Stat5303hw6

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P9.2

```r
library(cfcdae)
data("Yogurt")
head(Yogurt)
```

```
##   C S N score
## 1 H H H   2.6
## 2 H H H   2.5
## 3 H H H   2.9
## 4 H H L   1.5
## 5 H H L   1.6
## 6 H H L   1.5
```

```r
summary(Yogurt)
```

```
##  C      S      N          score      
##  L:18   L:16   L:25   Min.   :1.010  
##  M:18   M:18   H:27   1st Qu.:1.500  
##  H:16   H:18          Median :2.050  
##                       Mean   :2.634  
##                       3rd Qu.:3.300  
##                       Max.   :7.900
```

```r
# it's unbalanced data
par(mfrow = c(2,2))
m1 <- lm(score ~ C*S*N, data = Yogurt)
plot(m1)
```

```
## Warning: not plotting observations with leverage one:
##   16

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##   16
```
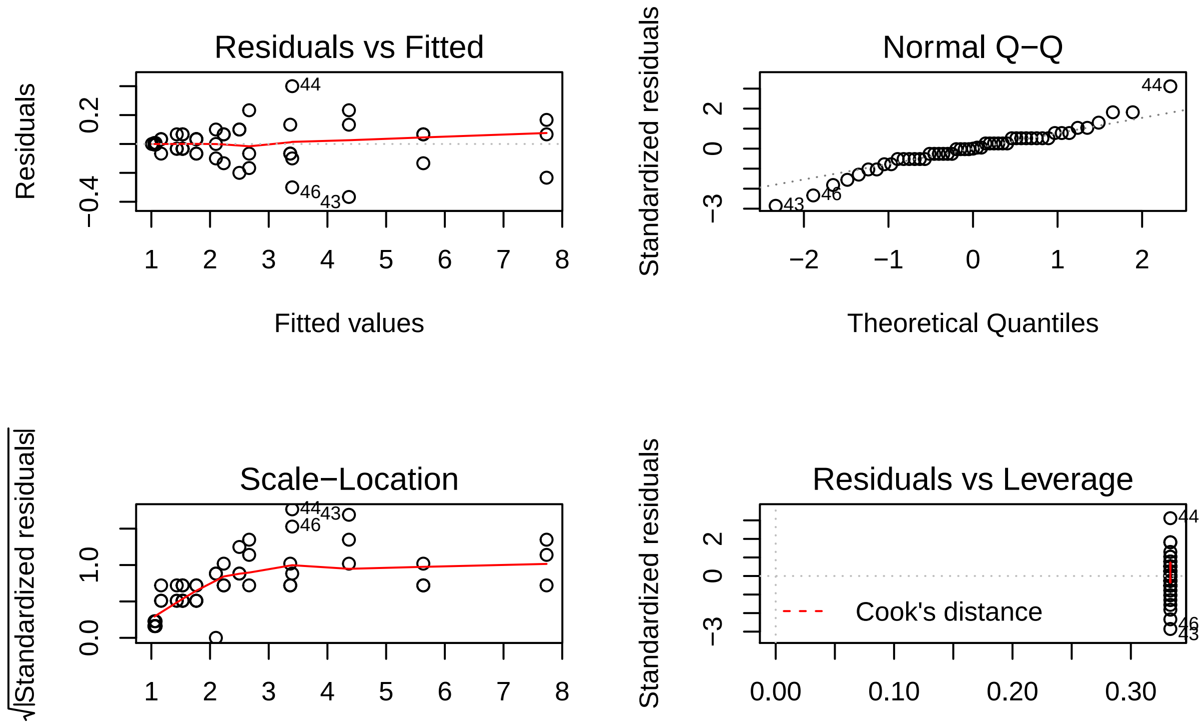
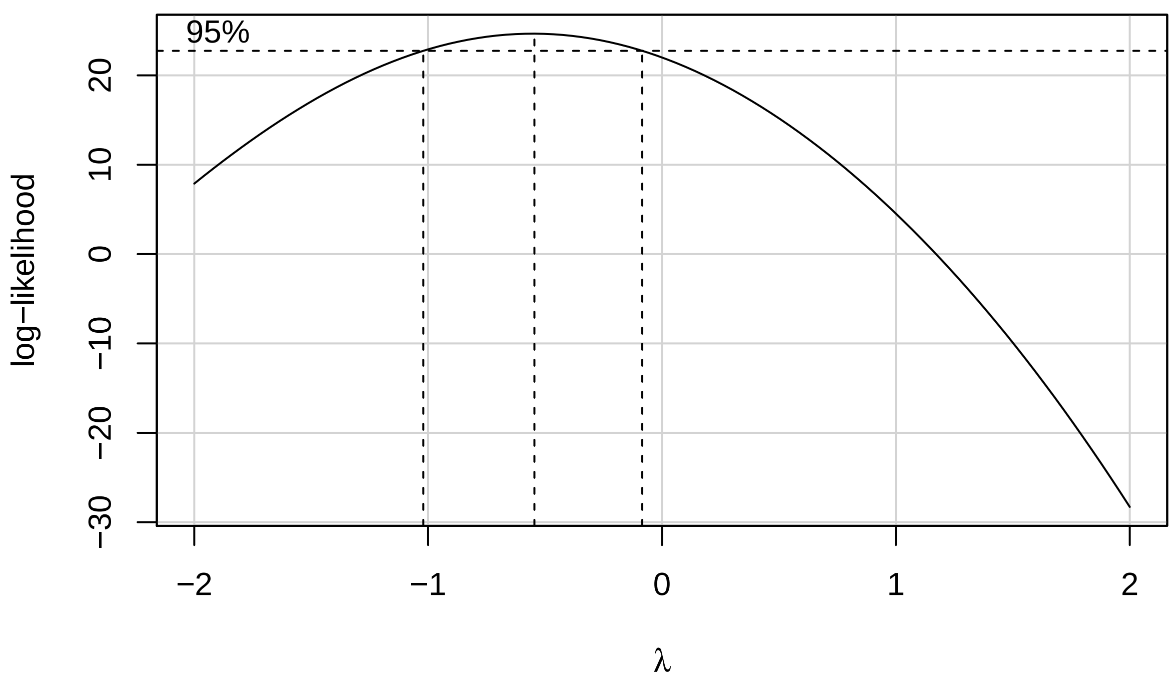




```r
library(car)
```

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

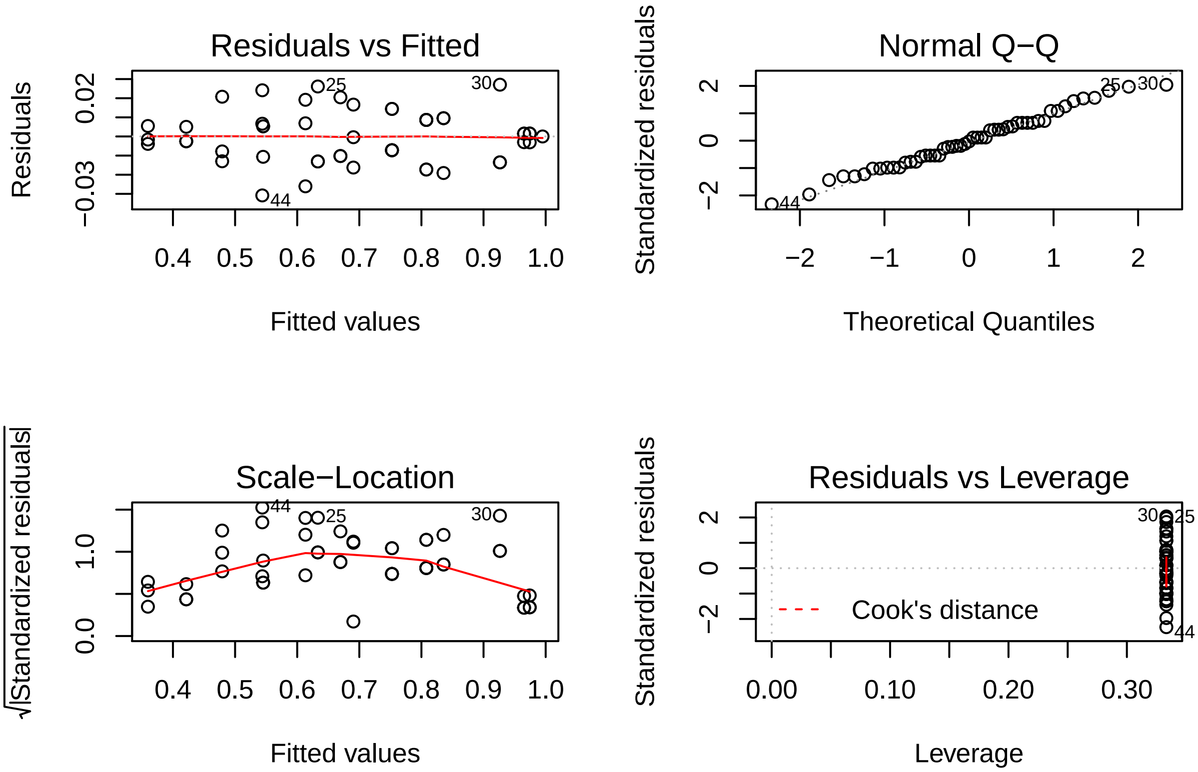
```r
par(mfrow = c(1,1))
boxCox(m1)
```




```r
Yogurt$scoreneg = (Yogurt$score)^(-1/2)
m1ne2 <- lm(scoreneg ~ C*S*N, data = Yogurt)
```

```r
par(mfrow = c(2,2))
plot(m1ne2)
```

```
## Warning: not plotting observations with leverage one:
##   16

## Warning: not plotting observations with leverage one:
##   16
```




```r
Anova(m1ne2,type=2)
```

```
## Anova Table (Type II tests)
##
## Response: scoreneg
##            Sum Sq Df  F value    Pr(>F)
## C         0.62492  2 1183.653 < 2.2e-16 ***
## S         1.05549  2 1999.194 < 2.2e-16 ***
## N         0.12929  1  489.777 < 2.2e-16 ***
## C:S       0.01569  4   14.859 4.063e-07 ***
## C:N       0.01228  2   23.264 4.305e-07 ***
## S:N       0.01561  2   29.561 3.642e-08 ***
## C:S:N     0.00960  4    9.092 4.172e-05 ***
## Residuals 0.00898 34
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m1ne2)
```

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

```
## lm(formula = scoreneg ~ C * S * N, data = Yogurt)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0308218 -0.0102284 -0.0001959  0.0086424  0.0270611
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.7096271  0.0023306 304.484  < 2e-16 ***
## C1          -0.1488810  0.0032125 -46.344  < 2e-16 ***
## C2           0.0425502  0.0032125  13.245 5.58e-15 ***
## S1           0.1939488  0.0034568  56.106  < 2e-16 ***
## S2          -0.0572867  0.0032125 -17.832  < 2e-16 ***
## N1           0.0481269  0.0023306  20.650  < 2e-16 ***
## C1:S1        0.0255118  0.0046612   5.473 4.17e-06 ***
## C2:S1       -0.0003048  0.0046612  -0.065   0.9483
## C1:S2        0.0080557  0.0044830   1.797   0.0812 .
## C2:S2       -0.0019898  0.0044830  -0.444   0.6600
## C1:N1       -0.0178613  0.0032125  -5.560 3.22e-06 ***
## C2:N1        0.0024483  0.0032125   0.762   0.4512
## S1:N1       -0.0289919  0.0034568  -8.387 8.60e-10 ***
## S2:N1        0.0101900  0.0032125   3.172   0.0032 **
## C1:S1:N1     0.0263739  0.0046612   5.658 2.40e-06 ***
## C2:S1:N1    -0.0021635  0.0046612  -0.464   0.6455
## C1:S2:N1    -0.0081596  0.0044830  -1.820   0.0776 .
## C2:S2:N1    -0.0011070  0.0044830  -0.247   0.8064
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01625 on 34 degrees of freedom
## Multiple R-squared:  0.9948, Adjusted R-squared:  0.9923
## F-statistic: 385.5 on 17 and 34 DF,  p-value: < 2.2e-16
```

```r
# all terms are significant!
Yogurt$comb = interaction(Yogurt$C,Yogurt$S,Yogurt$N)
m1comb = lm(scoreneg~comb,data=Yogurt)
sidelines(pairwise(m1comb,comb))
```

```
##
## L.H.H -0.3500
## L.H.L -0.2883
## L.M.H -0.2304
## L.M.L -0.1658 |
## M.H.H -0.1645 |
## H.H.H -0.0963   |
## M.M.H -0.0764   | |
## H.M.H -0.0400     | |
## M.H.L -0.0192       |
## L.L.H  0.0429         |
## M.M.L  0.0429         |
## H.H.L  0.0982           |
## L.L.L  0.0982           |
## H.M.L  0.1260           |
## M.L.H  0.2168             |
## M.L.L  0.2556             |
```

```
## H.L.H  0.2647             |
## H.L.L  0.2854             |
```

```r
compare.to.best(m1comb, comb, confidence = 0.95)
```

```
##                 difference   allowance
## best is H.L.L    0.00000000          NA
##   H.L.H - H.L.L -0.02067519 -0.05111526
##   M.L.L - H.L.L -0.02979605 -0.05111526
## * M.L.H - H.L.L -0.06863571 -0.05111526
## * H.M.L - H.L.L -0.15943549 -0.05111526
## * L.L.L - H.L.L -0.18718300 -0.05111526
## * H.H.L - H.L.L -0.18718300 -0.05111526
## * M.M.L - H.L.L -0.24247820 -0.05111526
## * L.L.H - H.L.L -0.24247820 -0.05111526
## * M.H.L - H.L.L -0.30457979 -0.05111526
## * H.M.H - H.L.L -0.32542835 -0.05111526
## * M.M.H - H.L.L -0.36179458 -0.05111526
## * H.H.H - H.L.L -0.38175405 -0.05111526
## * M.H.H - H.L.L -0.44987511 -0.05111526
## * L.M.L - H.L.L -0.45122623 -0.05111526
## * L.M.H - H.L.L -0.51581822 -0.05111526
## * L.H.L - H.L.L -0.57366744 -0.05111526
## * L.H.H - H.L.L -0.63537391 -0.05111526
```

```r
# first take a look at the pairwise comparison, I found that LHH is significant.
# then I found that the best combination is HLL, which makes sense because it is really bad choice for
```

P9.10

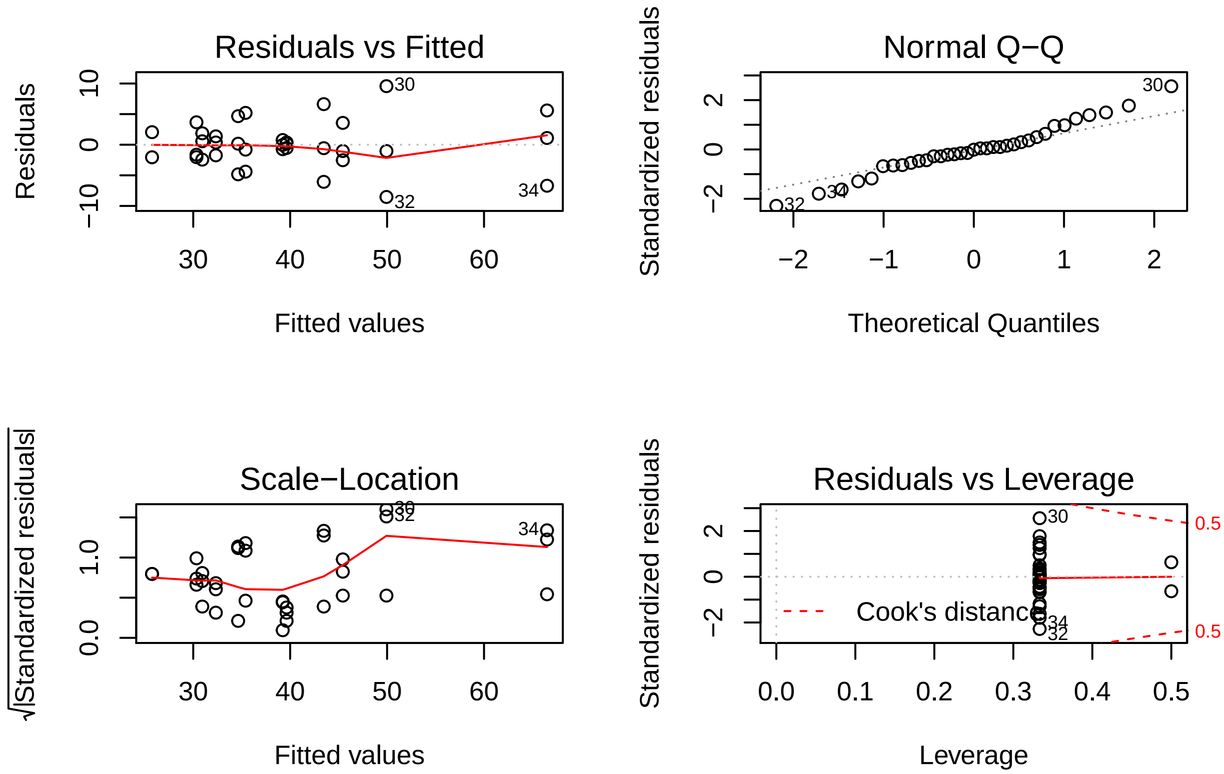
```r
data("PlasmaLeucine")
head(PlasmaLeucine)
```

```
##   source percent.z percent leucine
## 1   fish         9       9    27.8
## 2   fish         9       9    23.7
## 3   fish        12      12    31.5
## 4   fish        12      12    28.5
## 5   fish        12      12    32.8
## 6   fish        15      15    34.0
```

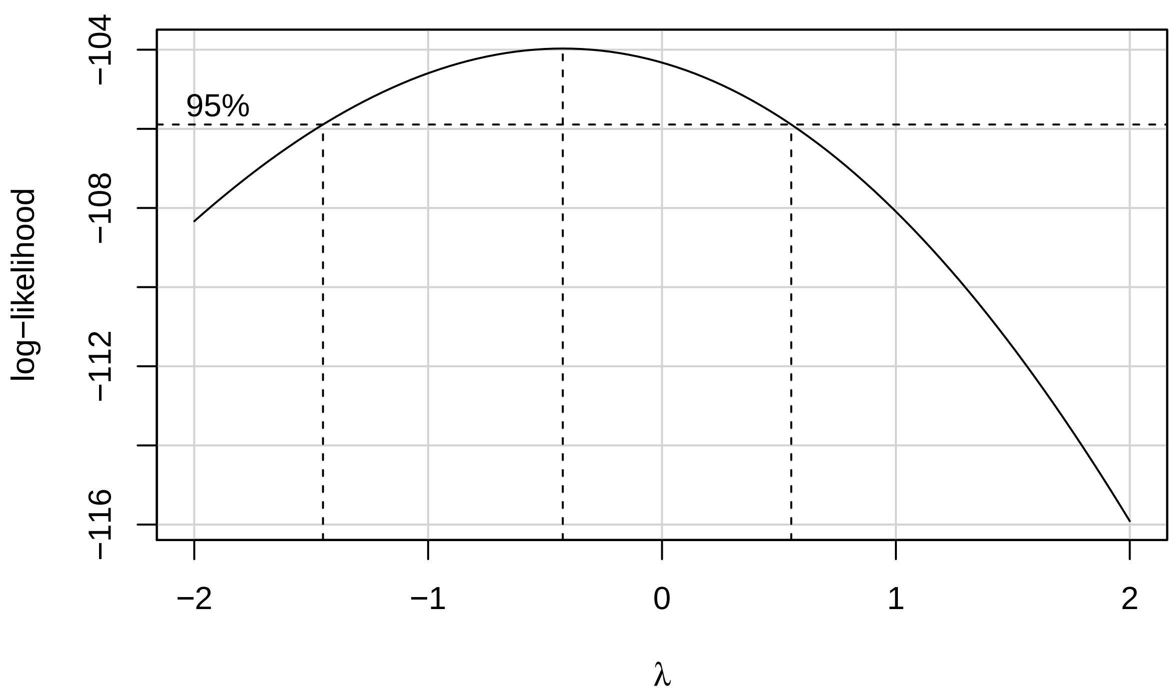
```r
summary(PlasmaLeucine)
```

```
##   source     percent.z     percent    leucine
##  fish:11   Min.   : 9.00   9 :8    Min.   :23.70
##  soy :12   1st Qu.:12.00   12:9    1st Qu.:32.10
##  skim:12   Median :15.00   15:9    Median :39.10
##            Mean   :13.63   18:9    Mean   :39.86
##            3rd Qu.:16.50           3rd Qu.:42.90
##            Max.   :18.00           Max.   :72.10
```

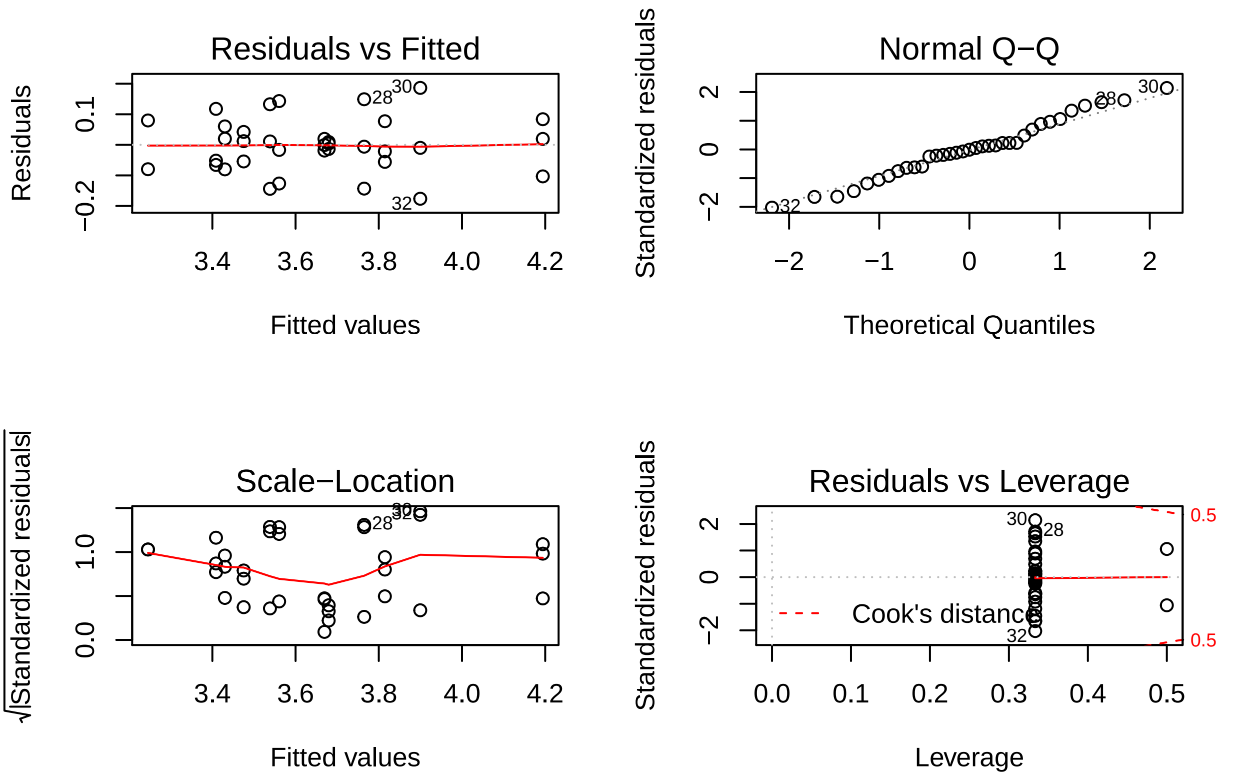
```r
par(mfrow = c(2,2))
m2 <- lm(leucine ~ percent*source, data = PlasmaLeucine)
plot(m2)
```




```r
par(mfrow = c(1,1))
boxCox(m2)
```




```r
#m21 <- lm(leucine^(-1) ~ percent*source, data = PlasmaLeucine)
m2log <- lm(log(leucine) ~ percent*source, data = PlasmaLeucine)
par(mfrow = c(2,2))
#plot(m21)
plot(m2log)
```




```r
Anova(m2log, type = 2)
```

```
## Anova Table (Type II tests)
##
## Response: log(leucine)
##                 Sum Sq Df F value    Pr(>F)
## percent        0.63506  3 18.6172 2.373e-06 ***
## source         1.27631  2 56.1235 1.419e-09 ***
## percent:source 0.18299  6  2.6821   0.04017 *
## Residuals      0.26152 23
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(m2log)
```

```
##
## Call:
## lm(formula = log(leucine) ~ percent * source, data = PlasmaLeucine)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.176397 -0.055032 -0.000728  0.051264  0.186298
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        3.6400644  0.0181386 200.680  < 2e-16 ***
## percent1          -0.1919838  0.0326495  -5.880 5.41e-06 ***
## percent2          -0.0152030  0.0309953  -0.490    0.628
## percent3           0.0191987  0.0309953   0.619    0.542
```

```
## source1          -0.2502245  0.0261599  -9.565 1.76e-09 ***
## source2           0.0354660  0.0253941   1.397    0.176
## percent1:source1  0.0473994  0.0486710   0.974    0.340
## percent2:source1  0.0554698  0.0441332   1.257    0.221
## percent3:source1 -0.0003322  0.0441332  -0.008    0.994
## percent1:source2  0.0549034  0.0448725   1.224    0.234
## percent2:source2  0.0192955  0.0436836   0.442    0.663
## percent3:source2 -0.0253244  0.0436836  -0.580    0.568
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1066 on 23 degrees of freedom
## Multiple R-squared:  0.8844, Adjusted R-squared:  0.8291
## F-statistic: 15.99 on 11 and 23 DF,  p-value: 2.957e-08
```

```
# all the terms are significant, and in the summary, the percent and source are significant
PlasmaLeucine$comb = interaction(PlasmaLeucine$source,PlasmaLeucine$percent)
m2log11 = lm(log(leucine)~comb,data=PlasmaLeucine)
sidelines(pairwise(m2log11,comb))
```

```
##
## fish.9  -0.3948 |
## fish.15 -0.2314 | |
## fish.12 -0.2100 | |
## fish.18 -0.1648 | | |
## soy.9   -0.1016 | | | |
## skim.9  -0.0795 | | | |
## soy.15   0.0293   | | | |
## soy.12   0.0396   | | | |
## skim.12  0.1248     | | |
## soy.18   0.1746       | |
## skim.15  0.2596         | |
## skim.18  0.5542           |
```

```
compare.to.best(m2log11,comb)
```

```
##                       difference  allowance
## best is skim.18        0.0000000         NA
## * skim.15 - skim.18 -0.2945444 -0.2301592
## * soy.18 - skim.18  -0.3795787 -0.2301592
## * skim.12 - skim.18 -0.4293680 -0.2301592
## * soy.12 - skim.18  -0.5145996 -0.2301592
## * soy.15 - skim.18  -0.5248177 -0.2301592
## * skim.9 - skim.18  -0.6336862 -0.2301592
## * soy.9 - skim.18   -0.6557725 -0.2301592
## * fish.18 - skim.18 -0.7189316 -0.2301592
## * fish.12 - skim.18 -0.7641158 -0.2301592
## * fish.15 - skim.18 -0.7855161 -0.2301592
## * fish.9 - skim.18  -0.9489670 -0.2573258
```

```
# I find that the best combination is skim 18.
# Since the percent is also numeric variable, we fit other model
m2lognum <- lm(log(leucine) ~ (percent.z + percent.z^2)*source, data = PlasmaLeucine)
summary(m2lognum)
```

```
##
```

```
## Call:
## lm(formula = log(leucine) ~ (percent.z + percent.z^2) * source,
##     data = PlasmaLeucine)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.233336 -0.066315 -0.003159  0.070075  0.160992
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          3.121889   0.074552  41.875  < 2e-16 ***
## percent.z            0.038502   0.005307   7.255 5.47e-08 ***
## source1             -0.002165   0.109540  -0.020   0.9844
## source2              0.185378   0.103318   1.794   0.0832 .
## percent.z:source1 -0.018137   0.007732  -2.346   0.0260 *
## percent.z:source2 -0.011223   0.007390  -1.519   0.1396
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1035 on 29 degrees of freedom
## Multiple R-squared:  0.8627, Adjusted R-squared:  0.839
## F-statistic: 36.44 on 5 and 29 DF,  p-value: 1.199e-11
```

```
Anova(m2lognum, type = 2)
```

```
## Anova Table (Type II tests)
##
## Response: log(leucine)
##                    Sum Sq Df F value    Pr(>F)
## percent.z         0.59890  1  55.925 3.051e-08 ***
## source            1.26920  2  59.258 5.710e-11 ***
## percent.z:source 0.17010  2   7.942  0.001776 **
## Residuals         0.31056 29
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# while in the summary of the numeric of the percent, I can only find the single term of percent is sig
```

P9.14

```
data("TropicalGrasses")
head(TropicalGrasses)
```

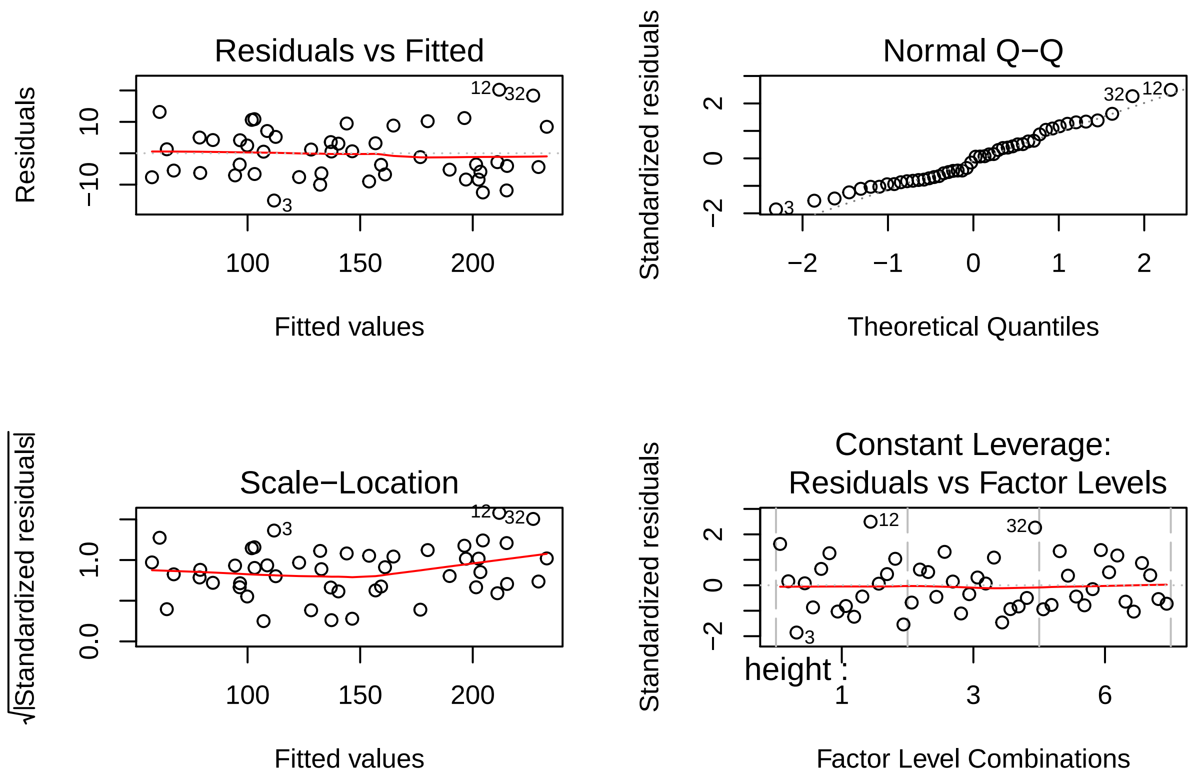
```
##   height fert interval height.z fert.z interval.z yield
## 1      1    0        1        1      0          1  74.1
## 2      1    0        3        1      0          3  65.4
## 3      1    0        6        1      0          6  96.7
## 4      1    0        9        1      0          9 147.1
## 5      1    8        1        1      8          1  87.4
## 6      1    8        3        1      8          3 117.7
```

```
summary(TropicalGrasses)
```

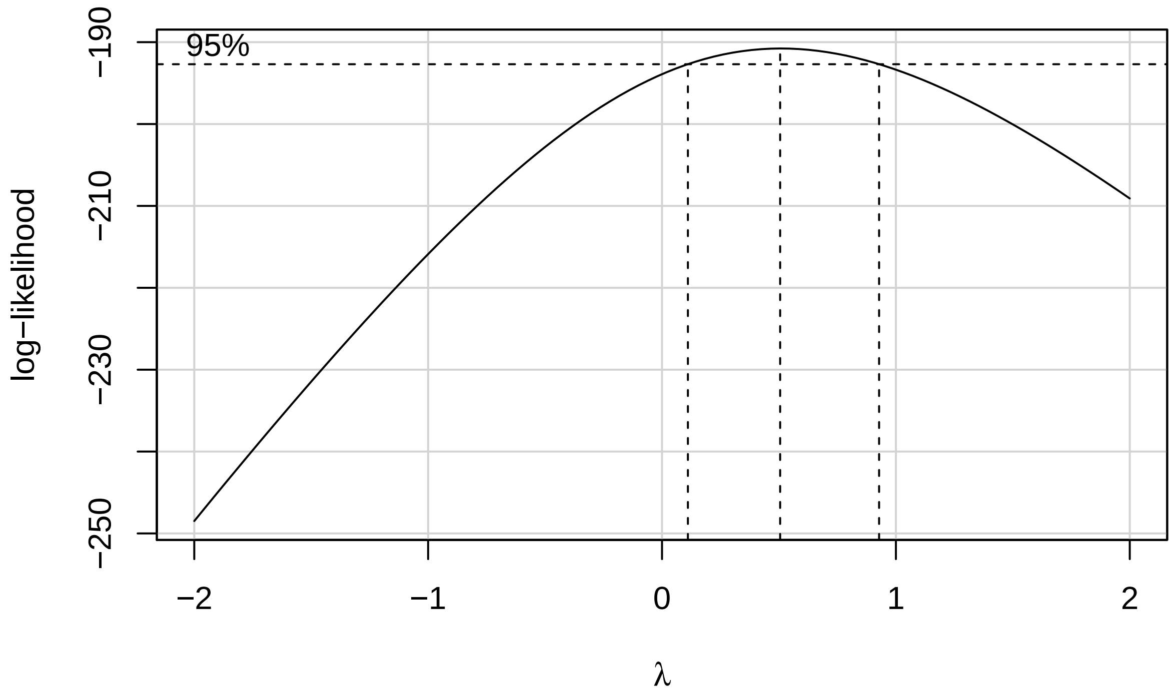
```
##  height fert     interval     height.z         fert.z     interval.z
```

```
##  1:16    0 :12   1:12     Min.   :1.000   Min.   : 0   Min.   :1.00
##  3:16    8 :12   3:12     1st Qu.:1.000   1st Qu.: 6   1st Qu.:2.50
##  6:16    16:12   6:12     Median :3.000   Median :12   Median :4.50
##          32:12   9:12     Mean   :3.333   Mean   :14   Mean   :4.75
##                           3rd Qu.:6.000   3rd Qu.:20   3rd Qu.:6.75
##                           Max.   :6.000   Max.   :32   Max.   :9.00
##      yield
##  Min.   : 49.9
##  1st Qu.:101.9
##  Median :141.9
##  Mean   :144.5
##  3rd Qu.:190.7
##  Max.   :245.2
```

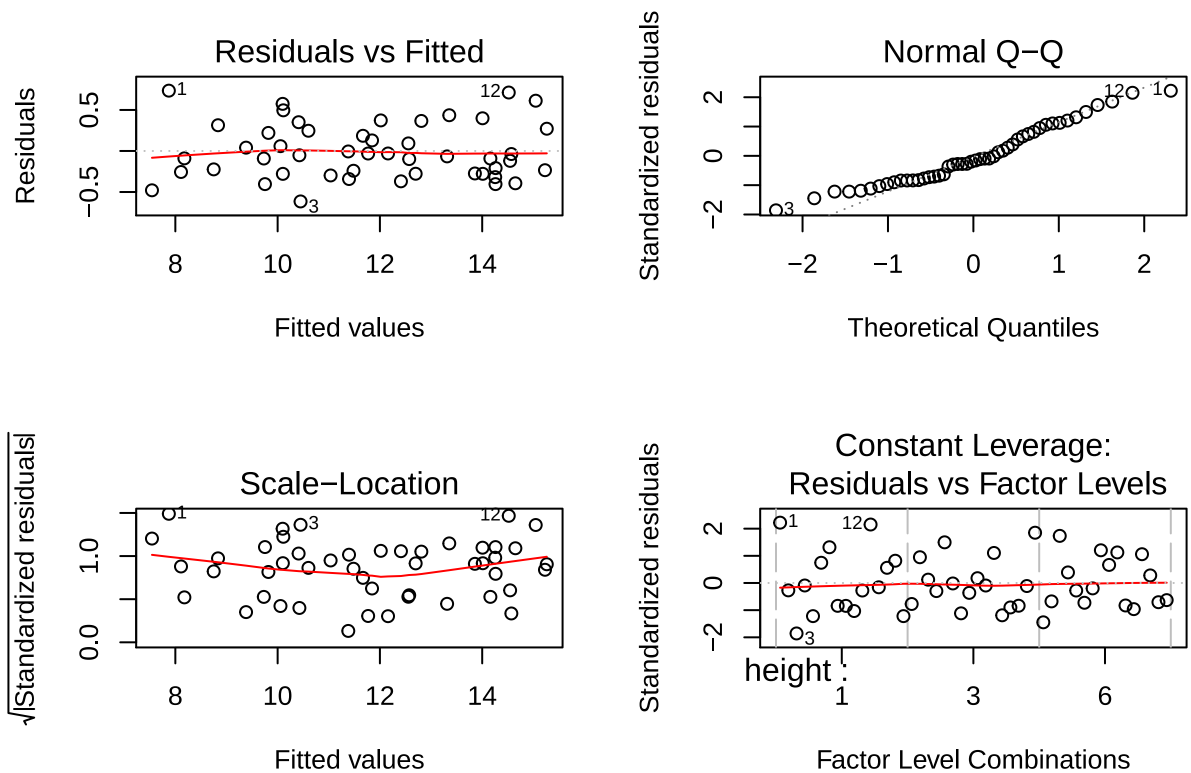
```
m3 <- lm(yield~(height+fert+interval)^2,data=TropicalGrasses)
par(mfrow = c(2,2))
plot(m3)
```




```
par(mfrow = c(1,1))
boxCox(m3)
```




```
TropicalGrasses$yield.5 = (TropicalGrasses$yield)^(1/2)
m3.5 <- lm(yield.5~(height+fert+interval)^2,data=TropicalGrasses)
par(mfrow = c(2,2))
plot(m3.5)
```

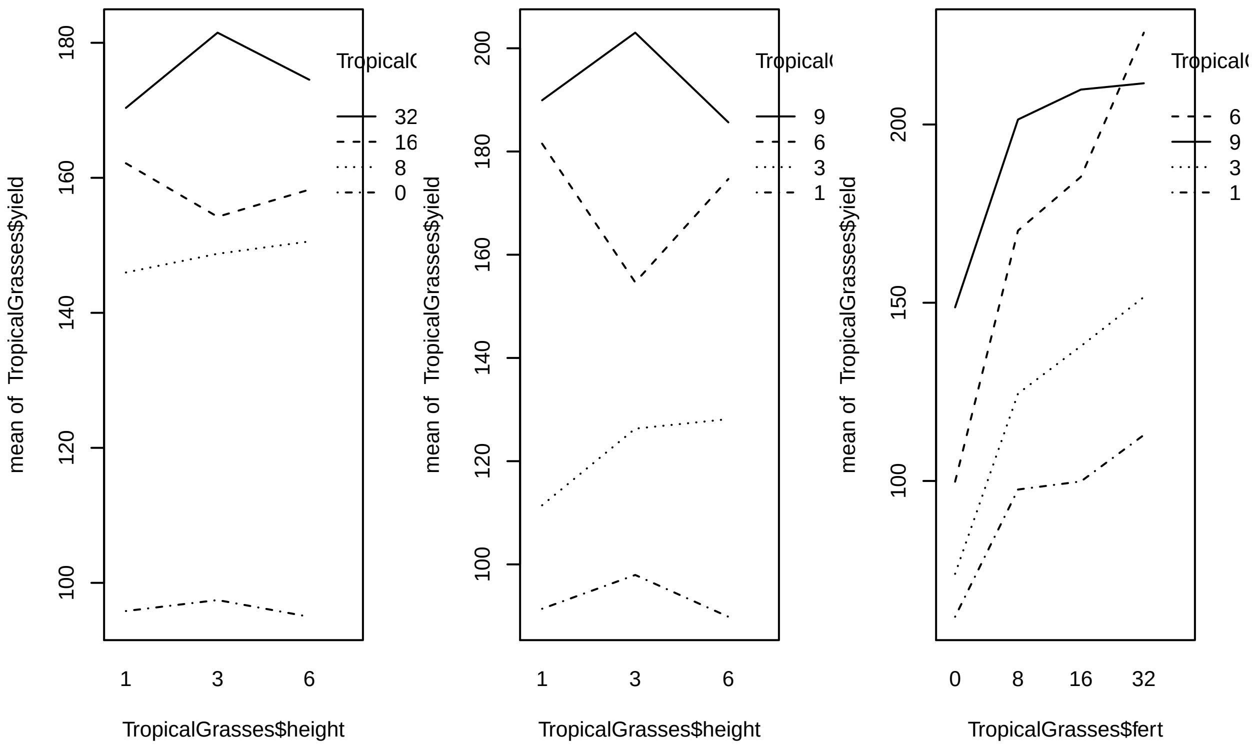



```
anova(m3.5)
```

```
## Analysis of Variance Table
```

```
##
## Response: yield.5
##                  Df  Sum Sq Mean Sq  F value    Pr(>F)
## height            2   0.103   0.052   0.1763   0.83979
## fert              3  82.222  27.407  93.8199 3.510e-11 ***
## interval          3 132.738  44.246 151.4617 5.865e-13 ***
## height:fert       6   0.537   0.089   0.3062   0.92553
## height:interval   6   4.873   0.812   2.7800   0.04303 *
## fert:interval     9   6.868   0.763   2.6123   0.03962 *
## Residuals        18   5.258   0.292
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
par(mfrow = c(1,3))
interaction.plot(TropicalGrasses$height, TropicalGrasses$fert,TropicalGrasses$yield)
interaction.plot(TropicalGrasses$height, TropicalGrasses$interval,TropicalGrasses$yield)
interaction.plot(TropicalGrasses$fert, TropicalGrasses$interval,TropicalGrasses$yield)
```




```r
# we can find the interaction between height:interval and fert:interval are significant.
# find the best combination
TropicalGrasses$comb = interaction(TropicalGrasses$fert,TropicalGrasses$interval)
m3.5rr = aov(yield.5~comb,data=TropicalGrasses)
pairwise(m3.5rr,comb)
```

```
##
## Pairwise comparisons ( hsd ) of comb
##                  estimate signif diff        lower       upper
## * 0.1 - 8.1   -2.02226646      1.7565 -3.778766381 -0.26576655
## * 0.1 - 16.1  -2.15021476      1.7565 -3.906714673 -0.39371484
## * 0.1 - 32.1  -2.78160098      1.7565 -4.538100895 -1.02510106
##   0.1 - 0.3   -0.74505430      1.7565 -2.501554219  1.01144561
```

```
## * 0.1 - 8.3   -3.31336233      1.7565 -5.069862242 -1.55686241
## * 0.1 - 16.3  -3.88522780      1.7565 -5.641727718 -2.12872789
## * 0.1 - 32.3  -4.46569056      1.7565 -6.222190481 -2.70919065
## * 0.1 - 0.6   -2.13410722      1.7565 -3.890607135 -0.37760730
## * 0.1 - 8.6   -5.18449128      1.7565 -6.940991196 -3.42799136
## * 0.1 - 16.6  -5.76648094      1.7565 -7.522980856 -4.00998102
## * 0.1 - 32.6  -7.17760798      1.7565 -8.934107898 -5.42110807
## * 0.1 - 0.9   -4.35012068      1.7565 -6.106620597 -2.59362077
## * 0.1 - 8.9   -6.34554658      1.7565 -8.102046492 -4.58904666
## * 0.1 - 16.9  -6.63162411      1.7565 -8.388124023 -4.87512419
## * 0.1 - 32.9  -6.68055848      1.7565 -8.437058397 -4.92405856
##   8.1 - 16.1  -0.12794829      1.7565 -1.884448209  1.62855162
##   8.1 - 32.1  -0.75933451      1.7565 -2.515834430  0.99716540
##   8.1 - 0.3    1.27721216      1.7565 -0.479287755  3.03371208
##   8.1 - 8.3   -1.29109586      1.7565 -3.047595777  0.46540406
## * 8.1 - 16.3  -1.86296134      1.7565 -3.619461253 -0.10646142
## * 8.1 - 32.3  -2.44342410      1.7565 -4.199924017 -0.68692418
##   8.1 - 0.6   -0.11184075      1.7565 -1.868340670  1.64465916
## * 8.1 - 8.6   -3.16222481      1.7565 -4.918724731 -1.40572490
## * 8.1 - 16.6  -3.74421448      1.7565 -5.500714392 -1.98771456
## * 8.1 - 32.6  -5.15534152      1.7565 -6.911841433 -3.39884160
## * 8.1 - 0.9   -2.32785422      1.7565 -4.084354133 -0.57135430
## * 8.1 - 8.9   -4.32328011      1.7565 -6.079780027 -2.56678019
## * 8.1 - 16.9  -4.60935764      1.7565 -6.365857558 -2.85285773
## * 8.1 - 32.9  -4.65829202      1.7565 -6.414791932 -2.90179210
##   16.1 - 32.1 -0.63138622      1.7565 -2.387886138  1.12511369
##   16.1 - 0.3   1.40516045      1.7565 -0.351339462  3.16166037
##   16.1 - 8.3  -1.16314757      1.7565 -2.919647485  0.59335235
##   16.1 - 16.3 -1.73501304      1.7565 -3.491512960  0.02148687
## * 16.1 - 32.3 -2.31547581      1.7565 -4.071975724 -0.55897589
##   16.1 - 0.6   0.01610754      1.7565 -1.740392378  1.77260745
## * 16.1 - 8.6  -3.03427652      1.7565 -4.790776439 -1.27777661
## * 16.1 - 16.6 -3.61626618      1.7565 -5.372766099 -1.85976627
## * 16.1 - 32.6 -5.02739322      1.7565 -6.783893141 -3.27089331
## * 16.1 - 0.9  -2.19990592      1.7565 -3.956405840 -0.44340601
## * 16.1 - 8.9  -4.19533182      1.7565 -5.951831735 -2.43883190
## * 16.1 - 16.9 -4.48140935      1.7565 -6.237909266 -2.72490943
## * 16.1 - 32.9 -4.53034372      1.7565 -6.286843640 -2.77384381
## * 32.1 - 0.3   2.03654668      1.7565  0.280046759  3.79304659
##   32.1 - 8.3  -0.53176135      1.7565 -2.288261263  1.22473857
##   32.1 - 16.3 -1.10362682      1.7565 -2.860126739  0.65287309
##   32.1 - 32.3 -1.68408959      1.7565 -3.440589503  0.07241033
##   32.1 - 0.6   0.64749376      1.7565 -1.109006156  2.40399368
## * 32.1 - 8.6  -2.40289030      1.7565 -4.159390217 -0.64639038
## * 32.1 - 16.6 -2.98487996      1.7565 -4.741379878 -1.22838005
## * 32.1 - 32.6 -4.39600700      1.7565 -6.152506919 -2.63950709
##   32.1 - 0.9  -1.56851970      1.7565 -3.325019619  0.18798021
## * 32.1 - 8.9  -3.56394560      1.7565 -5.320445513 -1.80744568
## * 32.1 - 16.9 -3.85002313      1.7565 -5.606523044 -2.09352321
## * 32.1 - 32.9 -3.89895750      1.7565 -5.655457418 -2.14245759
## * 0.3 - 8.3   -2.56830802      1.7565 -4.324807938 -0.81180811
## * 0.3 - 16.3  -3.14017350      1.7565 -4.896673414 -1.38367358
## * 0.3 - 32.3  -3.72063626      1.7565 -5.477136178 -1.96413635
##   0.3 - 0.6   -1.38905292      1.7565 -3.145552832  0.36744700
```

```
## * 0.3 - 8.6   -4.43943698      1.7565 -6.195936892 -2.68293706
## * 0.3 - 16.6  -5.02142664      1.7565 -6.777926553 -3.26492672
## * 0.3 - 32.6  -6.43255368      1.7565 -8.189053595 -4.67605376
## * 0.3 - 0.9   -3.60506638      1.7565 -5.361566294 -1.84856646
## * 0.3 - 8.9   -5.60049227      1.7565 -7.356992188 -3.84399236
## * 0.3 - 16.9  -5.88656980      1.7565 -7.643069720 -4.13006989
## * 0.3 - 32.9  -5.93550418      1.7565 -7.692004094 -4.17900426
##   8.3 - 16.3  -0.57186548      1.7565 -2.328365392  1.18463444
##   8.3 - 32.3  -1.15232824      1.7565 -2.908828156  0.60417168
##   8.3 - 0.6    1.17925511      1.7565 -0.577244809  2.93575502
## * 8.3 - 8.6   -1.87112895      1.7565 -3.627628870 -0.11462904
## * 8.3 - 16.6  -2.45311861      1.7565 -4.209618531 -0.69661870
## * 8.3 - 32.6  -3.86424566      1.7565 -5.620745572 -2.10774574
##   8.3 - 0.9   -1.03675836      1.7565 -2.793258272  0.71974156
## * 8.3 - 8.9   -3.03218425      1.7565 -4.788684166 -1.27568433
## * 8.3 - 16.9  -3.31826178      1.7565 -5.074761697 -1.56176186
## * 8.3 - 32.9  -3.36719616      1.7565 -5.123696071 -1.61069624
##   16.3 - 32.3 -0.58046276      1.7565 -2.336962680  1.17603715
##   16.3 - 0.6   1.75112058      1.7565 -0.005379333  3.50762050
##   16.3 - 8.6  -1.29926348      1.7565 -3.055763394  0.45723644
## * 16.3 - 16.6 -1.88125314      1.7565 -3.637753055 -0.12475322
## * 16.3 - 32.6 -3.29238018      1.7565 -5.048880097 -1.53588026
##   16.3 - 0.9  -0.46489288      1.7565 -2.221392796  1.29160704
## * 16.3 - 8.9  -2.46031877      1.7565 -4.216818690 -0.70381886
## * 16.3 - 16.9 -2.74639631      1.7565 -4.502896221 -0.98989639
## * 16.3 - 32.9 -2.79533068      1.7565 -4.551830595 -1.03883076
## * 32.3 - 0.6   2.33158335      1.7565  0.575083430  4.08808326
##   32.3 - 8.6  -0.71880071      1.7565 -2.475300631  1.03769920
##   32.3 - 16.6 -1.30079037      1.7565 -3.057290291  0.45570954
## * 32.3 - 32.6 -2.71191742      1.7565 -4.468417333 -0.95541750
##   32.3 - 0.9   0.11556988      1.7565 -1.640930032  1.87206980
## * 32.3 - 8.9  -1.87985601      1.7565 -3.636355927 -0.12335609
## * 32.3 - 16.9 -2.16593354      1.7565 -3.922433458 -0.40943363
## * 32.3 - 32.9 -2.21486792      1.7565 -3.971367832 -0.45836800
## * 0.6 - 8.6   -3.05038406      1.7565 -4.806883977 -1.29388414
## * 0.6 - 16.6  -3.63237372      1.7565 -5.388873637 -1.87587381
## * 0.6 - 32.6  -5.04350076      1.7565 -6.800000679 -3.28700085
## * 0.6 - 0.9   -2.21601346      1.7565 -3.972513379 -0.45951355
## * 0.6 - 8.9   -4.21143936      1.7565 -5.967939273 -2.45493944
## * 0.6 - 16.9  -4.49751689      1.7565 -6.254016804 -2.74101697
## * 0.6 - 32.9  -4.54645126      1.7565 -6.302951178 -2.78995135
##   8.6 - 16.6  -0.58198966      1.7565 -2.338489577  1.17451026
## * 8.6 - 32.6  -1.99311670      1.7565 -3.749616618 -0.23661679
##   8.6 - 0.9    0.83437060      1.7565 -0.922129318  2.59087051
##   8.6 - 8.9   -1.16105530      1.7565 -2.917555212  0.59544462
##   8.6 - 16.9  -1.44713283      1.7565 -3.203632743  0.30936709
##   8.6 - 32.9  -1.49606720      1.7565 -3.252567117  0.26043272
##   16.6 - 32.6 -1.41112704      1.7565 -3.167626958  0.34537287
##   16.6 - 0.9   1.41636026      1.7565 -0.340139657  3.17286017
##   16.6 - 8.9  -0.57906564      1.7565 -2.335565552  1.17743428
##   16.6 - 16.9 -0.86514317      1.7565 -2.621643083  0.89135675
##   16.6 - 32.9 -0.91407754      1.7565 -2.670577457  0.84242238
## * 32.6 - 0.9   2.82748730      1.7565  1.070987384  4.58398722
##   32.6 - 8.9   0.83206141      1.7565 -0.924438510  2.58856132
```

```
##   32.6 - 16.9  0.54598388      1.7565 -1.210516041  2.30248379
##   32.6 - 32.9  0.49704950      1.7565 -1.259450415  2.25354942
## * 0.9 - 8.9   -1.99542589      1.7565 -3.751925810 -0.23892598
## * 0.9 - 16.9  -2.28150343      1.7565 -4.038003342 -0.52500351
## * 0.9 - 32.9  -2.33043780      1.7565 -4.086937716 -0.57393788
##   8.9 - 16.9  -0.28607753      1.7565 -2.042577447  1.47042238
##   8.9 - 32.9  -0.33501191      1.7565 -2.091511821  1.42148801
##   16.9 - 32.9 -0.04893437      1.7565 -1.805434290  1.70756554
```

```
compare.to.best(m3.5rr,comb,confidence=0.95)
```

```
##                difference allowance
## best is 32.6   0.0000000        NA
##   32.9 - 32.6 -0.4970495 -1.275685
##   16.9 - 32.6 -0.5459839 -1.275685
##   8.9 - 32.6  -0.8320614 -1.275685
## * 16.6 - 32.6 -1.4111270 -1.275685
## * 8.6 - 32.6  -1.9931167 -1.275685
## * 32.3 - 32.6 -2.7119174 -1.275685
## * 0.9 - 32.6  -2.8274873 -1.275685
## * 16.3 - 32.6 -3.2923802 -1.275685
## * 8.3 - 32.6  -3.8642457 -1.275685
## * 32.1 - 32.6 -4.3960070 -1.275685
## * 16.1 - 32.6 -5.0273932 -1.275685
## * 0.6 - 32.6  -5.0435008 -1.275685
## * 8.1 - 32.6  -5.1553415 -1.275685
## * 0.3 - 32.6  -6.4325537 -1.275685
## * 0.1 - 32.6  -7.1776080 -1.275685
```

```
# take a look at the numeric term
m3.5fi = lm(yield~(interval.z+I(interval.z^2))*fert,data=TropicalGrasses)
summary(m3.5fi)
```

```
##
## Call:
## lm(formula = yield ~ (interval.z + I(interval.z^2)) * fert, data = TropicalGrasses)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -25.2347  -9.1086  -0.9329   8.8856  30.0997
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           71.4163     6.3685  11.214 2.67e-13 ***
## interval.z            20.5498     3.2096   6.403 2.02e-07 ***
## I(interval.z^2)       -0.7711     0.3113  -2.477  0.01808 *
## fert1                -10.4399    11.0306  -0.946  0.35023
## fert2                  8.3743    11.0306   0.759  0.45268
## fert3                  4.5539    11.0306   0.413  0.68217
## interval.z:fert1     -19.8159     5.5592  -3.565  0.00105 **
## interval.z:fert2      -3.6098     5.5592  -0.649  0.52024
## interval.z:fert3       3.6927     5.5592   0.664  0.51076
## I(interval.z^2):fert1   1.7670     0.5392   3.277  0.00233 **
## I(interval.z^2):fert2   0.3987     0.5392   0.740  0.46439
## I(interval.z^2):fert3  -0.2656     0.5392  -0.493  0.62532
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 14.73 on 36 degrees of freedom
## Multiple R-squared:  0.9389, Adjusted R-squared:  0.9203
## F-statistic: 50.31 on 11 and 36 DF,  p-value: < 2.2e-16
```

```
m3.5if = lm(yield~(fert.z+I(fert.z^2))*interval,data=TropicalGrasses)
summary(m3.5if)
```

```
##
## Call:
## lm(formula = yield ~ (fert.z + I(fert.z^2)) * interval, data = TropicalGrasses)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -22.029 -10.263  -2.727   9.248  34.705
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            99.504015   4.227863  23.535  < 2e-16 ***
## fert.z                  5.855270   0.670858   8.728 2.06e-10 ***
## I(fert.z^2)            -0.109917   0.019444  -5.653 2.02e-06 ***
## interval1             -34.636742   7.322873  -4.730 3.42e-05 ***
## interval2             -22.876136   7.322873  -3.124  0.00352 **
## interval3               5.102348   7.322873   0.697  0.49042
## fert.z:interval1       -2.208641   1.161960  -1.901  0.06536 .
## fert.z:interval2        0.154238   1.161960   0.133  0.89514
## fert.z:interval3        1.700999   1.161960   1.464  0.15190
## I(fert.z^2):interval1   0.041900   0.033678   1.244  0.22148
## I(fert.z^2):interval2  -0.005543   0.033678  -0.165  0.87019
## I(fert.z^2):interval3  -0.009461   0.033678  -0.281  0.78038
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.28 on 36 degrees of freedom
## Multiple R-squared:  0.9342, Adjusted R-squared:  0.9142
## F-statistic:  46.5 on 11 and 36 DF,  p-value: < 2.2e-16
```

```
# from the last part we can see there is no interaction significant, try to remove the interaction
m3.5num = lm(yield~fert.z+I(fert.z^2)+interval,data=TropicalGrasses)
summary(m3.5num)
```

```
##
## Call:
## lm(formula = yield ~ fert.z + I(fert.z^2) + interval, data = TropicalGrasses)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -36.442 -11.387   0.268  11.058  41.244
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  99.50402    4.98906  19.944  < 2e-16 ***
## fert.z        5.85527    0.79164   7.396 3.96e-09 ***
```

```
## I(fert.z^2)  -0.10992    0.02294  -4.791 2.10e-05 ***
## interval1   -51.47917    4.50905 -11.417 1.86e-14 ***
## interval2   -22.57917    4.50905  -5.008 1.04e-05 ***
## interval3    25.73750    4.50905   5.708 1.04e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18.04 on 42 degrees of freedom
## Multiple R-squared:  0.8932, Adjusted R-squared:  0.8805
## F-statistic: 70.24 on 5 and 42 DF,  p-value: < 2.2e-16
```

```
# then we can find that what matters is the numeric of the fert and interval
```