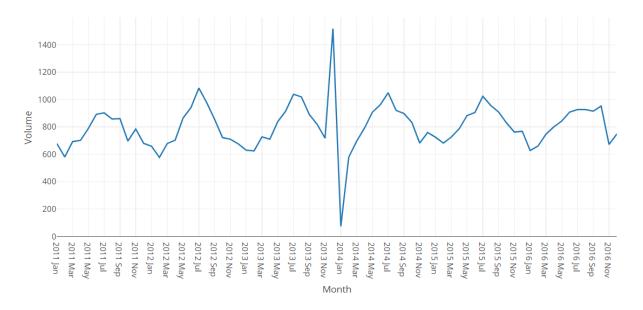
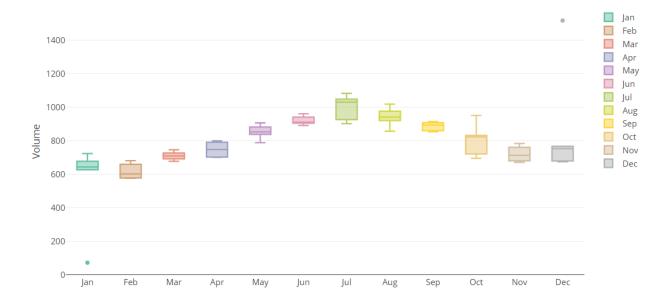
## **Outliers**



## Identification

- In the above example, outliers can be clearly identified by observing. However, observation cannot be scaled to thousands of records
- Common practices include checking percentiles and box plots

```
# Plotting the series
quantile(volume_ts, seq(0,1,by = 0.05))
##
           0%
                      5%
                                 10%
                                            15%
                                                        20%
                                                                   25%
##
     73.17155
               604.66837
                           658.51287
                                      677.44359
                                                  681.49081
                                                             695.91958
##
          30%
                     35%
                                 40%
                                            45%
                                                        50%
                                                                   55%
    710.03465
##
               724.15420
                          747.55286
                                      767.70870
                                                 790.53039
                                                             829.46234
##
          60%
                     65%
                                 70%
                                            75%
                                                        80%
                                                                   85%
##
    849.55585
               867.37696
                           895.95465
                                      907.46436
                                                 914.80318
                                                             932.19810
##
          90%
                     95%
                                100%
   961.21952 1030.37763 1518.07595
# Creating boxplots to understand high and low variation months
data$Month1 <- factor(substr(as.character(data$Month), 6,</pre>
nchar(as.character(data$Month))), levels = month.abb)
plot_ly(data, x = ~Month1, y = ~Volume, type = "box", color = ~Month1) %>%
layout(autosize=F, width=900, height = 450, xaxis = list(title = ""))
```



- We see two clear outlier points in January and December
- A possible reason for this is an aritifical inventory push at the end of 2013 to meet shipment targets

## **Treatment**

- Since the effect of shipments are cascading, exceptions have to be handled by redistributing volumes in proportion with historical values
- In the above case, January and December seem to be the only ones affected

```
proportion2012 <- c(data$Volume[12]/(data$Volume[12]+data$Volume[13]),</pre>
                     data$Volume[13]/(data$Volume[12]+data$Volume[13]))
proportion2012
## [1] 0.5080608 0.4919392
proportion2013 <- c(data$Volume[24]/(data$Volume[24]+data$Volume[25]),</pre>
                     data$Volume[25]/(data$Volume[24]+data$Volume[25]))
proportion2013
## [1] 0.51745 0.48255
proportion2014 <- c(data$Volume[36]/(data$Volume[36]+data$Volume[37]),</pre>
                     data$Volume[37]/(data$Volume[36]+data$Volume[37]))
proportion2014
## [1] 0.95401623 0.04598377
proportion2015 <- c(data$Volume[48]/(data$Volume[48]+data$Volume[49]),</pre>
                     data$Volume[49]/(data$Volume[48]+data$Volume[49]))
proportion2015
## [1] 0.5115344 0.4884656
```

• Re-proportioning 2013 December and 2014 January we arrive at the following plot:

```
total <- (data$Volume[36]+data$Volume[37])
data$Volume[36] <- total*0.51
data$Volume[37] <- total*0.49</pre>
```

```
plot_ly(data, x = ~Month, y = ~Volume, type = 'scatter', mode = 'lines') %>%
layout(autosize=F, width=900, height = 450, margin = list(b = 100))
```

