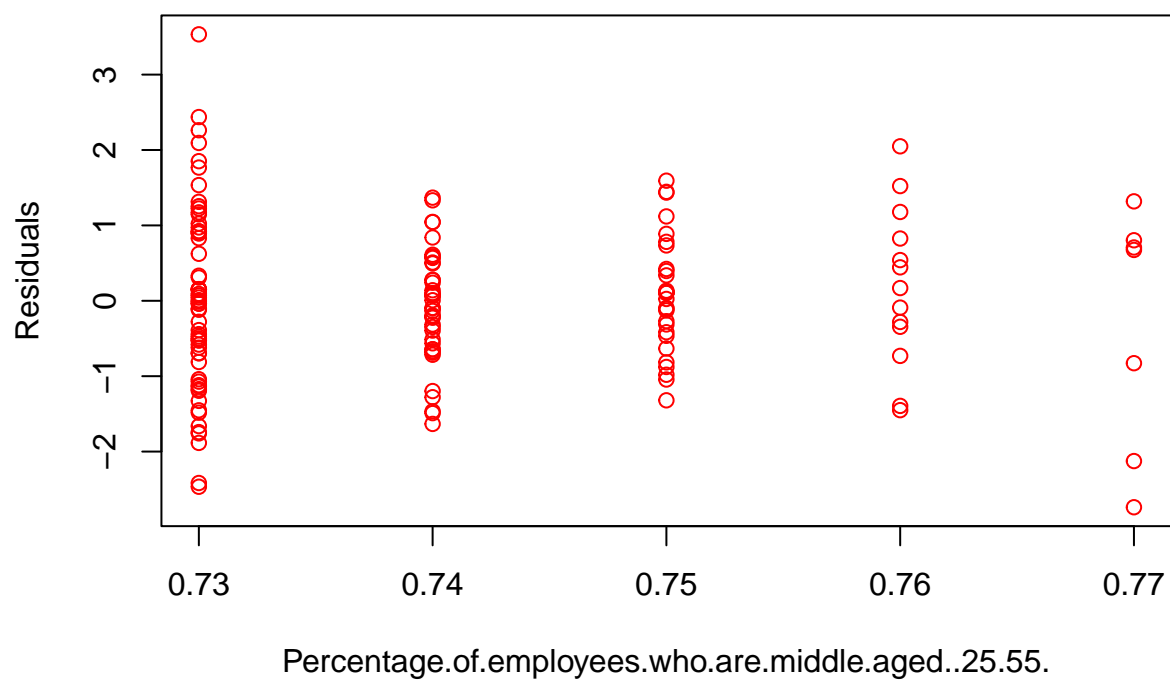
```
plot(data$Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education[4:nrow(da
```

Scatterplot



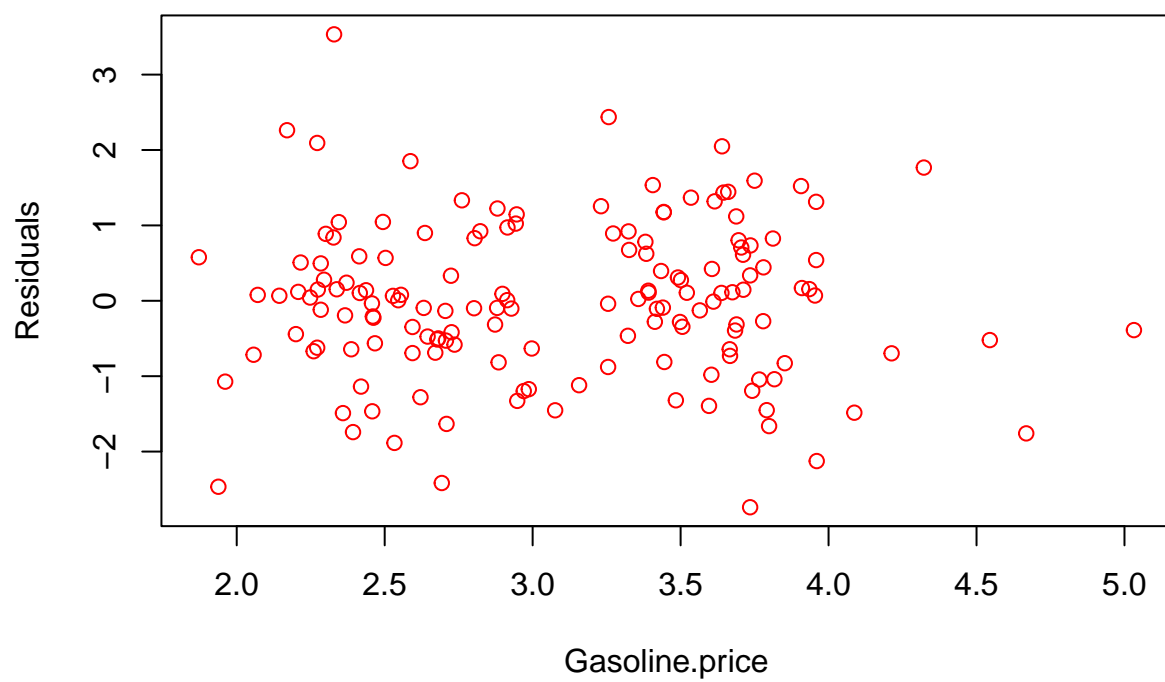
```
plot(data$Percentage.of.employees.who.are.middle.aged..25.55.[4:nrow(data)],resids,xlab=
```


Scatterplot



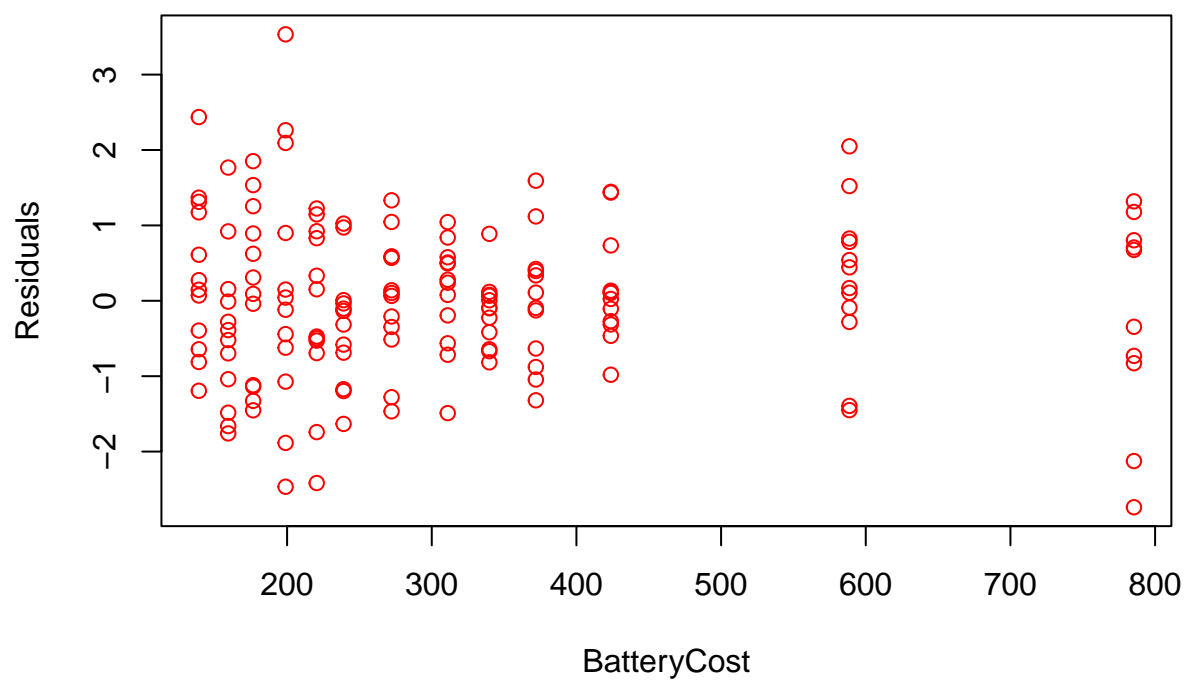
```
plot(data$Gasoline.price[4:nrow(data)],resids,xlab="Gasoline.price",ylab="Residuals",mai
```

Scatterplot



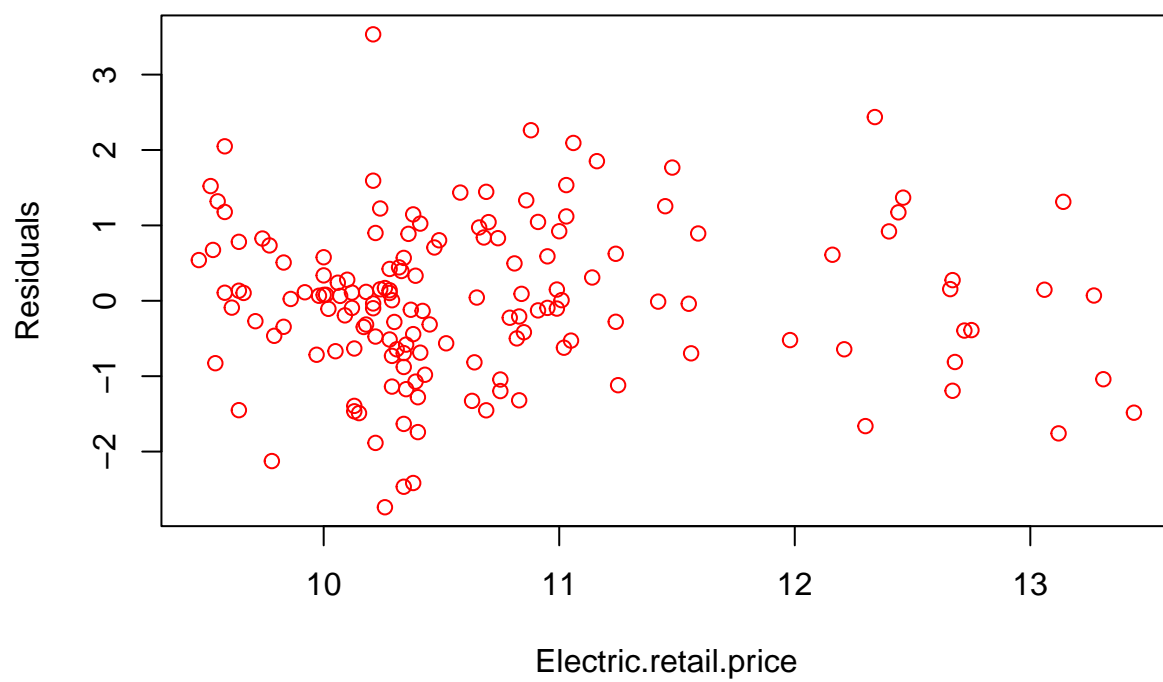
```
plot(data$BatteryCost[4:nrow(data)],resids,xlab="BatteryCost",ylab="Residuals",main="Scatterplot")
```

Scatterplot

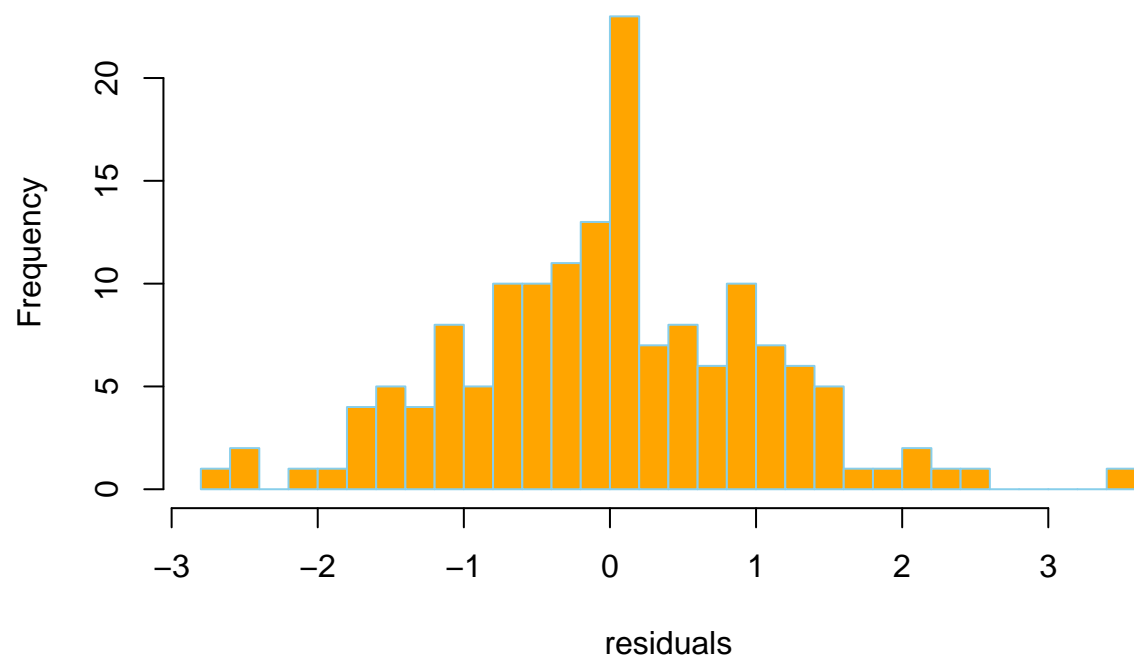


```
plot(data$Electric.retail.price[4:nrow(data)],resids,xlab="Electric.retail.price",ylab="
```

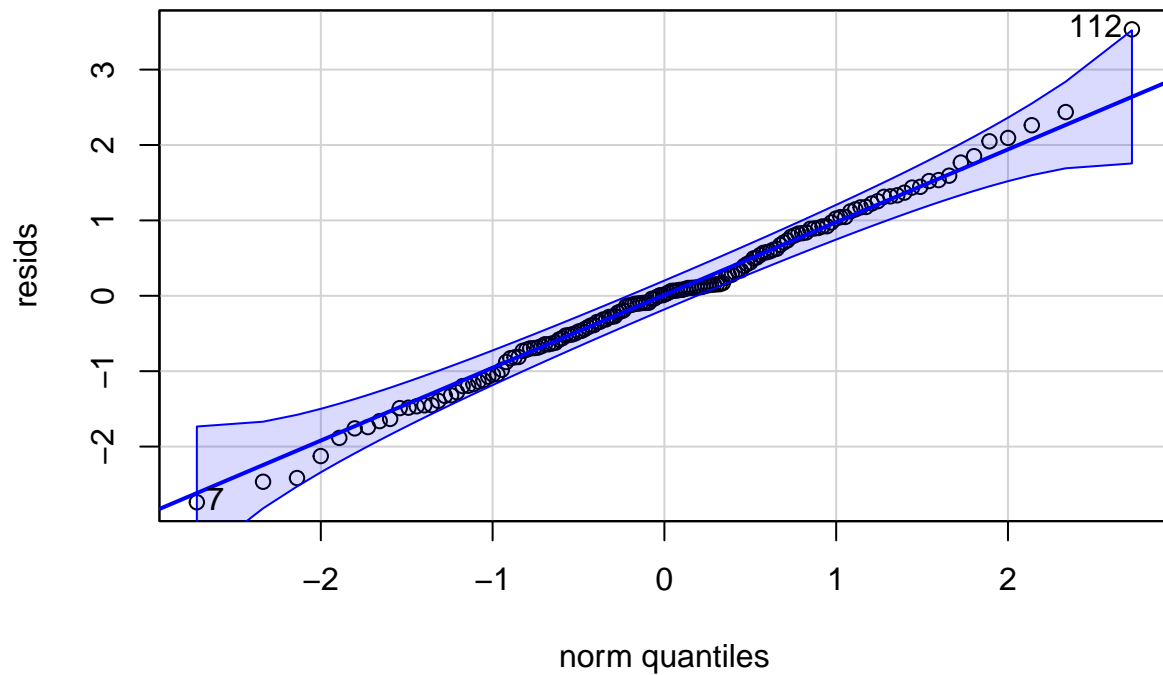
Scatterplot



```
# Normality Assumption: hold  
hist(resids,breaks = 30,main="",xlab="residuals",border = "skyblue",col="orange")
```



```
qqPlot(resids)
```



```
## 112 7
## 109 4
```

```
# Goodness of fit: Outliers
cook=cooks.distance(lagged_model2)
outlier_table <- data.frame(Standardized_Residuals=resids,Cooks_Distance = cook)
print(outlier_table)
```

##	Standardized_Residuals	Cooks_Distance
## 4	1.318873255	1.280524e-02
## 5	-0.827890540	6.613645e-03
## 6	-2.125730720	3.656977e-02
## 7	-2.738400964	6.268763e-02
## 8	0.707047540	5.704628e-03
## 9	0.802825531	5.882041e-03
## 10	-0.730981282	4.797001e-03
## 11	-0.344917609	1.065168e-03
## 12	1.178076709	1.293981e-02
## 13	0.674567870	3.573641e-03
## 14	-0.090510637	5.464039e-05
## 15	2.049052137	2.564434e-02
## 16	1.521580522	1.935937e-02

## 17	0.540073688	2.187315e-03
## 18	-1.450820421	1.429204e-02
## 19	-1.393934077	1.139757e-02
## 20	-0.280963009	4.198874e-04
## 21	0.443392547	1.049613e-03
## 22	0.168855118	1.273577e-04
## 23	0.825713704	5.733842e-03
## 24	0.106837854	1.011397e-04
## 25	0.781920741	6.157900e-03
## 26	0.133677082	9.643278e-05
## 27	0.734303521	3.161590e-03
## 28	-0.270697863	4.411891e-04
## 29	0.104255817	4.687857e-05
## 30	0.113039515	5.471776e-05
## 31	-0.313811568	3.862688e-04
## 32	1.445009979	1.161541e-02
## 33	1.435198526	9.352260e-03
## 34	-0.980953162	4.715081e-03
## 35	-0.106409150	8.566746e-05
## 36	-0.464613953	1.444501e-03
## 37	0.024257879	3.182997e-06
## 38	0.108693893	5.904110e-05
## 39	0.394953290	7.888445e-04
## 40	0.422175862	8.606240e-04
## 41	0.336846688	5.046400e-04
## 42	1.593103245	1.309515e-02
## 43	-1.044371661	4.556266e-03
## 44	1.118923448	8.067907e-03
## 45	-0.127320047	8.514419e-05
## 46	-1.320061095	7.884359e-03
## 47	-0.877874346	4.378189e-03
## 48	-0.632982709	2.393664e-03
## 49	-0.094537670	3.467461e-05
## 50	0.117959742	8.467226e-05
## 51	0.887700583	4.400974e-03
## 52	0.007259284	3.540186e-07
## 53	0.079296563	2.891347e-05
## 54	-0.098870942	5.821837e-05
## 55	-0.816349335	2.439691e-03
## 56	-0.094145997	4.654888e-05
## 57	-0.417304604	8.083407e-04
## 58	-0.224681766	1.892588e-04
## 59	-0.643140318	1.360337e-03
## 60	-0.668946816	1.497192e-03
## 61	0.066861228	2.215132e-05

## 62	-0.715762760	3.089234e-03
## 63	0.577381956	3.042694e-03
## 64	0.077977248	4.943646e-05
## 65	0.507401028	1.178790e-03
## 66	0.239793355	2.376969e-04
## 67	-0.563821882	1.490762e-03
## 68	1.043353158	4.612496e-03
## 69	0.495640722	1.355906e-03
## 70	0.839455327	2.536661e-03
## 71	-1.489953664	7.003614e-03
## 72	0.279262318	3.261494e-04
## 73	-0.193567000	2.851817e-04
## 74	-1.466031291	1.648252e-02
## 75	0.103424092	7.091027e-05
## 76	0.139492996	1.012007e-04
## 77	0.065122473	1.520491e-05
## 78	0.568709097	2.009168e-03
## 79	-0.208247959	1.273364e-04
## 80	0.589597765	2.832634e-03
## 81	1.045652740	2.410041e-03
## 82	1.332704211	5.767936e-03
## 83	-1.279169407	6.340623e-03
## 84	-0.513171955	1.355326e-03
## 85	-0.347622926	8.775396e-04
## 86	-0.688206296	2.927720e-03
## 87	-0.134304439	1.310334e-04
## 88	-1.633064883	1.807726e-02
## 89	-0.314950507	5.583732e-04
## 90	-1.172356942	9.408994e-03
## 91	-1.197387140	5.276728e-03
## 92	-0.103443147	7.536748e-05
## 93	0.008459442	3.054405e-07
## 94	0.972604497	3.329854e-03
## 95	1.024021900	4.869051e-03
## 96	-0.581413377	1.063181e-03
## 97	-0.035111532	6.327061e-06
## 98	0.152585582	1.533293e-04
## 99	-1.741830816	1.602726e-02
## 100	-0.693674035	3.746607e-03
## 101	1.224155839	8.280634e-03
## 102	1.145959792	8.043919e-03
## 103	0.830280726	3.478806e-03
## 104	0.922277586	4.557723e-03
## 105	-0.528282603	1.983495e-03
## 106	-0.498666306	1.172616e-03

## 107	0.332389481	5.442026e-04
## 108	-2.417044179	3.461226e-02
## 109	-0.474455499	1.989403e-03
## 110	0.899243006	1.013667e-02
## 111	-1.884981976	4.175172e-02
## 112	3.534029462	2.773797e-01
## 113	-2.466681075	4.241906e-01
## 114	-1.072506740	2.907432e-02
## 115	2.262323241	1.021906e-01
## 116	2.093488178	8.085797e-02
## 117	-0.622331239	3.629181e-03
## 118	0.149146592	1.718984e-04
## 119	0.043102895	9.674828e-06
## 120	-0.442247952	1.052066e-03
## 121	-0.119126285	1.197681e-04
## 122	-1.138027651	1.245745e-02
## 123	1.851962915	2.752749e-02
## 124	0.091684245	1.377569e-04
## 125	-1.327453922	2.372098e-02
## 126	-1.452742409	2.253422e-02
## 127	-1.119491159	9.407800e-03
## 128	1.254370091	1.323698e-02
## 129	-0.039463528	8.531127e-06
## 130	0.892548002	4.737300e-03
## 131	0.623503563	2.203396e-03
## 132	0.308947978	7.819442e-04
## 133	1.534667418	2.073486e-02
## 134	-0.278618061	6.947758e-04
## 135	-0.011167843	9.712139e-07
## 136	1.767010137	2.731544e-02
## 137	-0.696797969	4.159599e-03
## 138	-0.521068291	2.043547e-03
## 139	-0.388976383	1.741098e-03
## 140	-1.758862555	2.969062e-02
## 141	-1.484434329	2.304015e-02
## 142	-1.040456164	8.758900e-03
## 143	0.154739010	2.446211e-04
## 144	-1.662147844	3.119934e-02
## 145	0.920414392	9.020116e-03
## 146	-0.811901783	8.656039e-03
## 147	0.273928903	1.230224e-03
## 148	1.367997370	2.004612e-02
## 149	0.610676998	6.414160e-03
## 150	-0.643076364	8.013115e-03
## 151	-0.394821078	2.171496e-03

```
## 152      0.146795830    1.953388e-04
## 153      0.069766670    4.050768e-05
## 154      1.312530849    1.287868e-02
## 155     -1.193691728    1.246608e-02
## 156      1.173036367    1.451519e-02
## 157      2.436967434    7.143228e-02
```

```
plot(cook,type="h",lwd=3,col="orange",ylab="Cook's Distance",main="Cook's Distance")
```



```
condition <- (abs(resids) > 2) & (cook > 4 / 157)
count_rows <- sum(condition)
count_rows/157
```

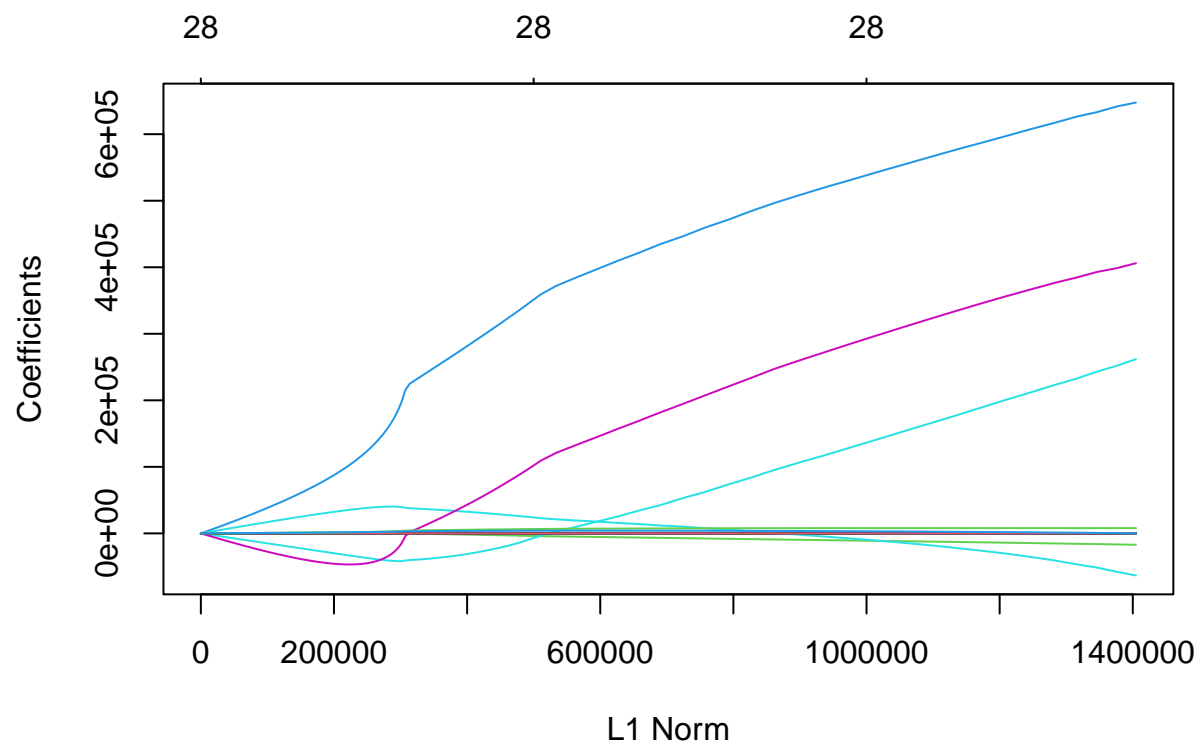
```
## [1] 0.05732484
```

```
# Conclusion: no need to transform the predicting variables
```

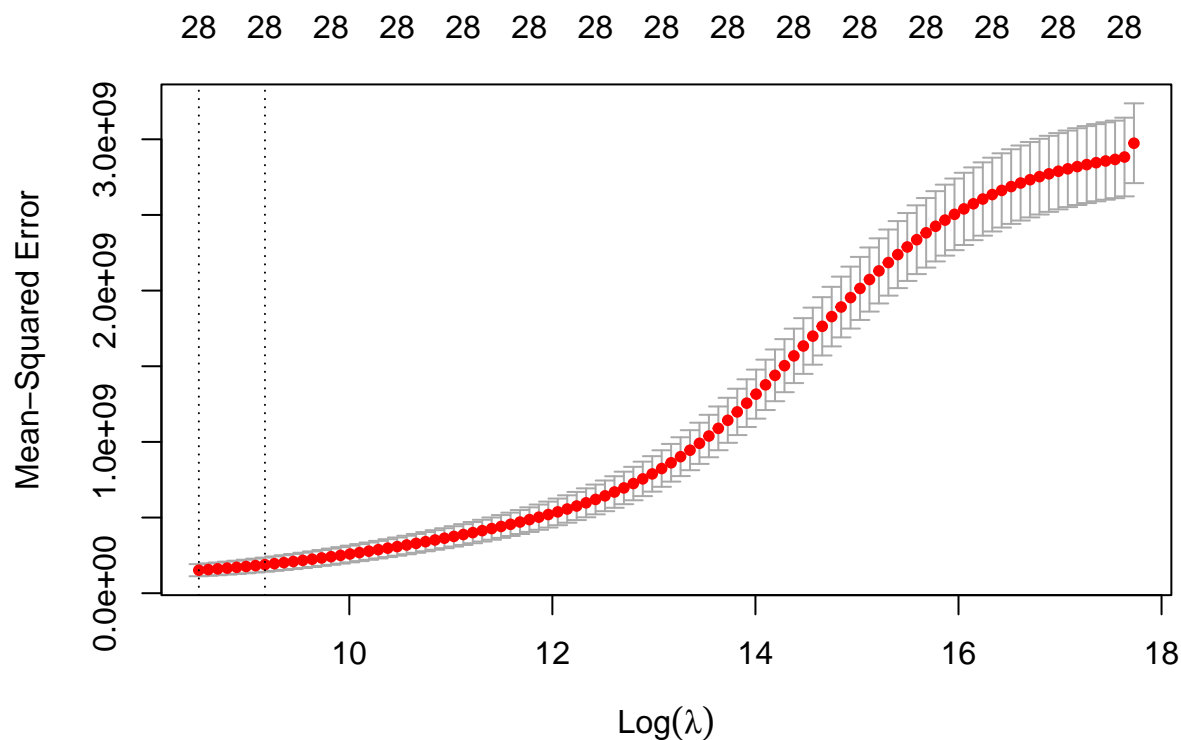
Ridge MLR (considering the dataset has high multicollinearity)

```
X <- as.matrix(data[, -which(names(data) == "Total.NEV.Sales")])
y <- data$Total.NEV.Sales
library(glmnet)
```

```
##      Matrix
##
##      'Matrix'
## The following objects are masked from 'package:tidyr':
##
##      expand, pack, unpack
## Loaded glmnet 4.1-8
ridge_model <- glmnet(X, y, alpha = 0)
plot(ridge_model )
```



```
cv_ridge_model <- cv.glmnet(X, y, alpha = 0)
plot(cv_ridge_model )
```



```
best_lambda2 <- cv_ride_model$lambda.min
print(best_lambda2)
```

```
## [1] 5003.271
```

```
final_ride_model <- glmnet(X, y, alpha = 0, lambda = best_lambda2)
print(final_ride_model$beta)
```

```
## 28 x 1 sparse Matrix of class "dgCMatrix"
```

```
##
## Month 5.622378e+02
## Date -8.760754e-02
## Covid.19 -1.707478e+04
## Number.of.new.energy.policies -1.088210e+02
## Production 4.564174e-02
## Inventory 4.621963e-03
## Gasoline.LDV.sales 2.751609e-02
## M1SL 1.263975e+00
## M2SL 5.417634e-01
## Federal.fund.effective.rate 6.405528e+05
## Umemployment.rate 2.701036e+05
## PPIBC -1.103099e+02
```

## PPIBM	2.166538e+02
## PCE	2.478844e+01
## GDP	1.960865e+00
## Durable.goods.consumption	2.536275e+01
## Nondurable.goods.consumption	1.631283e+01
## Nonresidential.fixed.Investment	1.062938e+01
## Residential.fixed.Investment	-3.438602e+00
## Tesla.model.S.price	2.411760e+00
## ElectricPorts	2.122293e-01
## BatteryCost	-2.308608e+00
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	-5.744401e+04
## Percentage.of.employees.who.are.middle.aged..25.55.	4.043770e+05
## Population	-6.745629e-01
## Per.capita.disposable.income	9.417733e-01
## Gasoline.price	7.844055e+03
## Electric.retail.price	-1.098814e+01

Poisson: not suitable (fail the goodness-of-fit test)

```
# Poisson regression is not suitable for this data set
poisson_model<- glm(Total.NEV.Sales~., family=poisson, data=data)
summary(poisson_model)
```

```
##
## Call:
## glm(formula = Total.NEV.Sales ~ ., family = poisson, data = data)
##
## Coefficients:
##
## Estimate
## (Intercept) 1.826e+01
## Month 1.461e-02
## Date 2.785e-03
## Covid.19 -1.597e-02
## Number.of.new.energy.policies -9.604e-05
## Production -9.801e-08
## Inventory 4.324e-07
## Gasoline.LDV.sales 5.841e-07
## M1SL -3.417e-05
## M2SL 2.034e-05
## Federal.fund.effective.rate 8.011e+00
## Unemployment.rate -3.328e+00
## PPIBC 7.212e-03
## PPIBM -7.119e-04
## PCE 4.180e-04
```

## GDP	-1.826e-04
## Durable.goods.consumption	1.610e-03
## Nondurable.goods.consumption	-7.930e-04
## Nonresidential.fixed.Investment	-6.890e-04
## Residential.fixed.Investment	-1.671e-03
## Tesla.model.S.price	3.786e-05
## ElectricPorts	8.340e-06
## BatteryCost	-1.642e-03
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	-4.855e+00
## Percentage.of.employees.who.are.middle.aged..25.55.	-4.713e+00
## Population	-3.633e-04
## Per.capita.disposable.income	-2.683e-06
## Gasoline.price	1.920e-01
## Electric.retail.price	-2.330e-02
##	Std. Error
## (Intercept)	4.784e-01
## Month	1.210e-04
## Date	3.674e-05
## Covid.19	2.282e-03
## Number.of.new.energy.policies	1.145e-05
## Production	1.109e-08
## Inventory	7.678e-09
## Gasoline.LDV.sales	3.133e-09
## M1SL	8.053e-07
## M2SL	3.996e-06
## Federal.fund.effective.rate	1.381e-01
## Unemployment.rate	6.389e-02
## PPIBC	3.134e-04
## PPIBM	2.873e-04
## PCE	1.053e-05
## GDP	5.858e-06
## Durable.goods.consumption	2.199e-05
## Nondurable.goods.consumption	3.298e-05
## Nonresidential.fixed.Investment	1.925e-05
## Residential.fixed.Investment	2.722e-05
## Tesla.model.S.price	7.865e-07
## ElectricPorts	2.163e-07
## BatteryCost	1.460e-05
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	9.943e-02
## Percentage.of.employees.who.are.middle.aged..25.55.	1.291e-01
## Population	3.918e-06
## Per.capita.disposable.income	6.154e-07
## Gasoline.price	1.955e-03
## Electric.retail.price	1.030e-03
##	z value

## (Intercept)	38.160
## Month	120.767
## Date	75.795
## Covid.19	-6.997
## Number.of.new.energy.policies	-8.391
## Production	-8.835
## Inventory	56.313
## Gasoline.LDV.sales	186.473
## M1SL	-42.430
## M2SL	5.091
## Federal.fund.effective.rate	57.993
## Unemployment.rate	-52.087
## PPIBC	23.015
## PPIBM	-2.478
## PCE	39.698
## GDP	-31.173
## Durable.goods.consumption	73.204
## Nondurable.goods.consumption	-24.047
## Nonresidential.fixed.Investment	-35.801
## Residential.fixed.Investment	-61.394
## Tesla.model.S.price	48.144
## ElectricPorts	38.562
## BatteryCost	-112.495
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education	-48.827
## Percentage.of.employees.who.are.middle.aged..25.55.	-36.509
## Population	-92.727
## Per.capita.disposable.income	-4.359
## Gasoline.price	98.197
## Electric.retail.price	-22.625
##	Pr(> z)
## (Intercept)	< 2e-16
## Month	< 2e-16
## Date	< 2e-16
## Covid.19	2.61e-12
## Number.of.new.energy.policies	< 2e-16
## Production	< 2e-16
## Inventory	< 2e-16
## Gasoline.LDV.sales	< 2e-16
## M1SL	< 2e-16
## M2SL	3.56e-07
## Federal.fund.effective.rate	< 2e-16
## Unemployment.rate	< 2e-16
## PPIBC	< 2e-16
## PPIBM	0.0132
## PCE	< 2e-16

```

## GDP < 2e-16
## Durable.goods.consumption < 2e-16
## Nondurable.goods.consumption < 2e-16
## Nonresidential.fixed.Investment < 2e-16
## Residential.fixed.Investment < 2e-16
## Tesla.model.S.price < 2e-16
## ElectricPorts < 2e-16
## BatteryCost < 2e-16
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education < 2e-16
## Percentage.of.employees.who.are.middle.aged..25.55. < 2e-16
## Population < 2e-16
## Per.capita.disposable.income 1.31e-05
## Gasoline.price < 2e-16
## Electric.retail.price < 2e-16
##
## (Intercept) ***
## Month ***
## Date ***
## Covid.19 ***
## Number.of.new.energy.policies ***
## Production ***
## Inventory ***
## Gasoline.LDV.sales ***
## M1SL ***
## M2SL ***
## Federal.fund.effective.rate ***
## Unemployment.rate ***
## PPIBC ***
## PPIBM *
## PCE ***
## GDP ***
## Durable.goods.consumption ***
## Nondurable.goods.consumption ***
## Nonresidential.fixed.Investment ***
## Residential.fixed.Investment ***
## Tesla.model.S.price ***
## ElectricPorts ***
## BatteryCost ***
## Percentage.of.employees.with.a.bachelor.s.degree.or.higher.education ***
## Percentage.of.employees.who.are.middle.aged..25.55. ***
## Population ***
## Per.capita.disposable.income ***
## Gasoline.price ***
## Electric.retail.price ***
## ---

```



```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 5123903  on 156  degrees of freedom
## Residual deviance:   72056  on 128  degrees of freedom
## AIC: 74128
##
## Number of Fisher Scoring iterations: 4
```

Overall significance

```
1-pchisq(poisson_model$null.deviance-poisson_model$deviance,38)

## [1] 0
```

Goodness-of-fit

```
c(deviance(poisson_model),1-pchisq(deviance(poisson_model),118))

## [1] 72056.26      0.00

pearres=residuals(poisson_model,type="pearson")
pearson.tvalue=sum(pearres^2)
c(pearson.tvalue,1-pchisq(pearson.tvalue,118))

## [1] 71256.07      0.00
# conclusion: not a good fit
```

Model Comparision - Prediction accuracy

```
install.packages("Metrics")

## Warning in download.file(url, destfile, method, mode = "wb", ...): URL
## 'https://cran.rstudio.com/bin/windows/contrib/4.4/Metrics_0.1.4.zip': status
## was 'SSL connect error'

## Error in download.file(url, destfile, method, mode = "wb", ...) :
##   URL'https://cran.rstudio.com/bin/windows/contrib/4.4/Metrics_0.1.4.zip'
## Warning in download.packages(pkgs, destdir = tmpd, available = available, :
##   'Metrics'

library(Metrics) # For MAE, MAPE, RMSE

## Warning:   'Metrics' R 4.4.2
```

```

library(glmnet)    # For ridge regression
library(MASS)      # For stepwise regression
library(caret)     # For cross-validation

##      lattice
##
##      'caret'
## The following objects are masked from 'package:Metrics':
##
##      precision, recall

set.seed(123)

calc_metrics <- function(predictions, actual) {
  # Mean Squared Prediction Error (MSPE)
  MSPE <- mean((predictions - actual)^2)

  # Mean Absolute Error (MAE)
  MAE <- mean(abs(predictions - actual))

  # Mean Absolute Percentage Error (MAPE)
  MAPE <- mean(abs((predictions - actual) / actual)) * 100

  # Precision Measure (PM)
  PM <- sum((predictions - actual)^2) / sum((actual - mean(actual))^2)

  # R-squared
  SS_res <- sum((predictions - actual)^2) # Residual sum of squares
  SS_tot <- sum((actual - mean(actual))^2) # Total sum of squares
  R_squared <- 1 - (SS_res / SS_tot)

  # Residuals
  residuals <- actual - predictions
  mean_residual <- mean(residuals) # Mean of residuals
  residual_sum_of_squares <- sum(residuals^2) # Sum of squared residuals

  # Return all metrics as a named vector
  return(c(MSPE = MSPE, MAE = MAE, MAPE = MAPE, PM = PM,
           R_squared = R_squared, Mean_Residual = mean_residual, Residual_Sum_of_Squares = residual_sum_of_squares))
}

# Cross-validation function
cv_model <- function(model, X, Y, k = 10) {
  folds <- createFolds(Y, k = k, list = TRUE, returnTrain = FALSE)

```

```

metrics <- matrix(NA, nrow = k, ncol = 7)
colnames(metrics) <- c("MSPE", "MAE", "MAPE", "PM", "R-squared", "Mean Residual", "Residual")

for (i in 1:k) {
  test_index <- folds[[i]]
  train_index <- setdiff(1:nrow(X), test_index)

  X_train <- X[train_index, , drop = FALSE]
  Y_train <- Y[train_index]
  X_test <- X[test_index, , drop = FALSE]
  Y_test <- Y[test_index]

  # Train model on training data
  if (inherits(model, "glmnet")) {
    # Ridge regression
    pred <- predict(model, newx = X_test)
    pred <- pred[, 1]
  } else if (inherits(model, "lm")) {
    # For linear models like stepwise and boxcox
    pred <- predict(model, newdata = data.frame(X_test))
  }

  # Calculate performance metrics
  metrics[i, ] <- calc_metrics(pred, Y_test)
}

# Return the mean of each metric over all folds
colMeans(metrics)
}

stepwise_metrics_multicollinearity_corrected <- cv_model(stepwise_model2, data_stepwise0[,
data_cv_step <- data_stepwise[4:nrow(data_stepwise),]
stepwise_metrics_multicollinearity_autocorrelation_corrected <- cv_model(lagged_model, data

boxcox_metrics_multicollinearity_corrected <- cv_model(model_boxcox2, data_boxcox0[, -1], (c

data_cv_boxcox <- data_boxcox[4:nrow(data_boxcox),]
boxcox_metrics_multicollinearity_autocorrelation_corrected <- cv_model(lagged_model2, data

ridge_metrics <- cv_model(final_ridge_model, as.matrix(data[, -1]), as.matrix(data$Total.

```

```

cat("Stepwise multicollinearity corrected Model Metrics:", "\n")

## Stepwise multicollinearity corrected Model Metrics:
print(stepwise_metrics_multicollinearity_corrected )

##                MSPE                MAE                MAPE
##      1.529660e+08      8.586711e+03      1.491908e+01
##                PM                R-squared      Mean Residual
##      7.987972e-02      9.201203e-01      -1.477414e+01
## Residual Sum of Squares
##      2.399444e+09

cat("Stepwise multicollinearity & autocorrelation corrected Model Metrics:", "\n")

## Stepwise multicollinearity & autocorrelation corrected Model Metrics:
print(stepwise_metrics_multicollinearity_autocorrelation_corrected)

##                MSPE                MAE                MAPE
##      5.281100e+07      5.343426e+03      8.998258e+00
##                PM                R-squared      Mean Residual
##      2.339006e-02      9.766099e-01      -1.935032e+01
## Residual Sum of Squares
##      8.143157e+08

cat("Box-Cox multicollinearity corrected Model Metrics:", "\n")

## Box-Cox multicollinearity corrected Model Metrics:
print(boxcox_metrics_multicollinearity_corrected)

##                MSPE                MAE                MAPE
##      2.218659e+02      1.091726e+01      4.475114e+00
##                PM                R-squared      Mean Residual
##      4.908420e-02      9.509158e-01      5.622677e-02
## Residual Sum of Squares
##      3.484675e+03

cat("Box-Cox multicollinearity & autocorrelation corrected Model Metrics:", "\n")

## Box-Cox multicollinearity & autocorrelation corrected Model Metrics:
print(boxcox_metrics_multicollinearity_autocorrelation_corrected)

##                MSPE                MAE                MAPE
##      1.082560e+02      8.089410e+00      3.355103e+00
##                PM                R-squared      Mean Residual
##      2.205188e-02      9.779481e-01      4.811473e-02

```

```
## Residual Sum of Squares
##          1.678848e+03
```

```
cat("Ridge Regression Model Metrics:", "\n")
```

```
## Ridge Regression Model Metrics:
```

```
print(ridge_metrics)
```

##	MSPE	MAE	MAPE
##	1.281676e+08	7.844014e+03	1.313336e+01
##	PM	R-squared	Mean Residual
##	4.450664e-02	9.554934e-01	-1.444706e+01
##	Residual Sum of Squares		
##	2.021927e+09		