The Co-operative University of Kenya

Outliers Detection and Treatment with R
Collins Kipkorir

2024-03-02

Outlier detection and treatment with R

Outliers in data can distort predictions and affect the accuracy, if you don't detect and handle them appropriately especially in regression models.

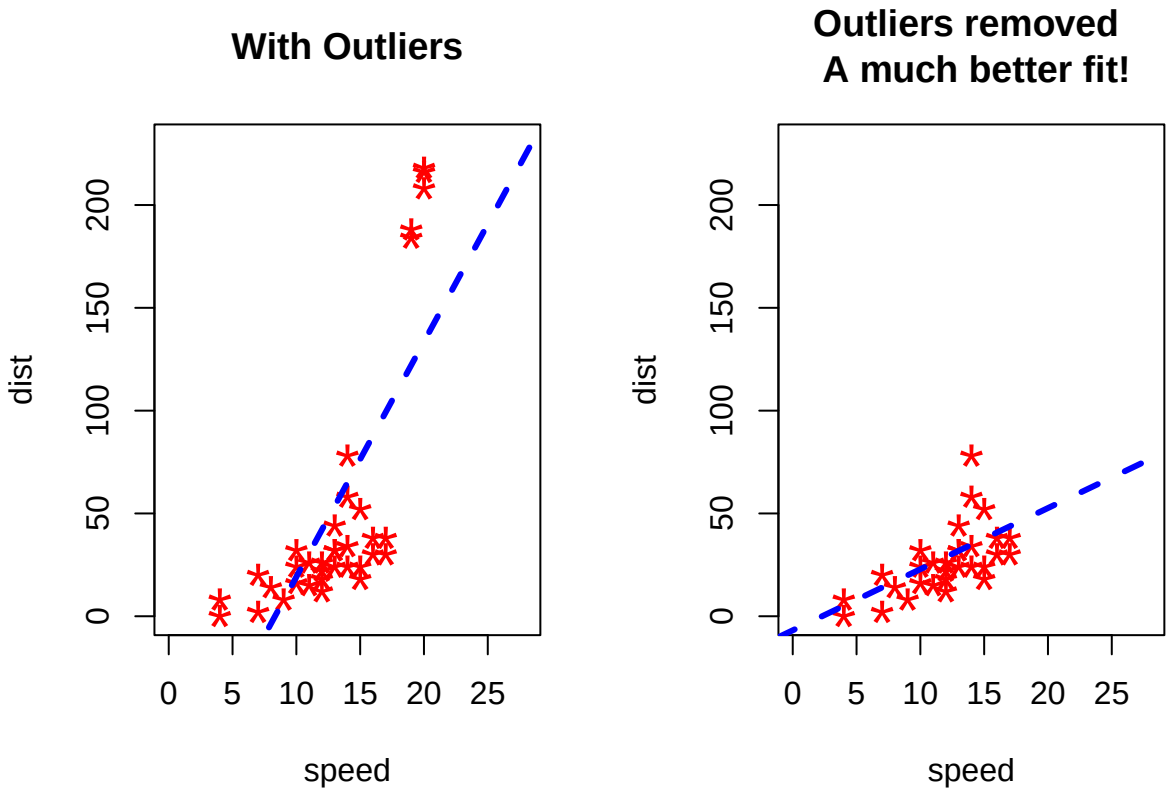
Why outliers treatment is important?

Because, it can drastically bias/change the fit estimates and predictions. Let me illustrate this using the cars dataset.

To better understand the implications of outliers better, I am going to compare the fit of a simple linear regression model on cars dataset with and without outliers. In order to distinguish the effect clearly, I manually introduce extreme values to the original cars dataset. Then, I predict on both the datasets.

```
# Inject outliers into data.  original data
cars1 <- cars[1:30, ]
# introduce outliers.
cars_outliers <- data.frame(speed = c(19, 19, 20, 20, 20), dist = c(190, 186, 210,
    220, 218))
# data with outliers.
cars2 <- rbind(cars1, cars_outliers)
# Plot of data with outliers.
par(mfrow = c(1, 2))
plot(cars2$speed, cars2$dist, xlim = c(0, 28), ylim = c(0, 230), main = "With Outliers",
    xlab = "speed", ylab = "dist", pch = "*", col = "red", cex = 2)
abline(lm(dist ~ speed, data = cars2), col = "blue", lwd = 3, lty = 2)

# Plot of original data without outliers. Note the change in slope (angle) of
# best fit line.
plot(cars1$speed, cars1$dist, xlim = c(0, 28), ylim = c(0, 230), main = "Outliers removed
↪  \n A much better fit!",
    xlab = "speed", ylab = "dist", pch = "*", col = "red", cex = 2)
abline(lm(dist ~ speed, data = cars1), col = "blue", lwd = 3, lty = 2)
```



Notice the change in slope of the best fit line after removing the outliers. Had we used the outliers to train the model(left chart), our predictions would be exagerated (high error) for larger values of speed because of the larger slope.

Detect Outliers

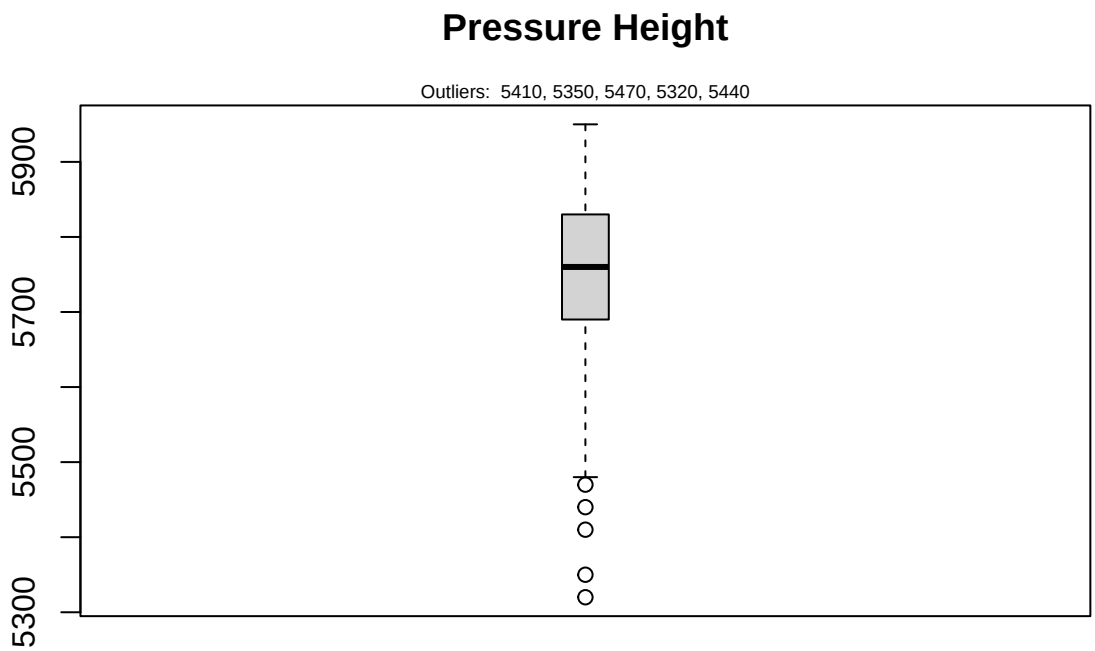
Univariate approach

For a given continuous variable, outliers are those observations that lie outside 1.5*IQR, where IQR, the 'Inter Quartile Range' is the difference between 75th and 25th quartiles. Look at the points outside the whiskers in below box plot.

```
ozone <- read.csv("ozone.csv")
outlier_values <- boxplot.stats(ozone$pressure_height)$out  # outlier values.
outlier_values
```

```
## [1] 5410 5350 5470 5320 5440
```

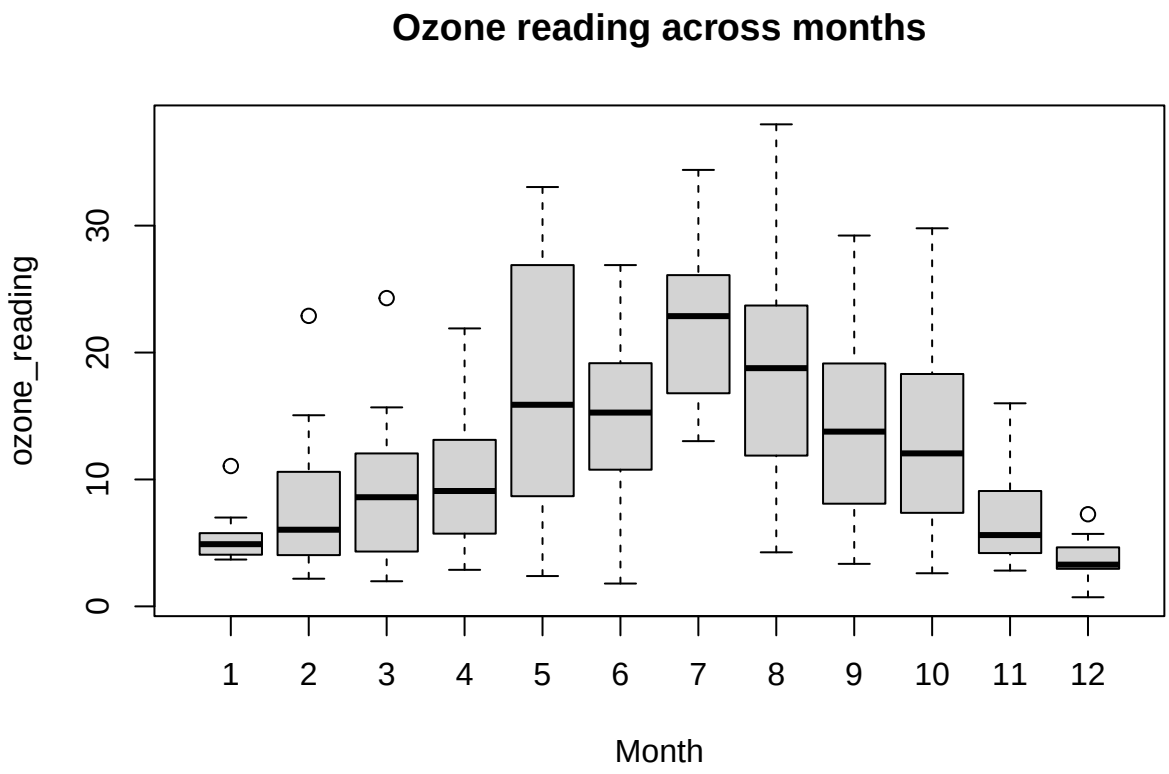
```
boxplot(ozone$pressure_height, main="Pressure Height", boxwex=0.1)
mtext(paste("Outliers: ", paste(outlier_values, collapse=", ")), cex=0.6)
```



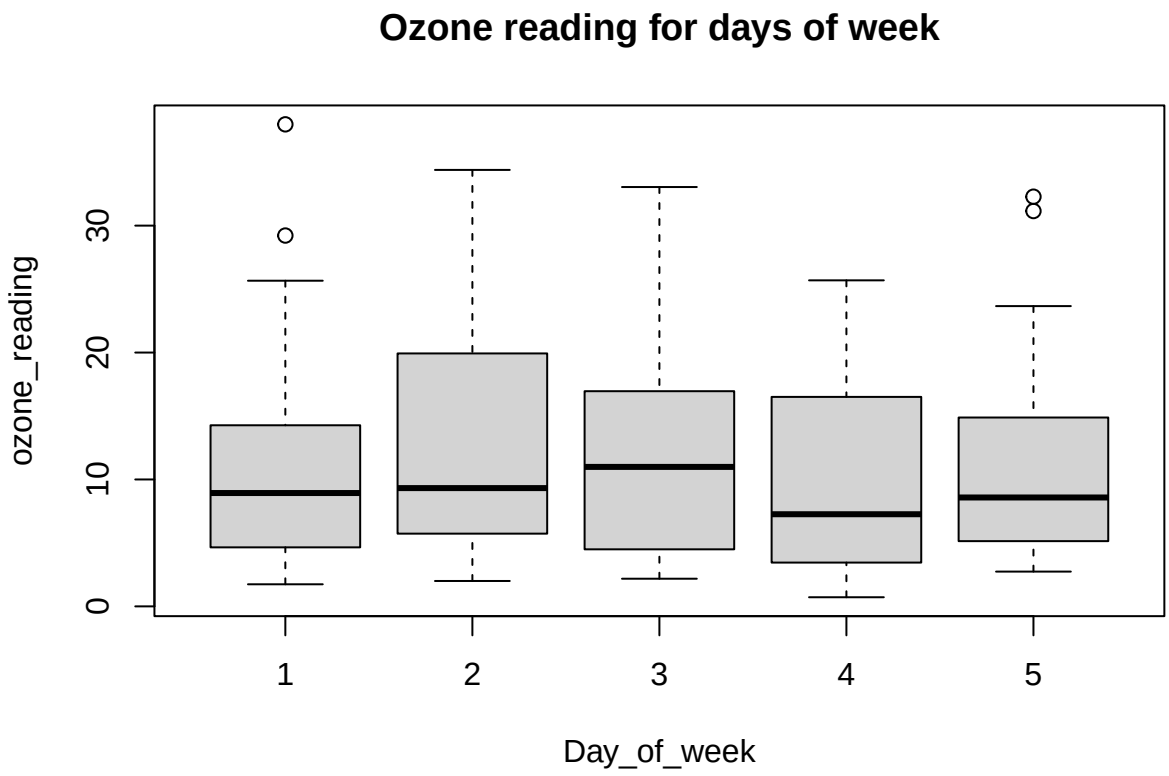
Bivariate approach

Visualize in box-plot of the X and Y, for categorical X's

```
# For categorical variable
boxplot(ozone_reading ~ Month, data=ozone, main="Ozone reading across months")  # clear
↪  pattern is noticeable.
```

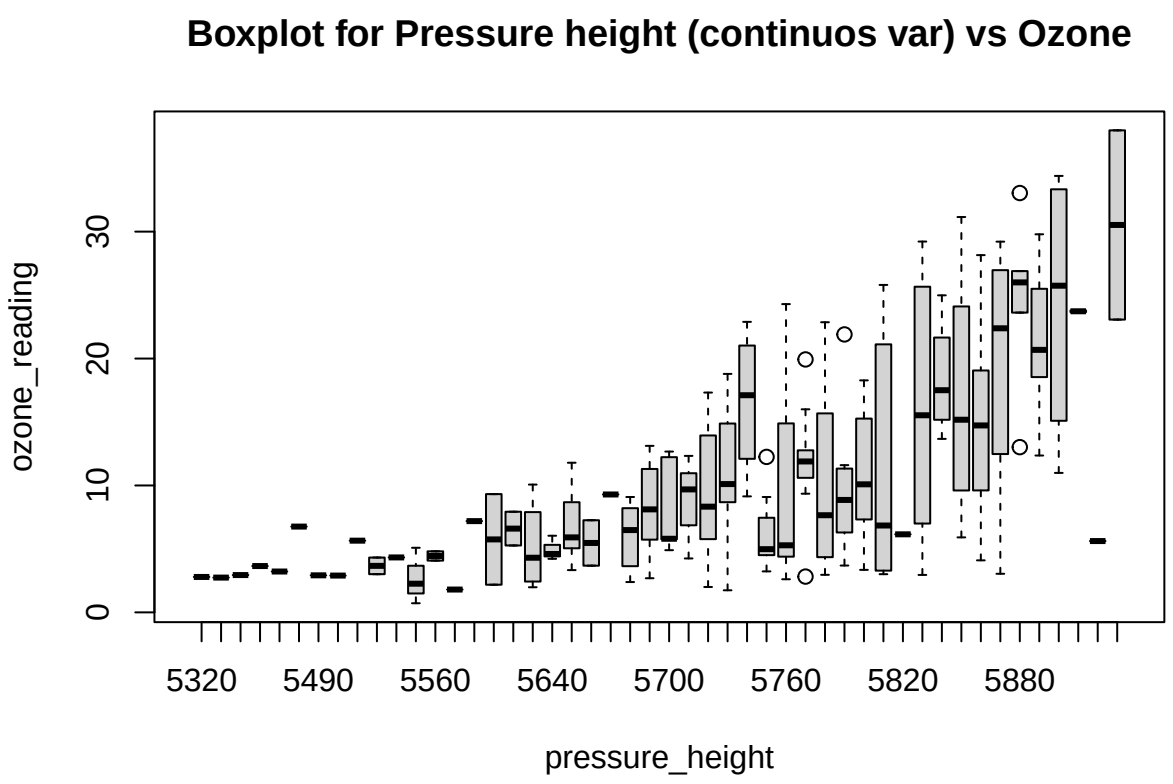



```
boxplot(ozone_reading ~ Day_of_week, data=ozone, main="Ozone reading for days of week")
↪  # this may not be significant, as day of week variable is a subset of the month var.
```

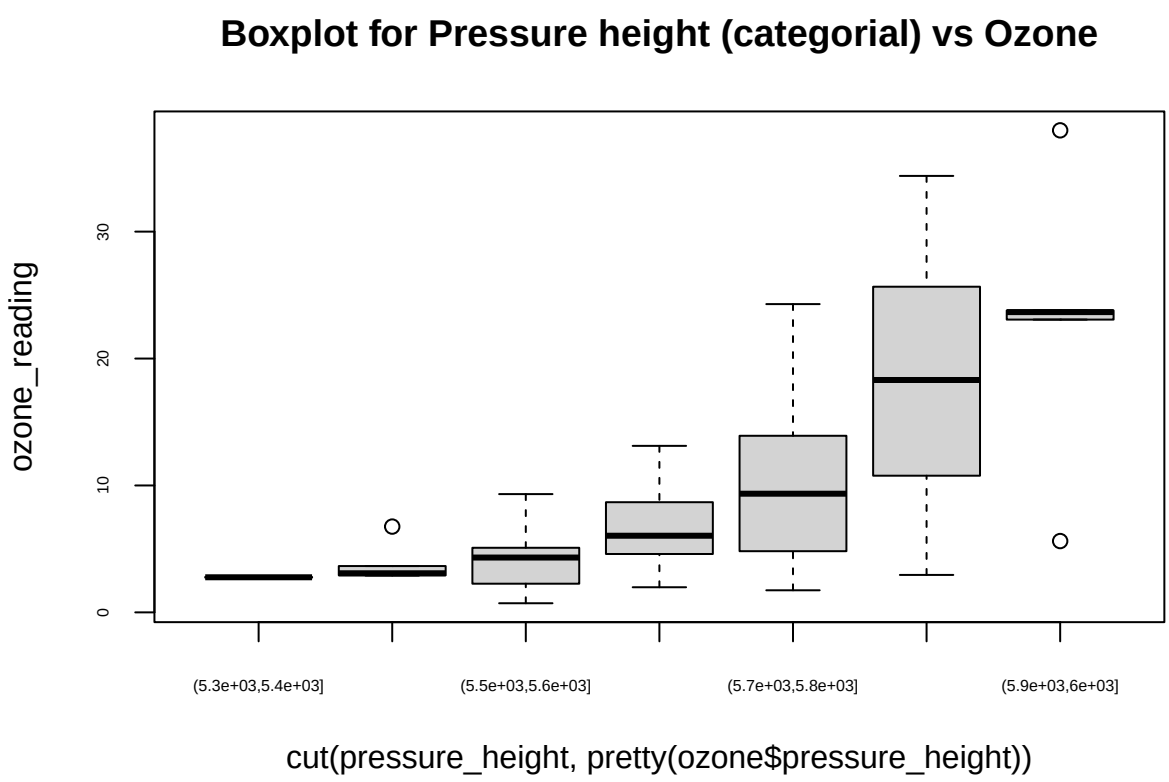


What is the inference? The change in the level of boxes suggests that Month seem to have an impact in ozone_reading while Day_of_week does not. Any outliers in respective categorical level show up as dots outside the whiskers of the boxplot.

```
# For continuous variable (convert to categorical if needed.)
boxplot(ozone_reading ~ pressure_height, data=ozone, main="Boxplot for Pressure height
↪  (continuos var) vs Ozone")
```




```
boxplot(ozone_reading ~ cut(pressure_height, pretty(ozone$pressure_height)), data=ozone,
↪  main="Boxplot for Pressure height (categorial) vs Ozone", cex.axis=0.5)
```



You can see few outliers in the box plot and how the ozone_reading increases with pressure_height. Thats clear.

Multivariate Model Approach

Cook's Distance

Cook's distance is a measure computed with respect to a given regression model and therefore is impacted only by the X variables included in the model. But, what does cook's distance mean? It computes the influence exerted by each data point (row) on the predicted outcome.

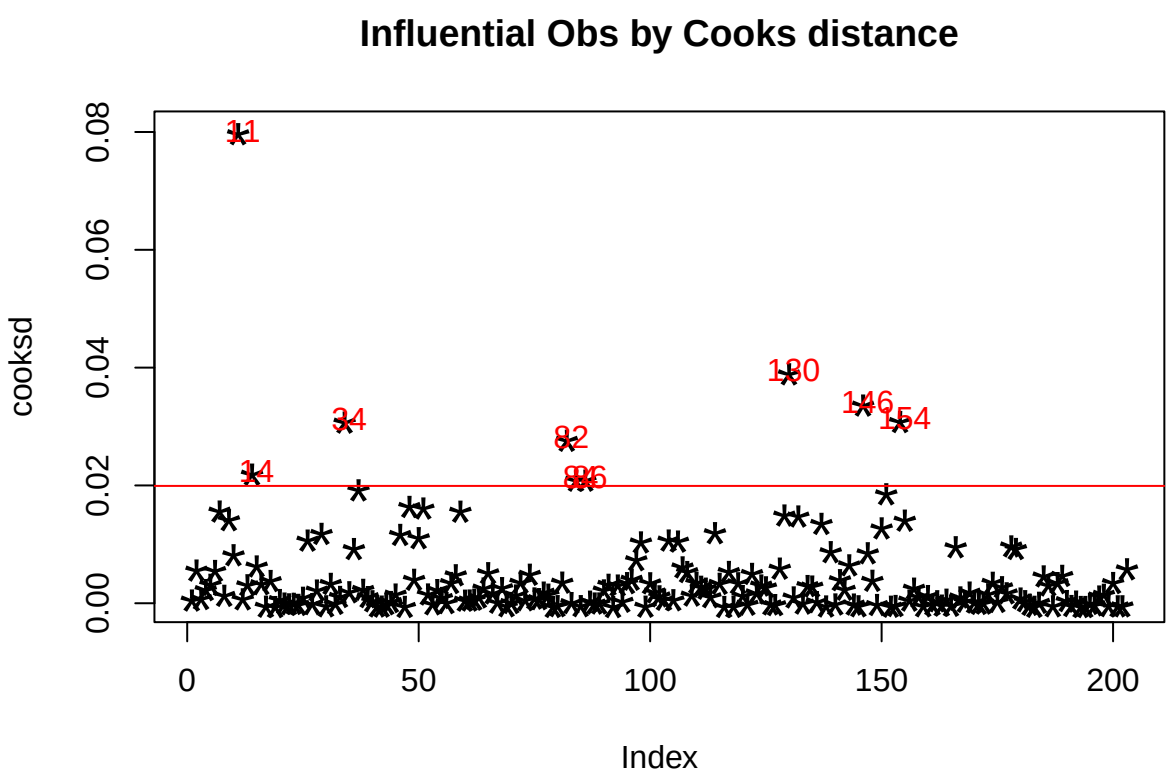
The cook's distance for each observation i measures the change in y hat (fitted Y) for all observations with and without the presence of observation i, so we know how much the observation i impacted the fitted values.

```
mod <- lm(ozone_reading ~ ., data=ozone)
cooksd <- cooks.distance(mod)
```

Influence measures

In general use, those observations that have a cook's distance greater than 4 times the mean may be classified as influential. This is not a hard boundary.

```
plot(cooksd, pch="*", cex=2, main="Influential Obs by Cooks distance")  # plot cook's
↪  distance
abline(h = 4*mean(cooksd, na.rm=T), col="red")  # add cutoff line
text(x=1:length(cooksd)+1, y=cooksd, labels=ifelse(cooksd>4*mean(cooksd,
↪  na.rm=T),names(cooksd),""), col="red")  # add labels
```



Now lets find out the influential rows from the original data. If you extract and examine each influential row 1-by-1 (from below output), you will be able to reason out why that row turned out influential. It is likely that one of the X variables included in the model had extreme values.

```
threshold <- 4*mean(cooksd, na.rm=T) #set threshold
influential<-which(cooksd>threshold)# influential row numbers
head(ozone[influential, ])  # influential observations.
```

```
##    Month Day_of_month Day_of_week ozone_reading pressure_height Wind_speed
## 11     1           19           1          4.07            5680          5
## 14     1           23           5          4.90            5700          5
## 34     2           27           5         22.89            5740          3
## 82     5           12           3         33.04            5880          3
## 84     5           14           5         31.15            5850          4
## 86     5           28           5          4.82            5750          3
##    Humidity Temperature_Sandburg Temperature_ElMonte Inversion_base_height
## 11       73                   52               56.48                  393
## 14       59                   69               51.08                 3044
## 34       47                   53               58.82                  885
## 82       80                   80               73.04                  436
## 84       76                   78               71.24                 1181
## 86       76                   65               51.08                 3644
##    Pressure_gradient Inversion_temperature Visibility
## 11               -68                69.80         10
## 14                18                52.88        150
## 34                -4                67.10         80
## 82                 0                86.36         40
```

```
## 84                50                  79.88          17
## 86                86                  59.36          70
```

Lets examine the first 6 rows from above output to find out why these rows could be tagged as influential observations.

- Rows 34, 82 and 84 have very high ozone_reading
- Rows 14, 84 and 86 have very high inversion_base_height
- Row 11 has very low pressure_gradient.

Outlier Test

The function outlierTest from car package gives the most extreme observation based on the given model.

```
car::outlierTest(mod)
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 130 3.045756          0.0026525      0.53845
```

This output suggests that observation 130 is most extreme.

Outliers Package

The outliers package provides a number of useful functions to systematically extract outliers. Some of these are convenient and come handy, especially the outlier() and scores() functions

Outliers

Outliers gets the extreme most observation from the mean. If you set the argument opposite=TRUE, it fetches from the other side.

```
set.seed(1234)
library(outliers)
y=rnorm(100)
outlier(y)
```

```
## [1] 2.548991
```

```
outlier(y,opposite=TRUE)
```

```
## [1] -2.345698
```

```
dim(y) <- c(20,5) # convert it to a matrix
outlier(y)
```

```
## [1] 2.415835 1.102298 1.647817 2.548991 2.121117
```

```
outlier(y,opposite=TRUE)
```

```
## [1] -2.345698 -2.180040 -1.806031 -1.390701 -1.372302
```

Scores

Sores function computes the normalized scores based on “z”, “t”, “Chisq” etc. Find out observations that lie beyond a given percentile based on a given score.

```
set.seed(1234)
x = rnorm(10)
scores(x) # z-scores => (x-mean)/sd
```

```
##  [1] -0.8273937  0.6633811  1.4738069 -1.9708424  0.8157183  0.8929749
##  [7] -0.1923930 -0.1641660 -0.1820615 -0.5090247
```

```
scores(x, type="chisq") # chi-sq scores => (x - mean(x))^2/var(x)
```

```
##  [1] 0.68458034 0.44007451 2.17210689 3.88421971 0.66539631 0.79740421
##  [7] 0.03701507 0.02695047 0.03314640 0.25910611
```

```
scores(x, type="t") # t scores
```

```
##  [1] -0.8115497  0.6413175  1.5952995 -2.4645688  0.7991765  0.8818782
##  [7] -0.1817640 -0.1550094 -0.1719662 -0.4869741
```

```
scores(x, type="chisq", prob=0.9) # beyond 90th %ile based on chi-sq
```

```
##  [1] FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE
```

```
scores(x, type="chisq", prob=0.95) # beyond 95th %ile
```

```
##  [1] FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE
```

```
scores(x, type="z", prob=0.95) # beyond 95th %ile based on z-scores
```

```
##  [1] FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE
```

```
scores(x, type="t", prob=0.95) # beyond 95th %ile based on t-scores
```

```
##  [1] FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE
```

Treatment

Once the outliers are identified, you may rectify it by using one of the following approaches

Imputation

Imputation with mean / median / mode. This method has been dealt with in detail in the discussion about treating missing values. Another robust method which we covered at DataScience+ is multivariate imputation by chained equations.

Capping

For missing values that lie outside the 1.5*IQR limits, we could cap it by replacing those observations outside the lower limit with the value of 5th percentile and those that lie above the upper limit, with the value of 95th percentile. Below is a sample code that achieves this.

```
x <- ozone$pressure_height
qnt <- quantile(x, probs=c(.25, .75), na.rm = T)
caps <- quantile(x, probs=c(.05, .95), na.rm = T)
H <- 1.5 * IQR(x, na.rm = T)
# Replace values below the lower bound with the lower cap
x[x < (qnt[1] - H)]<-caps[1]
# Replace values above the upper bound with the upper cap
x[x>(qnt[2] + H)] <- caps[2]
```

Prediction

In yet another approach, the outliers can be replaced with missing values NA and then can be predicted by considering them as a response variable. We already discussed how to predict missing values