

# sold\_units\_complete

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2/27/2022

## Analysis of the factors related with the number of units sold per year

```
#Importing the packages
```

```
library(readr)
library(car)
```

```
## Loading required package: carData
```

```
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loaded glmnet 4.1-3
```

```
library(leaps)
library(lmvar)
```

Importing the data

```
file_path<-"../raw/sold_units_complete.csv"
sold_units<-read_csv(file_path)
```

```
##
## -- Column specification -----
## cols(
##   Año = col_double(),
##   'Unidades Vendidas' = col_double(),
##   'ITCRB Estados Unidos Promedio' = col_double(),
##   'Importacion de autos' = col_double(),
##   'Crisis Semiconductores' = col_double(),
##   'Devaluacion Interanual' = col_double(),
##   Inflacion = col_double(),
##   'Restriccion de importaciones' = col_double(),
##   'PIB (Millones de US$ a precios actuales)' = col_double(),
##   'Reservas Internacionales' = col_double(),
##   'PIB/reservas' = col_double(),
##   'Brecha Cambiaria' = col_double(),
##   'Diferencia Trade Balance Industria' = col_number()
## )
```

```

#Dropping the year column.
sold_units<-sold_units[,-1]

#Centering the variables to reduce structural multicollinearity
sold_units[,8]<-scale(sold_units[,8],scale=FALSE)
sold_units[,9]<-scale(sold_units[,9],scale=FALSE)
sold_units[,10]<-scale(sold_units[,10],scale=FALSE)

#Renaming the columns
my_names<-c("num_units", "itcrb", "imported_cars", "semiconductor_crisis",
            "devaluacion_interanual", "inflation", "import_restriction",
            "PIB", "reserves", "PIB_over_reserves", "exchange_difference",
            "industry_trade_balance_difference")
names(sold_units)<-my_names

```

Building the model

```

sold_units_model<-lm(sold_units, y= TRUE, x = TRUE)
summary(sold_units_model)

```

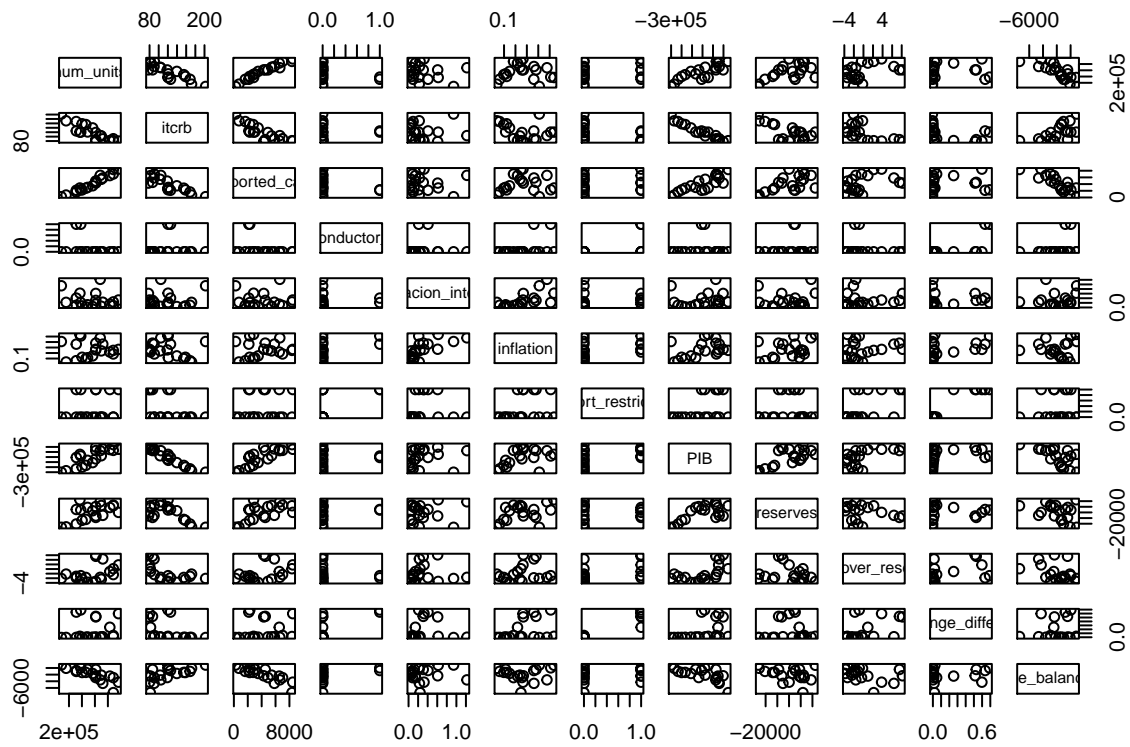
```

##
## Call:
## lm(formula = sold_units, x = TRUE, y = TRUE)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -62015 -12576  -1454   19485   66203
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    6.445e+05  4.954e+05   1.301  0.2295
## itcrb          -3.134e+03  3.815e+03  -0.822  0.4351
## imported_cars    8.011e+01  2.615e+01   3.063  0.0155 *
## semiconductor_crisis -8.198e+04  1.099e+05  -0.746  0.4770
## devaluacion_interanual -8.825e+04  5.990e+04  -1.473  0.1789
## inflation        5.412e+03  1.883e+05   0.029  0.9778
## import_restriction -3.926e+04  1.058e+05  -0.371  0.7202
## PIB             5.299e-01  8.115e-01   0.653  0.5321
## reserves        -8.287e+00  1.045e+01  -0.793  0.4506
## PIB_over_reserves -3.020e+04  3.780e+04  -0.799  0.4474
## exchange_difference  8.548e+04  2.097e+05   0.408  0.6942
## industry_trade_balance_difference 1.064e+01  1.747e+01   0.609  0.5594
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 43590 on 8 degrees of freedom
## Multiple R-squared:  0.9866, Adjusted R-squared:  0.9682
## F-statistic: 53.58 on 11 and 8 DF, p-value: 2.911e-06

```

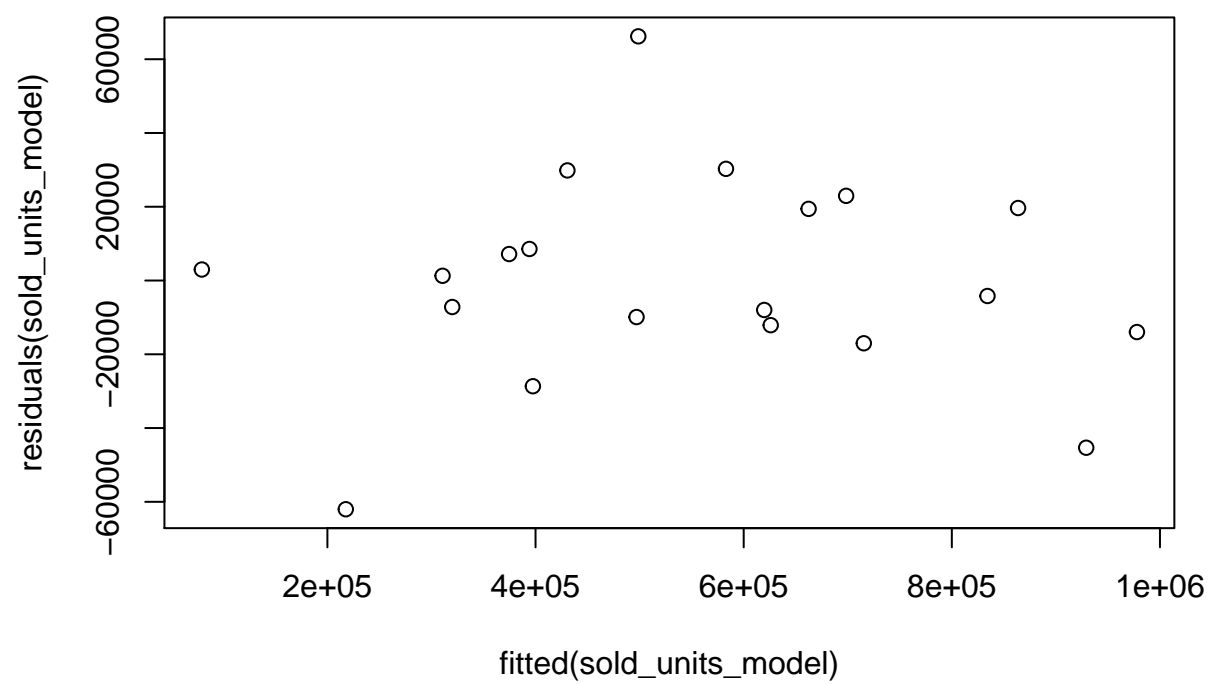
Pairwise plots of the features

```
pairs(sold_units)
```

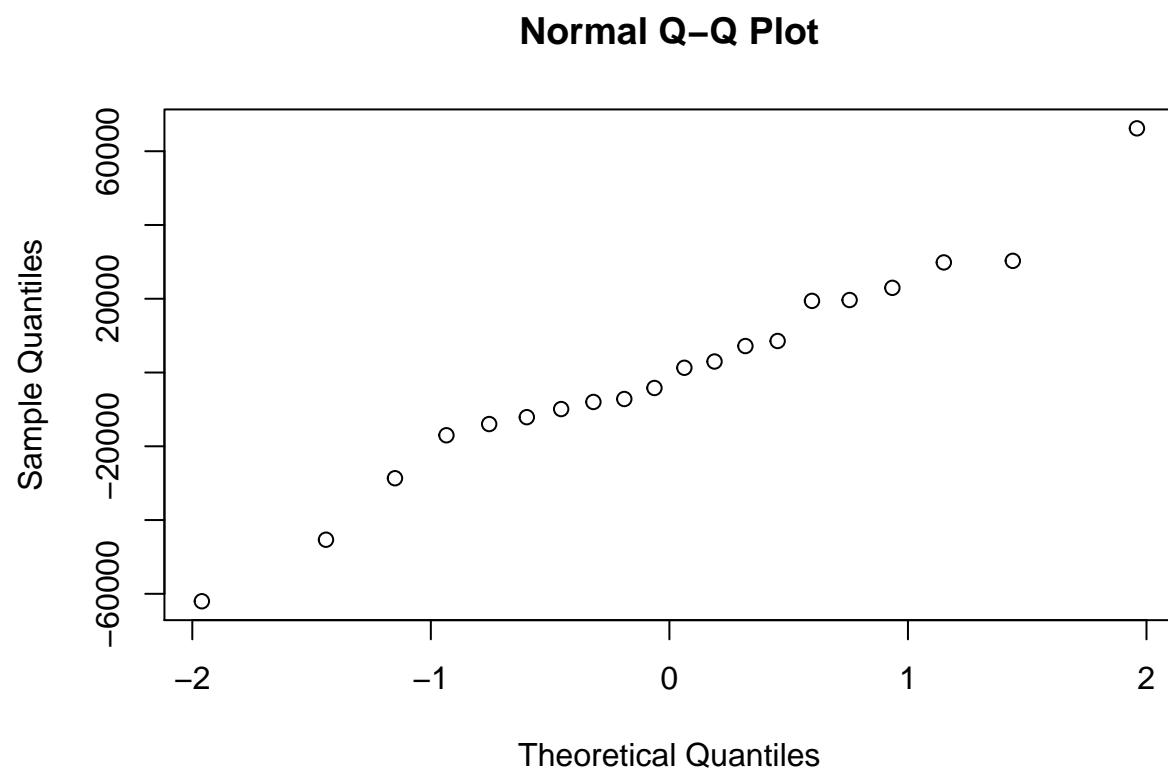


Analyzing the residuals

```
plot(fitted(sold_units_model),residuals(sold_units_model))
```

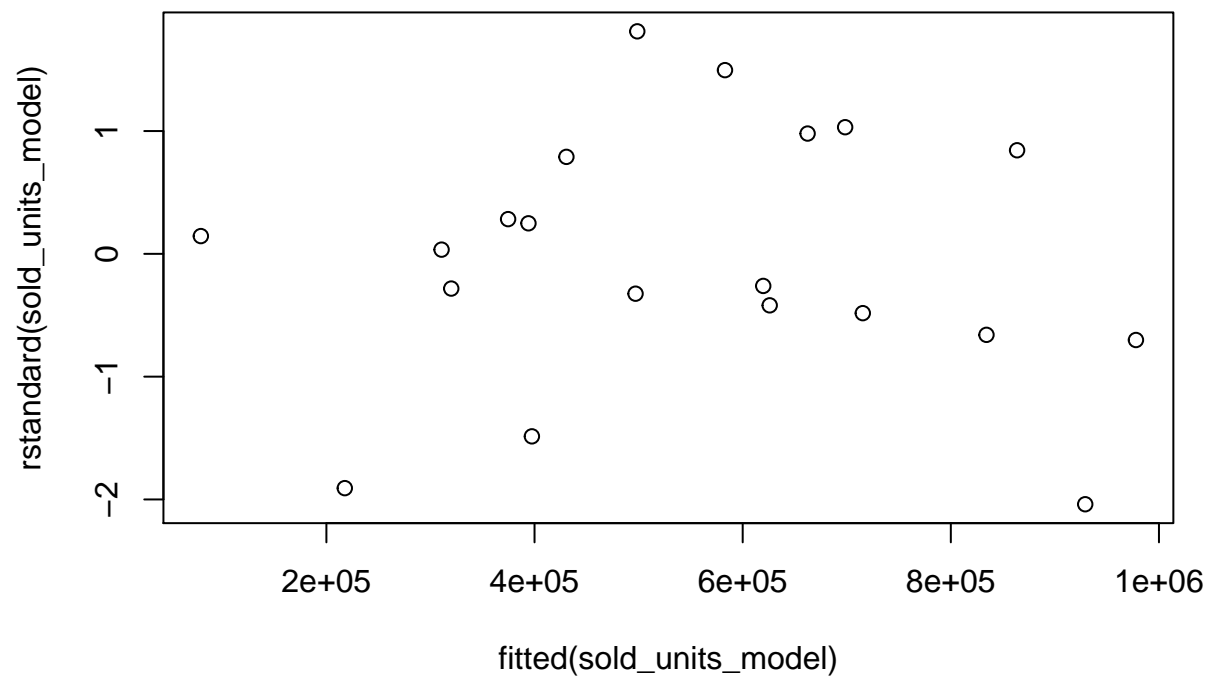


```
qqnorm(residuals(sold_units_model))
```

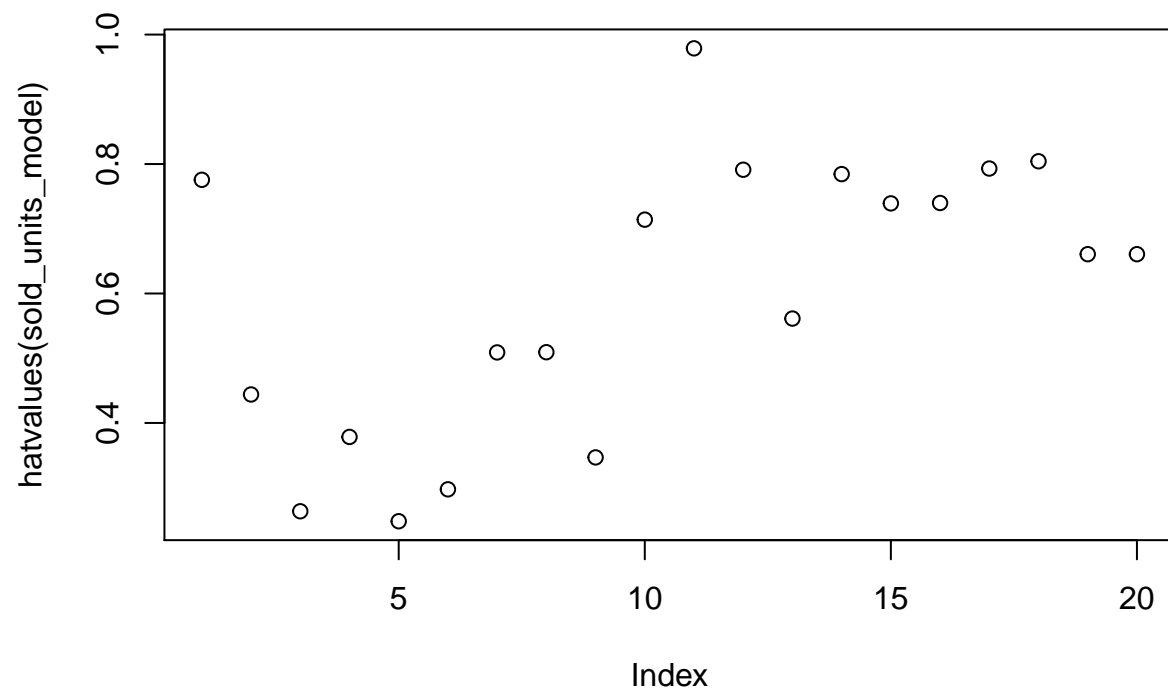


Looking for outliers and high leverage points

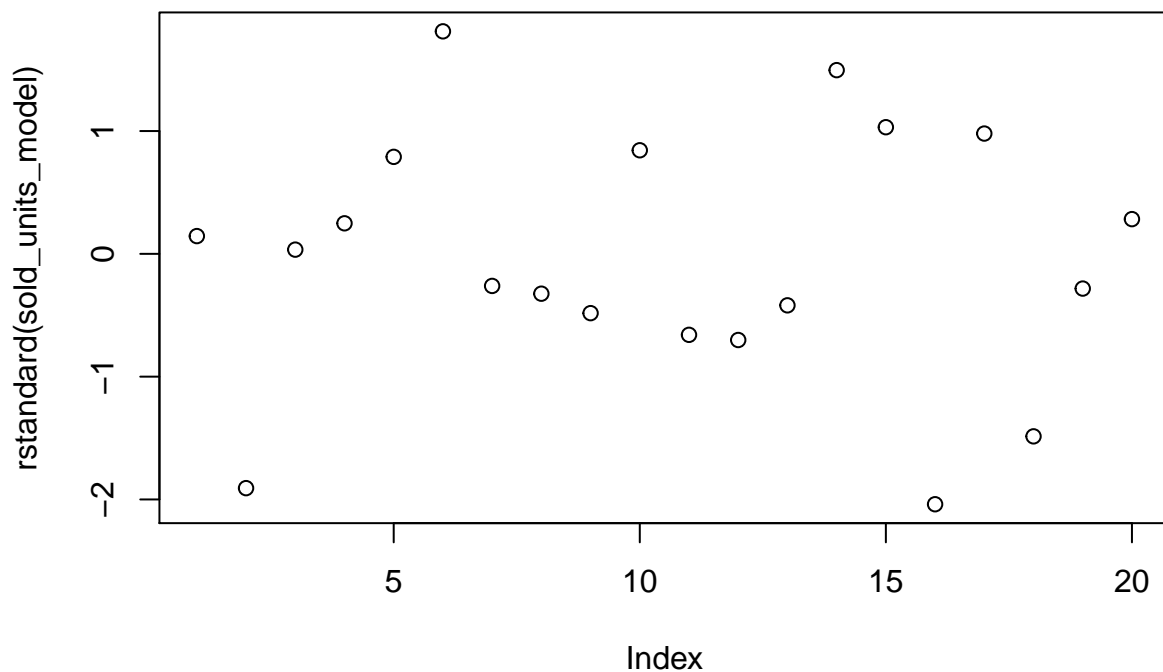
```
plot(fitted(sold_units_model),rstandard(sold_units_model))
```



```
plot(hatvalues(sold_units_model))  
abline(h=length(coef(sold_units_model))/nrow(sold_units)*2,  
       col = "red",lty = 2)
```



```
high_leverage_points<-hatvalues(sold_units_model)>
  (length(coef(sold_units_model))/nrow(sold_units)*2)
plot(rstandard(sold_units_model),
     col = factor(high_leverage_points))
```



Looking for colinearity Correlation matrix

```
cor(sold_units[, -1])
```

```
##               itcrb imported_cars
## itcrb          1.00000000 -0.84998083
## imported_cars -0.84998083  1.00000000
## semiconductor_crisis  0.03102529 -0.27546378
## devaluacion_interannual  0.04051446 -0.02721305
## inflation          -0.27166538  0.10875007
## import_restriction -0.45615253  0.15017680
## PIB              -0.97038025  0.84102366
## reserves         -0.64341540  0.59313786
## PIB_over_reserves -0.57391965  0.39056882
## exchange_difference -0.40454741  0.09171044
## industry_trade_balance_difference  0.62115112 -0.85146240
##
## semiconductor_crisis devaluacion_interannual
## itcrb                0.031025294  0.040514456
## imported_cars        -0.275463784 -0.027213050
## semiconductor_crisis  1.000000000  0.005059507
## devaluacion_interannual  0.005059507  1.000000000
## inflation            0.391827027  0.655280837
## import_restriction    0.509175077  0.060402026
## PIB                  0.011897026  0.125177055
## reserves             0.113498077  0.081914320
## PIB_over_reserves    -0.123565165  0.092155529
```



```

## exchange_difference          0.650902612          0.073825750
## industry_trade_balance_difference 0.258351230          0.079954149
##          inflation import_restriction          PIB
## itcrb          -0.27166538          -0.45615253 -0.97038025
## imported_cars          0.10875007          0.15017680 0.84102366
## semiconductor_crisis          0.39182703          0.50917508 0.01189703
## devaluacion_interanual          0.65528084          0.06040203 0.12517705
## inflation          1.00000000          0.31212355 0.42376923
## import_restriction          0.31212355          1.00000000 0.42912174
## PIB          0.42376923          0.42912174 1.00000000
## reserves          0.41050289          0.02503357 0.65862991
## PIB_over_reserves          0.14588345          0.53395398 0.58138567
## exchange_difference          0.38737953          0.95207008 0.39340556
## industry_trade_balance_difference 0.08132427          0.06360759 -0.64427806
##          reserves PIB_over_reserves
## itcrb          -0.64341540          -0.57391965
## imported_cars          0.59313786          0.39056882
## semiconductor_crisis          0.11349808          -0.12356516
## devaluacion_interanual          0.08191432          0.09215553
## inflation          0.41050289          0.14588345
## import_restriction          0.02503357          0.53395398
## PIB          0.65862991          0.58138567
## reserves          1.00000000          -0.21014720
## PIB_over_reserves          -0.21014720          1.00000000
## exchange_difference          0.03724469          0.48228198
## industry_trade_balance_difference -0.33854868          -0.37317620
##          exchange_difference
## itcrb          -0.40454741
## imported_cars          0.09171044
## semiconductor_crisis          0.65090261
## devaluacion_interanual          0.07382575
## inflation          0.38737953
## import_restriction          0.95207008
## PIB          0.39340556
## reserves          0.03724469
## PIB_over_reserves          0.48228198
## exchange_difference          1.00000000
## industry_trade_balance_difference 0.08784890
##          industry_trade_balance_difference
## itcrb          0.62115112
## imported_cars          -0.85146240
## semiconductor_crisis          0.25835123
## devaluacion_interanual          0.07995415
## inflation          0.08132427
## import_restriction          0.06360759
## PIB          -0.64427806
## reserves          -0.33854868
## PIB_over_reserves          -0.37317620
## exchange_difference          0.08784890
## industry_trade_balance_difference 1.00000000

```

Variance inflation factors

```
vif(sold_units_model)
```

```
##               itcrb               imported_cars
##           188.647668           40.041749
## semiconductor_crisis   devaluacion_interanual
##           11.435279           3.626339
##           inflation           import_restriction
##           7.827097           24.727457
##               PIB               reserves
##           182.555051           224.155138
##           PIB_over_reserves   exchange_difference
##           196.605341           29.934856
## industry_trade_balance_difference
##           12.545070
```

Eigenvalues of the correlation matrix

```
eigen(cor(sold_units[, -1]))$values
```

```
## [1] 4.518840497 2.690677954 1.652199919 1.222258483 0.450025634 0.278666946
## [7] 0.121728329 0.033478040 0.023565463 0.007116211 0.001442524
```

Testing the model using cross-validation

```
cv_sold_units<-cv.lm(sold_units_model, k=5,)
cv_sold_units
```

```
## Mean absolute error      : 119647.7
## Sample standard deviation : 60554.85
##
## Mean squared error       : 26183733607
## Sample standard deviation : 22321672589
##
## Root mean squared error  : 147794.4
## Sample standard deviation : 73659.23
```

## Feature selection

Applying best subset selection

```
sold_units_all<-regsubsets(sold_units$num_units~.,sold_units,nvmax = 12)
summary(sold_units_all)
```

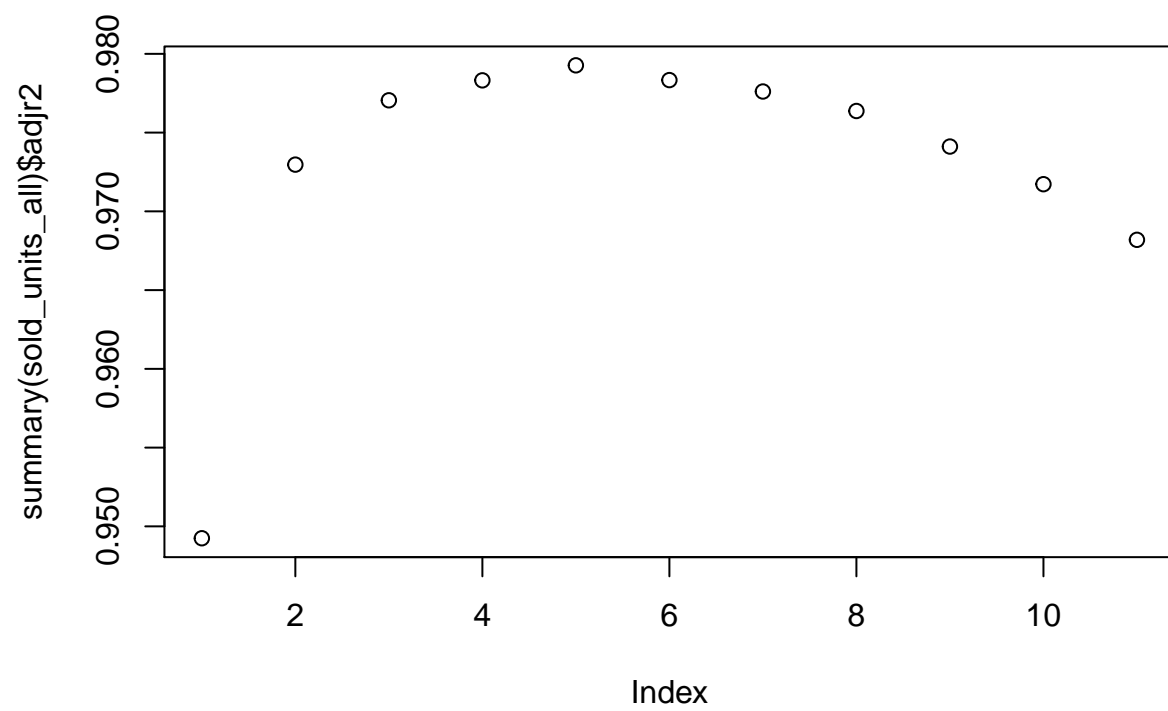
```
## Subset selection object
## Call: regsubsets.formula(sold_units$num_units ~ ., sold_units, nvmax = 12)
## 11 Variables (and intercept)
##               Forced in Forced out
## itcrb                FALSE      FALSE
## imported_cars         FALSE      FALSE
```

```

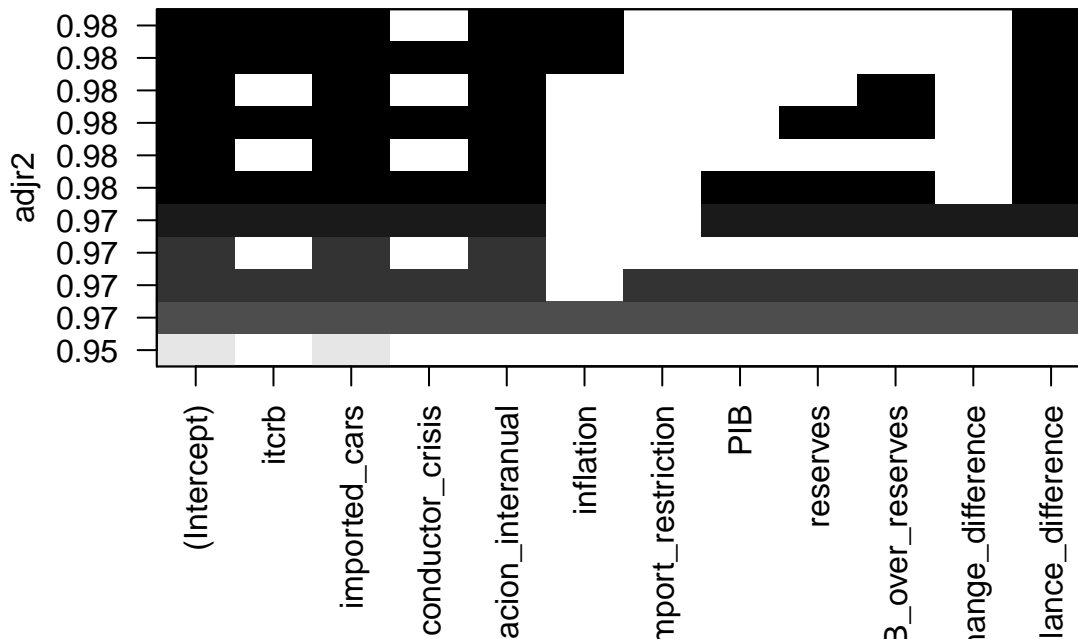
## semiconductor_crisis                FALSE      FALSE
## devaluacion_interanual              FALSE      FALSE
## inflation                          FALSE      FALSE
## import_restriction                  FALSE      FALSE
## PIB                                FALSE      FALSE
## reserves                           FALSE      FALSE
## PIB_over_reserves                   FALSE      FALSE
## exchange_difference                  FALSE      FALSE
## industry_trade_balance_difference    FALSE      FALSE
## 1 subsets of each size up to 11
## Selection Algorithm: exhaustive
##      itcrb imported_cars semiconductor_crisis devaluacion_interanual
## 1  ( 1 ) " "      "*"                " "                " "
## 2  ( 1 ) " "      "*"                " "                "*"
## 3  ( 1 ) " "      "*"                " "                "*"
## 4  ( 1 ) " "      "*"                " "                "*"
## 5  ( 1 ) "*"     "*"                " "                "*"
## 6  ( 1 ) "*"     "*"                "*"                "*"
## 7  ( 1 ) "*"     "*"                "*"                "*"
## 8  ( 1 ) "*"     "*"                "*"                "*"
## 9  ( 1 ) "*"     "*"                "*"                "*"
## 10 ( 1 ) "*"     "*"                "*"                "*"
## 11 ( 1 ) "*"     "*"                "*"                "*"
##      inflation import_restriction PIB reserves PIB_over_reserves
## 1  ( 1 ) " "          " "          " " " "      " "
## 2  ( 1 ) " "          " "          " " " "      " "
## 3  ( 1 ) " "          " "          " " " "      " "
## 4  ( 1 ) " "          " "          " " " "      "*"
## 5  ( 1 ) "*"         " "          " " " "      " "
## 6  ( 1 ) "*"         " "          " " " "      " "
## 7  ( 1 ) " "          " "          " " "*"      "*"
## 8  ( 1 ) " "          " "          "*" "*"      "*"
## 9  ( 1 ) " "          " "          "*" "*"      "*"
## 10 ( 1 ) " "          "*"         "*" "*"      "*"
## 11 ( 1 ) "*"         "*"         "*" "*"      "*"
##      exchange_difference industry_trade_balance_difference
## 1  ( 1 ) " "                " "
## 2  ( 1 ) " "                " "
## 3  ( 1 ) " "                "*"
## 4  ( 1 ) " "                "*"
## 5  ( 1 ) " "                "*"
## 6  ( 1 ) " "                "*"
## 7  ( 1 ) " "                "*"
## 8  ( 1 ) " "                "*"
## 9  ( 1 ) "*"                "*"
## 10 ( 1 ) "*"                "*"
## 11 ( 1 ) "*"                "*"

```

```
plot(summary(sold_units_all)$adjr2)
```



```
plot(sold_units_all, scale = "adjr2")
```



```
best_adjr2<-which.max(summary(sold_units_all)$adjr2)
subset_coef<-names(coef(sold_units_all, best_adjr2))
```

Building the selected model

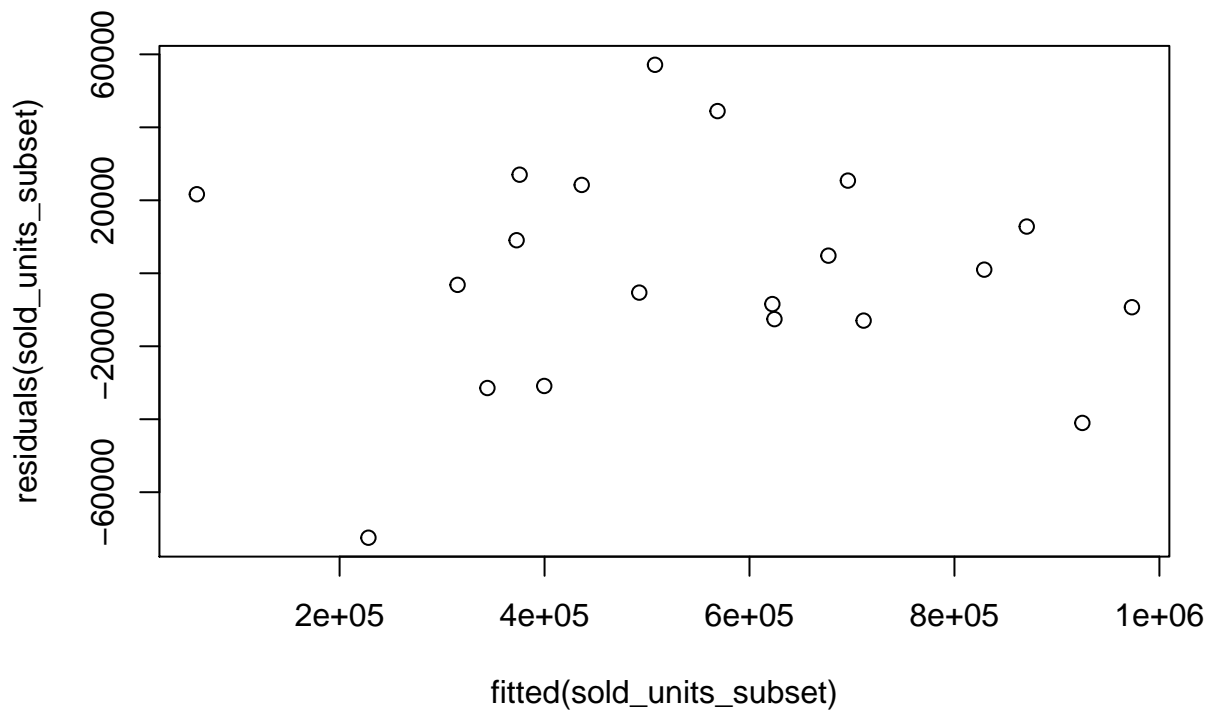
```
sold_units_subset<-
  lm(sold_units[,names(sold_units)%in%
    c("num_units",subset_coef)], y = TRUE, x = TRUE)
summary(sold_units_subset)
```

```
##
## Call:
## lm(formula = sold_units[, names(sold_units) %in% c("num_units",
##   subset_coef)], x = TRUE, y = TRUE)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -72464 -12668  -1086   22298   57133
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.343e+05  9.583e+04   3.489  0.00361 **
## itcrb          -8.901e+02  5.036e+02  -1.767  0.09894 .
## imported_cars    9.820e+01  1.028e+01   9.553 1.64e-07 ***
## devaluacion_interanual -8.505e+04  3.654e+04  -2.327  0.03547 *
```

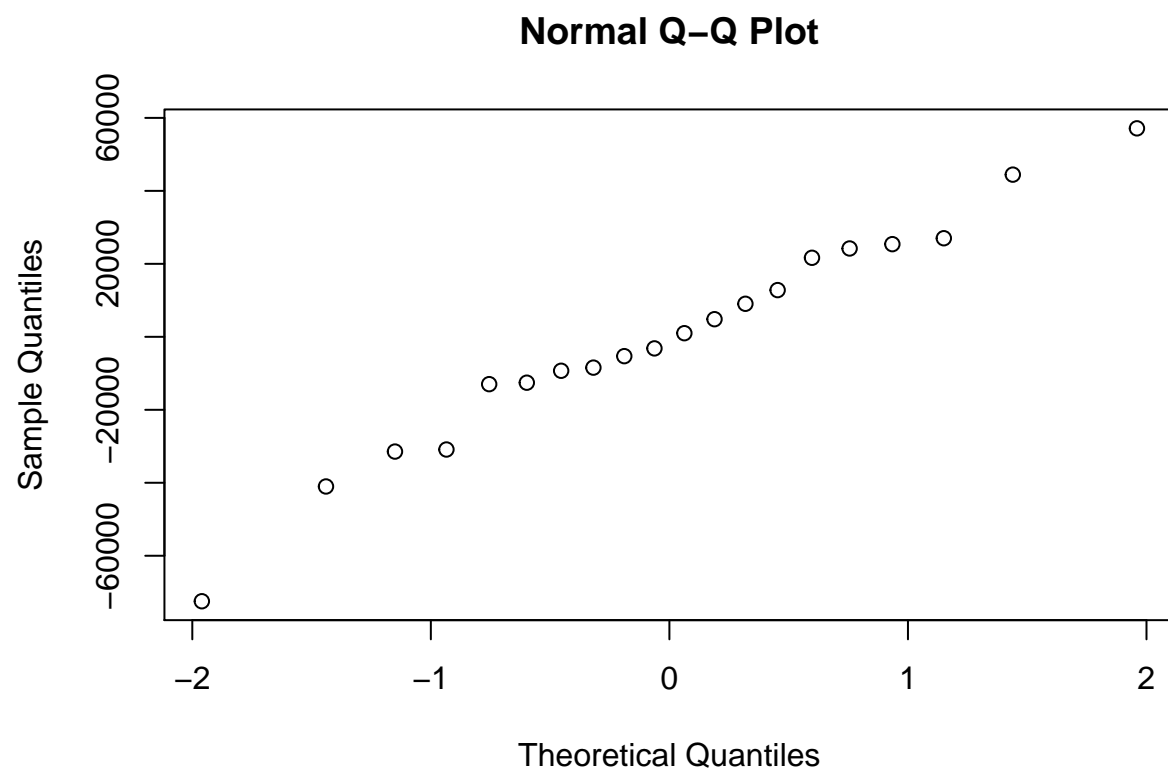
```
## inflation -1.214e+05 8.538e+04 -1.421 0.17709
## industry_trade_balance_difference 1.457e+01 8.434e+00 1.728 0.10602
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 35190 on 14 degrees of freedom
## Multiple R-squared:  0.9847, Adjusted R-squared:  0.9793
## F-statistic: 180.5 on 5 and 14 DF,  p-value: 3.385e-12
```

Analyzing the residuals

```
plot(fitted(sold_units_subset),residuals(sold_units_subset))
```

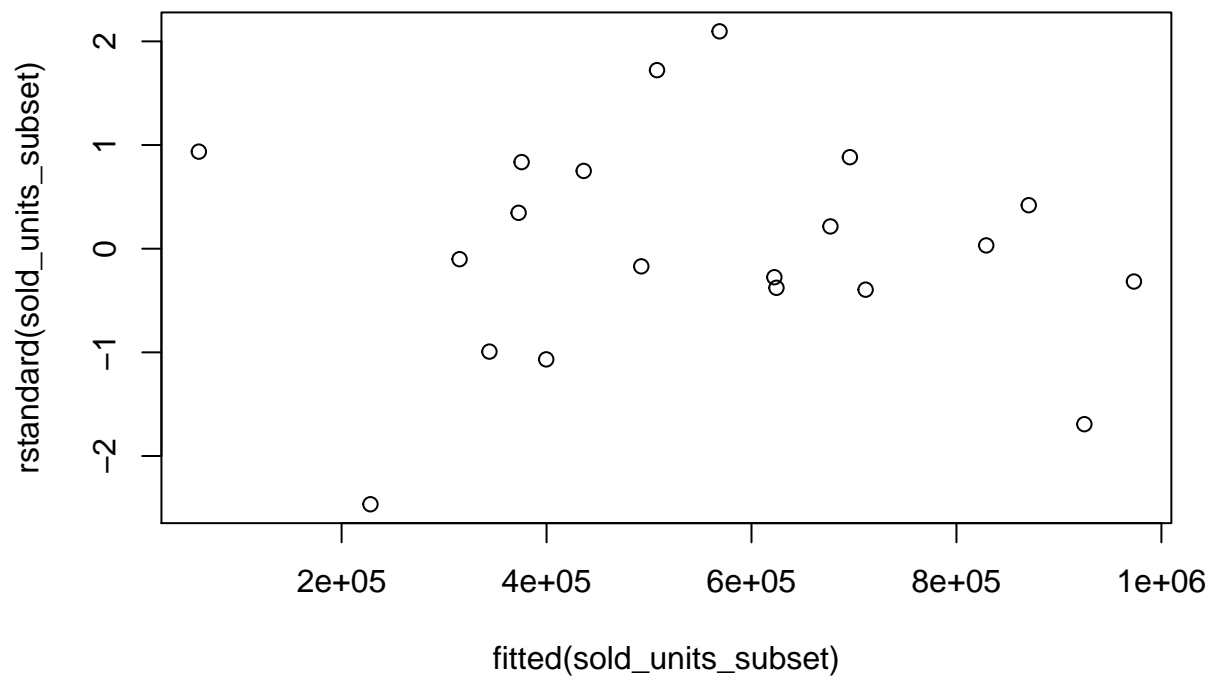


```
qqnorm(residuals(sold_units_subset))
```



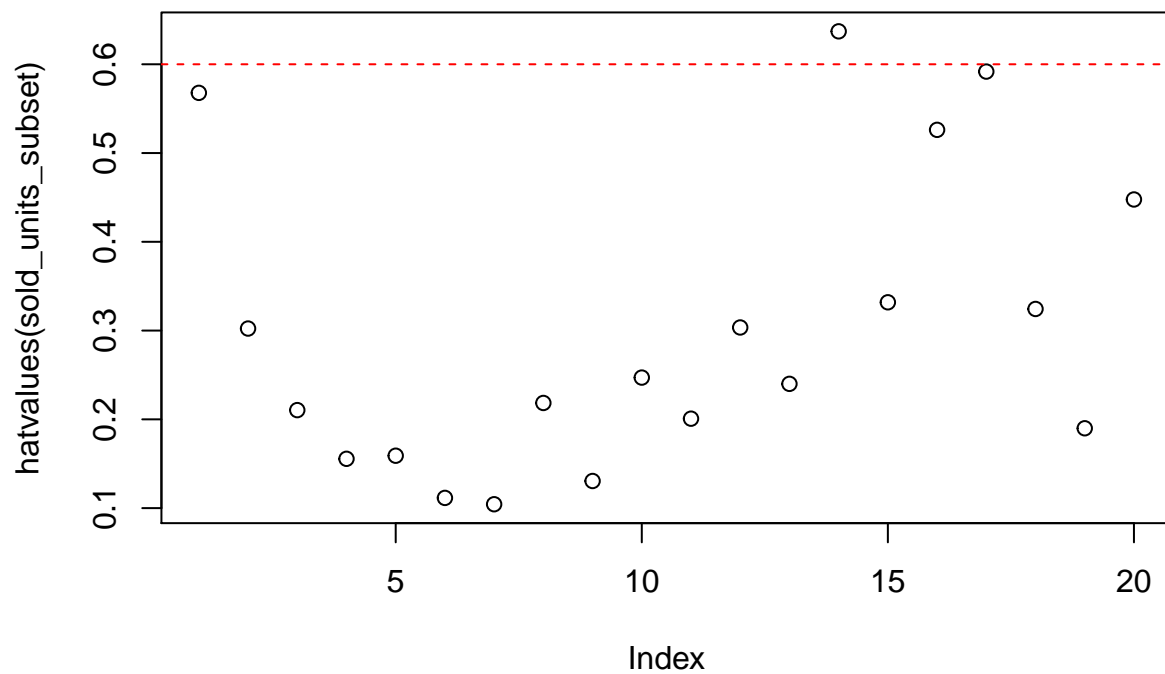
Looking for outliers and high leverage points

```
plot(fitted(sold_units_subset),rstandard(sold_units_subset))
```

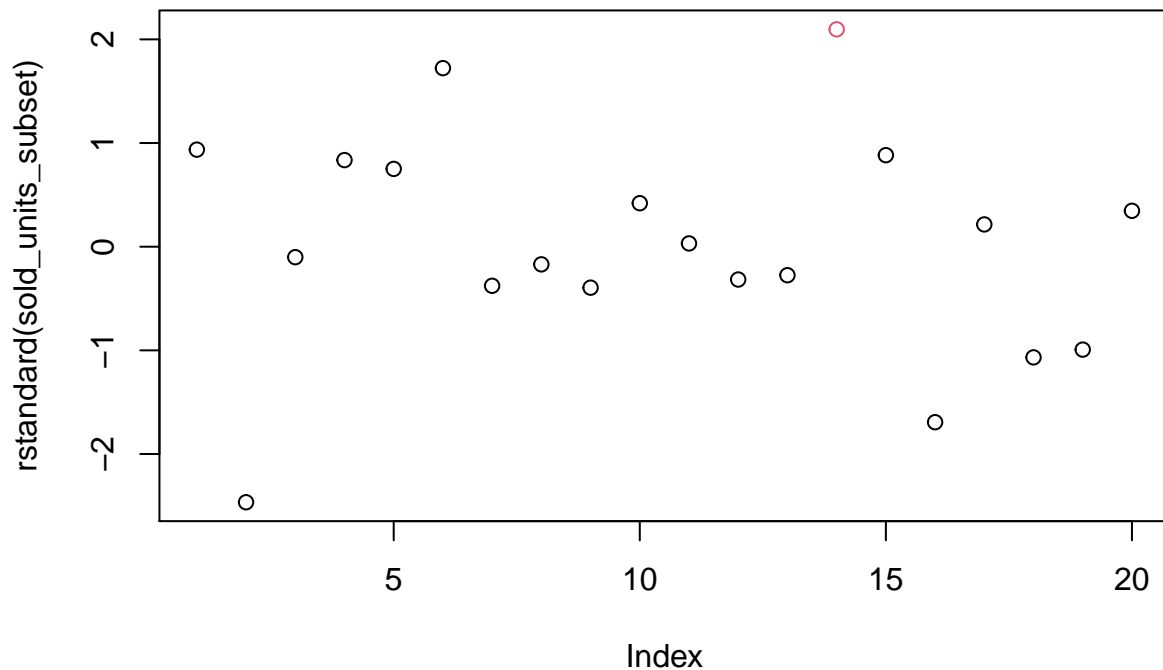


```
plot(hatvalues(sold_units_subset))  
abline(h=length(coef(sold_units_subset))/nrow(sold_units)*2,  
       col = "red",lty = 2)
```





```
high_leverage_points<-hatvalues(sold_units_subset)>
  (length(coef(sold_units_subset))/nrow(sold_units)*2)
plot(rstandard(sold_units_subset),
     col = factor(high_leverage_points))
```



Looking for colinearity Correlation matrix and its eigen values

```
subset_coef_cor<-cor(sold_units[,names(sold_units)%in%subset_coef])
subset_coef_cor
```

```
##               itcrb imported_cars
## itcrb          1.0000000    -0.84998083
## imported_cars  -0.84998083     1.00000000
## devaluacion_interannual  0.04051446    -0.02721305
## inflation      -0.27166538     0.10875007
## industry_trade_balance_difference  0.62115112    -0.85146240
##               devaluacion_interannual  inflation
## itcrb          0.04051446   -0.27166538
## imported_cars  -0.02721305    0.10875007
## devaluacion_interannual  1.00000000    0.65528084
## inflation        0.65528084    1.00000000
## industry_trade_balance_difference  0.07995415    0.08132427
##               industry_trade_balance_difference
## itcrb          0.62115112
## imported_cars  -0.85146240
## devaluacion_interannual  0.07995415
## inflation        0.08132427
## industry_trade_balance_difference  1.00000000
```

```
eigen(subset_coef_cor)$values
```

```
## [1] 2.5725655 1.6807642 0.4957628 0.1849049 0.0660026
```

Variance inflation factors

```
vif(sold_units_subset)
```

```
##                               itcrb                imported_cars
##                               5.045267                9.491226
##      devaluacion_interanual                inflation
##                               2.071411                2.468309
## industry_trade_balance_difference
##                               4.483669
```

Removing the high leverage outlier

```
sold_units_subset_rm<-
  lm(sold_units[!(high_leverage_points &
    (rstandard(sold_units_subset)>2)),
      names(sold_units)%in% c("num_units",subset_coef)],
    y = TRUE, x = TRUE)
summary(sold_units_subset_rm)

##
## Call:
## lm(formula = sold_units[!(high_leverage_points & (rstandard(sold_units_subset) >
##      2)), names(sold_units) %in% c("num_units", subset_coef)],
##      x = TRUE, y = TRUE)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -52469 -20381   4372  16455  48379
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    9.729e+04  1.274e+05   0.764  0.45869
## itcrb          3.519e+02  6.684e+02   0.527  0.60736
## imported_cars   1.172e+02  1.178e+01   9.951  1.9e-07 ***
## devaluacion_interanual -1.492e+05  4.096e+04  -3.642  0.00298 **
## inflation       8.452e+03  9.066e+04   0.093  0.92715
## industry_trade_balance_difference 2.090e+01  7.699e+00   2.714  0.01770 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 30250 on 13 degrees of freedom
## Multiple R-squared:  0.9895, Adjusted R-squared:  0.9854
## F-statistic: 244.6 on 5 and 13 DF,  p-value: 2.218e-12
```

```
summary(sold_units_subset)
```

```
##
## Call:
## lm(formula = sold_units[, names(sold_units) %in% c("num_units",
##   subset_coef)], x = TRUE, y = TRUE)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -72464 -12668  -1086   22298   57133
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.343e+05  9.583e+04   3.489  0.00361 **
## itcrb         -8.901e+02  5.036e+02  -1.767  0.09894 .
## imported_cars    9.820e+01  1.028e+01   9.553 1.64e-07 ***
## devaluacion_interanual -8.505e+04  3.654e+04  -2.327  0.03547 *
## inflation      -1.214e+05  8.538e+04  -1.421  0.17709
## industry_trade_balance_difference  1.457e+01  8.434e+00   1.728  0.10602
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 35190 on 14 degrees of freedom
## Multiple R-squared:  0.9847, Adjusted R-squared:  0.9793
## F-statistic: 180.5 on 5 and 14 DF,  p-value: 3.385e-12
```

```
vif(sold_units_subset_rm)
```

```
##              itcrb              imported_cars
##              11.106352              16.856451
##      devaluacion_interanual              inflation
##              3.343531              3.766226
## industry_trade_balance_difference
##              5.044398
```

Testing the model selected with best subset selection using cross-validation

```
cv_sold_units_subset<-cv.lm(sold_units_subset, k=5,)
cv_sold_units_subset
```

```
## Mean absolute error      : 29298.56
## Sample standard deviation : 18657.68
##
## Mean squared error       : 1609635599
## Sample standard deviation : 1622127045
##
## Root mean squared error  : 35510.34
## Sample standard deviation : 20876.17
```

Applying LASSO

```
sold_units_lasso<-glmnet(as.matrix(sold_units[,-1]),
                        as.matrix(sold_units[,1]),alpha=1)
sold_units_lasso
```

```
##
## Call:  glmnet(x = as.matrix(sold_units[, -1]), y = as.matrix(sold_units[,      1]), alpha = 1)
##
##      Df  %Dev Lambda
## 1    0  0.00 232400
## 2    1 16.16 211800
## 3    1 29.58 193000
## 4    1 40.72 175800
## 5    1 49.97 160200
## 6    1 57.65 146000
## 7    1 64.02 133000
## 8    1 69.31 121200
## 9    1 73.71 110400
## 10   1 77.35 100600
## 11   1 80.38  91680
## 12   1 82.90  83530
## 13   1 84.98  76110
## 14   1 86.72  69350
## 15   1 88.16  63190
## 16   2 89.38  57580
## 17   2 90.45  52460
## 18   2 91.34  47800
## 19   2 92.08  43550
## 20   2 92.69  39680
## 21   3 93.38  36160
## 22   3 94.17  32950
## 23   3 94.82  30020
## 24   3 95.37  27350
## 25   3 95.82  24920
## 26   3 96.19  22710
## 27   3 96.50  20690
## 28   3 96.76  18850
## 29   3 96.97  17180
## 30   3 97.15  15650
## 31   3 97.30  14260
## 32   3 97.42  12990
## 33   4 97.54  11840
## 34   4 97.66  10790
## 35   4 97.76   9830
## 36   4 97.85   8957
## 37   4 97.91   8161
## 38   4 97.97   7436
## 39   5 98.02   6776
## 40   5 98.06   6174
## 41   5 98.10   5625
## 42   6 98.14   5125
## 43   6 98.19   4670
## 44   6 98.22   4255
## 45   6 98.25   3877
```

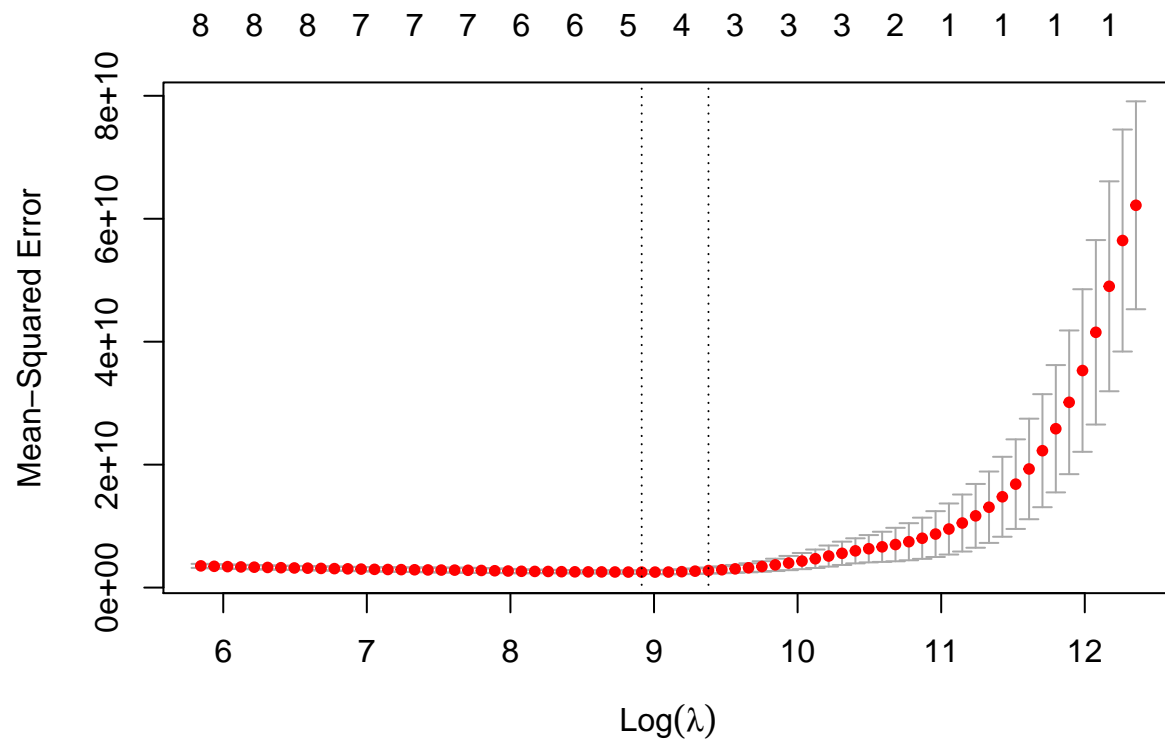
```
## 46 6 98.28 3533
## 47 6 98.30 3219
## 48 6 98.32 2933
## 49 6 98.33 2672
## 50 7 98.34 2435
## 51 7 98.38 2219
## 52 7 98.41 2022
## 53 7 98.43 1842
## 54 7 98.45 1678
## 55 7 98.47 1529
## 56 7 98.48 1393
## 57 7 98.49 1270
## 58 7 98.50 1157
## 59 7 98.51 1054
## 60 7 98.52 960
## 61 7 98.52 875
## 62 7 98.53 797
## 63 8 98.53 726
## 64 8 98.54 662
## 65 8 98.54 603
## 66 8 98.54 550
## 67 8 98.54 501
## 68 8 98.55 456
## 69 8 98.55 416
## 70 8 98.55 379
## 71 8 98.55 345
```

```
#selecting lambda using cross-validation
cv_sold_units_lasso<- cv.glmnet(as.matrix(sold_units[,-1]),
                                as.matrix(sold_units[,1]),
                                type.measure = c("mse"),
                                alpha=1,nfolds = 5)

cv_sold_units_lasso
```

```
##
## Call:  cv.glmnet(x = as.matrix(sold_units[, -1]), y = as.matrix(sold_units[,      1]), type.measure =
##
## Measure: Mean-Squared Error
##
##      Lambda Index  Measure      SE Nonzero
## min    7436     38 2.521e+09 284943795      4
## 1se   11840     33 2.777e+09 489821766      4
```

```
plot(cv_sold_units_lasso)
```



```
best_lambda <- cv_sold_units_lasso$lambda.min
sold_units_lasso_best <- glmnet(as.matrix(sold_units[, -1]),
                               as.matrix(sold_units[, 1]), alpha = 1,
                               lambda = best_lambda)
sold_units_lasso_best
```

```
##
## Call:  glmnet(x = as.matrix(sold_units[, -1]), y = as.matrix(sold_units[, 1]), alpha = 1, lambda = best_lambda)
##
##      Df  %Dev Lambda
## 1    4 97.97   7436
```

```
coef(sold_units_lasso_best)
```

```
## 12 x 1 sparse Matrix of class "dgCMatrix"
##                                     s0
## (Intercept)                   337228.05398
## itcrb                        -864.76212
## imported_cars                   83.51367
## semiconductor_crisis          -17664.18674
## devaluacion_interannual       -93852.92024
## inflation                       .
## import_restriction             .
## PIB                           .
## reserves                       .
```

```
## PIB_over_reserves .  
## exchange_difference .  
## industry_trade_balance_difference .
```

Comparing the MSE of the best subset and LASSO models

```
mse_lasso<-min(cv_sold_units_lasso$cvm)  
mse_subset<-cv_sold_units_subset$MSE$mean  
mse_lasso
```

```
## [1] 2521349932
```

```
mse_subset
```

```
## [1] 1609635599
```

```
sqrt(mse_lasso)
```

```
## [1] 50213.05
```

```
sqrt(mse_subset)
```

```
## [1] 40120.26
```