STAT 350 Final Project of predicting V-10

Xiaotian Ding, Jie Gu, De Lu, Huaiyi Liu

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```
# Import the data and pretreatment
load("~/Desktop/Study in NU/Winter/Regression analysis/Final/train & test.RData")
Zipcode= as.factor(train$`V-1`)
Zipcodetest=as.factor(test$`V-1`)
#strandized for train
y9=as.matrix(train$`V-9`)
colnames(y9)=c("V-9")
y10=as.matrix(train$`V-10`)
colnames(y10)=c("V-10")
train.v9<- cbind(Zipcode,train[2:27],y9)
train.v10<- cbind(Zipcode,train[2:27],y10)
for(i in 2:27)
 {
  train.v9[,i] <-(train[,i]-mean(train[,i])) /sd(train[,i])
}
for(i in 2:27)
 {
  train.v10[,i] <-(train[,i]-mean(train[,i])) /sd(train[,i])
}

#strandized for test data
yt9=as.matrix(test$`V-9`)
colnames(yt9)=c("V-9")
yt10=as.matrix(test$`V-10`)
colnames(yt10)=c("V-10")
test.v9<- cbind(test[1:27],yt9)
test.v10<- cbind(test[1:27],yt10)
for(i in 2:27)
 {
  test.v9[,i] <-(test[,i]-mean(test[,i])) /sd(test[,i])
}
for(i in 2:27)
 {
  test.v10[,i] <-(test[,i]-mean(test[,i])) /sd(test[,i])
}
```

```
# scatter plot & cor
fitv10 <- lm(train$`V-10`~ ., data = train.v10)
summary(fitv10)
```

```
##
## Call:
## lm(formula = train$`V-10` ~ ., data = train.v10)
##
## Residuals:
##     Min      1Q Median      3Q     Max
## -96.94 -11.10   0.13  11.22 195.69
##
```

```
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 235.4539     8.1451  28.907  < 2e-16 ***
## Zipcode2      3.2450     9.3795   0.346  0.72962
## Zipcode3     -9.8061     8.1755  -1.199  0.23134
## Zipcode4     -5.4482     9.8506  -0.553  0.58064
## Zipcode5     -0.7110    10.4575  -0.068  0.94584
## Zipcode6     -4.8886     9.8547  -0.496  0.62023
## Zipcode7    -12.5746    10.3617  -1.214  0.22591
## Zipcode8     -5.6590    10.5311  -0.537  0.59144
## Zipcode9     -7.8606    19.2677  -0.408  0.68360
## Zipcode10   -16.8070    16.3271  -1.029  0.30416
## Zipcode11   -14.2515    16.6566  -0.856  0.39293
## Zipcode12   -14.8322    12.3713  -1.199  0.23154
## Zipcode13   -17.3230    12.8140  -1.352  0.17747
## Zipcode14   -14.0094    11.3208  -1.237  0.21691
## Zipcode15   -26.3242    14.0832  -1.869  0.06261 .
## Zipcode16    -9.1743    14.7849  -0.621  0.53541
## Zipcode17   -15.7814    12.0238  -1.313  0.19039
## Zipcode18   -16.1880    12.8378  -1.261  0.20834
## Zipcode19   -11.4882    12.6624  -0.907  0.36502
## Zipcode20   -11.4787    11.4433  -1.003  0.31666
## `V-2`         4.1560     7.5873   0.548  0.58429
## `V-3`        -6.6246     5.9795  -1.108  0.26883
## `V-4`         7.5558     3.7532   2.013  0.04503 *
## `V-5`       150.2443     7.3503  20.441  < 2e-16 ***
## `V-6`        -7.3692     3.2394  -2.275  0.02365 *
## `V-7`        29.0769     1.7009  17.095  < 2e-16 ***
## `V-8`        -5.8754     4.2381  -1.386  0.16672
## `V-11`       -2.1577     3.9016  -0.553  0.58067
## `V-12`       -8.6235    41.5064  -0.208  0.83556
## `V-13`       17.5093    28.9961   0.604  0.54642
## `V-14`        4.0457     3.8376   1.054  0.29267
## `V-15`       63.3510    28.4569   2.226  0.02677 *
## `V-16`       14.3414     8.5742   1.673  0.09549 .
## `V-17`      -82.9451    15.5412  -5.337 1.92e-07 ***
## `V-18`      -11.6103     6.5866  -1.763  0.07901 .
## `V-19`       -4.9097     7.3955  -0.664  0.50730
## `V-20`       -0.8114     3.8823  -0.209  0.83460
## `V-21`       -2.9399    16.5997  -0.177  0.85955
## `V-22`      -55.8548    20.9688  -2.664  0.00816 **
## `V-23`       16.5962     7.3905   2.246  0.02549 *
## `V-24`      -13.1186     8.9559  -1.465  0.14407
## `V-25`       57.5260    78.4623   0.733  0.46405
## `V-26`       16.6635    62.8677   0.265  0.79116
## `V-27`      -11.0637     7.3525  -1.505  0.13348
## `V-28`        8.9552     4.6603   1.922  0.05565 .
## `V-29`       -7.1743    14.1937  -0.505  0.61362
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 27.61 on 288 degrees of freedom
## Multiple R-squared:  0.9729, Adjusted R-squared:  0.9687
## F-statistic: 229.7 on 45 and 288 DF,  p-value: < 2.2e-16
```

```r
cor(train.v10[,c(2:28)])
```

```
##               V-2          V-3         V-4         V-5         V-6
## V-2   1.000000000  0.945600958  0.77436762  0.23420508  0.21230859
## V-3   0.945600958  1.000000000  0.64019309  0.15528248  0.12979894
## V-4   0.774367618  0.640193087  1.00000000  0.57121240  0.33816723
## V-5   0.234205081  0.155282482  0.57121240  1.00000000  0.32722179
## V-6   0.212308594  0.129798937  0.33816723  0.32722179  1.00000000
## V-7   0.161547288  0.089225497  0.18086665  0.06782641  0.14136645
## V-8   0.226480811  0.145503571  0.47418223  0.80942131  0.16406550
## V-11 -0.035418005 -0.013619707  0.02290495  0.23425775 -0.06469386
## V-12  0.089149149  0.082405943  0.32119612  0.79164543 -0.19515942
## V-13  0.088261381  0.076359505  0.31999660  0.79468122 -0.18162136
## V-14 -0.031042870 -0.007498359  0.05373985  0.24842339 -0.06594751
## V-15  0.079502198  0.075962603  0.30494320  0.77237472 -0.20802750
## V-16  0.092661957  0.094008848  0.29144067  0.70758556 -0.17878957
## V-17  0.092216627  0.086045671  0.31811051  0.78139809 -0.18702009
## V-18  0.067722258  0.051402223  0.20398832  0.48986363 -0.05370173
## V-19  0.063634669  0.061394585  0.25013127  0.64261538 -0.16845274
## V-20 -0.007826318 -0.030715653 -0.04911039 -0.21740676  0.11616290
## V-21  0.083525605  0.073809085  0.31314787  0.78345004 -0.20180050
## V-22  0.100604965  0.092276694  0.32827391  0.78788394 -0.19693094
## V-23  0.094428570  0.062129772  0.31781905  0.72055691 -0.16593281
## V-24  0.082614838  0.062240681  0.26826007  0.64481091 -0.08200588
## V-25  0.089286179  0.073363554  0.32671357  0.79833830 -0.18004635
## V-26  0.090209687  0.074963521  0.32844952  0.79873355 -0.18638055
## V-27  0.098501142  0.066699364  0.32827781  0.72016802 -0.14959341
## V-28  0.081782289  0.065819345  0.15407731  0.30938116 -0.01506138
## V-29  0.079099698  0.074670140  0.30292846  0.78219642 -0.19173899
## V-10  0.263265794  0.166628000  0.59551162  0.96061711  0.31582150
##               V-7         V-8         V-11        V-12         V-13
## V-2   0.161547288  0.22648081 -0.035418005  0.08914915  0.088261381
## V-3   0.089225497  0.14550357 -0.013619707  0.08240594  0.076359505
## V-4   0.180866645  0.47418223  0.022904947  0.32119612  0.319996595
## V-5   0.067826410  0.80942131  0.234257753  0.79164543  0.794681216
## V-6   0.141366451  0.16406550 -0.064693859 -0.19515942 -0.181621357
## V-7   1.000000000  0.01776631  0.002002689 -0.01102056  0.001928748
## V-8   0.017766307  1.00000000  0.214791473  0.62970430  0.634816454
## V-11  0.002002689  0.21479147  1.000000000  0.31244811  0.344567028
## V-12 -0.011020564  0.62970430  0.312448115  1.00000000  0.990115542
## V-13  0.001928748  0.63481645  0.344567028  0.99011554  1.000000000
## V-14 -0.019721226  0.24596566  0.860365531  0.31564739  0.340203213
## V-15 -0.024051443  0.61691478  0.332852738  0.98696187  0.965649585
## V-16 -0.001528973  0.54631418  0.413873083  0.91047002  0.911852344
## V-17 -0.007634694  0.61852139  0.360611448  0.98089806  0.976602879
## V-18  0.103500897  0.41133991  0.234032892  0.51878542  0.526198919
## V-19 -0.006441351  0.54873449  0.299067350  0.80590755  0.775279122
## V-20  0.074979304 -0.13666349 -0.264273120 -0.35712077 -0.289603798
## V-21 -0.001781932  0.61813693  0.327402884  0.99252339  0.983217541
## V-22  0.005911640  0.61471306  0.307851986  0.99291719  0.980110935
## V-23  0.046973086  0.56744724  0.111823359  0.85524646  0.868914803
## V-24  0.066728819  0.51811642  0.409866559  0.74751228  0.810329992
## V-25  0.017701519  0.63912703  0.346748048  0.98283160  0.993948015
## V-26  0.012712520  0.64038848  0.328935009  0.98773368  0.992846711
```

```
## V-27  0.041148951  0.58009504  0.101545061  0.83897307  0.859104077
## V-28  0.097650836  0.27813186  0.104124516  0.29277178  0.286868723
## V-29 -0.020623125  0.63038431  0.302106965  0.98201195  0.970009704
## V-10  0.246356641  0.77602067  0.216265318  0.75362621  0.758385544
##             V-14        V-15         V-16         V-17        V-18
## V-2  -0.031042870  0.07950220  0.092661957  0.092216627  0.06772226
## V-3  -0.007498359  0.07596260  0.094008848  0.086045671  0.05140222
## V-4   0.053739850  0.30494320  0.291440666  0.318110514  0.20398832
## V-5   0.248423394  0.77237472  0.707585561  0.781398086  0.48986363
## V-6  -0.065947512 -0.20802750 -0.178789572 -0.187020090 -0.05370173
## V-7  -0.019721226 -0.02405144 -0.001528973 -0.007634694  0.10350090
## V-8   0.245965661  0.61691478  0.546314176  0.618521388  0.41133991
## V-11  0.860365531  0.33285274  0.413873083  0.360611448  0.23403289
## V-12  0.315647390  0.98696187  0.910470016  0.980898057  0.51878542
## V-13  0.340203213  0.96564959  0.911852344  0.976602879  0.52619892
## V-14  1.000000000  0.32141733  0.429650641  0.377683833  0.22975516
## V-15  0.321417327  1.00000000  0.891777513  0.965041224  0.53798776
## V-16  0.429650641  0.89177751  1.000000000  0.945888259  0.47463555
## V-17  0.377683833  0.96504122  0.945888259  1.000000000  0.51550667
## V-18  0.229755159  0.53798776  0.474635548  0.515506674  1.00000000
## V-19  0.280428299  0.85592540  0.710762676  0.763396891  0.76005321
## V-20 -0.223180633 -0.42477138 -0.460695728 -0.421048499 -0.04807152
## V-21  0.314238352  0.98479930  0.905593128  0.970529084  0.52651551
## V-22  0.308650562  0.98188751  0.922203466  0.977496291  0.54096321
## V-23  0.094598910  0.83560127  0.752719249  0.849345735  0.47191261
## V-24  0.385324013  0.67979203  0.660607493  0.721302456  0.51287317
## V-25  0.337258655  0.95920948  0.886957004  0.963501199  0.55244157
## V-26  0.321973307  0.96848328  0.892081494  0.969094040  0.54969275
## V-27  0.139606014  0.79419440  0.681317005  0.818461854  0.39502159
## V-28  0.169608370  0.30630060  0.229200249  0.291059956  0.86463576
## V-29  0.299937377  0.98315243  0.866570249  0.946223759  0.53018537
## V-10  0.217431999  0.74070323  0.657945916  0.731985430  0.47370439
##             V-19         V-20         V-21        V-22        V-23
## V-2   0.063634669 -0.007826318  0.083525605  0.10060497  0.09442857
## V-3   0.061394585 -0.030715653  0.073809085  0.09227669  0.06212977
## V-4   0.250131268 -0.049110392  0.313147874  0.32827391  0.31781905
## V-5   0.642615376 -0.217406759  0.783450035  0.78788394  0.72055691
## V-6  -0.168452740  0.116162896 -0.201800496 -0.19693094 -0.16593281
## V-7  -0.006441351  0.074979304 -0.001781932  0.00591164  0.04697309
## V-8   0.548734491 -0.136663489  0.618136933  0.61471306  0.56744724
## V-11  0.299067350 -0.264273120  0.327402884  0.30785199  0.11182336
## V-12  0.805907545 -0.357120769  0.992523387  0.99291719  0.85524646
## V-13  0.775279122 -0.289603798  0.983217541  0.98011094  0.86891480
## V-14  0.280428299 -0.223180633  0.314238352  0.30865056  0.09459891
## V-15  0.855925405 -0.424771384  0.984799301  0.98188751  0.83560127
## V-16  0.710762676 -0.460695728  0.905593128  0.92220347  0.75271925
## V-17  0.763396891 -0.421048499  0.970529084  0.97749629  0.84934574
## V-18  0.760053214 -0.048071518  0.526515511  0.54096321  0.47191261
## V-19  1.000000000 -0.277789904  0.817092309  0.81052043  0.63333981
## V-20 -0.277789904  1.000000000 -0.359643069 -0.36626055 -0.22614493
## V-21  0.817092309 -0.359643069  1.000000000  0.99053656  0.84433800
## V-22  0.810520432 -0.366260547  0.990536564  1.00000000  0.84869783
## V-23  0.633339813 -0.226144932  0.844337998  0.84869783  1.00000000
## V-24  0.531494188  0.097835932  0.745168073  0.73102304  0.65975292
```

```
## V-25  0.781298186 -0.248323465  0.977863958  0.97321585  0.88823633
## V-26  0.792637630 -0.283334553  0.981947612  0.97801582  0.89700001
## V-27  0.570548168 -0.069144581  0.824139284  0.81998426  0.91703848
## V-28  0.561385894  0.037568332  0.296720859  0.31415987  0.25026572
## V-29  0.828660567 -0.330418745  0.975786332  0.97155143  0.83140014
## V-10  0.625177036 -0.188652528  0.748987995  0.74845738  0.72261514
##              V-24        V-25        V-26        V-27        V-28
## V-2   0.08261484  0.08928618  0.09020969  0.09850114  0.08178229
## V-3   0.06224068  0.07336355  0.07496352  0.06669936  0.06581934
## V-4   0.26826007  0.32671357  0.32844952  0.32827781  0.15407731
## V-5   0.64481091  0.79833830  0.79873355  0.72016802  0.30938116
## V-6  -0.08200588 -0.18004635 -0.18638055 -0.14959341 -0.01506138
## V-7   0.06672882  0.01770152  0.01271252  0.04114895  0.09765084
## V-8   0.51811642  0.63912703  0.64038848  0.58009504  0.27813186
## V-11  0.40986656  0.34674805  0.32893501  0.10154506  0.10412452
## V-12  0.74751228  0.98283160  0.98773368  0.83897307  0.29277178
## V-13  0.81032999  0.99394802  0.99284671  0.85910408  0.28686872
## V-14  0.38532401  0.33725865  0.32197331  0.13960601  0.16960837
## V-15  0.67979203  0.95920948  0.96848328  0.79419440  0.30630060
## V-16  0.66060749  0.88695700  0.89208149  0.68131701  0.22920025
## V-17  0.72130246  0.96350120  0.96909404  0.81846185  0.29105996
## V-18  0.51287317  0.55244157  0.54969275  0.39502159  0.86463576
## V-19  0.53149419  0.78129819  0.79263763  0.57054817  0.56138589
## V-20  0.09783593 -0.24832347 -0.28333455 -0.06914458  0.03756833
## V-21  0.74516807  0.97786396  0.98194761  0.82413928  0.29672086
## V-22  0.73102304  0.97321585  0.97801582  0.81998426  0.31415987
## V-23  0.65975292  0.88823633  0.89700001  0.91703848  0.25026572
## V-24  1.00000000  0.83419437  0.80279114  0.70242848  0.25925649
## V-25  0.83419437  1.00000000  0.99785756  0.87754156  0.30716315
## V-26  0.80279114  0.99785756  1.00000000  0.88162945  0.31251731
## V-27  0.70242848  0.87754156  0.88162945  1.00000000  0.25408508
## V-28  0.25925649  0.30716315  0.31251731  0.25408508  1.00000000
## V-29  0.73163217  0.96492985  0.96786639  0.80227328  0.29412577
## V-10  0.61612424  0.76984469  0.77157245  0.71050664  0.30221239
##              V-29       V-10
## V-2   0.07909970  0.2632658
## V-3   0.07467014  0.1666280
## V-4   0.30292846  0.5955116
## V-5   0.78219642  0.9606171
## V-6  -0.19173899  0.3158215
## V-7  -0.02062312  0.2463566
## V-8   0.63038431  0.7760207
## V-11  0.30210697  0.2162653
## V-12  0.98201195  0.7536262
## V-13  0.97000970  0.7583855
## V-14  0.29993738  0.2174320
## V-15  0.98315243  0.7407032
## V-16  0.86657025  0.6579459
## V-17  0.94622376  0.7319854
## V-18  0.53018537  0.4737044
## V-19  0.82866057  0.6251770
## V-20 -0.33041874 -0.1886525
## V-21  0.97578633  0.7489880
## V-22  0.97155143  0.7484574
```

```
## V-23  0.83140014  0.7226151
## V-24  0.73163217  0.6161242
## V-25  0.96492985  0.7698447
## V-26  0.96786639  0.7715725
## V-27  0.80227328  0.7105066
## V-28  0.29412577  0.3022124
## V-29  1.00000000  0.7513661
## V-10  0.75136612  1.0000000
```

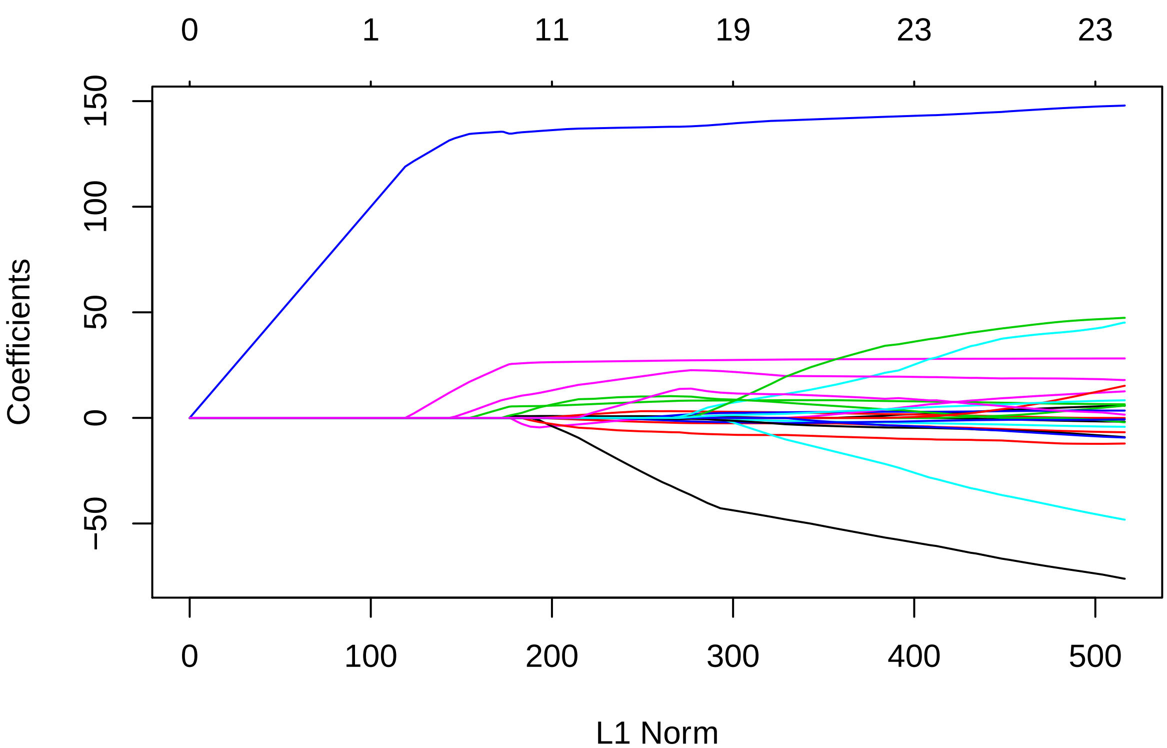
```
# Lasso to determine variable
library("glmnet")
```

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

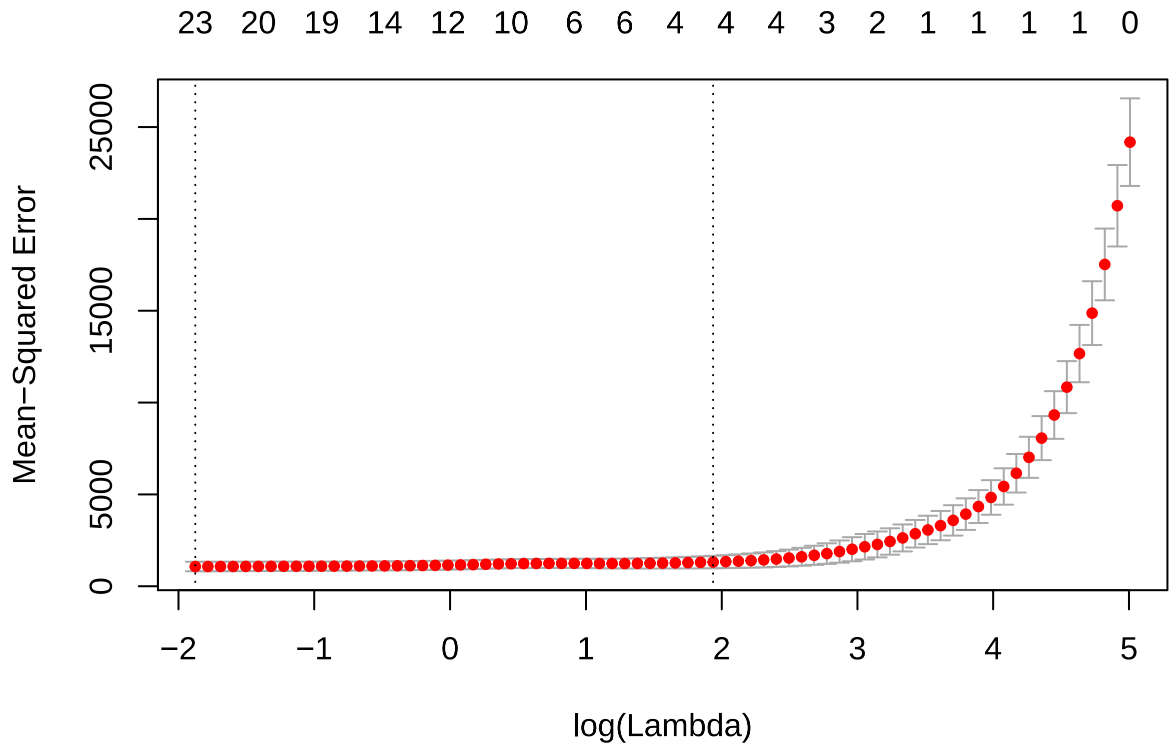
```
## Loading required package: foreach
```

```
## Loaded glmnet 2.0-16
```

```
x.simple=as.matrix(train.v10[,2:27])
y=train.v10$`V-10`
fitlasso=glmnet(x.simple,y,alpha = 1)
plot(fitlasso)
```



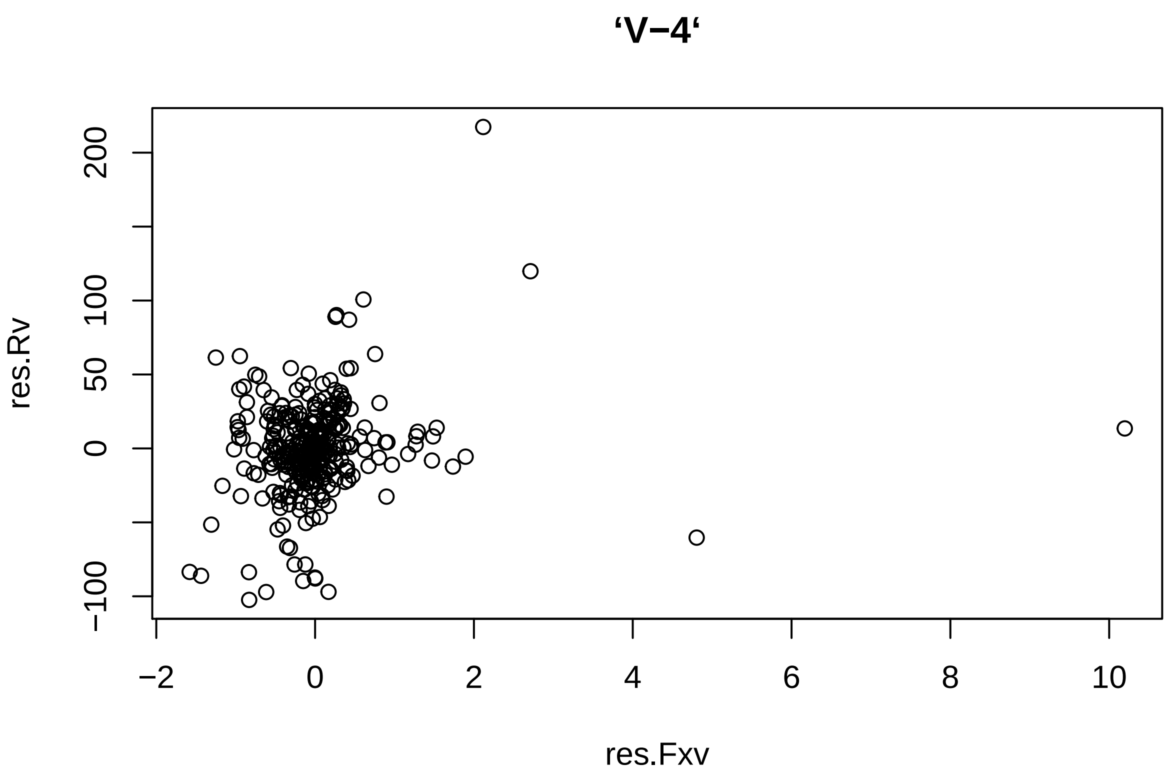

```
cv.lasso=cv.glmnet(x.simple,y)
plot(cv.lasso)
```

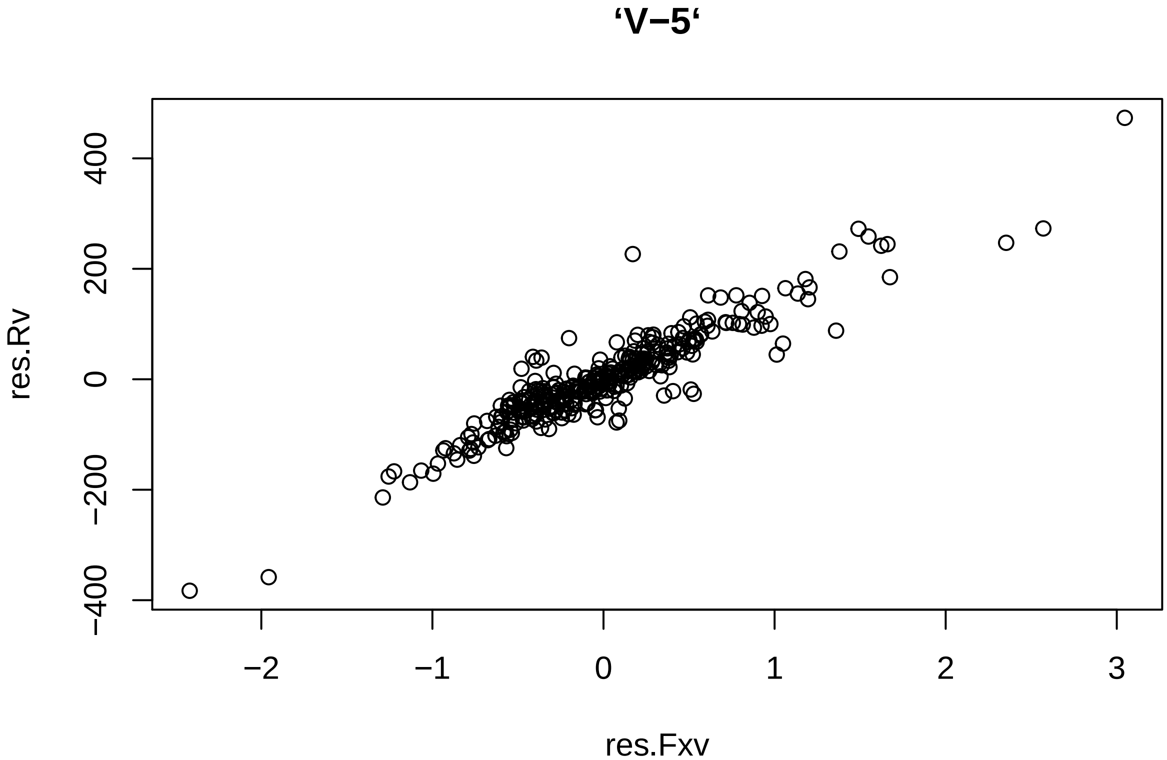


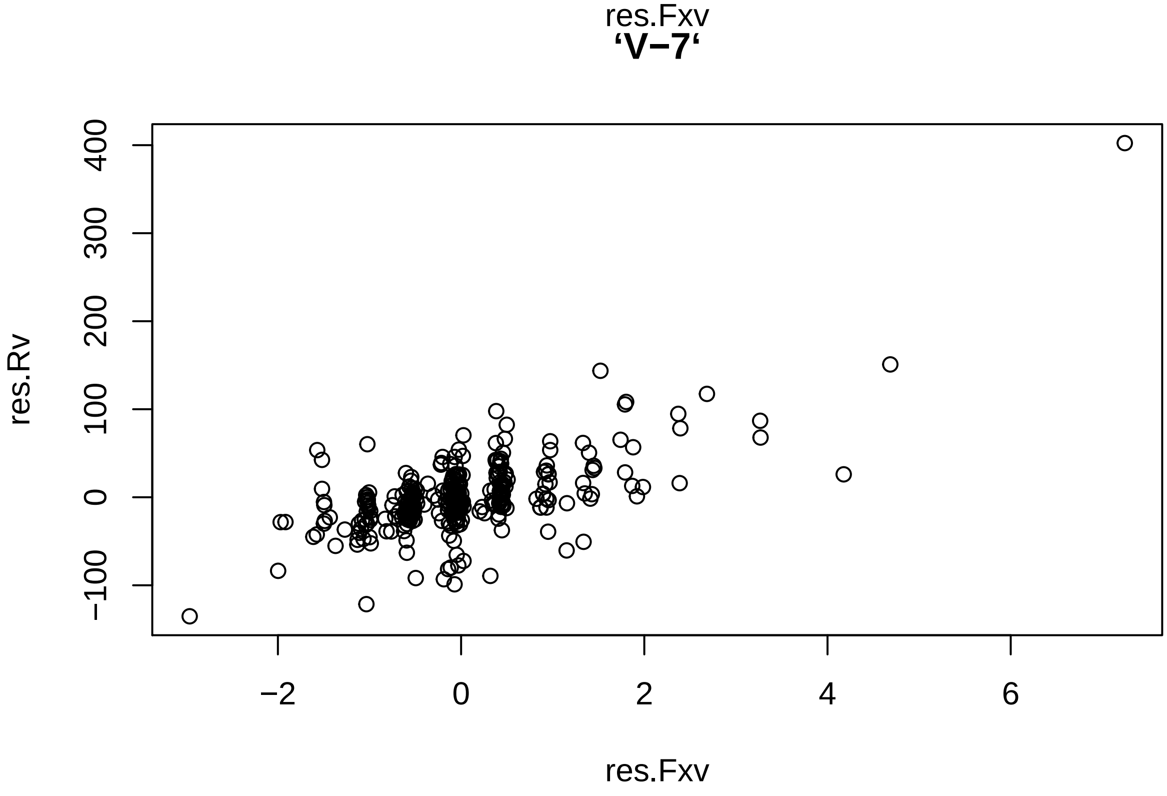

```r
coef(cv.lasso)
```

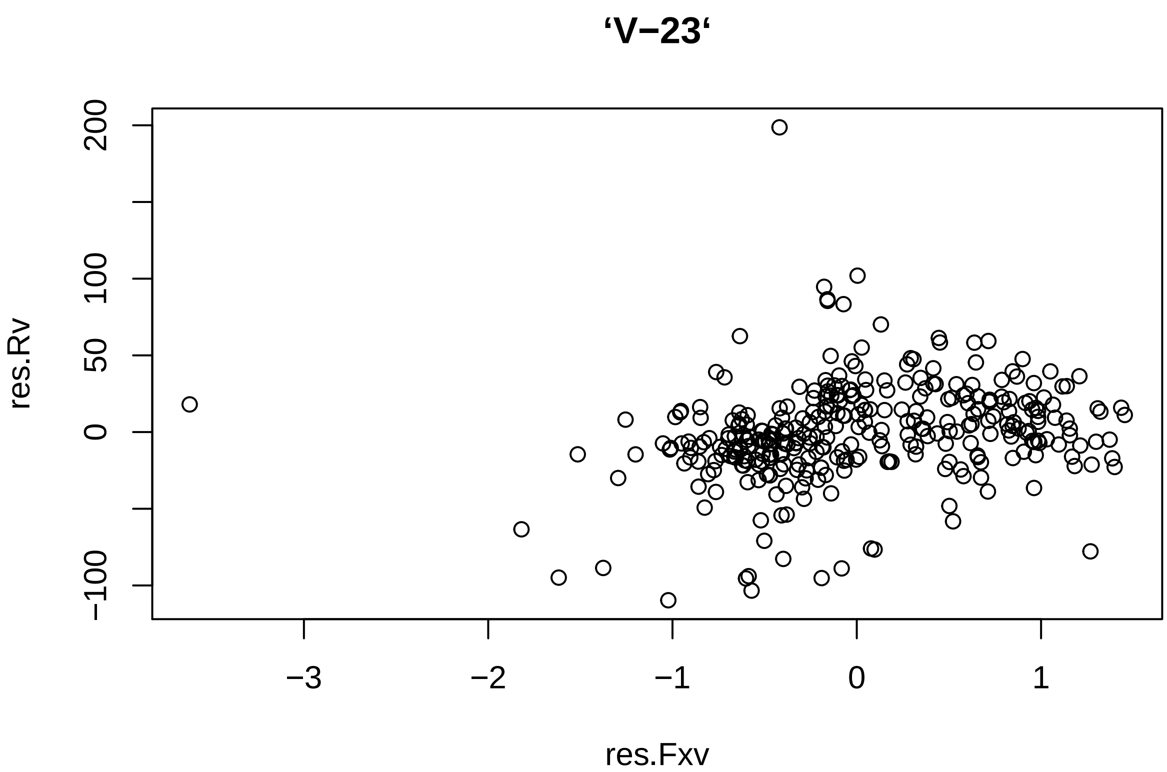
```
## 27 x 1 sparse Matrix of class "dgCMatrix"
##                      1
## (Intercept) 226.392216
## V-2            .
## V-3            .
## V-4           2.749670
## V-5         135.175905
## V-6            .
## V-7          21.494386
## V-8            .
## V-11           .
## V-12           .
## V-13           .
## V-14           .
## V-15           .
## V-16           .
## V-17           .
## V-18           .
## V-19           .
## V-20           .
## V-21           .
## V-22           .
## V-23          6.441003
## V-24           .
## V-25           .
## V-26           .
## V-27           .
## V-28           .
## V-29           .
```

```r
# Model 3
# added variable factor to determine ^
datamodel3=data.frame(train.v10[,c(4,5,7,21,28)])
fitmodel3=lm(datamodel3$V.10~.,data = datamodel3)
colData3 <- list("`V-4`", "`V-5`", "`V-7`", "`V-23`")
names(colData3) <- c("`V-4`", "`V-5`", "`V-7`", "`V-23`")
removeXList <- colData3

for (rmX in removeXList){
  tmpV <- colData3
  tmpV[[rmX]] = NULL
  test.Rv=lm(as.formula(paste("`V-10` ~", paste(tmpV, collapse = "+"))), data = train.v10)
  res.Rv= test.Rv$residuals

  test.Fxv=lm(as.formula(paste(paste(rmX," ~"), paste(tmpV, collapse = "+"))), data = train.v10)
  res.Fxv= test.Fxv$residuals

  plot(res.Fxv,res.Rv,main = rmX)
}
```




'V−5'
res.Rv
res.Fxv
−400
−200
0
200
400
−2
−1
0
1
2
3


'V−7'
res.Rv
res.Fxv
−100
0
100
200
300
400
−2
0
2
4
6




```
summary(fitmodel3)$r.squared
```

```
## [1] 0.9588816
```

```
summary(fitmodel3)$adj.r.squared
```

```
## [1] 0.9583816
```

```
#Brown test whether constant variance and transformation for Model 3
resmodel3=fitmodel3$residuals
mmodel3=mean(datamodel3$V.10)
nmodel3=dim(datamodel3)[1]
p1=5
#1. Break the residuals into two groups.
Group1 <- resmodel3[datamodel3$V.10<mmodel3]
Group2 <-resmodel3[datamodel3$V.10>=mmodel3]

#2. Obtain the median of each group, using the commands:
M1 <- median(Group1)
M2 <- median(Group2)

#3. Obtain the mean absolute deviation for each group, using the commands:
D1 <- sum( abs( Group1 - M1 )) / length(Group1)
D2 <- sum( abs( Group2 - M2 )) / length(Group2)

#4. Calculate the pooled standard error, using the command:
s <- sqrt( ( sum( ( abs(Group1 - M1) - D1 )^2 ) + sum( ( abs(Group2 - M2) - D2 )^2 ) ) / (nmodel3-2) )

#5. Finally, calculate the Brown-Forsythe test statistic, using the command:
 t <- ( D1 - D2 ) / ( s * sqrt( 1/length(Group1) + 1/length(Group2) ) )
 t
```

```
## [1] -2.798773
```

```r
#6 Once you obtain this value, you can compare it to the critical value for any given alpha level to de
# or you can find its P-value.
alpha <- 0.05
qt(1-alpha/2, nmodel3-p1-1)   # find the catical value
```

```
## [1] 1.967223
```

```r
# Weighted tranformation for model 3
wts <- 1/fitted(lm(abs(residuals(fitmodel3)) ~ ., data = datamodel3))^2

fitmodel3weight <- lm(datamodel3$V.10~ .,data = datamodel3, weights=wts)
datamodel3weight=cbind(datamodel3[1:4],datamodel3$V.10*wts)
summary(fitmodel3weight)$r.squared
```

```
## [1] 0.9615326
```

```r
summary(fitmodel3weight)$adj.r.squared
```

```
## [1] 0.961065
```

```r
#Brown test whether constant variance and transformation for Model 3 after tranformation
resmodel3b=fitmodel3weight $residuals
mmodel3=mean(datamodel3weight$`datamodel3$V.10 * wts`)
nmodel3=dim(datamodel3weight)[1]
#1. Break the residuals into two groups.
Group1 <- resmodel3b[datamodel3weight$`datamodel3$V.10 * wts`<mmodel3]
Group2 <-resmodel3b[datamodel3weight$`datamodel3$V.10 * wts`>=mmodel3]

#2. Obtain the median of each group, using the commands:
M1 <- median(Group1)
M2 <- median(Group2)

#3. Obtain the mean absolute deviation for each group, using the commands:
D1 <- sum( abs( Group1 - M1 )) / length(Group1)
D2 <- sum( abs( Group2 - M2 )) / length(Group2)

#4. Calculate the pooled standard error, using the command:
s <- sqrt( ( sum( ( abs(Group1 - M1) - D1 )^2 ) + sum( ( abs(Group2 - M2) - D2 )^2 ) ) / (nmodel3-2) )

#5. Finally, calculate the Brown-Forsythe test statistic, using the command:
t <- ( D1 - D2 ) / ( s * sqrt( 1/length(Group1) + 1/length(Group2) ) )
t
```

```
## [1] 0.3504877
```

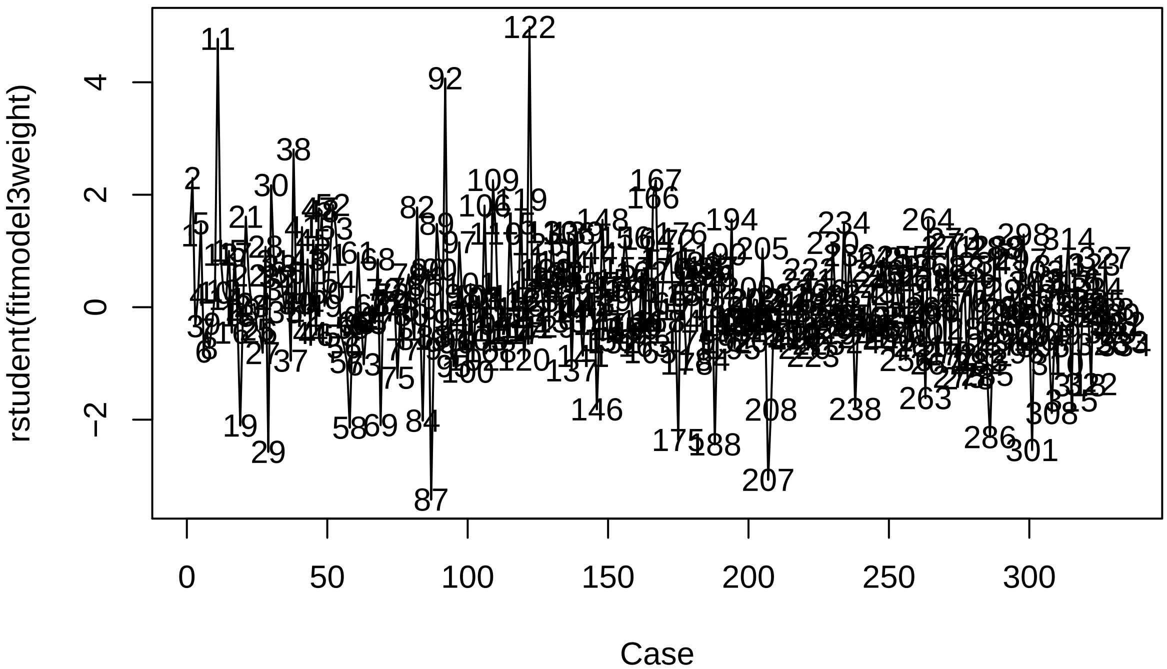
```r
#6 Once you obtain this value, you can compare it to the critical value for any given alpha level to de
# or you can find its P-value.
alpha <- 0.05
qt(1-alpha/2, nmodel3-p1-1)   # find the catical value
```

```
## [1] 1.967223
```

```r
# And the P-value can be found by typing:
 2*(1-pt( abs(t), nmodel3-p1-1))
```

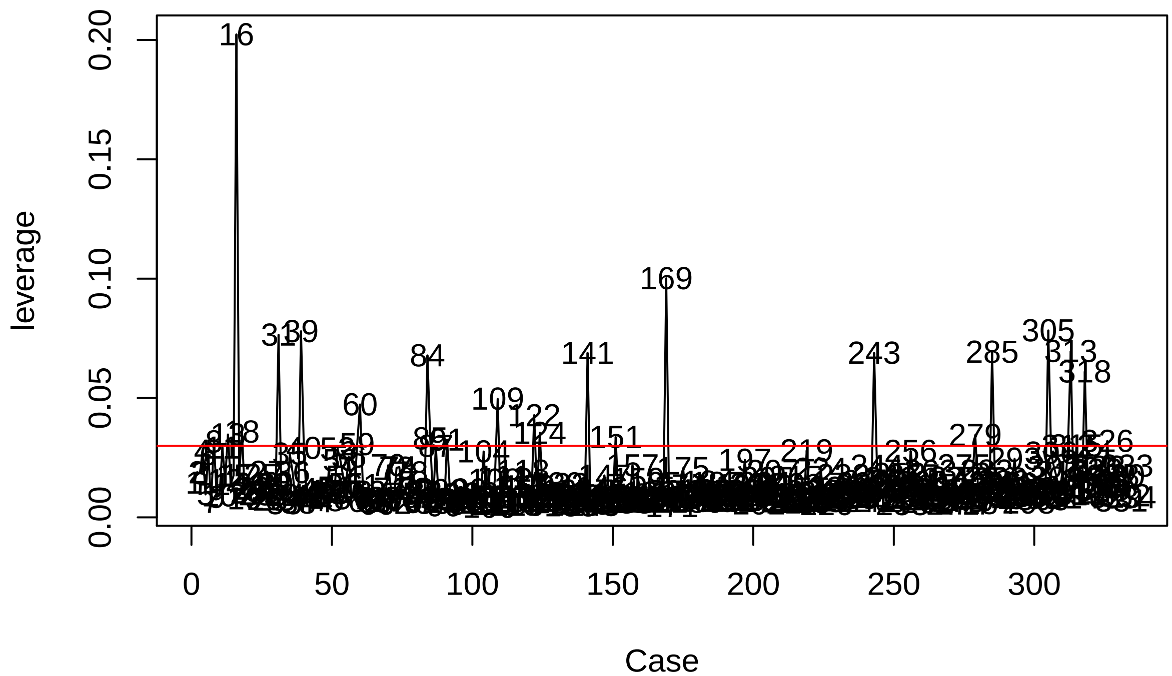
```
## [1] 0.7261977
```

```r
#y outlier for model3
Case <- c(1:nmodel3)
plot(Case, rstudent(fitmodel3weight), type="l")
text(Case, rstudent(fitmodel3weight), Case)
```




```r
alpha <- 0.05
crit <- qt(1-alpha/2/nmodel3, nmodel3-p1-1)
youtlier3=which(abs(rstudent(fitmodel3weight)) >=crit )
```

```r
#x outlier for model3
X <- as.matrix(cbind(rep(1,nmodel3), datamodel3[1:4]))
H <- X%*%solve(t(X)%*%X, tol=1e-20)%*%t(X)
leverage <- hatvalues(fitmodel3weight)
plot(Case, leverage, type="l")
text(Case, leverage, Case)
abline(h=2*p1/nmodel3, col=2)
```




```
xoutlier1=data.frame(which(leverage>2*p1/nmodel3) )
xoutlier1
```

```
##     which.leverage...2...p1.nmodel3.
## 8                                  8
## 13                                13
## 16                                16
## 18                                18
## 31                                31
## 39                                39
## 59                                59
## 60                                60
## 84                                84
## 85                                85
## 87                                87
## 91                                91
## 109                              109
## 122                              122
## 124                              124
## 141                              141
## 151                              151
## 169                              169
## 243                              243
## 279                              279
## 285                              285
## 305                              305
## 312                              312
## 313                              313
## 315                              315
## 318                              318
## 326                              326
```

```r
#test whether outlier in the extend of the model3
IM3=influence.measures(fitmodel3weight)
dxoutlier3=union(which(IM3$infmat[,8]>0.2),which(IM3$infmat[,6]>2*sqrt(p1/nmodel3)))
#combine x and y outlier
finaloutlier3=union(dxoutlier3,youtlier3)
datamodel3Final=datamodel3[-c(finaloutlier3),]
# get model1 without x y outlier
fitmodel3x1=lm(datamodel3Final$V.10~.,data = datamodel3Final)
wtsx3 <- 1/fitted(lm(abs(residuals(fitmodel3x1)) ~ ., data = datamodel3Final))^2
Fmodel3=lm(datamodel3Final$V.10~., data = datamodel3Final,weights =wtsx3)
# R2 & adj R2 for model3 test
summary(Fmodel3)$r.squared
```

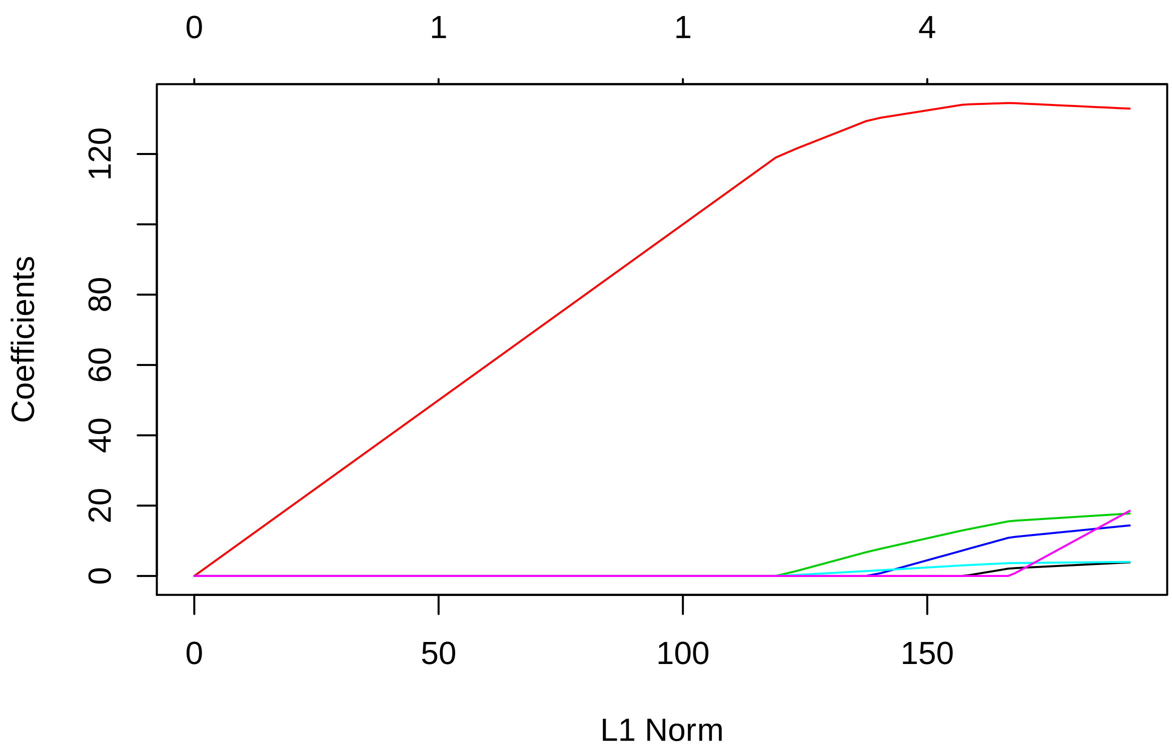
```
## [1] 0.9768281
```

```r
summary(Fmodel3)$adj.r.squared
```

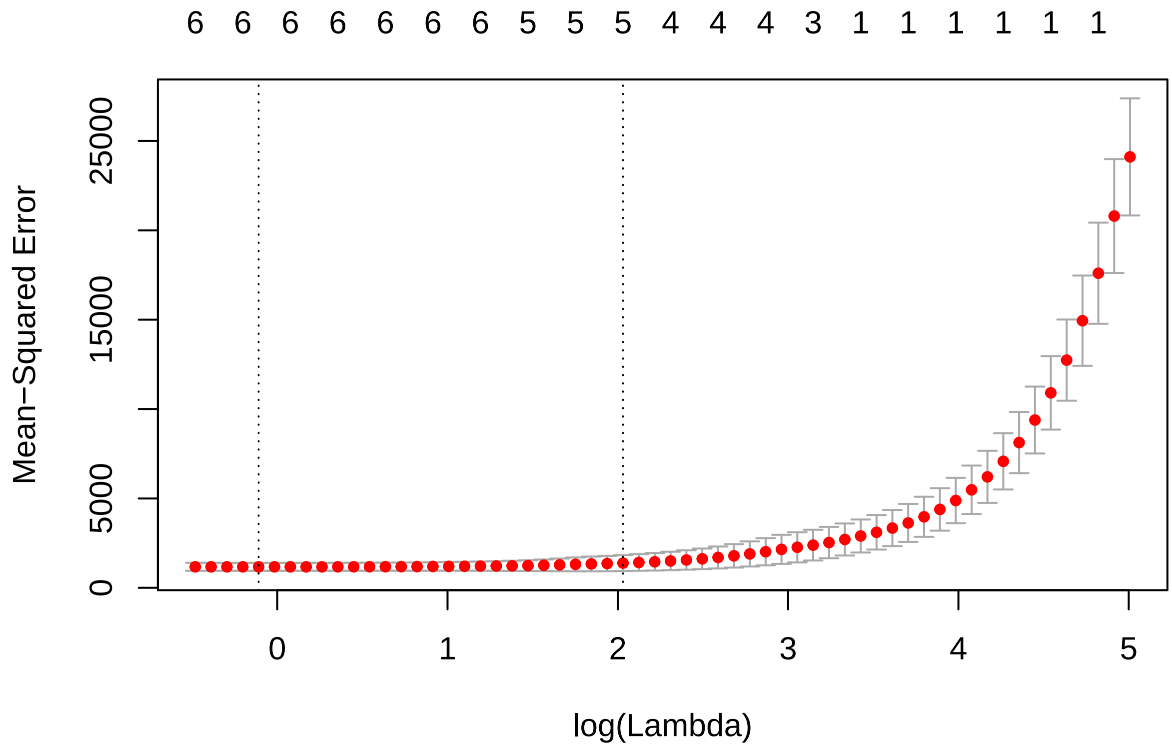
```
## [1] 0.9765403
```

```r
# add ^2 for model4
Data.new3 <- cbind(train.v10$`V-4`, train.v10$`V-5`, train.v10$`V-7`, train.v10$ `V-23`)
x3.new=as.matrix(cbind(Data.new3,((Data.new3)^2)[,-2]))
colnames(x3.new)=c("V-4","V-5","V-7","V-23","V-4.2","V-7.2","V-23.2")
```

```r
#lasso test x^2
library("glmnet")
fitlasso.x3add=glmnet(x3.new,y,alpha = 1)
plot(fitlasso.x3add)
```




```r
cv.lasso.x3add=cv.glmnet(x3.new,y)
plot(cv.lasso.x3add)
```




```r
coef(cv.lasso.x3add)
```

```
## 8 x 1 sparse Matrix of class "dgCMatrix"
##                       1
## (Intercept) 223.2886614
## V-4           0.2221622
## V-5         134.1264851
## V-7          13.3285514
## V-23          7.7699144
## V-4.2         .
## V-7.2         3.1128741
## V-23.2        .
```

```r
# Model 4
trainv14 = data.frame(x3.new,y)
datamodel4=data.frame(trainv14[,c(2,8)])
fitmodel4=lm(datamodel4$y~.,data = datamodel4)
summary(fitmodel4)$r.squared
```

```
## [1] 0.9227852
```

```r
summary(fitmodel4)$adj.r.squared
```

```
## [1] 0.9225527
```

```r
#Brown test whether constant variance and transformation for Model 4
fitmodel4=lm(datamodel4$y~.,data = datamodel4)
resmodel4=fitmodel4$residuals
mmodel4=mean(datamodel4$y)
nmodel4=dim(datamodel4)[1]
#1. Break the residuals into two groups.
Group3 <- resmodel4[datamodel4$y<mmodel4]
Group4 <-resmodel4[datamodel4$y>=mmodel4]
```

```r
#2. Obtain the median of each group, using the commands:
M3 <- median(Group3)
M4 <- median(Group4)

#3. Obtain the mean absolute deviation for each group, using the commands:
D3 <- sum( abs( Group3 - M3 )) / length(Group3)
D4 <- sum( abs( Group4 - M4 )) / length(Group4)

#4. Calculate the pooled standard error, using the command:
s <- sqrt( ( sum( ( abs(Group3 - M3) - D3 )^2 ) + sum( ( abs(Group4 - M4) - D4 )^2 ) ) / (nmodel4-2) )

#5. Finally, calculate the Brown-Forsythe test statistic, using the command:
 t <- ( D3 - D4 ) / ( s * sqrt( 1/length(Group3) + 1/length(Group4) ) )
 t
```

```
## [1] -5.216066
```

```r
#6 Once you obtain this value, you can compare it to the critical value for any given alpha level to de
# or you can find its P-value.
alpha <- 0.05
qt(1-alpha/2, nmodel4-p1-1)   # find the catical value
```

```
## [1] 1.967223
```

```r
# And the P-value can be found by typing:
 2*(1-pt( abs(t), nmodel4-p1-1))
```

```
## [1] 3.244961e-07
```

```r
# Weighted tranformation for model 4
wts <- 1/fitted(lm(abs(residuals(fitmodel4)) ~ ., data = datamodel4))^2

fitmodel4weight <- lm(datamodel4$y~ .,data = datamodel4, weights=wts)
datamodel4weight=cbind(datamodel4[1],datamodel4$y*wts)
summary(fitmodel4weight)$r.squared
```

```
## [1] 0.8608815
```

```r
summary(fitmodel4weight)$adj.r.squared
```

```
## [1] 0.8604625
```

```r
#Brown test whether constant variance and transformation for Model 2 after tranformation
resmode22b=fitmodel4weight$residuals
mmodel4=mean(datamodel4weight$`datamodel4$y * wts`)
nmodel4=dim(datamodel4weight)[1]
#1. Break the residuals into two groups.
Group6 <- resmode22b[datamodel4weight$`datamodel4$y * wts`<mmodel4]
Group7 <- resmode22b[datamodel4weight$`datamodel4$y * wts`>=mmodel4]

#2. Obtain the median of each group, using the commands:
M1 <- median(Group6)
M2 <- median(Group7)

#3. Obtain the mean absolute deviation for each group, using the commands:
D1 <- sum( abs( Group6 - M1 )) / length(Group6)
D2 <- sum( abs( Group7 - M2 )) / length(Group7)
```

```
#4. Calculate the pooled standard error, using the command:
s <- sqrt( ( sum( ( abs(Group6 - M1) - D1 )^2 ) + sum( ( abs(Group7 - M2) - D2 )^2 ) ) / (nmodel4-2) )

#5. Finally, calculate the Brown-Forsythe test statistic, using the command:
t <- ( D1 - D2 ) / ( s * sqrt( 1/length(Group6) + 1/length(Group7) ) )
t
```

```
## [1] 1.5684
```

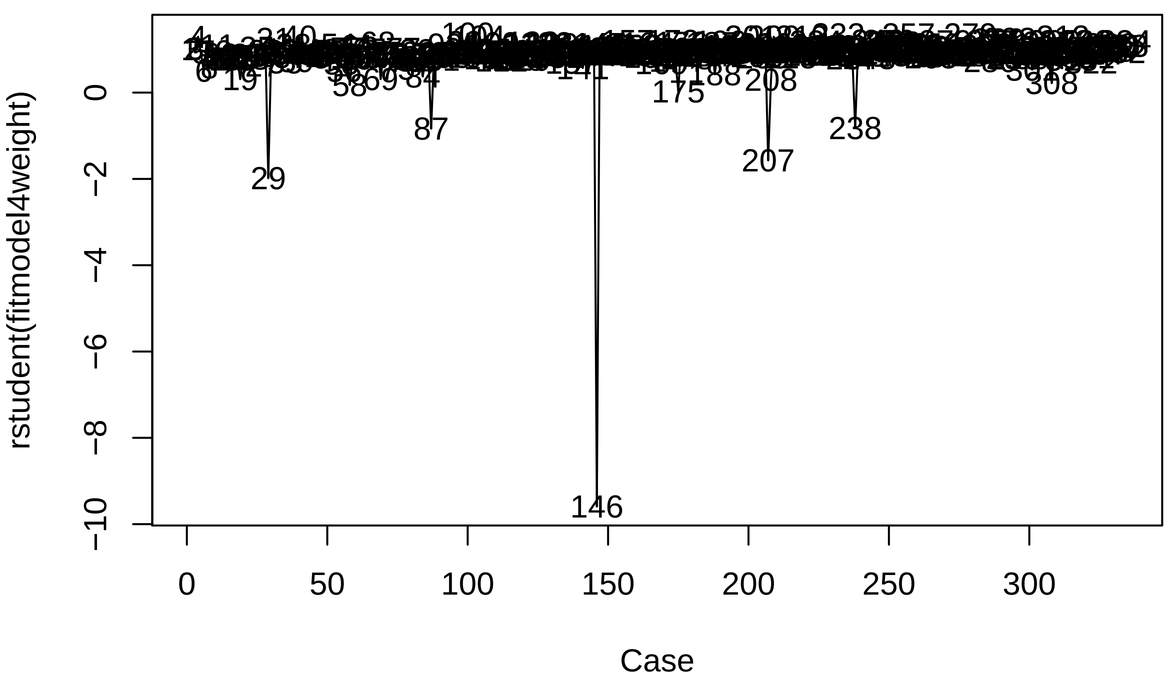
```
#6 Once you obtain this value, you can compare it to the critical value for any given alpha level to de
# or you can find its P-value.
alpha <- 0.05
qt(1-alpha/2, nmodel4-5)   # find the catical value
```

```
## [1] 1.967201
```

```
# And the P-value can be found by typing:
 2*(1-pt( abs(t), nmodel4-5))
```

```
## [1] 0.1177491
```

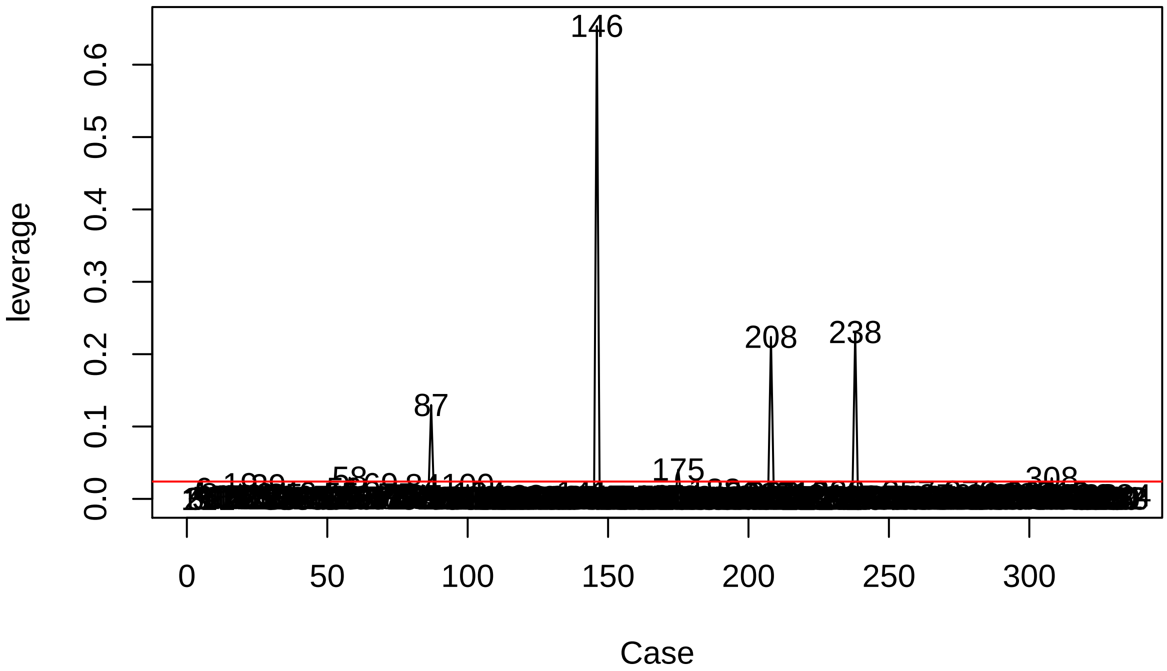
```
#y outlier
Case <- c(1:nmodel4)
plot(Case, rstudent(fitmodel4weight), type="l")
text(Case, rstudent(fitmodel4weight), Case)
```




```
alpha <- 0.01
p=4
crit <- qt(1-alpha/2/nmodel4, nmodel4-p-1)
youtlier=which(abs(rstudent(fitmodel4weight)) >=crit )
```

```
#x outlier
X <- as.matrix(cbind(rep(1,nmodel4), datamodel4weight[1]))
H <- X%*%solve(t(X)%*%X,tol=1e-30)%*%t(X)
leverage <- hatvalues(fitmodel4weight)
```

```r
plot(Case, leverage, type="l")
text(Case, leverage, Case)
abline(h=2*p/nmodel4, col=2)
```




```r
xoutlier=data.frame(which(leverage>2*p/nmodel4) )
xoutlier
```

```
##     which.leverage...2...p.nmodel4.
## 58                               58
## 87                               87
## 146                             146
## 175                             175
## 208                             208
## 238                             238
## 308                             308
```

```r
#test whether outlier in the extend of the model
IM4=influence.measures(fitmodel4weight)
dxoutlier=union(which(IM4$infmat[,5]>0.2),which(IM4$infmat[,3]>2*sqrt(p/nmodel4)))
#combine x and y outlier
finaloutlier=union(dxoutlier,youtlier)
datamodel4Final=datamodel4[-c(finaloutlier),]
# get model2 without x y outlier
fitmodel4x2=lm(datamodel4Final$y~.,data = datamodel4Final)
wtsx2 <- 1/fitted(lm(abs(residuals(fitmodel4x2)) ~ ., data = datamodel4Final))^2
Fmodel4=lm(datamodel4Final$y~., data = datamodel4Final,weights =wtsx2)
# R2 & adj R2 for model1
summary(Fmodel4)$r.squared
```

```
## [1] 0.8804859
```

```r
summary(Fmodel4)$adj.r.squared
```

```
## [1] 0.8801249
```

```r
# Test the model
#strandized for test data
yt9=as.matrix(test$`V-9`)
colnames(yt9)=c("V-9")
yt10=as.matrix(test$`V-10`)
colnames(yt10)=c("V-10")
test.v9<- cbind(test[1:27],yt9)
test.v10<- cbind(test[1:27],yt10)
for(i in 2:27)
 {
  test.v9[,i] <-(test[,i]-mean(test[,i])) /sd(test[,i])
}
for(i in 2:27)
 {
  test.v10[,i] <-(test[,i]-mean(test[,i])) /sd(test[,i])
}
```

```r
# scatter plot & cor
fitv10 <- lm(test$`V-10`~ ., data = test.v10)
summary(fitv10)
```

```
##
## Call:
## lm(formula = test$`V-10` ~ ., data = test.v10)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -10.870  -3.670   1.169   4.338  11.544
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  272.4457    11.3144  24.080 3.47e-10 ***
## `V-1`          1.5941     1.1706   1.362 0.203165
## `V-2`         -6.6147    24.4522  -0.271 0.792266
## `V-3`         40.1613    23.9268   1.679 0.124174
## `V-4`        -66.8744    22.6169  -2.957 0.014366 *
## `V-5`        233.8802    26.8405   8.714 5.53e-06 ***
## `V-6`         -6.9412    11.2577  -0.617 0.551292
## `V-7`         32.3178     3.2195  10.038 1.53e-06 ***
## `V-8`         30.6192     7.2639   4.215 0.001785 **
## `V-11`        -0.7395    14.8773  -0.050 0.961338
## `V-12`       113.1887   118.3086   0.957 0.361264
## `V-13`       140.3495    83.2022   1.687 0.122527
## `V-14`         1.3866    17.1699   0.081 0.937228
## `V-15`       169.7870    99.9927   1.698 0.120356
## `V-16`        10.0250    50.4989   0.199 0.846616
## `V-17`         9.1391    70.3806   0.130 0.899258
## `V-18`       -21.7666    18.2804  -1.191 0.261266
## `V-19`       -30.6981    21.3410  -1.438 0.180857
## `V-20`        77.3476    21.1456   3.658 0.004405 **
## `V-21`       -60.7189    42.0521  -1.444 0.179357
## `V-22`      -120.0430    66.2118  -1.813 0.099910 .
## `V-23`        73.7604    31.4409   2.346 0.040919 *
## `V-24`        11.8816    33.0547   0.359 0.726731
```

```
## `V-25`      -225.4046   268.3902  -0.840 0.420624
## `V-26`        66.3399   165.9609   0.400 0.697758
## `V-27`      -103.7999    22.2297  -4.669 0.000882 ***
## `V-28`        32.9507    15.8271   2.082 0.063992 .
## `V-29`       -19.0591    27.0856  -0.704 0.497699
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.78 on 10 degrees of freedom
## Multiple R-squared:  0.9991, Adjusted R-squared:  0.9968
## F-statistic:   423 on 27 and 10 DF,  p-value: 3.708e-12
```

```r
cor(test.v10[,c(2:28)])
```

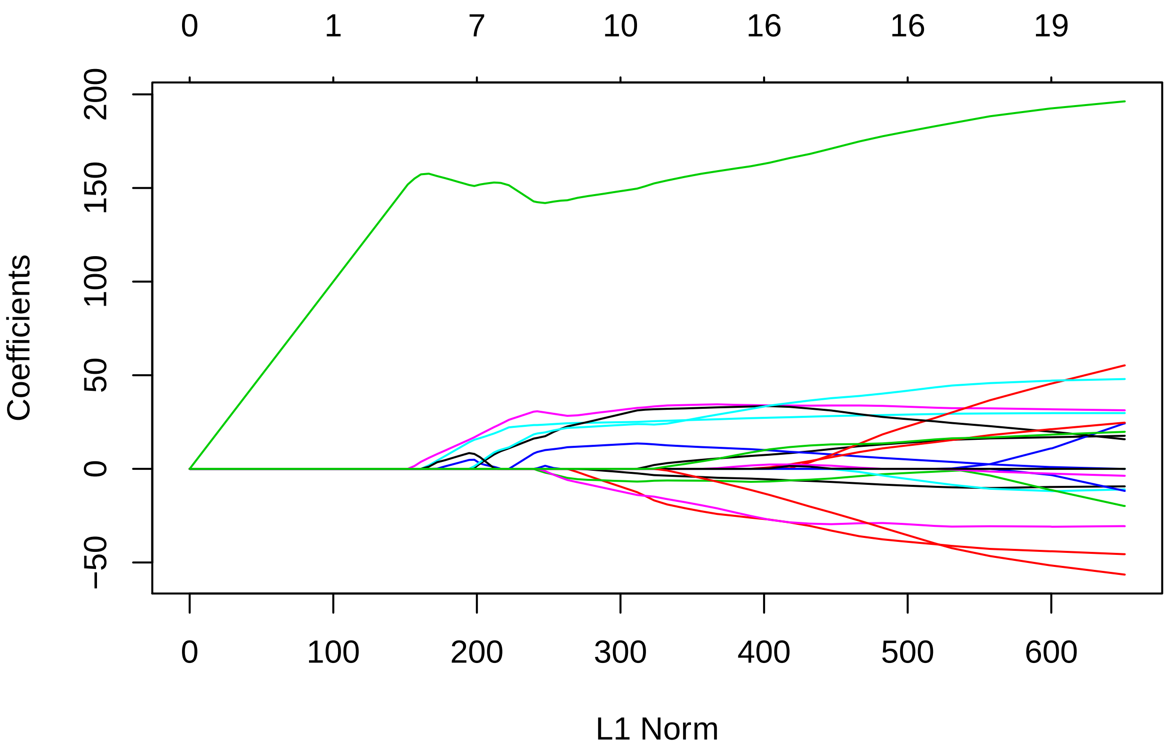
```
##              V-2         V-3         V-4         V-5         V-6
## V-2   1.00000000  0.98760515  0.73160086  0.37670831  0.22600652
## V-3   0.98760515  1.00000000  0.71209140  0.37228924  0.21567025
## V-4   0.73160086  0.71209140  1.00000000  0.84671012  0.24922766
## V-5   0.37670831  0.37228924  0.84671012  1.00000000  0.30351159
## V-6   0.22600652  0.21567025  0.24922766  0.30351159  1.00000000
## V-7  -0.02292599 -0.02186071  0.24412674  0.33620300  0.29322017
## V-8   0.53953700  0.53344562  0.86489429  0.82822710  0.30041366
## V-11  0.36533757  0.36353757  0.56934023  0.61657479  0.16658200
## V-12  0.33139692  0.31593503  0.73920733  0.86156959 -0.08532251
## V-13  0.32272403  0.30183748  0.73328812  0.85294637 -0.08492403
## V-14  0.28741154  0.26035082  0.55247646  0.64418155  0.26248596
## V-15  0.33136935  0.32684742  0.72021209  0.84528427 -0.09394580
## V-16  0.35132989  0.32660843  0.77856486  0.82834474 -0.03979719
## V-17  0.32506928  0.29793012  0.77490951  0.87052243 -0.05195761
## V-18 -0.13142833 -0.11399440  0.03433714  0.19025481 -0.24756714
## V-19  0.17836347  0.20812630  0.38801002  0.50391639 -0.18251913
## V-20 -0.29988016 -0.30073657 -0.69239049 -0.77660353 -0.05539371
## V-21  0.30817051  0.30110642  0.72947167  0.85704711 -0.10059098
## V-22  0.34513510  0.32903710  0.75979981  0.86558255 -0.08782856
## V-23  0.21719020  0.19529788  0.47802378  0.62976351 -0.21996723
## V-24  0.09327267  0.06689985  0.41470723  0.59337340 -0.12706560
## V-25  0.29584548  0.27747458  0.68387755  0.82511693 -0.12111300
## V-26  0.29535671  0.27861968  0.68366366  0.82505364 -0.13107651
## V-27  0.17990392  0.15830678  0.46120831  0.63685096 -0.13050909
## V-28 -0.22409534 -0.20295458 -0.13124054  0.04877237 -0.06067612
## V-29  0.35241519  0.33821433  0.74379471  0.84233751 -0.06839656
## V-10  0.37440101  0.37524116  0.81522709  0.97470602  0.31052398
##              V-7         V-8        V-11        V-12        V-13
## V-2  -0.02292599  0.53953700  0.36533757  0.33139692  0.32272403
## V-3  -0.02186071  0.53344562  0.36353757  0.31593503  0.30183748
## V-4   0.24412674  0.86489429  0.56934023  0.73920733  0.73328812
## V-5   0.33620300  0.82822710  0.61657479  0.86156959  0.85294637
## V-6   0.29322017  0.30041366  0.16658200 -0.08532251 -0.08492403
## V-7   1.00000000  0.30105455  0.11998472  0.22570889  0.23497926
## V-8   0.30105455  1.00000000  0.50374408  0.66459443  0.66941953
## V-11  0.11998472  0.50374408  1.00000000  0.57709819  0.58573941
## V-12  0.22570889  0.66459443  0.57709819  1.00000000  0.99284343
## V-13  0.23497926  0.66941953  0.58573941  0.99284343  1.00000000
## V-14  0.17104439  0.43539652  0.86567836  0.62321257  0.62133723
## V-15  0.24442844  0.65639165  0.60763465  0.98837433  0.97541628
```

```
## V-16  0.14701985  0.63479608  0.66093890  0.91934038  0.91825536
## V-17  0.22603833  0.65035736  0.60781001  0.97411641  0.97099506
## V-18  0.28047450 -0.04531235  0.16643626  0.35935593  0.36469287
## V-19  0.24933678  0.30909345  0.48169384  0.71663431  0.70108747
## V-20 -0.09126864 -0.60965008 -0.71249914 -0.75710367 -0.72547131
## V-21  0.24458981  0.67387434  0.61143932  0.98660922  0.97896018
## V-22  0.21226792  0.65935680  0.59549118  0.99072373  0.98163857
## V-23  0.21822375  0.46259694  0.38352358  0.79635337  0.82352013
## V-24  0.18430826  0.47278839  0.42093001  0.72829040  0.77718417
## V-25  0.24865855  0.63793373  0.56071173  0.98150465  0.99143887
## V-26  0.24245434  0.63248576  0.54894643  0.98406695  0.99057436
## V-27  0.29543427  0.44939056  0.22949717  0.77103403  0.79436596
## V-28  0.29970449 -0.19043096 -0.07412328  0.13729518  0.13530408
## V-29  0.23998363  0.66416219  0.57442695  0.98710408  0.97929565
## V-10  0.45747334  0.84754453  0.57655860  0.85482795  0.85117572
##               V-14       V-15        V-16        V-17        V-18
## V-2   0.2874115436  0.3313694  0.35132989  0.32506928 -0.13142833
## V-3   0.2603508218  0.3268474  0.32660843  0.29793012 -0.11399440
## V-4   0.5524764595  0.7202121  0.77856486  0.77490951  0.03433714
## V-5   0.6441815499  0.8452843  0.82834474  0.87052243  0.19025481
## V-6   0.2624859638 -0.0939458 -0.03979719 -0.05195761 -0.24756714
## V-7   0.1710443906  0.2444284  0.14701985  0.22603833  0.28047450
## V-8   0.4353965238  0.6563916  0.63479608  0.65035736 -0.04531235
## V-11  0.8656783621  0.6076346  0.66093890  0.60781001  0.16643626
## V-12  0.6232125688  0.9883743  0.91934038  0.97411641  0.35935593
## V-13  0.6213372286  0.9754163  0.91825536  0.97099506  0.36469287
## V-14  1.0000000000  0.6215299  0.72533932  0.69452099  0.15605408
## V-15  0.6215298730  1.0000000  0.90209227  0.94941667  0.40458450
## V-16  0.7253393223  0.9020923  1.00000000  0.96611641  0.27203608
## V-17  0.6945209943  0.9494167  0.96611641  1.00000000  0.31791123
## V-18  0.1560540827  0.4045845  0.27203608  0.31791123  1.00000000
## V-19  0.4083245027  0.7873891  0.59859493  0.62986553  0.73216288
## V-20 -0.7741418013 -0.7665163 -0.86187965 -0.80850985 -0.09154056
## V-21  0.6066935538  0.9906373  0.90719355  0.95103770  0.39962450
## V-22  0.6429662142  0.9786266  0.95341013  0.98380933  0.36255471
## V-23  0.4161109177  0.7774443  0.67084502  0.75610551  0.42932245
## V-24  0.4312455544  0.6872105  0.59685074  0.66803579  0.38651934
## V-25  0.5844609203  0.9675719  0.87566108  0.94225312  0.42548625
## V-26  0.5756684522  0.9713055  0.87711897  0.94478814  0.42811196
## V-27  0.3008578736  0.7255657  0.56500768  0.72278276  0.38691850
## V-28  0.0005952779  0.1613507  0.02801824  0.10393714  0.86355056
## V-29  0.5885690773  0.9831633  0.89956429  0.95135608  0.37296130
## V-10  0.5900117992  0.8516274  0.78108086  0.83674718  0.22666142
##            V-19        V-20       V-21        V-22       V-23        V-24
## V-2   0.1783635 -0.29988016  0.3081705  0.34513510  0.2171902  0.09327267
## V-3   0.2081263 -0.30073657  0.3011064  0.32903710  0.1952979  0.06689985
## V-4   0.3880100 -0.69239049  0.7294717  0.75979981  0.4780238  0.41470723
## V-5   0.5039164 -0.77660353  0.8570471  0.86558255  0.6297635  0.59337340
## V-6  -0.1825191 -0.05539371 -0.1005910 -0.08782856 -0.2199672 -0.12706560
## V-7   0.2493368 -0.09126864  0.2445898  0.21226792  0.2182237  0.18430826
## V-8   0.3090934 -0.60965008  0.6738743  0.65935680  0.4625969  0.47278839
## V-11  0.4816938 -0.71249914  0.6114393  0.59549118  0.3835236  0.42093001
## V-12  0.7166343 -0.75710367  0.9866092  0.99072373  0.7963534  0.72829040
## V-13  0.7010875 -0.72547131  0.9789602  0.98163857  0.8235201  0.77718417
```

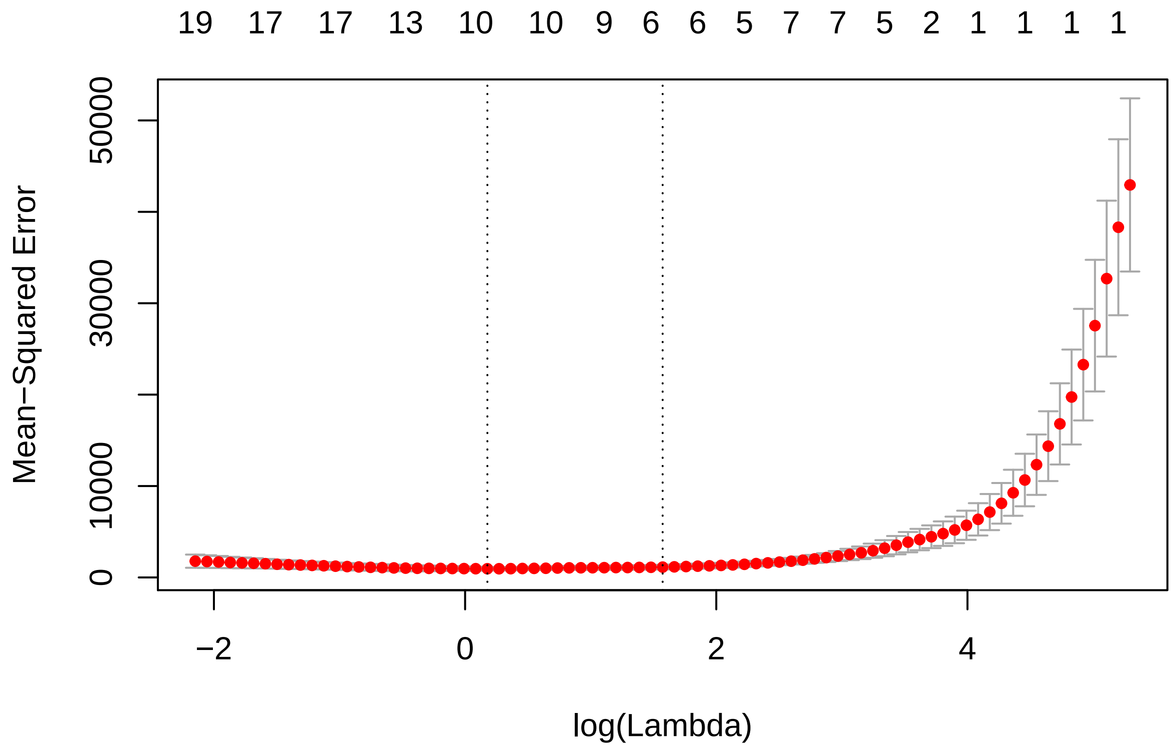
```
## V-14  0.4083245 -0.77414180  0.6066936  0.64296621  0.4161109  0.43124555
## V-15  0.7873891 -0.76651634  0.9906373  0.97862664  0.7774443  0.68721053
## V-16  0.5985949 -0.86187965  0.9071935  0.95341013  0.6708450  0.59685074
## V-17  0.6298655 -0.80850985  0.9510377  0.98380933  0.7561055  0.66803579
## V-18  0.7321629 -0.09154056  0.3996245  0.36255471  0.4293224  0.38651934
## V-19  1.0000000 -0.41602353  0.7641967  0.70151754  0.5605578  0.51266245
## V-20 -0.4160235  1.00000000 -0.7545829 -0.79468355 -0.4487491 -0.38553819
## V-21  0.7641967 -0.75458293  1.0000000  0.97974383  0.7731228  0.70924978
## V-22  0.7015175 -0.79468355  0.9797438  1.00000000  0.7662124  0.68447330
## V-23  0.5605578 -0.44874905  0.7731228  0.76621244  1.0000000  0.73658929
## V-24  0.5126625 -0.38553819  0.7092498  0.68447330  0.7365893  1.00000000
## V-25  0.7283520 -0.67082997  0.9695914  0.96181713  0.8723698  0.81802957
## V-26  0.7337861 -0.67297063  0.9715537  0.96501751  0.8762817  0.79843537
## V-27  0.4897397 -0.29678603  0.7330601  0.72350793  0.9020787  0.71872893
## V-28  0.5019291  0.13628274  0.1724028  0.13522069  0.2075548  0.13663264
## V-29  0.7447778 -0.73530060  0.9807783  0.97404091  0.7658337  0.71177550
## V-10  0.5596538 -0.70418735  0.8563429  0.84520316  0.6688126  0.61045344
##            V-25       V-26       V-27          V-28        V-29
## V-2   0.2958455  0.2953567  0.1799039 -0.2240953363  0.35241519
## V-3   0.2774746  0.2786197  0.1583068 -0.2029545779  0.33821433
## V-4   0.6838775  0.6836637  0.4612083 -0.1312405395  0.74379471
## V-5   0.8251169  0.8250536  0.6368510  0.0487723702  0.84233751
## V-6  -0.1211130 -0.1310765 -0.1305091 -0.0606761209 -0.06839656
## V-7   0.2486585  0.2424543  0.2954343  0.2997044861  0.23998363
## V-8   0.6379337  0.6324858  0.4493906 -0.1904309611  0.66416219
## V-11  0.5607117  0.5489464  0.2294972 -0.0741232850  0.57442695
## V-12  0.9815047  0.9840670  0.7710340  0.1372951846  0.98710408
## V-13  0.9914389  0.9905744  0.7943660  0.1353040806  0.97929565
## V-14  0.5844609  0.5756685  0.3008579  0.0005952779  0.58856908
## V-15  0.9675719  0.9713055  0.7255657  0.1613506662  0.98316326
## V-16  0.8756611  0.8771190  0.5650077  0.0280182377  0.89956429
## V-17  0.9422531  0.9447881  0.7227828  0.1039371380  0.95135608
## V-18  0.4254862  0.4281120  0.3869185  0.8635505633  0.37296130
## V-19  0.7283520  0.7337861  0.4897397  0.5019290952  0.74477779
## V-20 -0.6708300 -0.6729706 -0.2967860  0.1362827396 -0.73530060
## V-21  0.9695914  0.9715537  0.7330601  0.1724027847  0.98077831
## V-22  0.9618171  0.9650175  0.7235079  0.1352206913  0.97404091
## V-23  0.8723698  0.8762817  0.9020787  0.2075548473  0.76583369
## V-24  0.8180296  0.7984354  0.7187289  0.1366326393  0.71177550
## V-25  1.0000000  0.9989211  0.8352226  0.1848733515  0.96894426
## V-26  0.9989211  1.0000000  0.8395187  0.1902107103  0.97039969
## V-27  0.8352226  0.8395187  1.0000000  0.2995912846  0.73230796
## V-28  0.1848734  0.1902107  0.2995913  1.0000000000  0.14344307
## V-29  0.9689443  0.9703997  0.7323080  0.1434430723  1.00000000
## V-10  0.8365705  0.8355670  0.6675232  0.0919203396  0.84459157
##             V-10
## V-2   0.37440101
## V-3   0.37524116
## V-4   0.81522709
## V-5   0.97470602
## V-6   0.31052398
## V-7   0.45747334
## V-8   0.84754453
## V-11  0.57655860
```

```
## V-12  0.85482795
## V-13  0.85117572
## V-14  0.59001180
## V-15  0.85162743
## V-16  0.78108086
## V-17  0.83674718
## V-18  0.22666142
## V-19  0.55965376
## V-20 -0.70418735
## V-21  0.85634287
## V-22  0.84520316
## V-23  0.66881263
## V-24  0.61045344
## V-25  0.83657051
## V-26  0.83556696
## V-27  0.66752317
## V-28  0.09192034
## V-29  0.84459157
## V-10  1.00000000
```

```
# Lasso to determine variable
library("glmnet")
x.simple=as.matrix(test.v10[,2:27])
y=test.v10$`V-10`
fitlasso=glmnet(x.simple,y,alpha = 1)
plot(fitlasso)
```



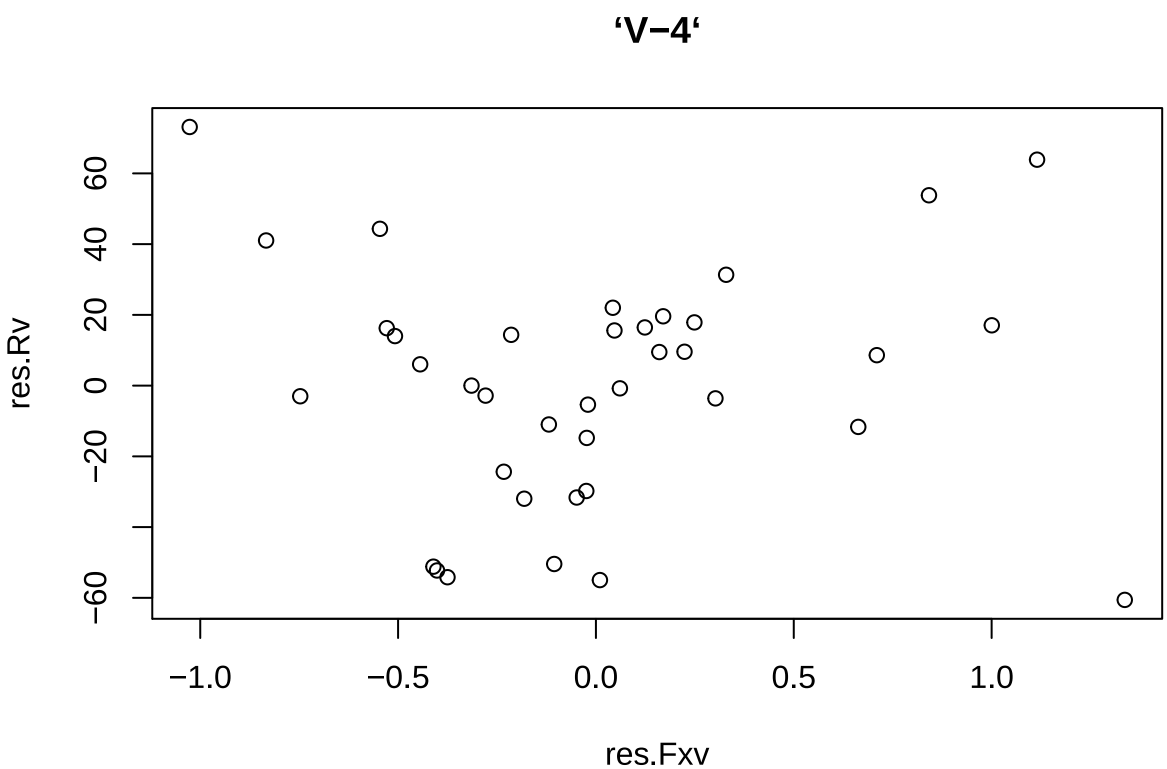

```
cv.lasso=cv.glmnet(x.simple,y)
plot(cv.lasso)
```

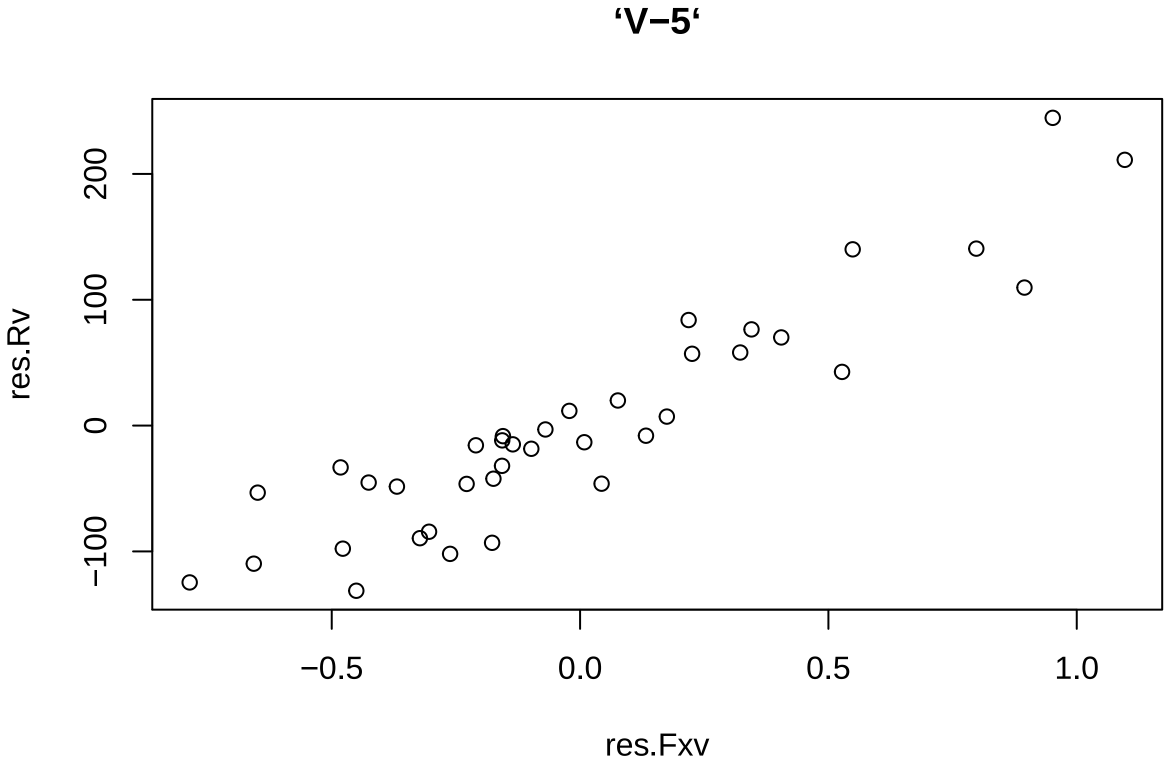


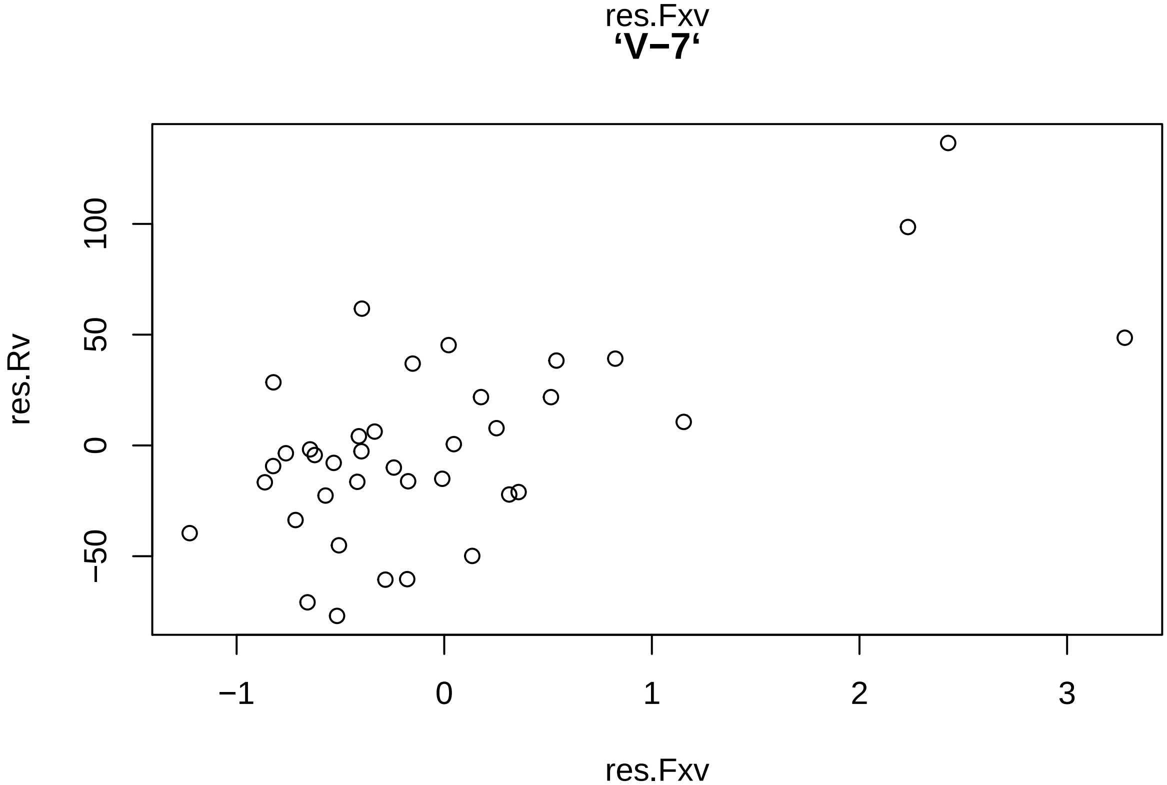

```r
coef(cv.lasso)
```

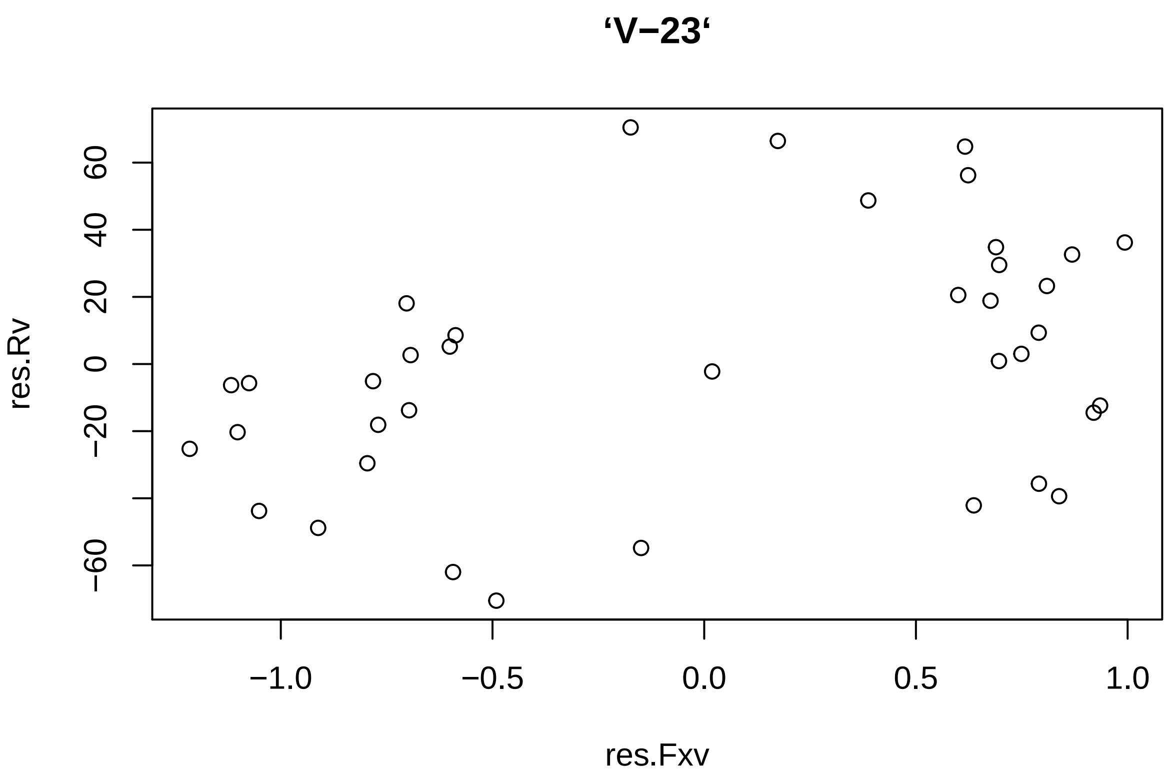
```
## 27 x 1 sparse Matrix of class "dgCMatrix"
##                      1
## (Intercept) 287.631579
## V-2           .
## V-3           .
## V-4           .
## V-5         144.960511
## V-6           6.192732
## V-7          23.099944
## V-8          29.472063
## V-11          .
## V-12          .
## V-13          .
## V-14          .
## V-15          .
## V-16          .
## V-17          .
## V-18          .
## V-19         14.891914
## V-20          .
## V-21          .
## V-22          .
## V-23         16.689107
## V-24          .
## V-25          .
## V-26          .
## V-27          .
## V-28          .
## V-29          .
```

```
# Model 3
# added variable factor to determine ^
datamodel3=data.frame(test.v10[,c(4,5,7,21,28)])
fitmodel3=lm(datamodel3$V.10~.,data = datamodel3)
colData3 <- list("`V-4`", "`V-5`", "`V-7`", "`V-23`")
names(colData3) <- c("`V-4`", "`V-5`", "`V-7`", "`V-23`")
removeXList <- colData3

for (rmX in removeXList){
  tmpV <- colData3
  tmpV[[rmX]] = NULL
  test.Rv=lm(as.formula(paste("`V-10` ~", paste(tmpV, collapse = "+"))), data = test.v10)
  res.Rv= test.Rv$residuals

  test.Fxv=lm(as.formula(paste(paste(rmX," ~"), paste(tmpV, collapse = "+"))), data = test.v10)
  res.Fxv= test.Fxv$residuals

  plot(res.Fxv,res.Rv,main = rmX)
}
```




'V−5'
res.Rv
200
100
0
−100
−0.5
0.0
0.5
1.0
res.Fxv


'V−7'
res.Rv
100
50
0
−50
−1
0
1
2
3
res.Fxv




```r
# Weighted tranformation for model 3
wts <- 1/fitted(lm(abs(residuals(fitmodel3)) ~ ., data = datamodel3))^2

fitmodel3weight <- lm(datamodel3$V.10~ .,data = datamodel3, weights=wts)
datamodel3weight=cbind(datamodel3[1:4],datamodel3$V.10*wts)
summary(fitmodel3weight)$r.squared
```

```
## [1] 0.9776405
```

```r
summary(fitmodel3weight)$adj.r.squared
```

```
## [1] 0.9749303
```

```r
#Brown test whether constant variance and transformation for Model 3 after tranformation
resmodel3b=fitmodel3weight $residuals
mmodel3=mean(datamodel3weight$`datamodel3$V.10 * wts`)
nmodel3=dim(datamodel3weight)[1]
#1. Break the residuals into two groups.
Group1 <- resmodel3b[datamodel3weight$`datamodel3$V.10 * wts`<mmodel3]
Group2 <-resmodel3b[datamodel3weight$`datamodel3$V.10 * wts`>=mmodel3]

#2. Obtain the median of each group, using the commands:
M1 <- median(Group1)
M2 <- median(Group2)

#3. Obtain the mean absolute deviation for each group, using the commands:
D1 <- sum( abs( Group1 - M1 )) / length(Group1)
D2 <- sum( abs( Group2 - M2 )) / length(Group2)

#4. Calculate the pooled standard error, using the command:
s <- sqrt( ( sum( ( abs(Group1 - M1) - D1 )^2 ) + sum( ( abs(Group2 - M2) - D2 )^2 ) ) / (nmodel3-2) )
```

```r
#5. Finally, calculate the Brown-Forsythe test statistic, using the command:
t <- ( D1 - D2 ) / ( s * sqrt( 1/length(Group1) + 1/length(Group2) ) )
t
```

```
## [1] 1.422665
```

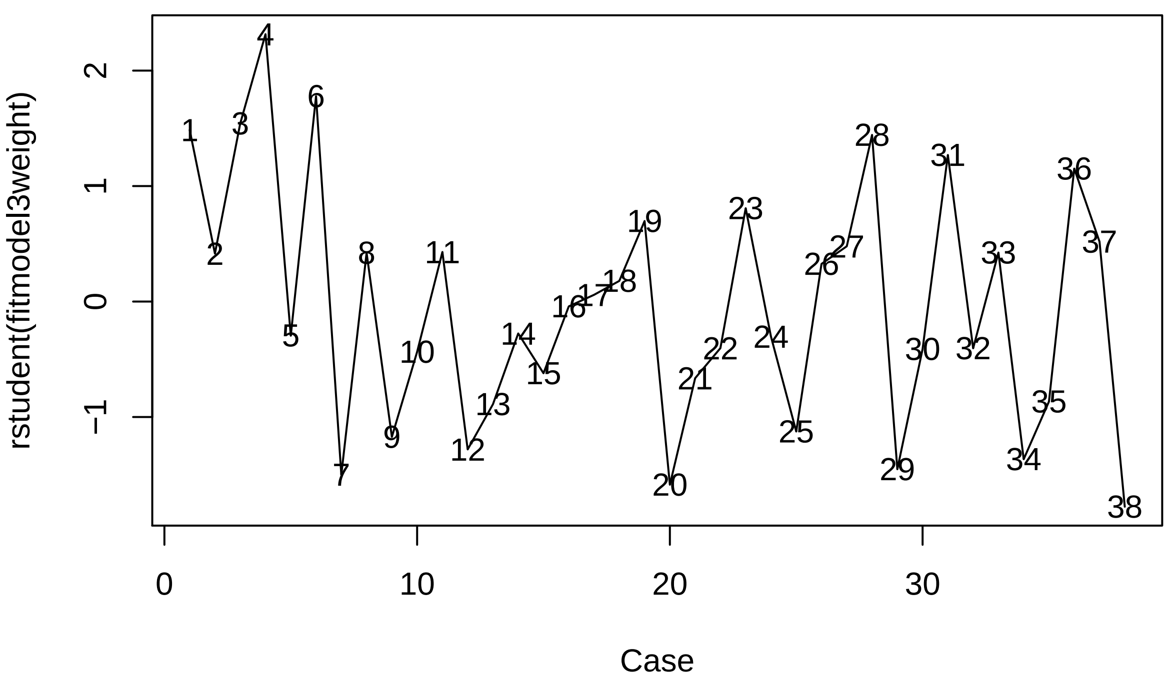
```r
#6 Once you obtain this value, you can compare it to the critical value for any given alpha level to de
# or you can find its P-value.
alpha <- 0.05
qt(1-alpha/2, nmodel3-p1-1)   # find the catical value
```

```
## [1] 2.036933
```

```r
# And the P-value can be found by typing:
 2*(1-pt( abs(t), nmodel3-p1-1))
```

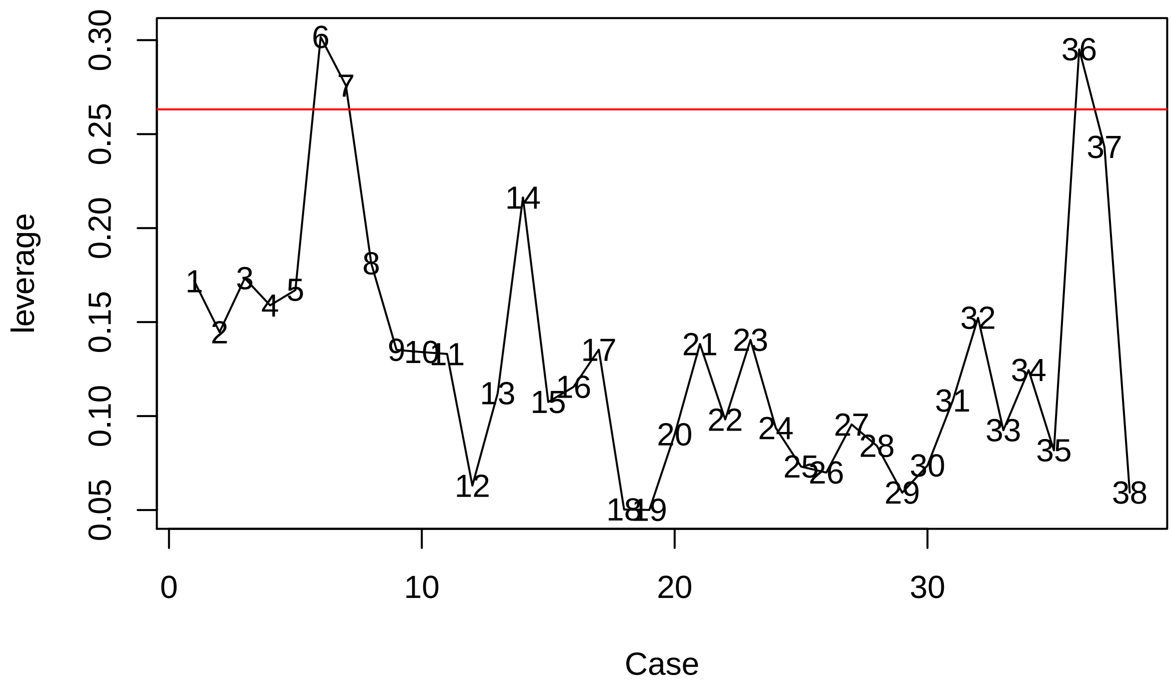
```
## [1] 0.1645093
```

```r
#y outlier for model3
Case <- c(1:nmodel3)
plot(Case, rstudent(fitmodel3weight), type="l")
text(Case, rstudent(fitmodel3weight), Case)
```




```r
alpha <- 0.05
crit <- qt(1-alpha/2/nmodel3, nmodel3-p1-1)
youtlier3=which(abs(rstudent(fitmodel3weight)) >=crit )
```

```r
#x outlier for model3
X <- as.matrix(cbind(rep(1,nmodel3), datamodel3[1:4]))
H <- X%*%solve(t(X)%*%X, tol=1e-20)%*%t(X)
leverage <- hatvalues(fitmodel3weight)
plot(Case, leverage, type="l")
text(Case, leverage, Case)
abline(h=2*p1/nmodel3, col=2)
```




```r
xoutlier1=data.frame(which(leverage>2*p1/nmodel3) )
xoutlier1
```

```
##    which.leverage...2...p1.nmodel3.
## 6                                 6
## 7                                 7
## 36                               36
```

```r
#test whether outlier in the extend of the model3
IM3=influence.measures(fitmodel3weight)
dxoutlier3=union(which(IM3$infmat[,8]>0.2),which(IM3$infmat[,6]>2*sqrt(p1/nmodel3)))
#combine x and y outlier
finaloutlier3=union(dxoutlier3,youtlier3)
datamodel3Final=datamodel3[-c(finaloutlier3),]
# get model1 without x y outlier
fitmodel3x1=lm(datamodel3Final$V.10~.,data = datamodel3Final)
wtsx3 <- 1/fitted(lm(abs(residuals(fitmodel3x1)) ~ ., data = datamodel3Final))^2
Fmodel3=lm(datamodel3Final$V.10~., data = datamodel3Final,weights =wtsx3)
# R2 & adj R2 for model3 test
summary(Fmodel3)$r.squared
```

```
## [1] 0.9797508
```

```r
summary(Fmodel3)$adj.r.squared
```

```
## [1] 0.9770509
```

```r
# add ^2 for model4
Data.new3 <- cbind(test.v10$`V-4`, test.v10$`V-5`, test.v10$`V-7`, test.v10$ `V-23`)
x3.new=as.matrix(cbind(Data.new3,((Data.new3)^2)[,-2]))
colnames(x3.new)=c("V-4","V-5","V-7","V-23","V-4.2","V-7.2","V-23.2")
```

```r
# Model 4
testv14 = data.frame(x3.new,y)
datamodel4=data.frame(testv14[,c(2,8)])
```

```r
fitmodel4=lm(datamodel4$y~.,data = datamodel4)
summary(fitmodel4)$r.squared
```

```
## [1] 0.9500518
```

```r
summary(fitmodel4)$adj.r.squared
```

```
## [1] 0.9486644
```

```r
# Weighted tranformation for model 4
wts <- 1/fitted(lm(abs(residuals(fitmodel4)) ~ ., data = datamodel4))^2

fitmodel4weight <- lm(datamodel4$y~ .,data = datamodel4, weights=wts)
datamodel4weight=cbind(datamodel4[1],datamodel4$y*wts)
summary(fitmodel4weight)$r.squared
```

```
## [1] 0.9524123
```

```r
summary(fitmodel4)$adj.r.squared
```

```
## [1] 0.9486644
```

```r
#Brown test whether constant variance and transformation for Model 2 after tranformation
resmode22b=fitmodel4weight$residuals
mmodel4=mean(datamodel4weight$`datamodel4$y * wts`)
nmodel4=dim(datamodel4weight)[1]
#1. Break the residuals into two groups.
Group6 <- resmode22b[datamodel4weight$`datamodel4$y * wts`<mmodel4]
Group7 <- resmode22b[datamodel4weight$`datamodel4$y * wts`>=mmodel4]

#2. Obtain the median of each group, using the commands:
M1 <- median(Group6)
M2 <- median(Group7)

#3. Obtain the mean absolute deviation for each group, using the commands:
D1 <- sum( abs( Group6 - M1 )) / length(Group6)
D2 <- sum( abs( Group7 - M2 )) / length(Group7)

#4. Calculate the pooled standard error, using the command:
s <- sqrt( ( sum( ( abs(Group6 - M1) - D1 )^2 ) + sum( ( abs(Group7 - M2) - D2 )^2 ) ) / (nmodel4-2) )

#5. Finally, calculate the Brown-Forsythe test statistic, using the command:
t <- ( D1 - D2 ) / ( s * sqrt( 1/length(Group6) + 1/length(Group7) ) )
t
```

```
## [1] 1.582472
```

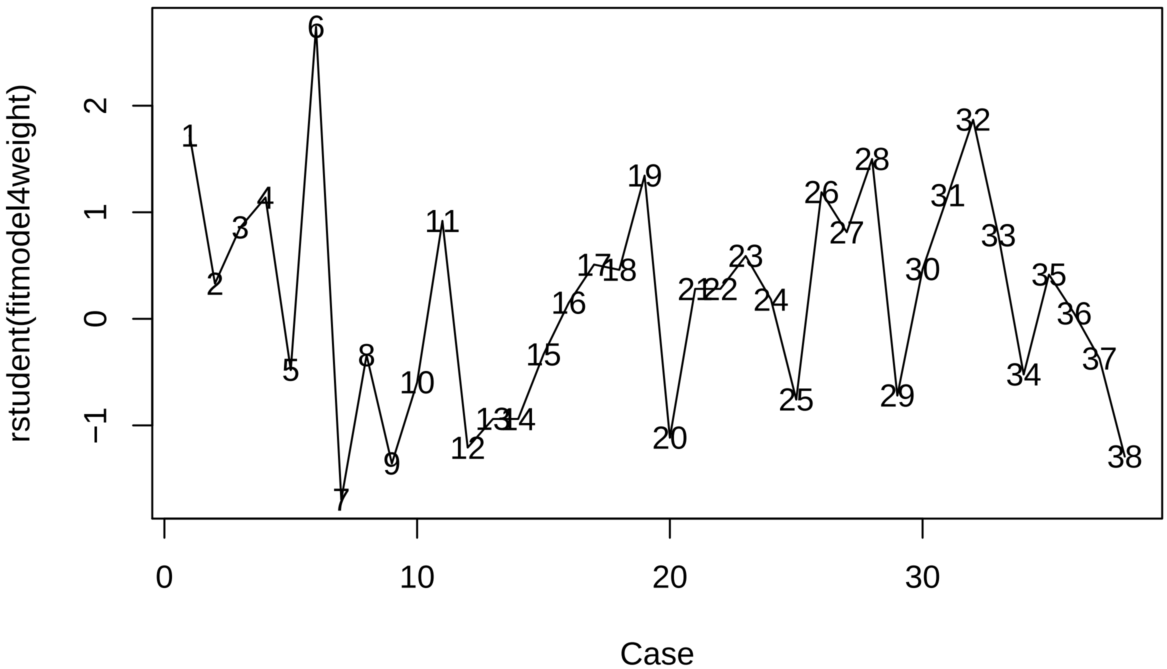
```r
#6 Once you obtain this value, you can compare it to the critical value for any given alpha level to de
# or you can find its P-value.
alpha <- 0.05
qt(1-alpha/2, nmodel4-5)   # find the catical value
```

```
## [1] 2.034515
```

```r
# And the P-value can be found by typing:
 2*(1-pt( abs(t), nmodel4-5))
```

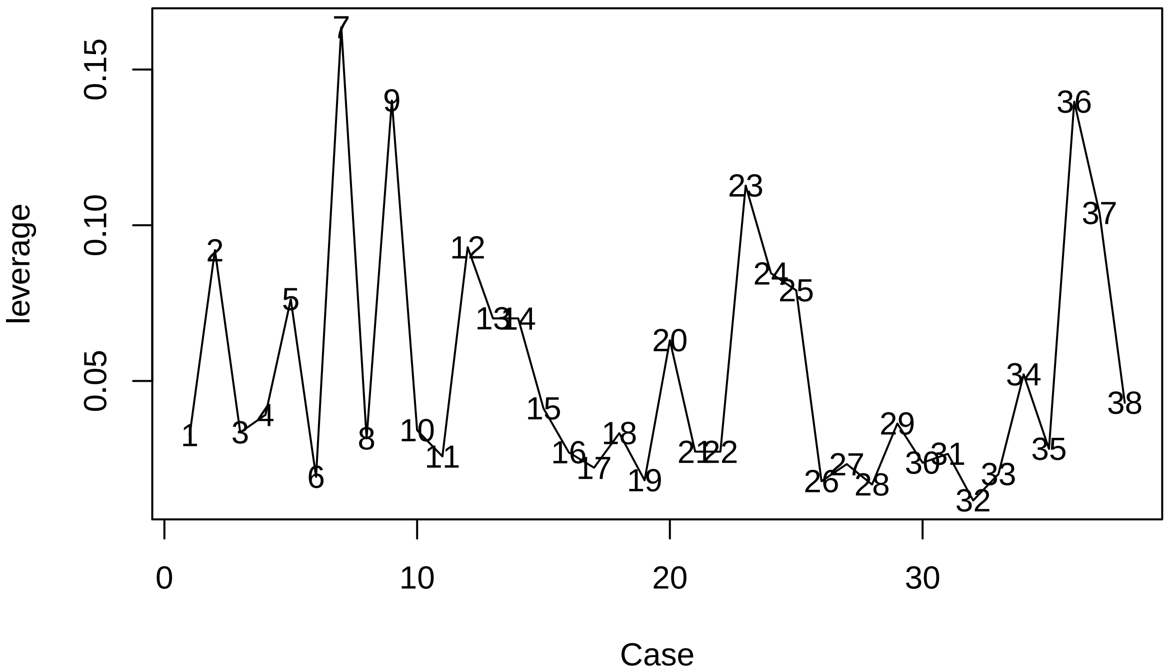
```
## [1] 0.1230801
```

```r
#y outlier
Case <- c(1:nmodel4)
plot(Case, rstudent(fitmodel4weight), type="l")
text(Case, rstudent(fitmodel4weight), Case)
```




```r
alpha <- 0.01
p=4
crit <- qt(1-alpha/2/nmodel4, nmodel4-p-1)
youtlier=which(abs(rstudent(fitmodel4weight)) >=crit )
```

```r
#x outlier
X <- as.matrix(cbind(rep(1,nmodel4), datamodel4weight[1]))
H <- X%*%solve(t(X)%*%X,tol=1e-30)%*%t(X)
leverage <- hatvalues(fitmodel4weight)
plot(Case, leverage, type="l")
text(Case, leverage, Case)
abline(h=2*p/nmodel4, col=2)
```




```
xoutlier=data.frame(which(leverage>2*p/nmodel4) )
xoutlier
```

```
## [1] which.leverage...2...p.nmodel4.
## <0 rows> (or 0-length row.names)
```

```
#test whether outlier in the extend of the model
IM4=influence.measures(fitmodel4weight)
dxoutlier=union(which(IM4$infmat[,5]>0.2),which(IM4$infmat[,3]>2*sqrt(p/nmodel4)))
#combine x and y outlier
finaloutlier=union(dxoutlier,youtlier)
datamodel4Final=datamodel4[-c(finaloutlier),]
# get model2 without x y outlier
fitmodel4x2=lm(datamodel4Final$y~.,data = datamodel4Final)
wtsx2 <- 1/fitted(lm(abs(residuals(fitmodel4x2)) ~ ., data = datamodel4Final))^2
Fmodel4=lm(datamodel4Final$y~., data = datamodel4Final,weights =wtsx2)
# R2 & adj R2 for model1
summary(Fmodel4)$r.squared
```

```
## [1] 0.9516841
```

```
summary(Fmodel4)$adj.r.squared
```

```
## [1] 0.9503037
```