STAT 5120 Final Project

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Contents

1 Introduction

This report is to build and select a model for the response y, using the generated data set "dat.cvs" given by the course instructor. Most of the tools studied in course STAT 5120 (Linear Regression) will be used to facilitate model selection, model estimation, model validation, and model diagnosis procedures. This report is written by Shaoran Sun individually.

2 Materials and methods

Data is given by the instructor. Data contains one response variable, y, and 10 predictors, $x_1, x_2, \ldots, x_{10}$. There are 100 intances of data, in total of 100 rows. See the data on Appendix I

The analysis method used are:

- Linear Transformation
- Detecting Outliers in Predictors with leverages
- Detecting Infuential Observations with DFFITS and Cook's Distance
- Automated Forward Selection Procedure
- Diagnosing Multicollinearity with Variance Inflation Factor (VIF)
- General Linear F Test

The criteria for statistical significance is $P < 0.05$.

3 Results

With the given data set "dat.cvs",

- y is log-transformed
- Entry 10 is reomoved due to large influence to the overall data
- Predictors x1, x6, x7, x8, x9, and x10 are *removed* due to insignificance.
- Predictors x2, x3, x4,and x5 are kept, and combined as a first order model.

The final model is:

$$\mathbf{y = 2.00 \cdot x_2 + 0.91 \cdot x_3 + 0.40 \cdot x_4 + 3.35 \cdot x_5 + 1.51}$$

```
Call:
lm(formula = y ~ x2 + x3 + x4 + x5)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.29129 -0.46534  0.00512  0.62212  1.87873 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.50163    0.09635  15.584  < 2e-16 ***
x2           1.99583    0.08829  22.605  < 2e-16 ***
x3           0.91006    0.10112   8.999 2.46e-14 ***
x4           0.40358    0.08986   4.491 2.01e-05 ***
x5           3.34805    0.09792  34.191  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9338 on 94 degrees of freedom
Multiple R-squared:  0.955,	Adjusted R-squared:  0.9531 
F-statistic: 498.6 on 4 and 94 DF,  p-value: < 2.2e-16
```

The intercept, x2, and x5 all have p-values of $(< 2e - 16)$, x3 has p-value of $2.46e - 14$, and x4 has p-value of $2.01e - 05$. The overall p-value is $(< 2.2e - 16)$. These p-values are all less than 0.05 and significant.

The R^2 is 0.955, which means the model represents 95.5% of the data.

4 Detailed Procedures

4.1 Read in data and fit the originial data to a model

I first plot in all 10 variables in responsing to y. All the p-values to the variables are greater than 0.05, which indicates that none of the variable is significant.

The 5 assumptions about linear regression are:

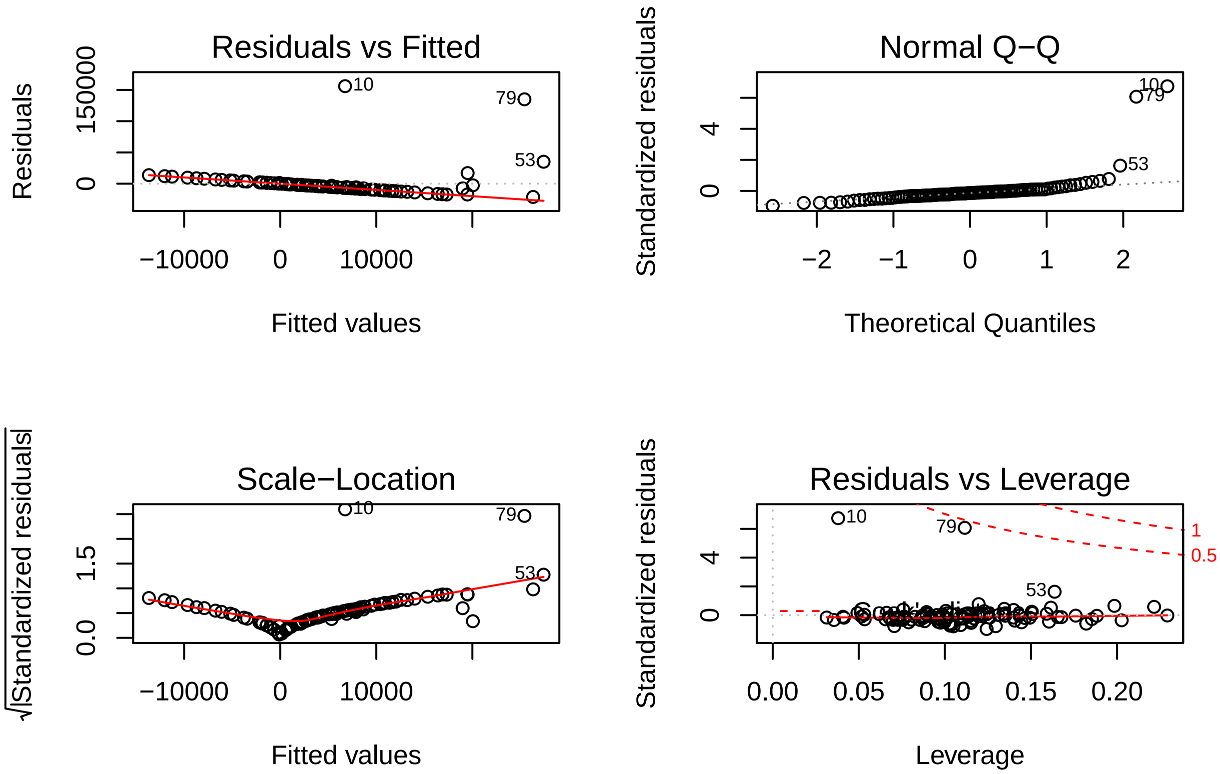
1. There exists a linear relation between the response and predictor variable(s).
2. The error terms have the constant variance
3. The error terms are independent, have mean 0.
4. Model fits all observations well (no outliers).
5. The errors follow a Normal distribution.

The Residuals vs Fitted graph suggested that residuals do not fall in a horizontal band around 0, and they have an apparent pattern. Assumption 1 and 3 are not met.

The residuals also do not have similar vertical variation across fits. Assumption 2 is not met.

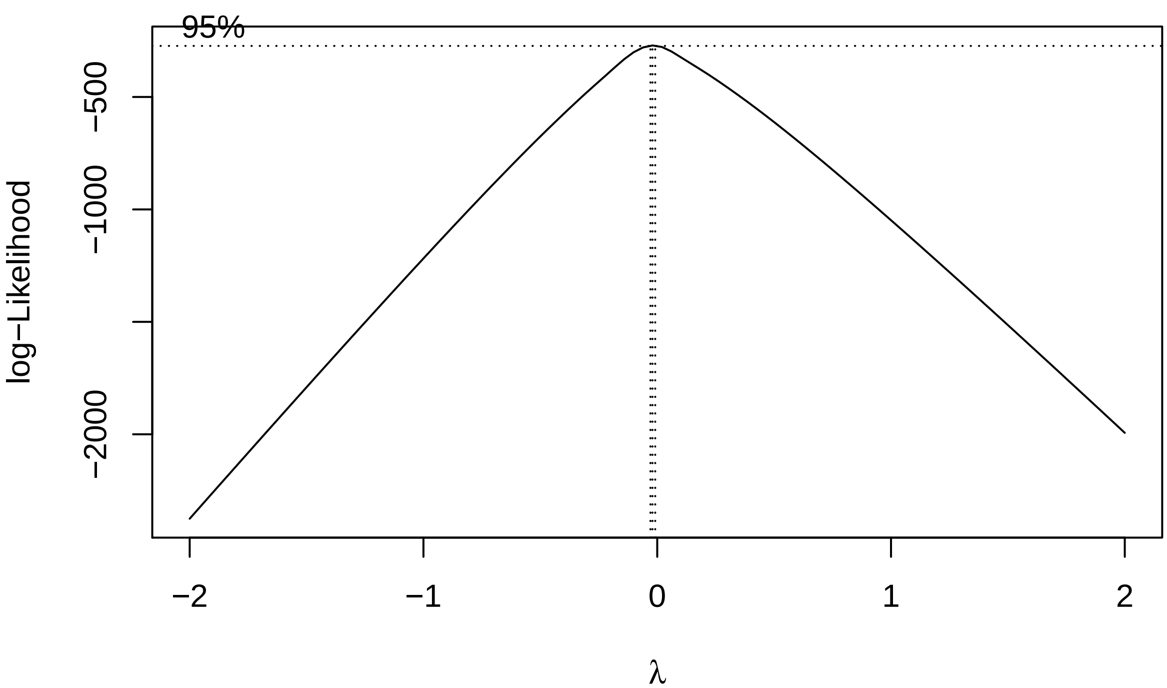
Hence, we consider using a boxcox transformation to test for log-likelihood.

```
##
## Call:
## lm(formula = dat$y ~ ., data = dat)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -21213  -7359  -3119   1056 156003
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4856.9     2554.0   1.902   0.0604 .
## x1           18253.4    50397.7   0.362   0.7181
## x2          -16220.4    50336.8  -0.322   0.7480
## x3            -723.3     2565.5  -0.282   0.7786
## x4             520.9     2317.8   0.225   0.8227
## x5            4563.1     2562.1   1.781   0.0783 .
## x6           -2807.6     2457.2  -1.143   0.2563
## x7           -2535.7     2810.4  -0.902   0.3694
## x8            2839.7     2348.2   1.209   0.2297
## x9           -3654.9     2392.7  -1.527   0.1302
## x10           -577.3     2607.0  -0.221   0.8253
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23590 on 89 degrees of freedom
## Multiple R-squared:  0.1113, Adjusted R-squared:  0.01149
## F-statistic: 1.115 on 10 and 89 DF,  p-value: 0.36
```



4.2 Boxcox transformation

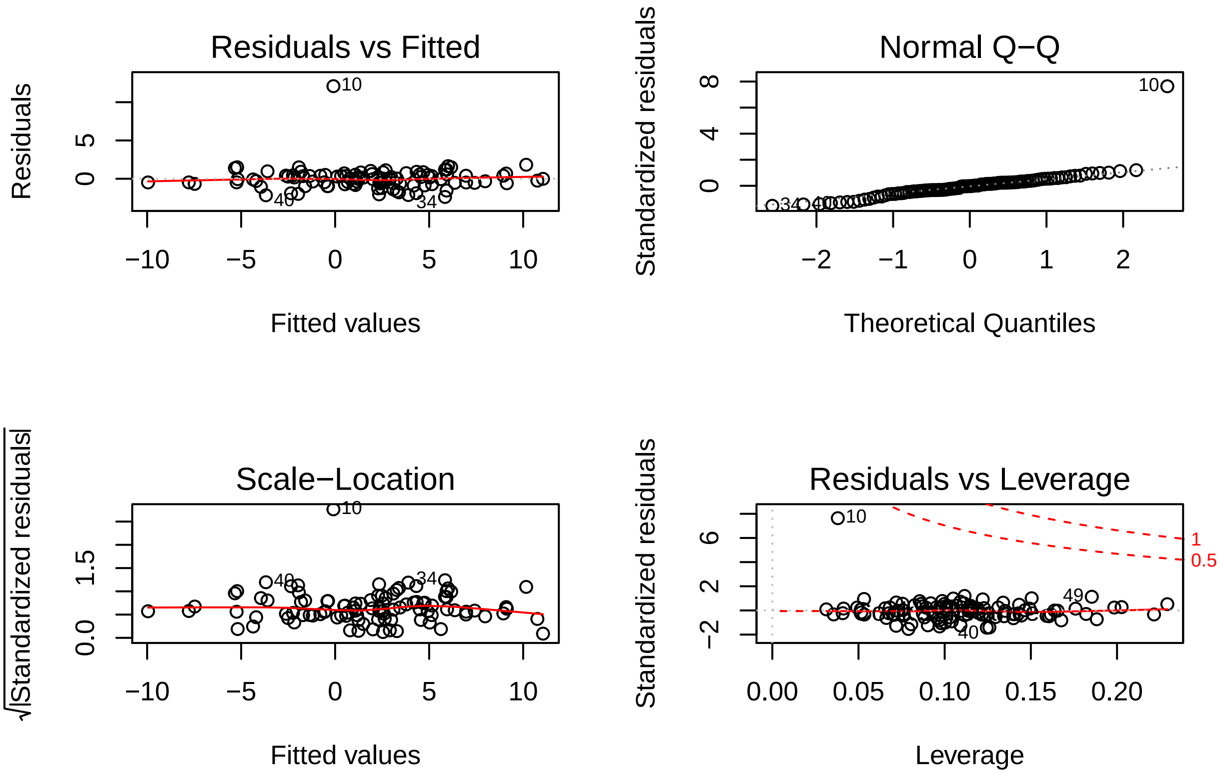
As we can see from the boxcox graph, λ is very close to 0. So we consider a log-transformation.



4.3 Fit the log-transformed y

After the transformation, some of the predictors are starting to become significant, namely, x3, x5, and intercept. The overall p-value also becomes very significant, comparing to before the transformaiton, where p-value $= 0.36$.

```
##
## Call:
## lm(formula = dat$y ~ ., data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.3787 -0.6130 -0.0369  0.4978 12.0928
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.610750   0.174805   9.215 1.35e-14 ***
## x1          -1.323510   3.449464  -0.384   0.7021
## x2           3.262825   3.445294   0.947   0.3462
## x3           0.945029   0.175598   5.382 5.92e-07 ***
## x4           0.349093   0.158641   2.201   0.0304 *
## x5           3.261169   0.175364  18.597  < 2e-16 ***
## x6          -0.104953   0.168182  -0.624   0.5342
## x7           0.001392   0.192358   0.007   0.9942
## x8           0.086216   0.160720   0.536   0.5930
## x9          -0.066157   0.163769  -0.404   0.6872
## x10          0.080254   0.178437   0.450   0.6540
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.614 on 89 degrees of freedom
## Multiple R-squared:  0.8795, Adjusted R-squared:  0.866
## F-statistic: 64.97 on 10 and 89 DF,  p-value: < 2.2e-16
```



4.4 Detect and remove outliers

Next, I will detect outliers.

From the above graphs, we can see that outliers definitely exist, possibly, data 10.

Obtain leverages and two measures that can be used to identify influential points, DFFITS (difference in fts) and Cook's Distance.

From the output of influence, DFFITS (difference in fts), and Cook's Distance, we can see that observation 10 is indeed an influential outlier. Hence we remove it.

After removing observation 10, the model fits the data better than before, as we can see in the following output table. Next, we will be choosing which predictors are actually significant.

```
##
## Call:
## lm(formula = no10$y ~ ., data = no10)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.3706 -0.4279  0.0241  0.5760  1.8382
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.482703   0.103688  14.300  < 2e-16 ***
## x1          0.692642   2.042699   0.339    0.735
## x2          1.295552   2.039959   0.635    0.527
## x3          0.909189   0.103719   8.766 1.25e-13 ***
## x4          0.407380   0.093778   4.344 3.73e-05 ***
```

```
## x5           3.322817   0.103653  32.057  < 2e-16 ***
## x6          -0.007948   0.099586  -0.080    0.937    
## x7           0.130916   0.114019   1.148    0.254    
## x8           0.070550   0.094905   0.743    0.459    
## x9           0.027593   0.096969   0.285    0.777    
## x10          0.052156   0.105381   0.495    0.622    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 0.9533 on 88 degrees of freedom
## Multiple R-squared:  0.9561, Adjusted R-squared:  0.9511 
## F-statistic: 191.6 on 10 and 88 DF,  p-value: < 2.2e-16
```

4.5 Check for multicolinearity issue

```
##          y     x1     x2     x3     x4     x5     x6     x7     x8     x9
## y    1.000  0.554  0.555  0.324  0.042  0.808 -0.015  0.141  0.205 -0.096
## x1   0.554  1.000  0.999  0.060 -0.020  0.063  0.001 -0.003  0.077 -0.085
## x2   0.555  0.999  1.000  0.060 -0.020  0.064  0.003  0.008  0.079 -0.088
## x3   0.324  0.060  0.060  1.000 -0.003  0.126  0.028  0.063  0.017 -0.007
## x4   0.042 -0.020 -0.020 -0.003  1.000 -0.061  0.000  0.071 -0.144  0.085
## x5   0.808  0.063  0.064  0.126 -0.061  1.000 -0.030  0.125  0.211 -0.087
## x6  -0.015  0.001  0.003  0.028  0.000 -0.030  1.000  0.034  0.109 -0.166
## x7   0.141 -0.003  0.008  0.063  0.071  0.125  0.034  1.000  0.019 -0.068
## x8   0.205  0.077  0.079  0.017 -0.144  0.211  0.109  0.019  1.000  0.044
## x9  -0.096 -0.085 -0.088 -0.007  0.085 -0.087 -0.166 -0.068  0.044  1.000
## x10  0.033  0.158  0.160 -0.069 -0.112 -0.042  0.100 -0.051  0.078 -0.058
##        x10
## y    0.033
## x1   0.158
## x2   0.160
## x3  -0.069
## x4  -0.112
## x5  -0.042
## x6   0.100
## x7  -0.051
## x8   0.078
## x9  -0.058
## x10  1.000
```

```
##         x1         x2         x3         x4         x5         x6 
## 515.180302 515.882996   1.028513   1.049128   1.099961   1.060420 
##         x7         x8         x9        x10 
##   1.095493   1.101787   1.069866   1.068766
```

We can see that x1 and x2 are highly correlated with 0.999 correlation, and 515 VIFs, which is way greater than 10, the threshold. We will next apply automated search to search for significant predictors. If x1 and x2 are both in the result, we will remove one of them in the final predictors.

4.6 Use automated search

Now I use automated search, after removing data 10 from the data set.

```
##
## Call:
## lm(formula = y ~ x5 + x2 + x3 + x4, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.29129 -0.46534  0.00512  0.62212  1.87873
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.50163    0.09635  15.584  < 2e-16 ***
## x5           3.34805    0.09792  34.191  < 2e-16 ***
## x2           1.99583    0.08829  22.605  < 2e-16 ***
## x3           0.91006    0.10112   8.999 2.46e-14 ***
## x4           0.40358    0.08986   4.491 2.01e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9338 on 94 degrees of freedom
## Multiple R-squared:  0.955,  Adjusted R-squared:  0.9531
## F-statistic: 498.6 on 4 and 94 DF,  p-value: < 2.2e-16
```

Using automated forward search, we get x2, x3, x4, and x5 are chosen, among which all are significant with p-values way less than 0.05. The over all fitting of the 4 predictors results in a p-value of $<$ 2.2e-16. This proves that after log-transformation, removing data 10 and automated forward selection, the model fits better. x1 and x2 are not both in the result, so there is no multicolinearity issue.

4.7 Model Comparison and Selection

Next, we will check use techniques in Model Comparison and Selection, by comparing R2.adj, PRESS, AIC, BIC, and Cp. We will be using data after removing outlier and log-transformation.

After comparing all permutation's R2.adj, PRESS, AIC, BIC, and Cp. We have the following results:

Permutation Number	Criteria	Result Predictors	p-value	R-squared
489	R2.adj	x2+x3+x4+x5+x7	$<$ 2.2e-16	0.9556
481	PRESS, AIC, BIC, Cp	x2+x3+x4+x5	$<$ 2.2e-16	0.9550

4.8 General F-test

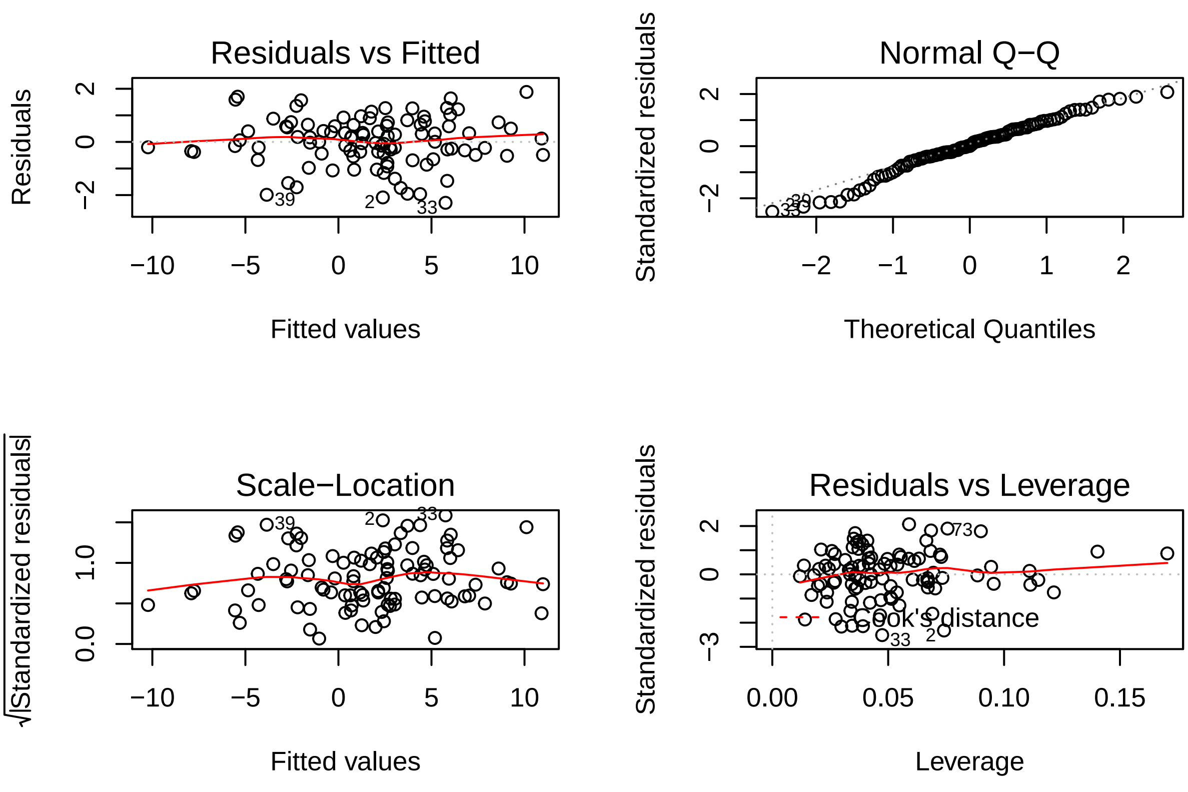
Model 481 is a reduced model of 489, with an extra x7. We apply a general F-test to test if x7 is significant.

```
## Analysis of Variance Table
##
## Model 1: y ~ x2 + x3 + x4 + x5
## Model 2: y ~ x2 + x3 + x4 + x5 + x7
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1     94 81.960
## 2     93 80.929  1    1.0317 1.1856  0.279
```

p-value is greater than 0.05. Hence, x7 is not significant, we only need x2, x3, x4, and x5.

Finally, fit our final model again, and test for goodness of fit.

```
##
## Call:
## lm(formula = y ~ x2 + x3 + x4 + x5)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.29129 -0.46534  0.00512  0.62212  1.87873
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.50163    0.09635  15.584  < 2e-16 ***
## x2           1.99583    0.08829  22.605  < 2e-16 ***
## x3           0.91006    0.10112   8.999 2.46e-14 ***
## x4           0.40358    0.08986   4.491 2.01e-05 ***
## x5           3.34805    0.09792  34.191  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9338 on 94 degrees of freedom
## Multiple R-squared:  0.955,  Adjusted R-squared:  0.9531
## F-statistic: 498.6 on 4 and 94 DF,  p-value: < 2.2e-16
```



5 Conclusion

With the given data set "dat.cvs",

- y is log-transformed
- Entry 10 is reomoved due to large influence to the overall data
- Predictors x1, x6, x7, x8, x9, and x10 are *removed* due to insignificance.
- Predictors x2, x3, x4,and x5 are kept, and combined as a first order model.

The final model is:

$$\mathbf{y = 2.00 \cdot x_2 + 0.91 \cdot x_3 + 0.40 \cdot x_4 + 3.35 \cdot x_5 + 1.51}$$

```
##
## Call:
## lm(formula = y ~ x2 + x3 + x4 + x5)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.29129 -0.46534  0.00512  0.62212  1.87873
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.50163    0.09635  15.584  < 2e-16 ***
## x2           1.99583    0.08829  22.605  < 2e-16 ***
## x3           0.91006    0.10112   8.999 2.46e-14 ***
## x4           0.40358    0.08986   4.491 2.01e-05 ***
## x5           3.34805    0.09792  34.191  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9338 on 94 degrees of freedom
## Multiple R-squared:  0.955,  Adjusted R-squared:  0.9531
## F-statistic: 498.6 on 4 and 94 DF,  p-value: < 2.2e-16
```

Predictor	P-value
intercept	$(< 2e - 16)$
x2	$(< 2e - 16)$
x3	$2.46e - 14$
x4	$2.01e - 05$
x5	$(< 2e - 16)$
overall	$(< 2.2e - 16)$

The intercept, x2, and x5 all have p-values of $(< 2e - 16)$, x3 has p-value of $2.46e - 14$, and x4 has p-value of $2.01e - 05$. The overall p-value is $(< 2.2e - 16)$. These p-values are all less than 0.05 and significant.

The R^2 is 0.955, which means the model represents 95.5% of the data. The model fits the data very well.

6 Appendix

6.1 Data

```
##               y          x1           x2          x3          x4
## 1  2.436641e+02  1.08580359  1.114076637  0.45462375  1.69147892
## 2  1.348317e+00  1.30488896  1.311393972 -2.01623853 -0.14386029
## 3  2.785373e+00  1.03064839  1.032495758  1.02785284 -0.30580807
## 4  4.870431e+01  0.15783723  0.115275934 -0.12345028  1.71466970
## 5  5.107077e+03  1.32553541  1.270779866 -0.47953329 -1.26886600
## 6  2.461621e+01  0.17907553  0.169041211  1.10933527 -1.54807478
## 7  4.053033e-01 -1.15115545 -1.158052862 -0.26611181 -1.04691094
## 8  1.273015e+00  0.34749784  0.413766183 -1.14806766  2.07995485
## 9  1.750351e+04  1.09237146  1.068349232 -0.31490694  0.78322136
## 10 1.627548e+05 -0.12377383 -0.101591919  0.14495762 -0.80827415
## 11 1.142597e+04  3.62769114  3.608260193  0.08461995 -2.67794463
## 12 3.286586e+00  1.30989523  1.307003554  0.14383078 -0.93232006
## 13 1.317835e+01  0.75371880  0.861374750 -0.47295516  0.72538498
## 14 7.994837e+01  1.08365898  1.057540228  0.40165760 -2.39403767
## 15 1.254888e+01  0.36798425  0.355010226 -0.91801520 -1.46354593
## 16 6.475994e+02  0.56864183  0.640659644  0.54047899  0.18522984
## 17 1.883914e+02 -1.28581387 -1.212272920  1.48905504 -0.41666222
## 18 1.435408e-02 -1.26743305 -1.234753509  0.97972598 -0.19470807
## 19 2.152715e+03 -1.06712497 -1.084466308  0.53220005  0.22177933
## 20 2.748900e+01 -1.38924287 -1.443990181  2.09600223 -0.67593870
## 21 4.269482e+00  1.54605968  1.601931488 -0.23083356  0.04281459
## 22 9.142846e+01  1.40197875  1.357894118  2.57464218 -2.13216101
## 23 1.362112e+00 -1.32641841 -1.315556541 -0.46236821 -0.07518034
## 24 1.557144e+03  0.35885165  0.341494903  0.29181328  0.73709888
## 25 2.503421e-01 -1.13524440 -1.129708685 -0.07397919  1.20814059
## 26 5.816126e+00 -0.12596809 -0.143102696  1.09787376  0.84864383
## 27 6.741841e-01 -1.08959331 -1.148468804 -1.00854906  0.32894141
## 28 2.615835e-01 -0.80121686 -0.768502037 -0.26400286 -1.98235826
## 29 3.706270e-01  1.65612148  1.622377304 -0.43629692 -1.22394032
## 30 4.953901e+00  0.15058629  0.135064308 -1.33142033  0.03848109
## 31 2.597080e-04 -2.53107104 -2.505959283 -1.30320557  0.00049758
## 32 3.564594e+00 -0.18153431 -0.253450070  1.17657303 -1.85181932
## 33 1.081779e-01 -1.38348270 -1.408735905 -1.22537602 -0.27192656
## 34 3.198690e+01  1.88159981  1.874747994  0.43157478  0.91527663
## 35 1.989805e+00 -0.60581127 -0.592719513 -0.62328645  0.30325301
## 36 5.305765e-03  0.58361327  0.528917046 -0.18197329  0.28060109
## 37 7.083158e+00 -0.84461949 -0.883527854  1.91593170  1.52952326
## 38 9.732534e-01 -0.72132166 -0.721717588  0.65413664  1.66975546
## 39 8.182734e-01  0.25261865  0.283697303 -0.61464193  0.79174582
## 40 2.902513e-03 -1.03292033 -0.980865674 -0.28024369 -0.23159184
## 41 1.257483e+01 -0.67510456 -0.666402448  0.52190114 -0.77282839
## 42 1.649000e-01 -0.39816292 -0.410390828 -1.68731670 -1.04893744
## 43 7.227816e-02  0.93858479  0.886642035 -1.51878437  0.32664528
## 44 2.300922e+00  0.20579738  0.240324984  1.10446829 -0.85297338
## 45 1.840516e+01  0.23249175  0.238624787 -0.27242598  1.58819474
## 46 5.036520e+00  0.07543418 -0.009001722  0.23625602 -0.15096018
## 47 1.587850e+02 -1.11552973 -1.183864277  0.71806593 -0.10832554
## 48 2.266285e+02  0.12797868  0.197831749 -0.10367126  0.81746507
## 49 2.103047e+03  0.47872975  0.407202656 -0.43740217 -0.11192762
```

```
## 50  1.132980e+01  1.03329881  0.945368691 -0.99770994 -0.80953017
## 51  3.306079e-03 -0.75883165 -0.698295514 -0.26168555 -1.01764340
## 52  1.071461e+01  0.50535547  0.562841300 -0.15480350 -0.08928677
## 53  6.252071e+04  1.97540640  2.022707360 -1.06790809 -1.07014097
## 54  1.287958e+00 -0.07329602 -0.143874188 -0.55971338  1.35908249
## 55  6.659074e-03  0.19541958  0.211574619  0.04815683  0.59368838
## 56  2.690739e+01  0.12752347  0.208074066 -0.53552187  0.24887243
## 57  2.940000e-05 -0.41541674 -0.494214472 -0.23662847 -0.28910232
## 58  2.975394e+01  1.68323258  1.663675494 -0.99888433  1.54195691
## 59  2.920670e-04 -2.44654200 -2.488391942  0.14588764 -1.73328437
## 60  6.307318e+00  0.34100938  0.302777031 -0.08609828  0.66903108
## 61  1.193899e+02 -0.18924895 -0.288557906  1.43968231 -0.06564846
## 62  7.696165e-02 -0.76369536 -0.883269646 -0.83050063  1.30934590
## 63  1.672548e+01  0.01165956  0.096513307 -0.94760951 -2.03652077
## 64  3.648559e+04  0.82425511  0.774069393  0.74772505 -0.04836412
## 65  5.497997e+00 -0.14192249 -0.098859346  0.98504724 -1.92635500
## 66  5.130241e+00 -0.23270481 -0.242229449 -0.27862360 -0.13957151
## 67  6.441906e-01  0.30558641  0.290689350 -0.65171173  0.87539299
## 68  3.404922e+02  0.46611254  0.528902504  0.96794395 -0.40101247
## 69  2.566154e-01  0.62581862  0.558346997 -0.67825142  0.58769228
## 70  1.759111e+01  0.85003368  0.812606327  0.51304928  0.72763581
## 71  1.113728e-02 -0.94471441 -1.075045805 -0.92857612 -0.06104308
## 72  2.119511e-01 -0.08572455 -0.033742947 -0.47742476 -0.02729820
## 73  1.161045e-02 -1.30038218 -1.257658260 -0.56671344 -1.18622081
## 74  1.937389e-02 -1.07592262 -1.101434275 -1.86585366 -1.70593077
## 75  2.096970e+03 -0.07949225 -0.039044588  1.38451027 -1.17504176
## 76  1.140421e+03  0.52876397  0.588710603  0.97256422  0.88795657
## 77  6.825316e+02  1.84080141  1.823142945 -0.85451309 -1.18813479
## 78  8.503310e+01  2.73513491  2.701251153  1.55863973  1.07017669
## 79  1.604147e+05  1.14786183  1.076712312  0.16096038  0.56421133
## 80  8.874957e+00  2.01690019  2.011348457  0.85080296 -0.79997528
## 81  3.340411e+00 -0.91269148 -0.959555564  1.00999031 -0.46185769
## 82  2.224338e+00  0.86804623  0.857885282 -0.35598100 -0.70646613
## 83  5.213965e+00  0.54884570  0.573991163  1.13458700 -1.10844945
## 84  9.729204e+02  0.90238651  0.927947423  0.64271667 -0.98890188
## 85  2.568767e+02  0.28912132  0.245031745 -0.09302933 -0.57104074
## 86  1.798269e+02  0.85320283  0.893602153  1.30646113  0.26420252
## 87  8.867621e+00  0.35337766  0.300787443  0.80271550  1.18431669
## 88  3.570715e-01  0.75767741  0.749203259 -0.12250077 -1.52831193
## 89  2.444073e-02 -0.33085611 -0.360392140  0.46498725 -1.71305365
## 90  1.919601e-02 -0.53951992 -0.533460585 -0.16224967  0.74267012
## 91  1.099085e-01 -1.16200586 -1.215341928  0.01830939 -0.58786565
## 92  2.522732e+00  0.66898554  0.681065108 -0.63230742  0.13901909
## 93  1.487809e+00 -0.55842836 -0.544165424  1.72685772  0.71848450
## 94  1.344393e-01 -1.29742868 -1.223401507 -0.99316974  0.79462799
## 95  2.626604e+02  0.95731501  0.942356124  1.73279356  1.34003018
## 96  5.862148e+00  1.48626190  1.551085923 -0.45254324 -0.46271087
## 97  7.357203e+00  0.79175894  0.792401715 -0.46968650 -0.71305170
## 98  1.226574e+03  1.39698691  1.399955091  1.17417859  0.55071969
## 99  1.305502e+01  0.30679588  0.242993584 -1.68151109 -0.85418856
## 100 4.444400e+01  1.31951096  1.343514903  0.70519380  0.51040363
##              x5          x6          x7          x8           x9
## 1    0.106603041  1.90546080 -0.64313318  0.83133738  0.069397226
## 2    0.048113406  0.13304981  0.77112214 -1.00337110 -0.637381125
```

```
## 3   -0.689535891 -0.96139722 -0.42695282 -2.03898688 -1.327918885
## 4    0.726207244  0.13140390  0.34750769  1.62399961 -0.702380618
## 5    1.783569221 -0.38016806 -1.69596388  1.17447004 -0.444843952
## 6    0.111867633  0.72595169  1.42055461  0.27589284 -0.815191465
## 7   -0.234039291  0.24481605  0.97600319  1.83334807  0.185934914
## 8   -0.522305869  0.28911221 -0.90288983  0.16025309 -2.035447258
## 9    1.674133143  0.23688817 -0.47114442  0.20716043 -0.798898709
## 10  -0.469902806 -0.58441930 -0.68181262 -0.06050827 -0.629779662
## 11   0.271191966 -1.28401940 -0.55178324  0.14962121 -0.624638810
## 12  -1.072868526  1.44455897  1.95752485  0.74129585 -1.516699256
## 13  -0.417091415  0.28162045  0.71172742  0.45612887  0.713363388
## 14   0.846814894 -0.67379802  0.40452412 -0.22245711  0.940187027
## 15   0.606506960 -0.04757949 -0.34626245  0.68569564 -1.695373745
## 16   1.028743441  0.04754917 -0.16413534  0.21921100  0.364608977
## 17   1.107018328 -0.56406240  0.12190554 -0.36376932 -0.241138967
## 18  -0.760967134 -0.80492656 -0.86978750  0.39825746  1.158414868
## 19   1.829845819 -0.73342870 -0.94666949  0.19451624 -0.905648810
## 20   0.831477112  0.13696804 -0.05774661 -0.76973991 -0.788922227
## 21  -1.103237249 -0.43830930  2.71029359  0.20913206 -1.170123589
## 22  -0.595501385 -0.33002193 -1.93515195 -1.67960528  0.841716695
## 23   0.660742855 -0.62337290  0.79310289  0.22332240 -0.069931890
## 24   1.277794077 -0.19302307  0.36741309  0.54070993  1.578376651
## 25   0.006477450 -0.19545180  0.32556015 -1.09316541  1.106197464
## 26   0.344472105 -0.75029863  2.29815638 -0.67631217 -1.007589516
## 27   0.230299672 -0.07183219 -0.69532621 -1.35099094  0.665157761
## 28   0.051483369 -1.01026450 -1.20622548  0.69385552 -0.226950504
## 29  -1.639354604 -1.71285686 -0.68068843 -0.38012039  1.646191506
## 30   0.227475120  1.27095593  0.54184668 -0.78465842  0.006866338
## 31  -0.962824638 -0.82055062 -0.50390831 -3.71666465  0.147991891
## 32   0.334373806  0.50178516  0.09219205  1.98368334  1.917987357
## 33  -0.080795698 -0.81023288 -0.37316075  0.03634908 -0.233534655
## 34  -0.074325193  1.06945246  0.01082879  1.15854431 -0.835067690
## 35   0.143999844  0.66648608  0.19368505 -0.91332612  0.760951052
## 36  -2.331155078  0.94379764 -1.68707155 -0.65986776 -1.258608935
## 37  -0.030598786  0.81315420 -0.66453940  0.14655152  0.265973462
## 38  -0.515142922  0.40762951 -1.09066780 -0.55211951  1.108107710
## 39  -0.293450681  2.06573211  0.23969523 -0.49416974  1.784205557
## 40  -0.910760616 -0.79746786  0.68803614 -0.65368461 -0.029511134
## 41   0.538701964 -0.72237000  0.31719450 -0.59548843  0.204709211
## 42  -0.379373368 -1.33663099 -0.36466150  0.28464055 -0.719051993
## 43  -1.649353154 -0.90813227 -0.13618015 -2.42328543 -0.111159099
## 44  -0.587146856  1.35898135  0.68224837 -0.70483893  0.399725069
## 45  -0.178258312  0.02239690 -0.38183419  1.32645517  0.820034528
## 46   0.511254635 -0.16785673 -0.65089906 -0.89565732  0.000981539
## 47   1.394295955 -0.63117192  0.39522009  1.76262402  1.002257090
## 48   0.751390370 -1.36665842  1.27679956 -0.03452018 -1.264967063
## 49   1.360312084 -0.54764007  1.21249499 -1.46879553  0.343642876
## 50   0.668041103  0.65942119 -1.80600241  0.73713093  0.212311038
## 51  -1.497937838  0.92783553  0.33461328  1.64629052  1.270520162
## 52  -0.001121686 -0.36074558  0.28086720  0.64195012  1.304493929
## 53   2.025708921  0.18372060  0.32747127  0.85675322 -2.434304298
## 54  -0.135071269 -1.57990902  0.10195429  1.29633293 -0.747062182
## 55  -1.953302876 -3.32045561 -0.75547571 -1.08434120  1.079579708
## 56   0.733094038  0.66993500 -0.68709033  0.97455377  0.067599046
```

```
## 57  -3.110706679  0.21091427 -0.94814810  0.50479839  1.448104278
## 58  -0.560684284  0.72928295  0.01218412 -0.07001845  0.485269016
## 59  -1.113642189  0.90204810 -0.43588234 -0.29226662 -1.412875319
## 60   0.099917732  1.33957013 -1.00504540 -1.27988134  0.010248035
## 61   0.678790584 -1.37578479  1.58067168 -0.17721153  0.903785763
## 62  -0.328917315 -1.03580965 -0.19824551 -1.56607538 -0.083228044
## 63   0.902234190 -0.51993425  1.55323708  0.02340231 -1.725675371
## 64   2.176541490  1.25439732  0.01221935  0.53989788 -1.176444197
## 65   0.359155361 -0.38137468 -0.21197593  1.06951079 -1.437608440
## 66   0.175534351 -0.65950463  0.30733107 -0.41385941  0.241848292
## 67  -1.149128635  0.68920141  0.30618828  0.64407819  0.294383024
## 68   0.838351139 -0.18738236  0.24405404 -0.29996224  0.875283830
## 69  -1.125241257  1.59653610  1.63733360 -1.94479562  0.352309840
## 70  -0.368528506 -0.85826810  0.07802833  1.15353352  0.804810292
## 71  -0.828135290 -0.08516574 -0.69509037  0.09517886  0.985063420
## 72  -0.749955503 -0.22971663 -0.36249241  0.25308145 -0.001017382
## 73  -0.851768270 -1.23800605 -0.92535162  0.52885085  0.803418511
## 74  -0.731668258  1.35741196  0.38386335  0.80694433 -0.126094011
## 75   1.691575384  0.83540373  1.09031679  0.22570345  0.009331247
## 76   0.624028040  0.23273456  1.00896086 -1.03580403  0.613231664
## 77   0.614029002 -0.03046943  0.98165223  0.51575063  1.194503979
## 78  -1.089315254 -1.26292043 -0.38436811 -0.62779261 -0.363265560
## 79   1.816590555 -0.98607306 -0.18009314  1.68261597 -0.204480248
## 80  -1.088306167  0.94007138 -0.20274248  0.56399795 -0.724853921
## 81   0.279441416  2.95171219 -0.12877507 -0.30540863 -2.141559914
## 82  -0.428174906 -0.28351003 -0.76705812  0.17748279  1.411135532
## 83  -0.058817748  1.25912009  0.63157173  0.72074879 -1.970260344
## 84   1.144135369  0.10655278 -0.02424298  0.14306334  0.777691117
## 85   0.873171495 -0.07761400 -0.29553356  1.26574014  1.681854681
## 86   0.181052974  1.27242068 -0.51875229 -2.01387625 -0.079564773
## 87  -0.625515250 -1.64171035 -0.40230057 -0.66624567 -0.787110302
## 88  -0.986388177  0.69065410 -2.06836333  0.92654073 -0.690501123
## 89  -1.770361614  1.71259812 -0.18706843 -1.22297350 -1.986949883
## 90  -0.846689080  0.04733734  0.13436506 -0.81681853 -1.841003952
## 91  -0.481208263  0.92316435  0.25664424  1.72950423  0.830516979
## 92  -0.485354570  0.95476905 -0.16132746 -2.38182018 -0.093828781
## 93  -0.737795961 -0.82398117  1.81235077  0.15040187  0.920305706
## 94  -0.200039016  0.60943564  1.10171351 -0.51613173  0.642118668
## 95   0.105960702 -0.25820161  0.12448903 -1.02063243  0.860383689
## 96  -0.555747690 -0.69003614  0.38342397  0.50078504  2.059735896
## 97   0.020224070 -0.40333495 -0.74090945 -0.71827456 -0.115692554
## 98   0.074184141 -1.19916492  0.80995952 -1.23494372 -0.885696554
## 99   0.793337809 -0.35857612 -0.62057603 -0.53959174  1.010234700
## 100 -0.749197139  1.73137720  0.18763258  1.88859218 -0.606162042
##             x10
## 1    1.13955430
## 2    0.36182605
## 3    0.50456596
## 4   -0.53134563
## 5    0.47327357
## 6    2.17941996
## 7    1.06412371
## 8    1.41167025
## 9   -0.46691668
```

```
## 10   0.55953961
## 11   1.82517774
## 12   0.18046497
## 13   1.64755010
## 14   0.02070462
## 15   0.54561368
## 16   1.21556816
## 17   0.72169162
## 18  -0.30776948
## 19  -0.18771025
## 20   1.45771451
## 21   1.28044712
## 22   0.23462303
## 23   1.41575945
## 24   0.56858929
## 25  -0.81765305
## 26   0.40475753
## 27   1.85524370
## 28   0.65924981
## 29   1.02656510
## 30  -0.89032164
## 31   0.62618347
## 32  -1.11311773
## 33   0.77693533
## 34   0.98145266
## 35   0.65527363
## 36   0.02572670
## 37   0.11347937
## 38  -1.15593094
## 39  -0.53636143
## 40  -2.16853334
## 41  -0.44425598
## 42  -0.68087290
## 43  -0.65405770
## 44   0.85179036
## 45   0.42393059
## 46   1.69118235
## 47  -0.80354661
## 48  -0.30648334
## 49  -2.42375948
## 50   0.73293923
## 51  -0.63928612
## 52   0.41350240
## 53   0.24463690
## 54   0.08462778
## 55  -0.69888375
## 56   0.99111492
## 57   0.55902480
## 58   1.05353168
## 59  -0.90060787
## 60  -0.24721684
## 61   0.23984043
## 62   1.06366407
## 63   0.41491551
```

```
## 64  -0.89119739
## 65  -0.52471453
## 66   1.09703071
## 67   0.12833406
## 68   2.47980070
## 69   1.91084613
## 70   1.21482615
## 71   1.18321540
## 72   0.72596536
## 73   0.16631868
## 74   0.45776133
## 75   0.50387033
## 76  -1.24822048
## 77   0.96434421
## 78  -0.57090721
## 79   0.24812163
## 80   1.49124498
## 81   0.51753355
## 82  -0.80164123
## 83  -0.46179780
## 84   0.39187139
## 85   1.16138340
## 86   0.20073253
## 87  -0.79295204
## 88   2.43258380
## 89   0.01108954
## 90   0.65262878
## 91  -0.52023995
## 92   0.82471275
## 93   0.20835946
## 94  -0.58733443
## 95  -1.58502046
## 96   1.13572107
## 97   0.12638203
## 98  -0.33588327
## 99  -0.93919173
## 100  0.19932810
```

6.2 R Code

```
dat <- read.csv("~/Desktop/5120 Final/dat.csv")
attach(dat)
```

```
## The following object is masked _by_ .GlobalEnv:
##
##     y

## The following objects are masked from dat (pos = 3):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y

## The following objects are masked from dat (pos = 5):
```

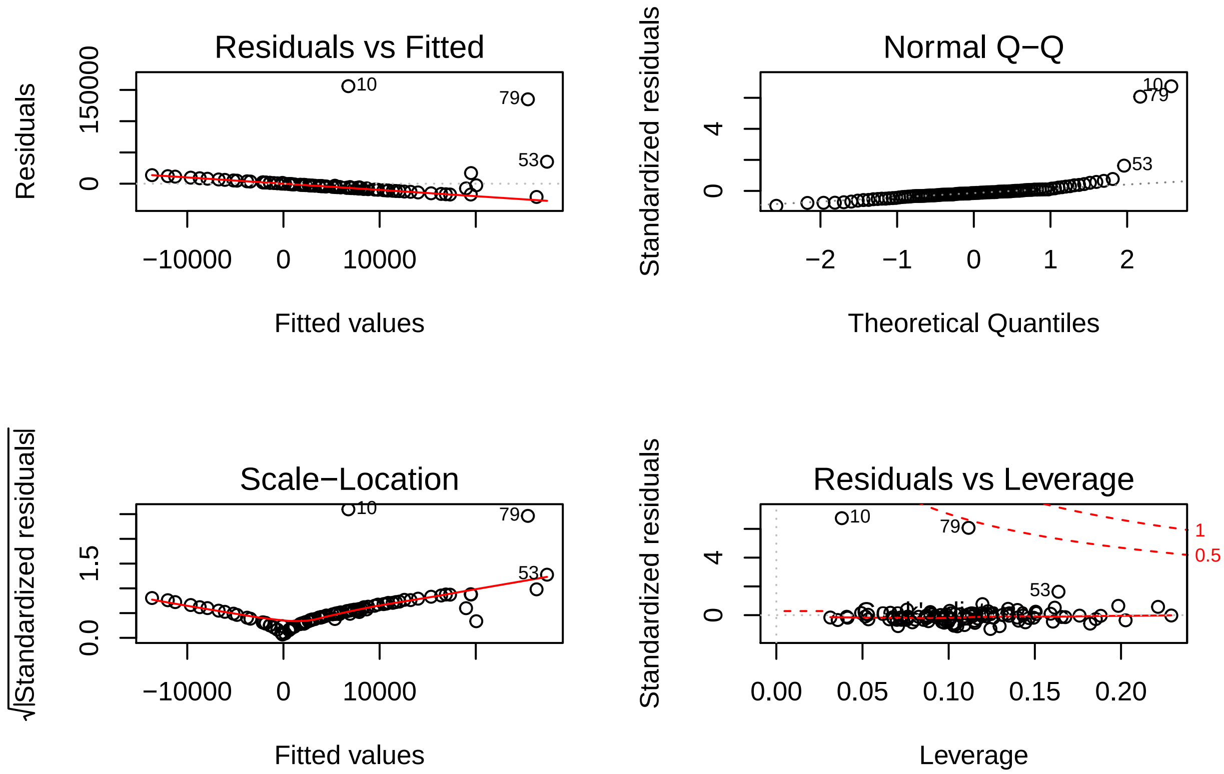
```
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y

## The following objects are masked from dat (pos = 7):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y
```

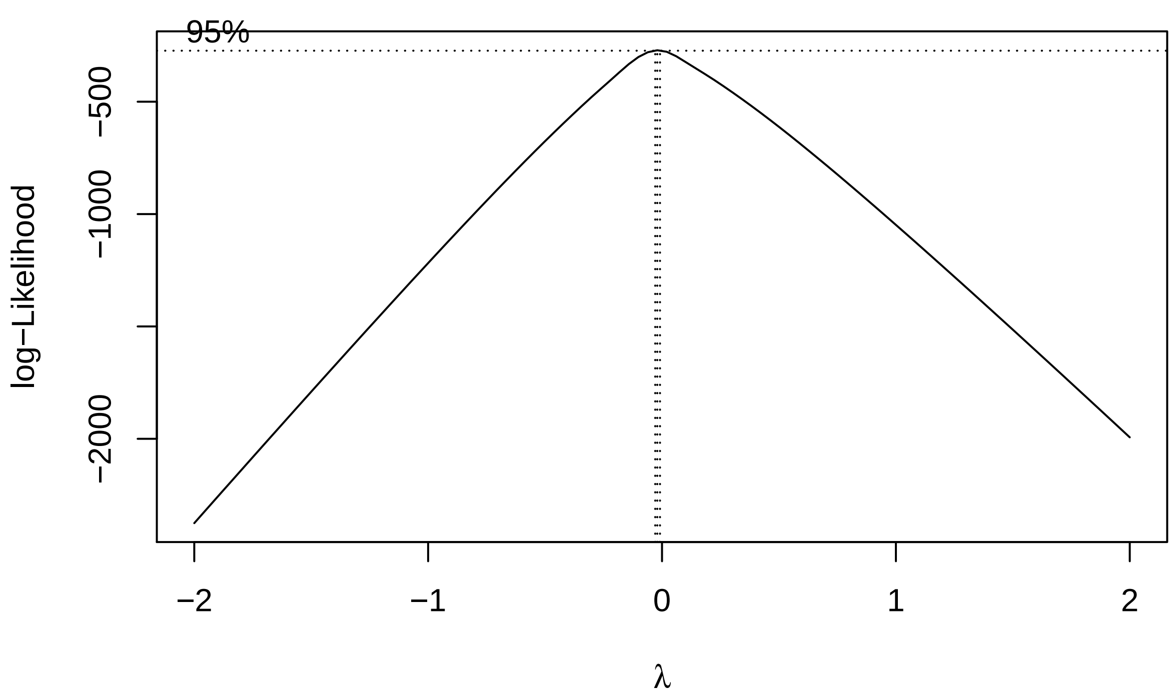
```r
dat.lm=lm(dat$y~.,data=dat)
summary(dat.lm)
```

```
##
## Call:
## lm(formula = dat$y ~ ., data = dat)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -21213  -7359  -3119   1056 156003
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4856.9     2554.0   1.902   0.0604 .
## x1           18253.4    50397.7   0.362   0.7181
## x2          -16220.4    50336.8  -0.322   0.7480
## x3            -723.3     2565.5  -0.282   0.7786
## x4             520.9     2317.8   0.225   0.8227
## x5            4563.1     2562.1   1.781   0.0783 .
## x6           -2807.6     2457.2  -1.143   0.2563
## x7           -2535.7     2810.4  -0.902   0.3694
## x8            2839.7     2348.2   1.209   0.2297
## x9           -3654.9     2392.7  -1.527   0.1302
## x10           -577.3     2607.0  -0.221   0.8253
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23590 on 89 degrees of freedom
## Multiple R-squared:  0.1113, Adjusted R-squared:  0.01149
## F-statistic: 1.115 on 10 and 89 DF,  p-value: 0.36
```

```r
par(mfrow=c(2,2))
plot(dat.lm)
```




```
par(mfrow=c(1,1))
library(MASS)
boxcox(dat.lm, plotit = TRUE)
```

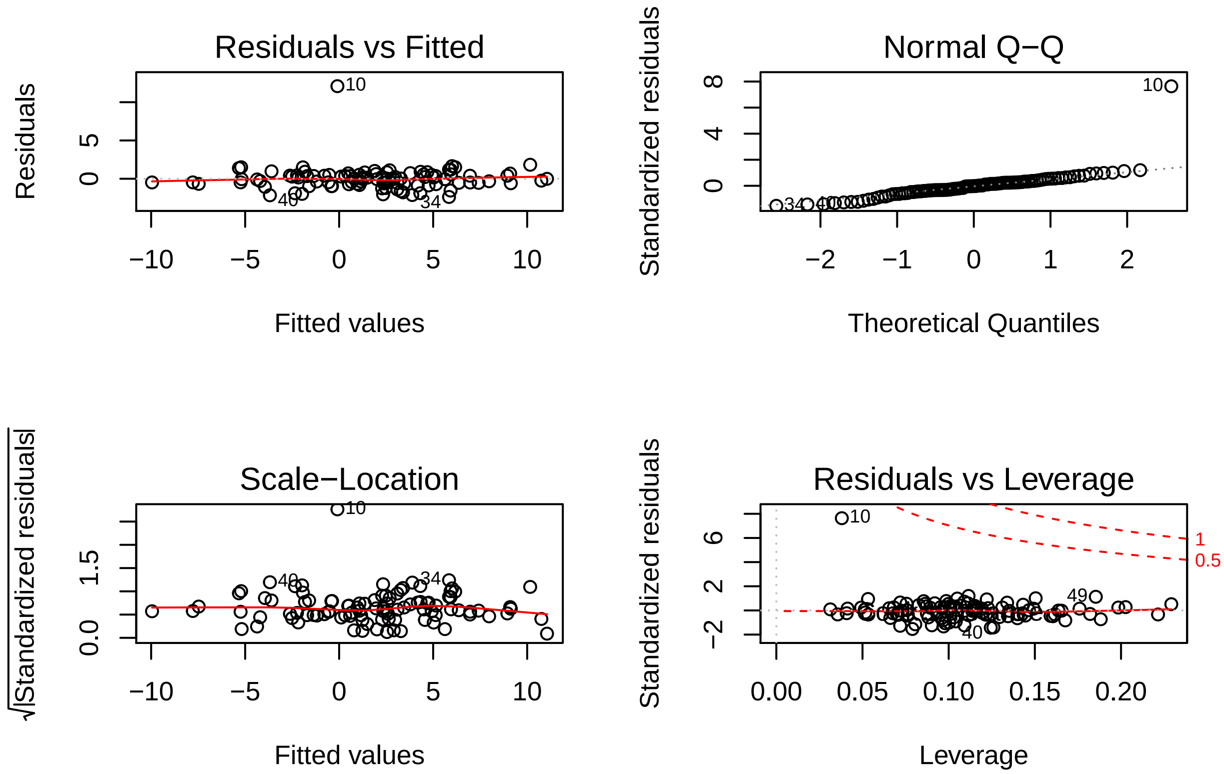



```
dat$y=log(dat$y)
dat.lm=lm(dat$y~.,data=dat)
```

```r
summary(dat.lm)
```

```
##
## Call:
## lm(formula = dat$y ~ ., data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.3787 -0.6130 -0.0369  0.4978 12.0928
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.610750   0.174805   9.215 1.35e-14 ***
## x1          -1.323510   3.449464  -0.384   0.7021
## x2           3.262825   3.445294   0.947   0.3462
## x3           0.945029   0.175598   5.382 5.92e-07 ***
## x4           0.349093   0.158641   2.201   0.0304 *
## x5           3.261169   0.175364  18.597  < 2e-16 ***
## x6          -0.104953   0.168182  -0.624   0.5342
## x7           0.001392   0.192358   0.007   0.9942
## x8           0.086216   0.160720   0.536   0.5930
## x9          -0.066157   0.163769  -0.404   0.6872
## x10          0.080254   0.178437   0.450   0.6540
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.614 on 89 degrees of freedom
## Multiple R-squared:  0.8795, Adjusted R-squared:  0.866
## F-statistic: 64.97 on 10 and 89 DF,  p-value: < 2.2e-16
```

```r
par(mfrow=c(2,2))
plot(dat.lm)
```




```r
attach(dat)
```

```
## The following object is masked _by_ .GlobalEnv:
##
##     y

## The following objects are masked from dat (pos = 3):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y

## The following objects are masked from dat (pos = 4):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y

## The following objects are masked from dat (pos = 6):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y

## The following objects are masked from dat (pos = 8):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y
```

```r
dat.lm$residuals
```

```
##           1           2           3           4           5           6
##  0.36165149 -2.03679604 -1.25990826 -0.87294012 -0.59094408  0.22694916
```

```
##           7           8           9          10          11          12
##  0.91445506 -0.42747145  0.67615956 12.09277675  0.39684465  0.70673482
##          13          14          15          16          17          18
##  0.61301290 -1.54270869 -0.57145897 -0.49268510  0.90761831 -1.89567053
##          19          20          21          22          23          24
##  1.50472567  0.03107907  0.21320996  0.73273280 -0.66043868  0.39177543
##          25          26          27          28          29          30
## -0.97302267 -2.12985599  0.39241405 -0.96315529  0.36131924  0.52319298
##          31          32          33          34          35          36
## -0.47421161 -1.21115573  0.28165607 -2.37873048  0.36915979 -0.05378739
##          37          38          39          40          41          42
## -0.05074383  0.49917022 -0.72100531 -2.16000066  0.24585338  0.43959228
##          43          44          45          46          47          48
##  0.97031349  0.04012755  1.02409875 -1.77783334  0.56734973  0.49731647
##          49          50          51          52          53          54
##  1.64630937 -1.89003794 -0.47072953 -0.26611134 -0.01188162 -0.82421181
##          55          56          57          58          59          60
## -1.06336897 -0.88784144 -0.48258014  0.84599502 -0.66984518 -0.51079971
##          61          62          63          64          65          66
##  0.22063896 -0.96786752 -0.63538811 -0.24984842 -1.38626689  0.14034692
##          67          68          69          70          71          72
##  1.48881825 -0.53317116  0.34388223 -0.04063531 -0.29729509 -0.36282110
##          73          74          75          76          77          78
## -0.09116264  1.38740278 -0.32815101  1.19629503  0.57524205 -0.71165091
##          79          80          81          82          83          84
##  1.82581743 -0.41373586 -0.03320768 -0.36846335 -1.62344667 -0.53836283
##          85          86          87          88          89          90
##  0.86190740  0.16400262  0.82308678 -0.46164896  1.50089022 -1.98097576
##          91          92          93          94          95          96
##  0.40999962  0.34303544  0.28850747  0.16727313 -0.05365871 -0.60549986
##          97          98          99         100
## -0.52297153  1.18638495  0.02364513  1.10739083
```

```
tmp<-lm.influence(dat.lm)
tmp$hat[tmp$hat>2*10/100]
```

```
##        11        22        31
## 0.2026707 0.2291824 0.2214943
```

```
DFFITS<-dffits(dat.lm)
DFFITS[DFFITS>1]
```

```
##      10
## 2.57098
```

```
dat[DFFITS>1,]
```

```
##     y         x1         x2        x3         x4         x5         x6
## 10 12 -0.1237738 -0.1015919 0.1449576 -0.8082742 -0.4699028 -0.5844193
##            x7          x8         x9       x10
## 10 -0.6818126 -0.06050827 -0.6297797 0.5595396
```

```r
COOKS<-cooks.distance(dat.lm)
round(COOKS,3)
```

```
##     1     2     3     4     5     6     7     8     9    10    11    12
## 0.001 0.017 0.007 0.003 0.002 0.000 0.003 0.002 0.002 0.209 0.002 0.003
##    13    14    15    16    17    18    19    20    21    22    23    24
## 0.002 0.010 0.001 0.001 0.004 0.014 0.010 0.000 0.000 0.007 0.001 0.000
##    25    26    27    28    29    30    31    32    33    34    35    36
## 0.003 0.026 0.001 0.004 0.001 0.001 0.003 0.012 0.000 0.018 0.000 0.000
##    37    38    39    40    41    42    43    44    45    46    47    48
## 0.000 0.001 0.003 0.026 0.000 0.001 0.006 0.000 0.003 0.011 0.002 0.001
##    49    50    51    52    53    54    55    56    57    58    59    60
## 0.026 0.017 0.001 0.000 0.000 0.004 0.011 0.003 0.002 0.003 0.004 0.001
##    61    62    63    64    65    66    67    68    69    70    71    72
## 0.000 0.006 0.003 0.000 0.009 0.000 0.005 0.002 0.001 0.000 0.000 0.000
##    73    74    75    76    77    78    79    80    81    82    83    84
## 0.000 0.011 0.000 0.006 0.001 0.004 0.016 0.001 0.000 0.000 0.011 0.001
##    85    86    87    88    89    90    91    92    93    94    95    96
## 0.002 0.000 0.003 0.001 0.016 0.011 0.001 0.000 0.000 0.000 0.000 0.002
##    97    98    99   100
## 0.000 0.005 0.000 0.006
```

```r
COOKS>qf(0.5,10,90)
```

```
##     1     2     3     4     5     6     7     8     9    10    11    12
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##    13    14    15    16    17    18    19    20    21    22    23    24
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##    25    26    27    28    29    30    31    32    33    34    35    36
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##    37    38    39    40    41    42    43    44    45    46    47    48
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##    49    50    51    52    53    54    55    56    57    58    59    60
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##    61    62    63    64    65    66    67    68    69    70    71    72
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##    73    74    75    76    77    78    79    80    81    82    83    84
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##    85    86    87    88    89    90    91    92    93    94    95    96
## FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##    97    98    99   100
## FALSE FALSE FALSE FALSE
```

```r
no10<- dat[-10, ]
no10.lm=lm(no10$y~.,data=no10)
summary(no10.lm)
```

```
##
## Call:
## lm(formula = no10$y ~ ., data = no10)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -2.3706 -0.4279  0.0241  0.5760  1.8382
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.482703   0.103688  14.300  < 2e-16 ***
## x1           0.692642   2.042699   0.339    0.735
## x2           1.295552   2.039959   0.635    0.527
## x3           0.909189   0.103719   8.766 1.25e-13 ***
## x4           0.407380   0.093778   4.344 3.73e-05 ***
## x5           3.322817   0.103653  32.057  < 2e-16 ***
## x6          -0.007948   0.099586  -0.080    0.937
## x7           0.130916   0.114019   1.148    0.254
## x8           0.070550   0.094905   0.743    0.459
## x9           0.027593   0.096969   0.285    0.777
## x10          0.052156   0.105381   0.495    0.622
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9533 on 88 degrees of freedom
## Multiple R-squared:  0.9561, Adjusted R-squared:  0.9511
## F-statistic: 191.6 on 10 and 88 DF,  p-value: < 2.2e-16
```

```r
round(cor(no10),3)
```

```
##          y     x1     x2     x3     x4     x5     x6     x7     x8     x9
## y    1.000  0.554  0.555  0.324  0.042  0.808 -0.015  0.141  0.205 -0.096
## x1   0.554  1.000  0.999  0.060 -0.020  0.063  0.001 -0.003  0.077 -0.085
## x2   0.555  0.999  1.000  0.060 -0.020  0.064  0.003  0.008  0.079 -0.088
## x3   0.324  0.060  0.060  1.000 -0.003  0.126  0.028  0.063  0.017 -0.007
## x4   0.042 -0.020 -0.020 -0.003  1.000 -0.061  0.000  0.071 -0.144  0.085
## x5   0.808  0.063  0.064  0.126 -0.061  1.000 -0.030  0.125  0.211 -0.087
## x6  -0.015  0.001  0.003  0.028  0.000 -0.030  1.000  0.034  0.109 -0.166
## x7   0.141 -0.003  0.008  0.063  0.071  0.125  0.034  1.000  0.019 -0.068
## x8   0.205  0.077  0.079  0.017 -0.144  0.211  0.109  0.019  1.000  0.044
## x9  -0.096 -0.085 -0.088 -0.007  0.085 -0.087 -0.166 -0.068  0.044  1.000
## x10  0.033  0.158  0.160 -0.069 -0.112 -0.042  0.100 -0.051  0.078 -0.058
##        x10
## y    0.033
## x1   0.158
## x2   0.160
## x3  -0.069
## x4  -0.112
## x5  -0.042
## x6   0.100
## x7  -0.051
## x8   0.078
## x9  -0.058
## x10  1.000
```

```r
library(faraway)
vif(no10.lm)
```

```
##         x1         x2         x3         x4         x5         x6
```

```
## 515.180302 515.882996   1.028513   1.049128   1.099961   1.060420
##          x7          x8          x9         x10
##    1.095493    1.101787    1.069866    1.068766
```

```r
data=no10
start<-lm(y~1, data=data)
end<-lm(y~.,data=data)
result<-step(start, scope=list(lower=start, upper=end), direction="forward", trace=FALSE)
summary(result)
```

```
##
## Call:
## lm(formula = y ~ x5 + x2 + x3 + x4, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.29129 -0.46534  0.00512  0.62212  1.87873
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.50163    0.09635  15.584  < 2e-16 ***
## x5           3.34805    0.09792  34.191  < 2e-16 ***
## x2           1.99583    0.08829  22.605  < 2e-16 ***
## x3           0.91006    0.10112   8.999 2.46e-14 ***
## x4           0.40358    0.08986   4.491 2.01e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9338 on 94 degrees of freedom
## Multiple R-squared:  0.955,  Adjusted R-squared:  0.9531
## F-statistic: 498.6 on 4 and 94 DF,  p-value: < 2.2e-16
```

```r
dat=data
attach(dat)
```

```
## The following object is masked _by_ .GlobalEnv:
##
##     y

## The following objects are masked from dat (pos = 3):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y

## The following objects are masked from dat (pos = 4):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y

## The following objects are masked from dat (pos = 5):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y

## The following objects are masked from dat (pos = 7):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y
```

```
## The following objects are masked from dat (pos = 9):
##
##     x1, x10, x2, x3, x4, x5, x6, x7, x8, x9, y
```

```
##################################################
##STEP 1: create design matrix for maximal model##
##################################################

x<-cbind(Const=1, x1, x2,x3,x4,x5,x6,x7,x8,x9,x10)
y<-y

###########################################################################################
##STEP 2: logical matrix to indicate for each possible model, which predictors are in/out##
###########################################################################################

models<-matrix(F, 2^10, 10) ##10 predictors, change accordingly
dimnames(models)<-list(NULL, c("x1","x2","x3","x4","x5","x6","x7","x8","x9","x10"))

row<-0

for (a in c(F,T)) { ##loop has 10 for statements, one for each predictor
  for (b in c(F,T)) {
    for (c in c(F,T)) {
      for (d in c(F,T)) {
        for (e in c(F,T)) {
          for (f in c(F,T)) {
            for (g in c(F,T)) {
              for (h in c(F,T)) {
                for (i in c(F,T)) {
                  for (j in c(F,T)) {
row<-row+1
models[row,]<-c(a,b,c,d,e,f,g,h,i,j)
}}}}}}}}}}

#################################################
##STEP 3: Matrix to store results from criteria##
#################################################

results<-matrix(NA, 2^10, 7) ##10 predictors, store 7 statistics
dimnames(results)<-list(NULL, c("p","R2","R2.adj","PRESS","AIC","BIC","Cp"))

#################################
##STEP 4: MSE for maximal model##
#################################

tmp<-lsfit(x,y,intercept=F)
n<-nrow(dat)
p<-ncol(x)
MSE.max<-sum(tmp$res^2)/(n-p)

###################################
##STEP 5: Fit all possible models##
###################################
```

```r
time1<-Sys.time()

for (i in 1:(2^10)){ ##10 predictors
  which<-c(T, models[i,]) ##pull out the row of model and append an intercept
  tmp<-lsfit(x[,which], y, intercept=F) ##fit the model and compute the criteria
  p<-sum(which) ##number of parameters for chosen model
  SSTo<-(n-1)*var(y)
  MSTo<-var(y)
  SSE<-sum(tmp$res^2)
  MSE<-SSE/(n-p)
  R2<-1-(SSE/SSTo)
  R2.adj<-1-(MSE/MSTo)
  hi<-ls.diag(tmp)$hat ##leverages
  res.PRESS<-tmp$res/(1-hi)
  PRESS<-sum(res.PRESS^2)
  AIC<-n*log(SSE/n)+2*p
  BIC<-n*log(SSE/n)+p*log(n)
  Cp<-(SSE/MSE.max)-n+2*p
  ##store the results
  results[i,1]<-p
  results[i,2]<-R2
  results[i,3]<-R2.adj
  results[i,4]<-PRESS
  results[i,5]<-AIC
  results[i,6]<-BIC
  results[i,7]<-Cp
  ##have R print out the iteration we are at
  print(paste("run",i))}
```

```
## [1] "run 1"
## [1] "run 2"
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## [1] "run 999"
## [1] "run 1000"
## [1] "run 1001"
## [1] "run 1002"
## [1] "run 1003"
## [1] "run 1004"
## [1] "run 1005"
## [1] "run 1006"
## [1] "run 1007"
## [1] "run 1008"
## [1] "run 1009"
## [1] "run 1010"
## [1] "run 1011"
## [1] "run 1012"
## [1] "run 1013"
## [1] "run 1014"
## [1] "run 1015"
## [1] "run 1016"
## [1] "run 1017"
## [1] "run 1018"
## [1] "run 1019"
## [1] "run 1020"
## [1] "run 1021"
## [1] "run 1022"
## [1] "run 1023"
## [1] "run 1024"
```

```
Sys.time()-time1 ##see how long it takes!
```

```
## Time difference of 0.6356552 secs
```

```
################
##Save results##
################

save(x,y,results,models,file="results.RData")

######################
##Give results names##
######################

p<-results[,1]
R2<-results[,2]
R2.adj<-results[,3]
PRESS<-results[,4]
AIC<-results[,5]
BIC<-results[,6]
Cp<-results[,7]

###############################
##Find model with best R2.adj##
```

```r
################################

i<-R2.adj == max(R2.adj) ##what index has the maximum R2.adj
(1:2^10)[i] ##2^10 because 10 potential predictors
```

```
## [1] 489
```

```r
round(results[i,],3)
```

```
##      p     R2 R2.adj  PRESS    AIC    BIC     Cp
##  6.000  0.956  0.953 92.026 -7.954  7.617  2.057
```

```r
models[i,]
```

```
##    x1    x2    x3    x4    x5    x6    x7    x8    x9   x10
## FALSE  TRUE  TRUE  TRUE  TRUE FALSE  TRUE FALSE FALSE FALSE
```

```r
############################################
##Find model with best PRESS, AIC, BIC, Cp##
############################################

i2<-PRESS == min(PRESS) ##what index has the min PRESS
(1:2^10)[i2] ##2^10 because 10 potential predictors
```

```
## [1] 481
```

```r
i3<-AIC == min(AIC) ##what index has the min AIC
(1:2^10)[i3] ##2^10 because 10 potential predictors
```

```
## [1] 481
```

```r
i4<-BIC == min(BIC) ##what index has the min BIC
(1:2^10)[i4] ##2^10 because 10 potential predictors
```

```
## [1] 481
```

```r
i5<-Cp == min(Cp) ##what index has the min Cp
(1:2^10)[i5] ##2^10 because 10 potential predictors
```

```
## [1] 481
```

```r
models[i2,]
```

```
##    x1    x2    x3    x4    x5    x6    x7    x8    x9   x10
## FALSE  TRUE  TRUE  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE
```

```r
models[i3,]
```

```
##    x1    x2    x3    x4    x5    x6    x7    x8    x9   x10
## FALSE  TRUE  TRUE  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE
```

```r
models[i4,]
```

```
##    x1    x2    x3    x4    x5    x6    x7    x8    x9   x10
## FALSE  TRUE  TRUE  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE
```

```r
models[i5,]
```

```
##    x1    x2    x3    x4    x5    x6    x7    x8    x9   x10
## FALSE  TRUE  TRUE  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE
```

```r
###########################################
##plot the residual against fitted values##
###########################################

dat489.lm=lm(y ~ x2+x3+x4+x5+x7)
summary(dat489.lm)
```

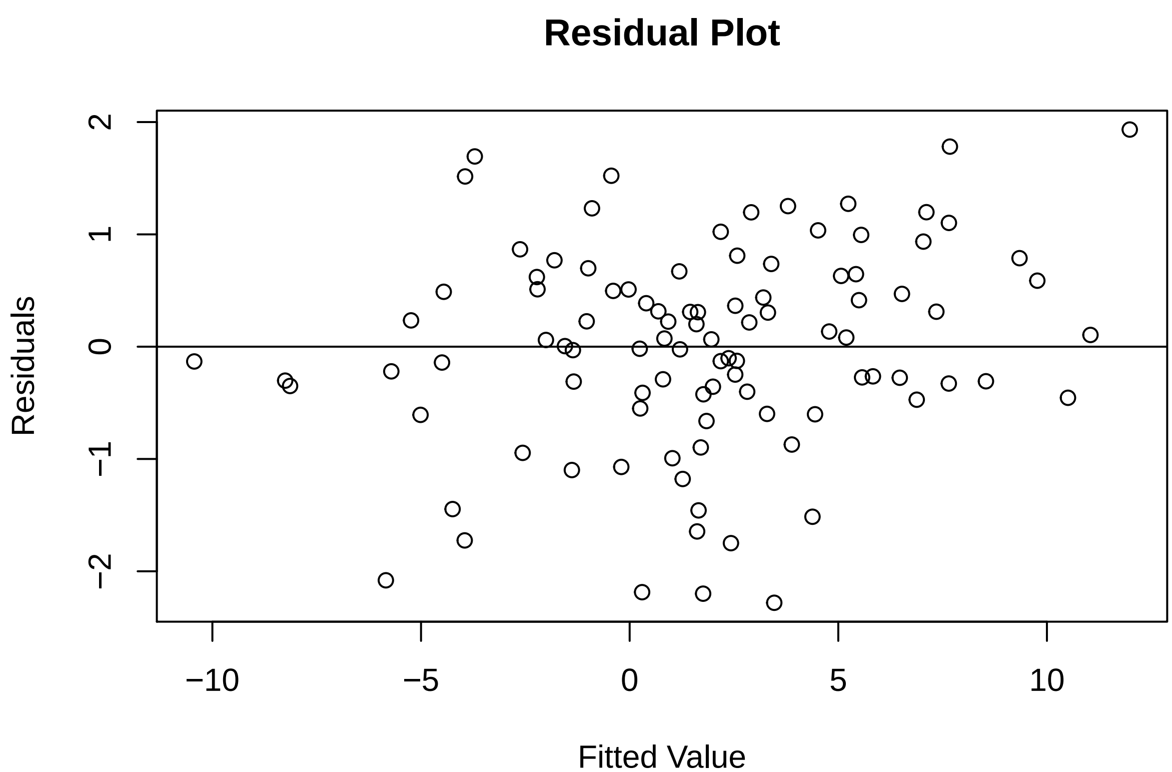
```
##
## Call:
## lm(formula = y ~ x2 + x3 + x4 + x5 + x7)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.28020 -0.41751  0.06503  0.60385  1.93313
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.49739    0.09634  15.543  < 2e-16 ***
## x2           1.99599    0.08820  22.629  < 2e-16 ***
## x3           0.90480    0.10114   8.946 3.47e-14 ***
## x4           0.39580    0.09006   4.395 2.94e-05 ***
## x5           3.33487    0.09857  33.832  < 2e-16 ***
## x7           0.11749    0.10791   1.089    0.279
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9328 on 93 degrees of freedom
## Multiple R-squared:  0.9556, Adjusted R-squared:  0.9532
## F-statistic: 399.9 on 5 and 93 DF,  p-value: < 2.2e-16
```

```r
dat481.lm=lm(y ~ x2+x3+x4+x5)
summary(dat481.lm)
```

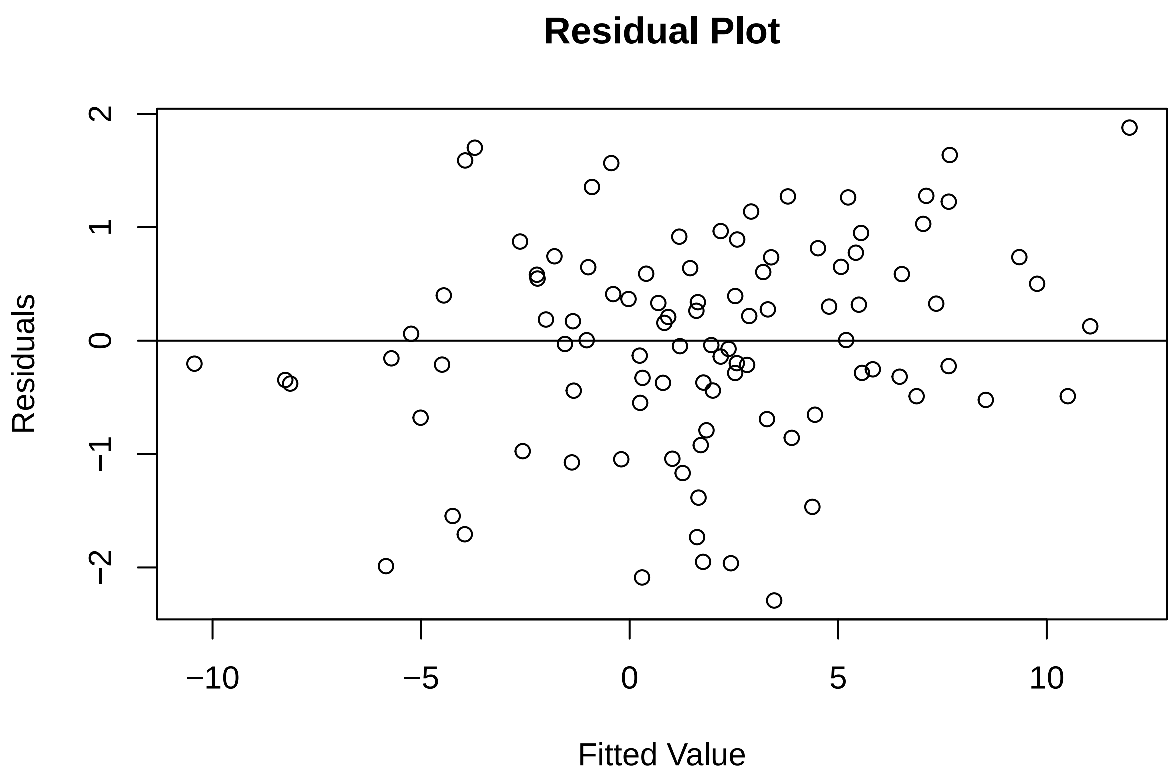
```
##
## Call:
```

```
## lm(formula = y ~ x2 + x3 + x4 + x5)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.29129 -0.46534  0.00512  0.62212  1.87873
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.50163    0.09635  15.584  < 2e-16 ***
## x2           1.99583    0.08829  22.605  < 2e-16 ***
## x3           0.91006    0.10112   8.999 2.46e-14 ***
## x4           0.40358    0.08986   4.491 2.01e-05 ***
## x5           3.34805    0.09792  34.191  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9338 on 94 degrees of freedom
## Multiple R-squared:  0.955,  Adjusted R-squared:  0.9531
## F-statistic: 498.6 on 4 and 94 DF,  p-value: < 2.2e-16
```

```
dat489.res=resid(dat489.lm)
par(mfrow=c(1,1))
plot(y, dat489.res, ylab="Residuals", xlab="Fitted Value", main="Residual Plot")
abline(0, 0)                    # the horizon
```




```
dat481.res=resid(dat481.lm)
par(mfrow=c(1,1))
plot(y, dat481.res, ylab="Residuals", xlab="Fitted Value", main="Residual Plot")
abline(0, 0)                    # the horizon
```




```r
anova(dat481.lm,dat489.lm)
```

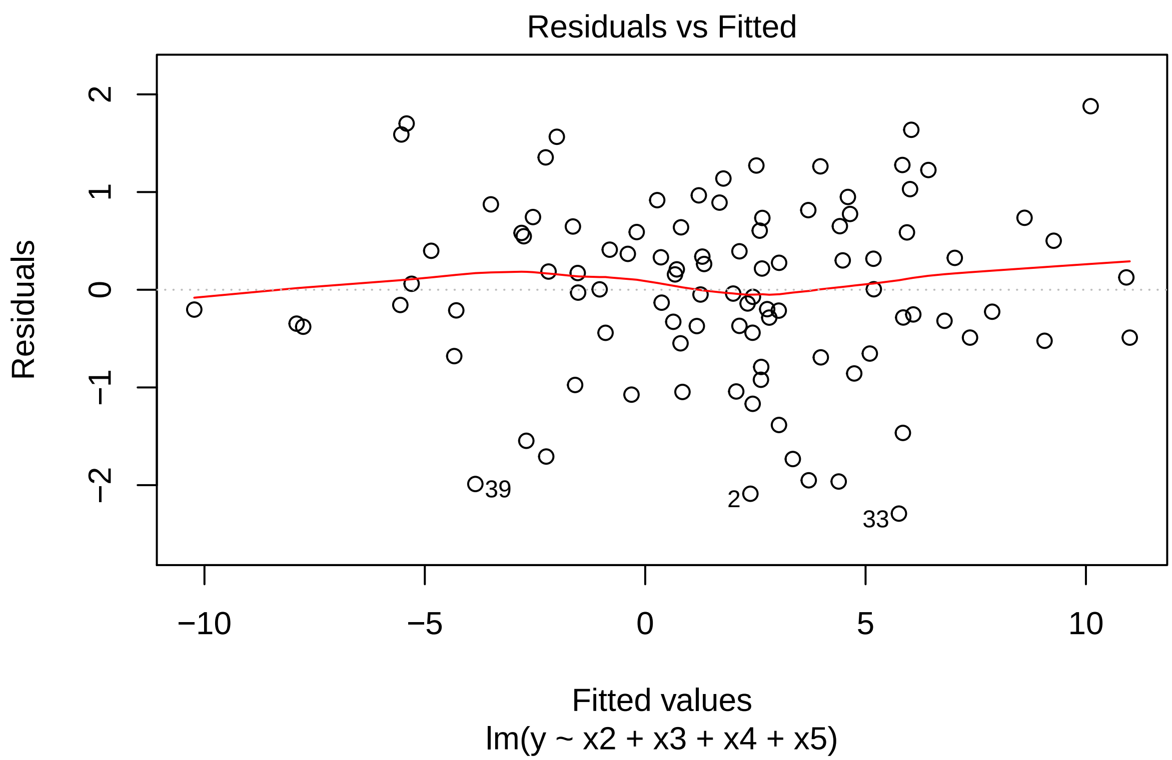
```
## Analysis of Variance Table
##
## Model 1: y ~ x2 + x3 + x4 + x5
## Model 2: y ~ x2 + x3 + x4 + x5 + x7
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1     94 81.960
## 2     93 80.929  1    1.0317 1.1856  0.279
```

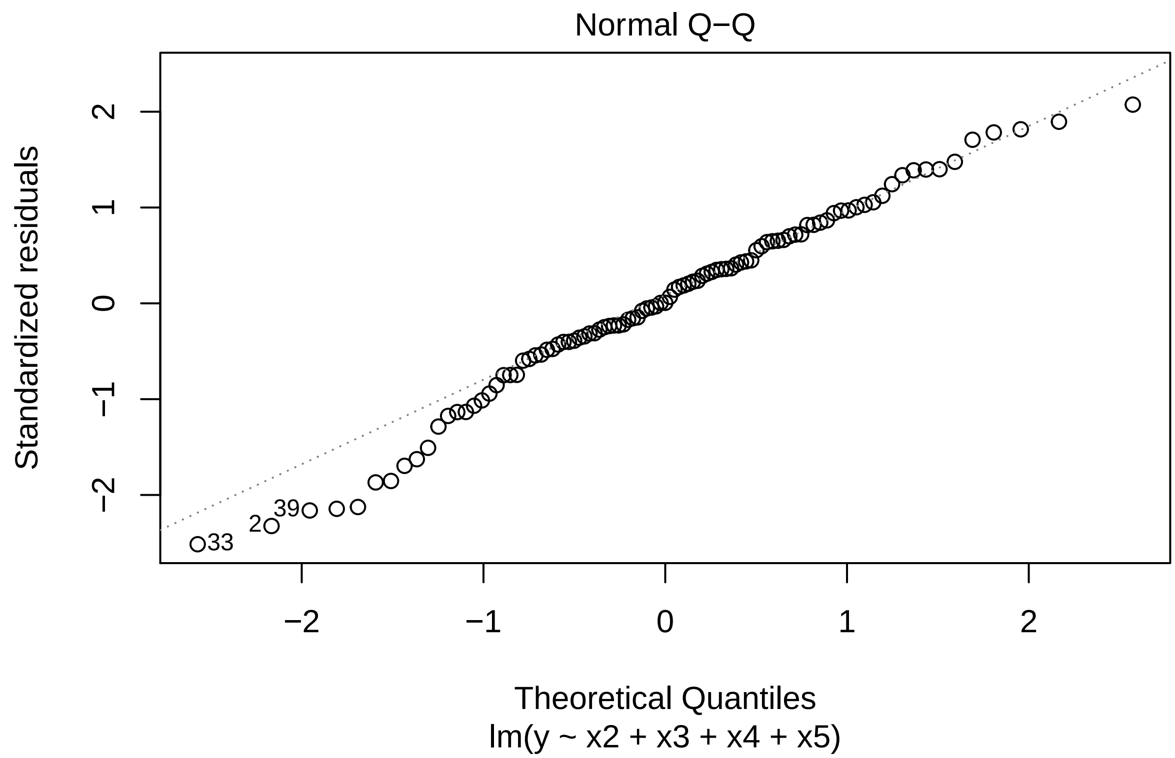
```r
result.lm=lm(y ~ x2+x3+x4+x5)
summary(result.lm)
```

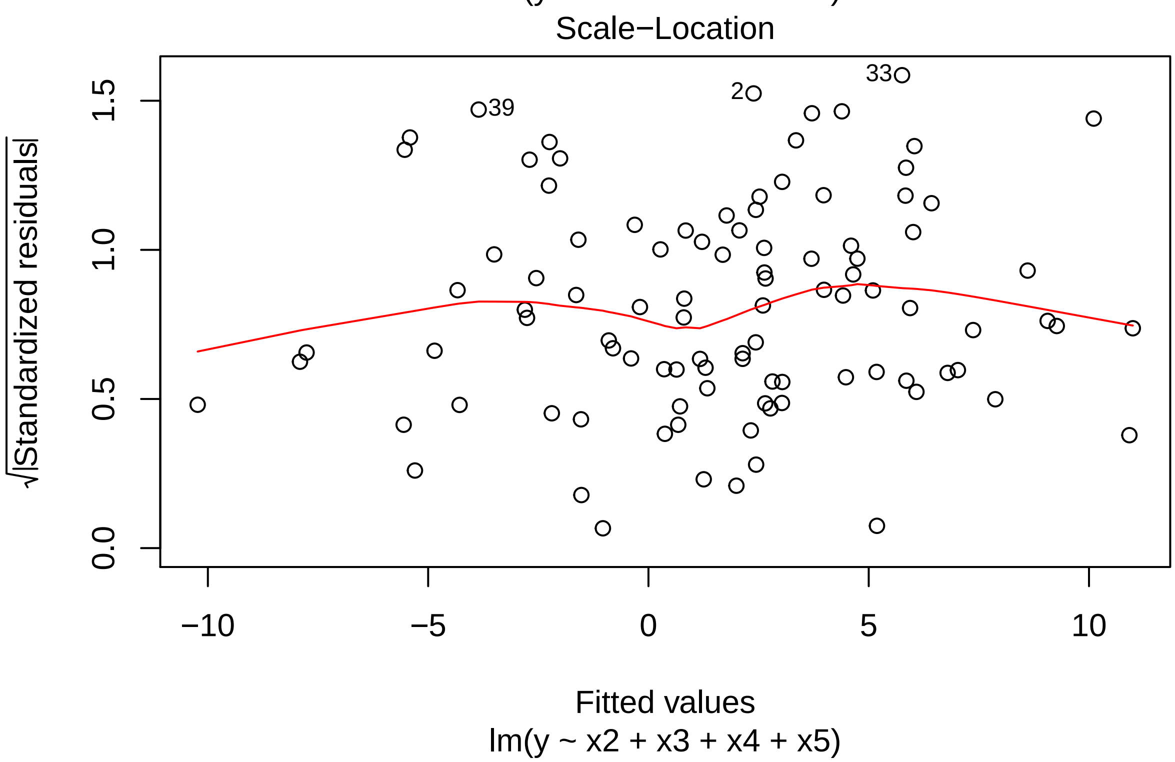
```
##
## Call:
## lm(formula = y ~ x2 + x3 + x4 + x5)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.29129 -0.46534  0.00512  0.62212  1.87873
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.50163    0.09635  15.584  < 2e-16 ***
## x2           1.99583    0.08829  22.605  < 2e-16 ***
## x3           0.91006    0.10112   8.999 2.46e-14 ***
## x4           0.40358    0.08986   4.491 2.01e-05 ***
## x5           3.34805    0.09792  34.191  < 2e-16 ***
```

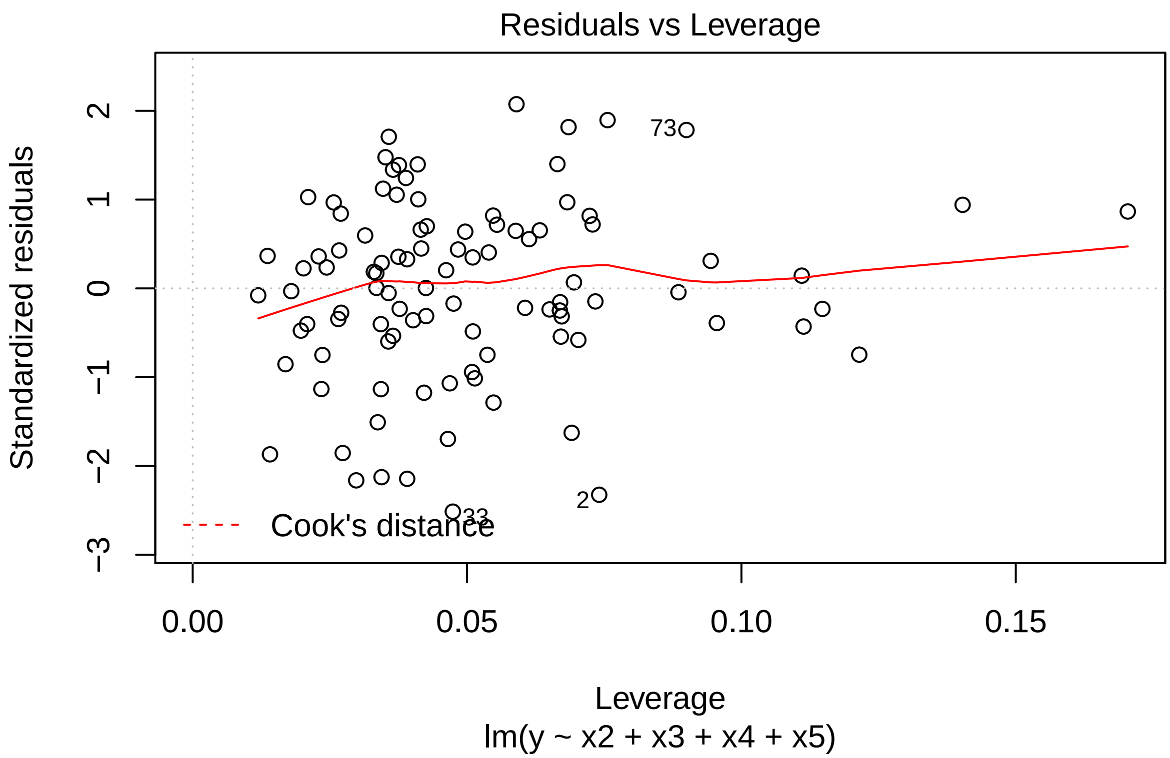
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9338 on 94 degrees of freedom
## Multiple R-squared:  0.955,  Adjusted R-squared:  0.9531
## F-statistic: 498.6 on 4 and 94 DF,  p-value: < 2.2e-16
```

```r
plot(result.lm)
```




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(y ~ x2 + x3 + x4 + x5)
33
2
39
−2
−1
0
1
2


Scale−Location
√|Standardized residuals|
Fitted values
lm(y ~ x2 + x3 + x4 + x5)
33
2
39
0.0
0.5
1.0
1.5
−10
−5
0
5
10



Residuals vs Leverage
Standardized residuals
Leverage
lm(y ~ x2 + x3 + x4 + x5)
Cook's distance
73
2
33
0.00
0.05
0.10
0.15
−3
−2
−1
0
1
2