Doctor_Effectiveness.R

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```
#Objective: Determine the effectivenss of indivdual doctors and doctor pairs
#            by considering their effect on net profit.


#Methods:1.Clean the data and put it in usable form.
#        2.Do power analysis to determine what we should expect.
#        3A.Determine the effectiveness of each doctor individually. (block by month and day)
#        3B.Determine if certain doctor pairs work better or worse together.
#        3C. Model adequcy checking.
#        4.Interpretation and discussion.
#        5. Final words.
################################################################################
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#1) Clean the data.

#First we clean the data and put in all in a dataframe so that it is usable.
#This first part is parsing the data to get in a usable form.
#It is not important to follow this part.
sw <- read.csv("SW2018.csv",header=T)
swp <- sw[11:153,c(8,9,13,6,7,10,20,23:26)]
swp <- swp[swp[,"X..OF.DOCTORS"]!=0,]
#there is only one day with one doctor,
#this is not included in the analysis.
swp <- swp[-135,]

swp[,"Pediatric.Dentist.Day."] <- factor(swp[,"Pediatric.Dentist.Day."])
swp[,"TOTAL.PRODUCTION"] <- as.numeric(substring(gsub(",","",gsub(" ","",
                                                as.character(swp[,"TOTAL.PRODUCTION"]))),2))
swp[,"X..OF.DOCTORS"] <- as.integer(as.character(swp[,"X..OF.DOCTORS"]))

#Now we have some missing values for total patients, we delete them
swp <- swp[-(136:139),]

#This will make the indicator matrix of each doctor:
library(ade4)
docsn <- swp[,8:11]
docsn[docsn==""] <- NA
docsn <- data.frame(sapply(docsn,function(x){as.factor(x)}))
docs <- acm.disjonctif(docsn)
#we can just add repeat docs together to consolidate
names(docs) <- sapply(names(docs),function(x){substring(x,13)})

for(i in 1:22){
  for(j in (i+1):23){
    if(names(docs)[i] == names(docs)[j]){
      docs[i] <- docs[i]+docs[j]
    }
```

```r
  }
}
#I nulled out the duplicates by hand to avoid a complicated for loop.
docs[,c(8,16,9,17,10,11,18,12,15,19,22,20,21,23)] <- NULL

#I changed a single day with 2 temps to 1 temp to smooth out the analysis
#it makes understanding the data easier and will have little
#effect on the final analysis.

docs[c(32,118),9] <- 1
docs <- data.frame(sapply(docs,function(x){y <- as.factor(x);y}))

#and combind docs with swp:

swp <- cbind(swp[,1:7],docs)
#I remove the factor pediatric here because the effect is included
#when we test for "pino", who is the only pediatric doctor.

names(swp) <- c("Total_Operative","Total_Hygiene","Total_Production",
                "Number_of_Doctors","Pediatric","Total_Patients",
                "Appt_Scheduled", names(swp)[8:16])

sx <- sw[11:153,c(3,4,6)]
sx <- sx[sx[,"X..OF.DOCTORS"]!=0,]
#there is only one day with one doctor,
#this is not included in the analysis.
sx <- sx[-135,]
sx <- sx[-(136:139),]

swp <- cbind(swp,sx[,c(1,2)])

#there is an extranous level in DAY

swp$DAY <- factor(swp$DAY)
swp$MONTH <- factor(swp$MONTH)

#Our data is now usable. The data frame is swp.
#The first few rows are:
head(swp,4)
```

```
##    Total_Operative Total_Hygiene Total_Production Number_of_Doctors
## 11              24            30          8042.12                 2
## 12              20            35          7774.81                 3
## 13              30            40          9680.57                 3
## 14               0            62          6583.58                 2
##    Pediatric Total_Patients Appt_Scheduled BRITTANY HEATHER KEVIN OLIMBI
## 11        NO             54            107        0       0     1      0
## 12        NO             55            102        1       0     1      0
## 13        NO             70            100        1       0     0      1
## 14        NO             62            109        0       0     1      0
##    PINO POUYAN ABBY SAMARA TEMP       DAY   MONTH
## 11    0      1    0      0    0   Tuesday January
## 12    0      0    0      0    1 Wednesday January
```

```
## 13    0      0    0      0    1  Thursday January
## 14    0      0    0      1    0    Friday January
```

```r
##########################################################
##########################################################
#2) Do power analysis. What should we expect with
#   different numbers of predictors?

#I included a power analysis because the number of predictors
#is high compared to the number of data points (p=46, n=135)

#We want to use each doctor and also each doctor pair as a predictor.
#and block by 8 months.
#Thats 9 doctors + (9 choose 2) pairs + 8 months + a constant

9+choose(9,2)+8+1
```

```
## [1] 54
```

```r
#54 predictors total. We use the library pwr.
#with an effect ratio of .15 and alpha level .05

library(pwr)
pwr.f2.test(u=54,v=135-54,f2=.15,sig.level=.05)
```

```
##
##      Multiple regression power calculation
##
##               u = 54
##               v = 81
##              f2 = 0.15
##       sig.level = 0.05
##           power = 0.3642497
```

```r
#our power is 36%, that means we have much worse than
#equal chance of finding significance. The standard
#is to want a power of 80%

#At best, assuming the month factor is insignificant we have
#9 + 9 choose 2 + 1 predictors

pwr.f2.test(u=46,v=135-46,f2=.15,sig.level=.05)
```

```
##
##      Multiple regression power calculation
##
##               u = 46
##               v = 89
##              f2 = 0.15
##       sig.level = 0.05
##           power = 0.4244568
```

```r
#A power of 42% that is too low.
#Effectivly we don't have enough data.

#If we just had the doctors and the 8 months

pwr.f2.test(u=18,v=135-18,f2=.15,sig.level=.05)
```

```
##
##      Multiple regression power calculation
##
##               u = 18
##               v = 117
##              f2 = 0.15
##       sig.level = 0.05
##           power = 0.7440315
```

```r
#That's not terrible. 74% is just about good enough.
#Unfortunately, the answer they want is whether
#doctor pairs make any difference.

#The answer is "Not enough data"

#It is determined that we do not have enough data to
#reasonably expect to get significance from each doctor pair.
#I'll run the models, but I don't expect to get anything.

########################################################################
#############################################################################
#3a) Detrmine the effectiveness of individual doctors.

#Lets build just the blocked factors.

swlm <- lm(Total_Production ~ DAY + MONTH,data=swp)
summary(swlm)
```

```
##
## Call:
## lm(formula = Total_Production ~ DAY + MONTH, data = swp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3657.5  -702.2    53.4   711.1  3823.0
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)     7570.4      470.9  16.076  < 2e-16 ***
## DAYMonday       3800.5      448.7   8.470 6.53e-14 ***
## DAYSaturday     2454.0     1088.0   2.256   0.0259 *
## DAYThursday     2784.6      446.4   6.238 6.63e-09 ***
## DAYTuesday      3100.3      443.8   6.986 1.61e-10 ***
## DAYWednesday    3121.9      452.4   6.901 2.47e-10 ***
## MONTHAugust     1051.8      516.2   2.038   0.0437 *
```

```
## MONTHFebruary   -460.9      467.5  -0.986   0.3262
## MONTHJanuary   -1113.8      532.0  -2.094   0.0384 *
## MONTHJuly        558.3      454.4   1.229   0.2216
## MONTHJune        196.3      454.6   0.432   0.6666
## MONTHMarch      -285.6      468.6  -0.610   0.5433
## MONTHMay        -256.7      449.5  -0.571   0.5690
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1408 on 122 degrees of freedom
## Multiple R-squared:  0.4414, Adjusted R-squared:  0.3864
## F-statistic: 8.033 on 12 and 122 DF,  p-value: 6.236e-11
```

```r
#adj R is .39
#Lets build the main effects.

docsnam <- paste0(c("(",paste0(names(docs),collapse="+"),")"),collapse="")

form <- formula(paste0(c("Total_Production ~  MONTH + DAY +",docsnam), collapse=""))
swlm1 <- lm(form,data=swp)

#Lets look at the model:
anova(swlm1)
```

```
## Analysis of Variance Table
##
## Response: Total_Production
##             Df    Sum Sq  Mean Sq F value    Pr(>F)
## MONTH        7  39155687  5593670  3.1656 0.0042864 **
## DAY          5 151922573 30384515 17.1954 1.269e-12 ***
## BRITTANY     1   1325897  1325897  0.7504 0.3881982
## HEATHER      1   6856670  6856670  3.8804 0.0513007 .
## KEVIN        1    672235   672235  0.3804 0.5386114
## OLIMBI       1    111817   111817  0.0633 0.8018415
## PINO         1  20566109 20566109 11.6389 0.0008969 ***
## POUYAN       1  11528687 11528687  6.5244 0.0119714 *
## ABBY         1     93299    93299  0.0528 0.8186755
## SAMARA       1    212346   212346  0.1202 0.7294928
## TEMP         1    791152   791152  0.4477 0.5047782
## Residuals  113 199672926  1767017
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(swlm1)
```

```
##
## Call:
## lm(formula = form, data = swp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3323.5  -717.8   -34.3   672.7  2997.7
##
```

```
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     6681.53    1257.47   5.313 5.47e-07 ***
## MONTHAugust     1409.60     532.46   2.647  0.00927 **
## MONTHFebruary   -718.17     459.93  -1.561  0.12121
## MONTHJanuary    -810.66     529.86  -1.530  0.12882
## MONTHJuly        257.78     458.88   0.562  0.57539
## MONTHJune         -5.53     441.49  -0.013  0.99003
## MONTHMarch      -172.35     492.35  -0.350  0.72695
## MONTHMay        -340.20     438.07  -0.777  0.43903
## DAYMonday       2457.49    1153.30   2.131  0.03527 *
## DAYSaturday     1869.27    1490.99   1.254  0.21253
## DAYThursday     2850.57    1378.38   2.068  0.04092 *
## DAYTuesday      2442.42    1228.41   1.988  0.04920 *
## DAYWednesday    2754.90    1324.63   2.080  0.03981 *
## BRITTANY1       -215.98     698.09  -0.309  0.75760
## HEATHER1         738.06     504.95   1.462  0.14661
## KEVIN1           427.10     452.57   0.944  0.34733
## OLIMBI1          674.77     565.99   1.192  0.23568
## PINO1           1489.99     461.48   3.229  0.00163 **
## POUYAN1         1267.48     568.94   2.228  0.02787 *
## ABBY1             69.98     545.51   0.128  0.89815
## SAMARA1          325.97    1109.23   0.294  0.76939
## TEMP1           -223.37     333.82  -0.669  0.50478
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1329 on 113 degrees of freedom
## Multiple R-squared:  0.5388, Adjusted R-squared:  0.453
## F-statistic: 6.285 on 21 and 113 DF,  p-value: 3.002e-11
```

```r
#Adjusted R^2 is low: .45


###########################################################################
###########################################################################
#Lets run the doctor pairs.

#3b) Determine effectiveness of doctors indivdually and in pairs.
#We build a linear model.
#Net_Production ~ DAY + Month + (each doct)+(each doc pair interaction)

#These are the pairs for interaction term.
interact <- NULL
for(i in 1:8){
  for(j in (i+1):9){
    intname <- paste0(c(names(docs)[i],names(docs)[j]),collapse = "*")
    interact <- c(interact,intname)
  }
}

#There should be 9 Choose 2 of them:

choose(9,2);length(interact)
```

```
## [1] 36
```

```
## [1] 36
```

```r
#Good. Now lets put it all together.
docsnam_all <- paste0(c("(",paste0(c(names(docs),interact),collapse="+"),")"),collapse="")

form <- formula(paste0(c("Total_Production ~ MONTH + DAY+",docsnam_all), collapse=""))
swlm2 <- lm(form,data=swp)
summary(swlm2)
```

```
##
## Call:
## lm(formula = form, data = swp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2949.2  -569.5     0.0   610.5  2790.9
##
## Coefficients: (10 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        10019.712   6988.728   1.434  0.15524
## MONTHAugust         1146.062    718.649   1.595  0.11440
## MONTHFebruary      -1374.369    510.468  -2.692  0.00851 **
## MONTHJanuary       -1214.638    613.412  -1.980  0.05085 .
## MONTHJuly            -40.632    507.903  -0.080  0.93642
## MONTHJune            -36.136    452.762  -0.080  0.93657
## MONTHMarch         -1015.099    585.670  -1.733  0.08660 .
## MONTHMay            -587.995    464.084  -1.267  0.20854
## DAYMonday           3368.931   3478.179   0.969  0.33543
## DAYSaturday         1420.201   4396.653   0.323  0.74746
## DAYThursday         2785.943   3231.274   0.862  0.39096
## DAYTuesday          3399.377   3211.257   1.059  0.29272
## DAYWednesday        3479.019   3175.784   1.095  0.27633
## BRITTANY1           2076.941   3125.798   0.664  0.50816
## HEATHER1           -2250.602   5193.987  -0.433  0.66586
## KEVIN1             -3338.416   4748.989  -0.703  0.48395
## OLIMBI1            -1622.324   4475.137  -0.363  0.71784
## PINO1               3247.622   2285.800   1.421  0.15895
## POUYAN1            -2362.111   4518.736  -0.523  0.60249
## ABBY1                162.752   2880.732   0.056  0.95508
## SAMARA1              687.728   3102.980   0.222  0.82512
## TEMP1              -2380.519   3024.127  -0.787  0.43332
## BRITTANY1:HEATHER1 -1589.102   3387.480  -0.469  0.64016
## BRITTANY1:KEVIN1   -1908.608   2127.787  -0.897  0.37220
## BRITTANY1:OLIMBI1   -143.104   2186.230  -0.065  0.94796
## BRITTANY1:PINO1    -1784.775   2054.147  -0.869  0.38731
## BRITTANY1:POUYAN1      3.225   1471.836   0.002  0.99826
## BRITTANY1:ABBY1    -1041.043   1942.431  -0.536  0.59336
## BRITTANY1:SAMARA1         NA         NA      NA       NA
## BRITTANY1:TEMP1     -819.726   1302.425  -0.629  0.53075
## HEATHER1:KEVIN1     3986.581   2797.327   1.425  0.15769
## HEATHER1:OLIMBI1     470.870   3448.790   0.137  0.89172
```

```
## HEATHER1:PINO1     -1570.968   2008.048  -0.782  0.43614
## HEATHER1:POUYAN1    2480.802   5443.504   0.456  0.64972
## HEATHER1:ABBY1      2376.933   3660.742   0.649  0.51785
## HEATHER1:SAMARA1     522.425   3085.062   0.169  0.86592
## HEATHER1:TEMP1      2162.418   1697.789   1.274  0.20617
## KEVIN1:OLIMBI1      2567.263   3740.818   0.686  0.49436
## KEVIN1:PINO1       -1933.533   3083.603  -0.627  0.53228
## KEVIN1:POUYAN1      3147.764   4438.147   0.709  0.48006
## KEVIN1:ABBY1         204.675   2814.974   0.073  0.94220
## KEVIN1:SAMARA1            NA         NA      NA       NA
## KEVIN1:TEMP1        2486.975   1926.974   1.291  0.20026
## OLIMBI1:PINO1             NA         NA      NA       NA
## OLIMBI1:POUYAN1     2295.499   5460.032   0.420  0.67522
## OLIMBI1:ABBY1             NA         NA      NA       NA
## OLIMBI1:SAMARA1           NA         NA      NA       NA
## OLIMBI1:TEMP1        413.798   1567.182   0.264  0.79237
## PINO1:POUYAN1        259.291   2566.908   0.101  0.91977
## PINO1:ABBY1        -1905.191   1893.199  -1.006  0.31705
## PINO1:SAMARA1             NA         NA      NA       NA
## PINO1:TEMP1         -821.314   1616.391  -0.508  0.61266
## POUYAN1:ABBY1             NA         NA      NA       NA
## POUYAN1:SAMARA1           NA         NA      NA       NA
## POUYAN1:TEMP1        952.290   1297.067   0.734  0.46481
## ABBY1:SAMARA1             NA         NA      NA       NA
## ABBY1:TEMP1        -1382.947   1256.336  -1.101  0.27403
## SAMARA1:TEMP1             NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1250 on 87 degrees of freedom
## Multiple R-squared:  0.686,  Adjusted R-squared:  0.5163
## F-statistic: 4.044 on 47 and 87 DF,  p-value: 8.949e-09
```

```r
anova(swlm2)
```

```
## Analysis of Variance Table
##
## Response: Total_Production
##                   Df    Sum Sq  Mean Sq F value    Pr(>F)
## MONTH              7  39155687  5593670  3.5798 0.0019729 **
## DAY                5 151922573 30384515 19.4451 5.965e-13 ***
## BRITTANY           1   1325897  1325897  0.8485 0.3595162
## HEATHER            1   6856670  6856670  4.3880 0.0390997 *
## KEVIN              1    672235   672235  0.4302 0.5136182
## OLIMBI             1    111817   111817  0.0716 0.7897131
## PINO               1  20566109 20566109 13.1616 0.0004813 ***
## POUYAN             1  11528687 11528687  7.3780 0.0079644 **
## ABBY               1     93299    93299  0.0597 0.8075329
## SAMARA             1    212346   212346  0.1359 0.7132930
## TEMP               1    791152   791152  0.5063 0.4786440
## BRITTANY:HEATHER   1    569140   569140  0.3642 0.5477364
## BRITTANY:KEVIN     1  14215675 14215675  9.0975 0.0033552 **
## BRITTANY:OLIMBI    1    387182   387182  0.2478 0.6198960
## BRITTANY:PINO      1   8741360  8741360  5.5942 0.0202436 *
```

```
## BRITTANY:POUYAN   1      2579      2579  0.0017 0.9676842
## BRITTANY:ABBY     1     62710     62710  0.0401 0.8416894
## BRITTANY:TEMP     1   6618671   6618671  4.2357 0.0425740 *
## HEATHER:KEVIN     1   6406779   6406779  4.1001 0.0459462 *
## HEATHER:OLIMBI    1    813746    813746  0.5208 0.4724485
## HEATHER:PINO      1    783535    783535  0.5014 0.4807628
## HEATHER:POUYAN    1    126585    126585  0.0810 0.7766093
## HEATHER:ABBY      1    639749    639749  0.4094 0.5239468
## HEATHER:SAMARA    1    976285    976285  0.6248 0.4314224
## HEATHER:TEMP      1      7583      7583  0.0049 0.9446239
## KEVIN:OLIMBI      1   1741903   1741903  1.1148 0.2939731
## KEVIN:PINO        1   4146718   4146718  2.6538 0.1069213
## KEVIN:POUYAN      1     58913     58913  0.0377 0.8464951
## KEVIN:ABBY        1     35330     35330  0.0226 0.8808238
## KEVIN:TEMP        1  12342277  12342277  7.8986 0.0061106 **
## OLIMBI:POUYAN     1    222283    222283  0.1423 0.7069690
## OLIMBI:TEMP       1    272456    272456  0.1744 0.6772924
## PINO:POUYAN       1    293090    293090  0.1876 0.6660209
## PINO:ABBY         1    577918    577918  0.3698 0.5446715
## PINO:TEMP         1    343279    343279  0.2197 0.6404512
## POUYAN:TEMP       1   1449057   1449057  0.9273 0.3382223
## ABBY:TEMP         1   1893399   1893399  1.2117 0.2740299
## Residuals        87 135944724   1562583
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#Adj R squared is .52, not terrible, but not good.

#I'll fit one more model with just the significant terms of the above model.
docsnam_int_sig <- paste0(c("(",paste0(c(names(docs),interact[c(21,9,8,4,2)]),
                                       collapse="+"),")"),collapse="")

form <- formula(paste0(c("Total_Production ~ MONTH + DAY +",docsnam_int_sig), collapse=""))
swlm3 <- lm(form,data=swp)
summary(swlm3)
```

```
##
## Call:
## lm(formula = form, data = swp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2944.7  -657.4    55.7   731.0  3353.6
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)          7119.4     1205.2   5.907  4.1e-08 ***
## MONTHAugust          1043.2      515.2   2.025  0.04535 *
## MONTHFebruary       -1254.4      446.5  -2.809  0.00589 **
## MONTHJanuary        -1049.8      519.4  -2.021  0.04574 *
## MONTHJuly             219.4      423.3   0.518  0.60530
## MONTHJune             107.5      403.4   0.266  0.79047
## MONTHMarch           -795.9      487.5  -1.633  0.10547
## MONTHMay             -453.4      402.2  -1.127  0.26213
```

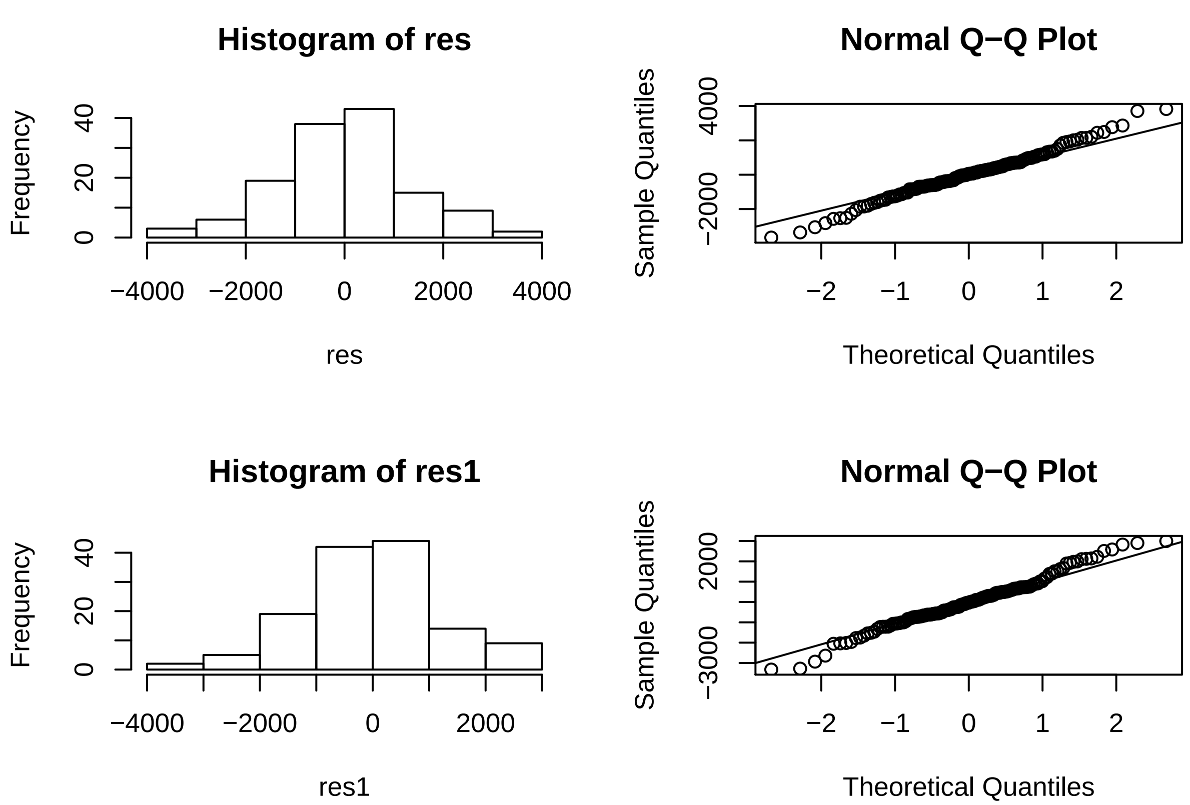
```
## DAYMonday          3891.2     1173.1   3.317  0.00124 **
## DAYSaturday        4514.6     1570.4   2.875  0.00487 **
## DAYThursday        3314.0     1344.0   2.466  0.01525 *
## DAYTuesday         3112.2     1202.8   2.587  0.01100 *
## DAYWednesday       3406.5     1335.4   2.551  0.01214 *
## BRITTANY1          1056.2      970.1   1.089  0.27869
## HEATHER1           -484.6      677.2  -0.716  0.47578
## KEVIN1             -505.9      663.6  -0.762  0.44753
## OLIMBI1             699.5      563.6   1.241  0.21722
## PINO1               425.7      523.5   0.813  0.41792
## POUYAN1            1377.9      533.0   2.585  0.01107 *
## ABBY1              -192.7      516.7  -0.373  0.70986
## SAMARA1             801.8     1028.3   0.780  0.43728
## TEMP1             -1237.2      566.5  -2.184  0.03111 *
## KEVIN1:TEMP1       1536.4      631.0   2.435  0.01653 *
## HEATHER1:KEVIN1    2048.7      748.5   2.737  0.00725 **
## BRITTANY1:TEMP1    -920.8      578.2  -1.593  0.11417
## BRITTANY1:PINO1    1130.9      908.4   1.245  0.21586
## BRITTANY1:KEVIN1  -1381.6      744.7  -1.855  0.06628 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1206 on 108 degrees of freedom
## Multiple R-squared:  0.6372, Adjusted R-squared:  0.5498
## F-statistic: 7.295 on 26 and 108 DF,  p-value: 4.209e-14
```

```
#Adj R is .55

#########################################################################################
#########################################################################################
#3c) Model Adequecy


#We need to first look at correlation of the factors.

docs_n <- sapply(docs,FUN=as.numeric)
cor(docs_n)
```

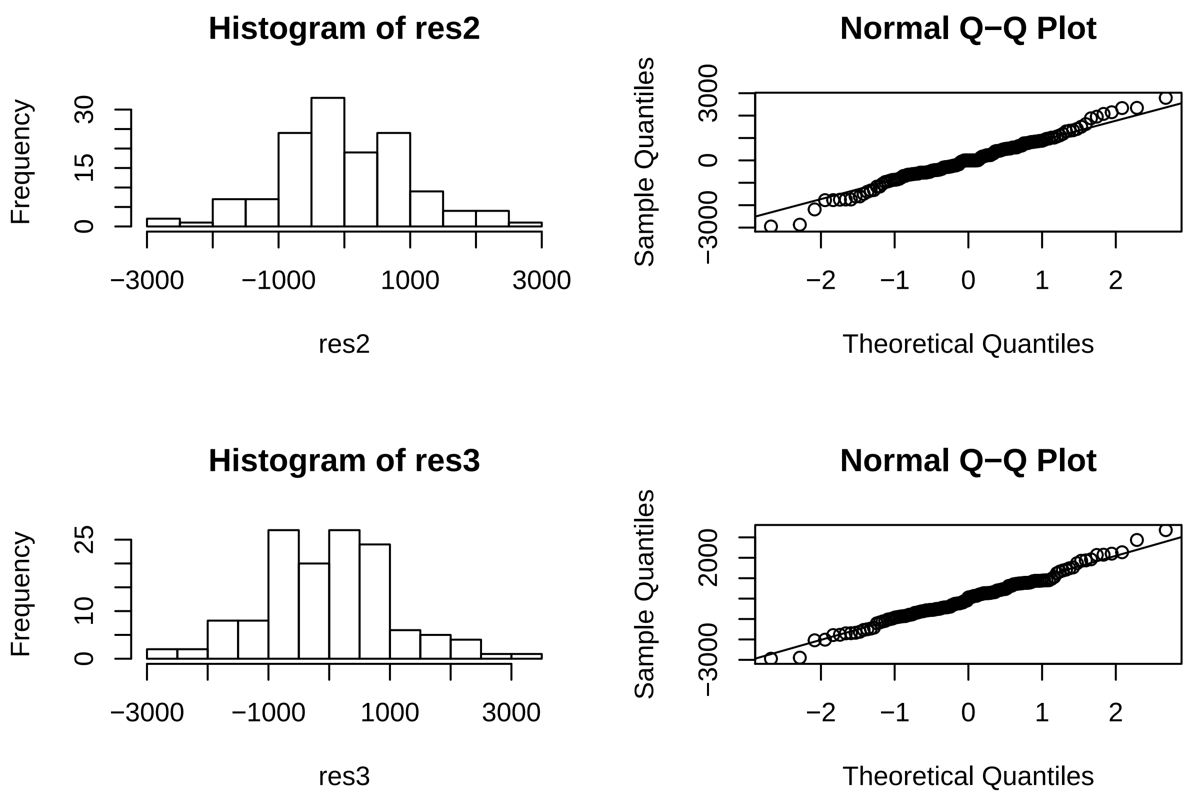
```
##               BRITTANY      HEATHER       KEVIN     OLIMBI       PINO
## BRITTANY  1.000000000 -0.361619132  0.06471087  0.1557398 -0.2455069
## HEATHER  -0.361619132  1.000000000 -0.39575357  0.1462642  0.5038487
## KEVIN     0.064710870 -0.395753572  1.00000000 -0.5994312 -0.4871723
## OLIMBI    0.155739825  0.146264181 -0.59943122  1.0000000  0.3033686
## PINO     -0.245506885  0.503848722 -0.48717227  0.3033686  1.0000000
## POUYAN    0.004929401 -0.395313285  0.32727069 -0.5468531 -0.3144680
## ABBY     -0.323974995 -0.217536034  0.10839166 -0.3124638 -0.2119115
## SAMARA   -0.262435613 -0.015854406  0.20431380 -0.2543532 -0.1856730
## TEMP     -0.109913438  0.005837572 -0.19951223  0.1361255  0.1632187
##                 POUYAN        ABBY      SAMARA         TEMP
## BRITTANY  0.004929401 -0.32397500 -0.26243561 -0.109913438
## HEATHER  -0.395313285 -0.21753603 -0.01585441  0.005837572
## KEVIN     0.327270691  0.10839166  0.20431380 -0.199512232
## OLIMBI   -0.546853073 -0.31246379 -0.25435320  0.136125543
## PINO     -0.314468033 -0.21191154 -0.18567295  0.163218722
```

```
## POUYAN     1.000000000  0.36312704 -0.24246706 -0.185517066
## ABBY       0.363127038  1.00000000 -0.14792673 -0.083024467
## SAMARA    -0.242467064 -0.14792673  1.00000000 -0.238560949
## TEMP      -0.185517066 -0.08302447 -0.23856095  1.000000000
```

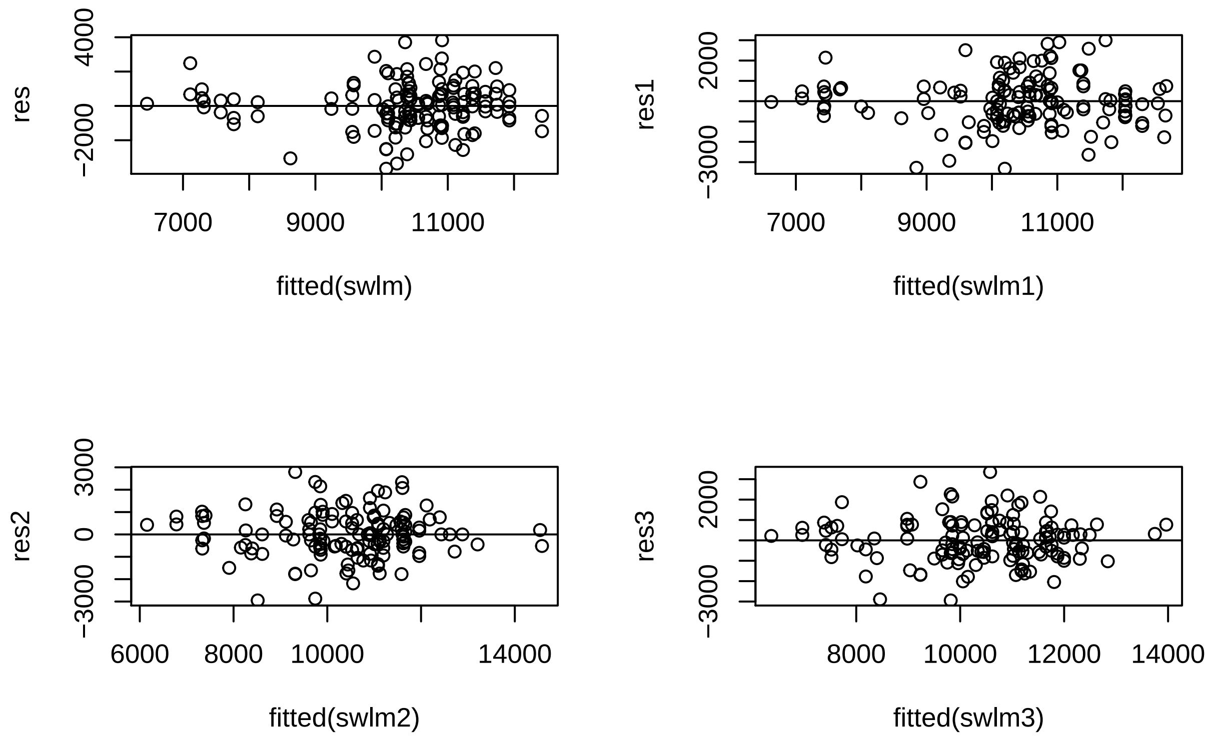
```
#We have two stronger than .5, but not by much. .59 and .54

res <- resid(swlm)
res1 <- resid(swlm1)
res2 <- resid(swlm2)
res3 <- resid(swlm3)

par(mfrow=c(2,2))
hist(res)
qqnorm(res);qqline(res)

hist(res1)
qqnorm(res1);qqline(res1)
```



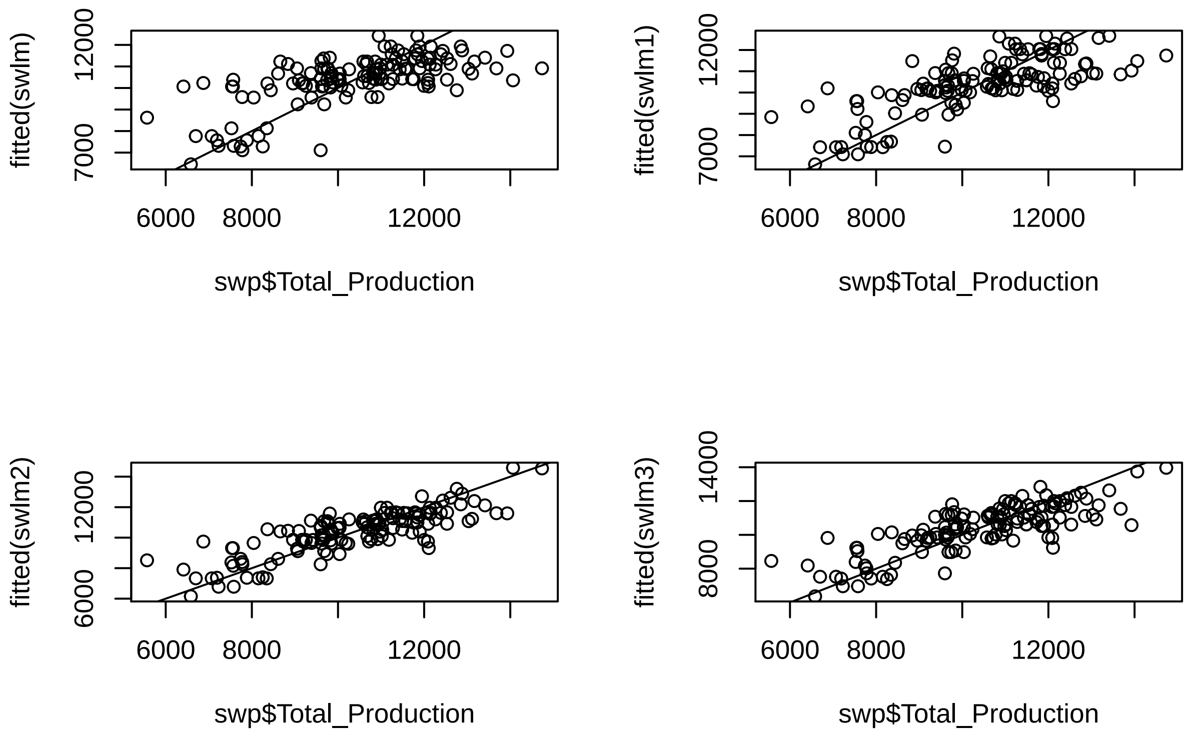

```
hist(res2)
qqnorm(res2);qqline(res2)

hist(res3)
qqnorm(res3);qqline(res3)
```



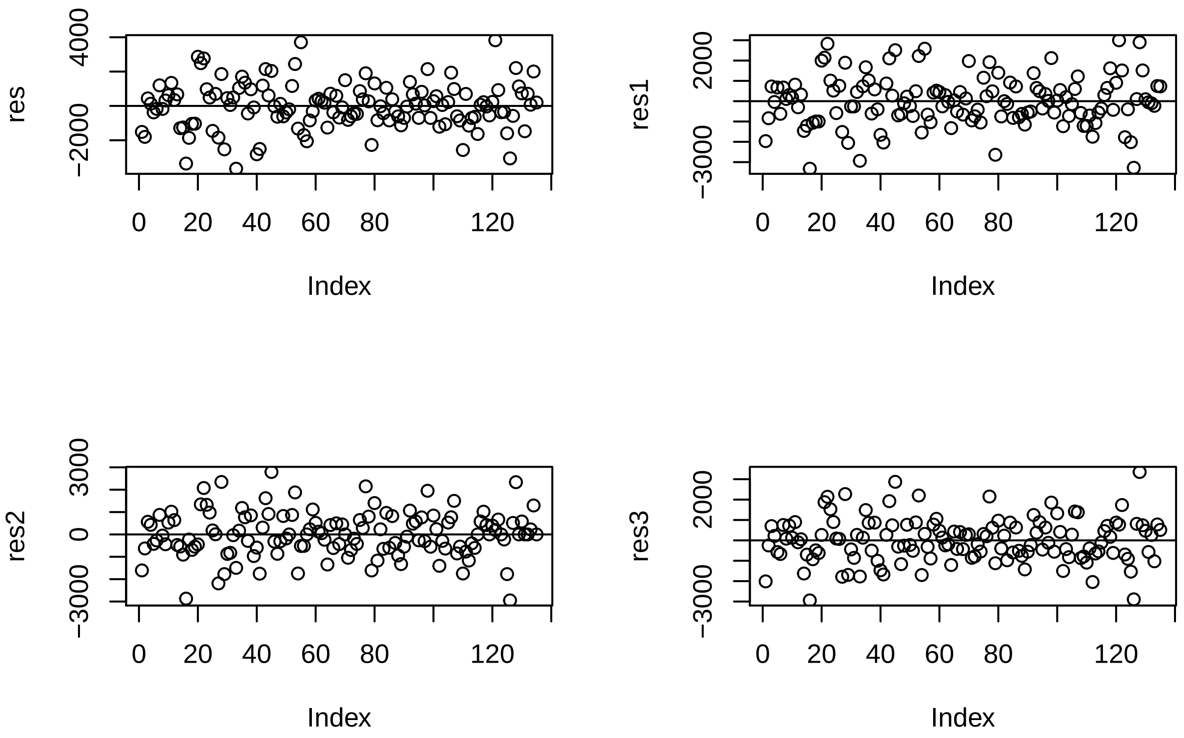

```
#Residuals are normal across the board.

plot(res~fitted(swlm));abline(h=0)
plot(res1~fitted(swlm1));abline(h=0)
plot(res2~fitted(swlm2));abline(h=0)
plot(res3~fitted(swlm3));abline(h=0)
```



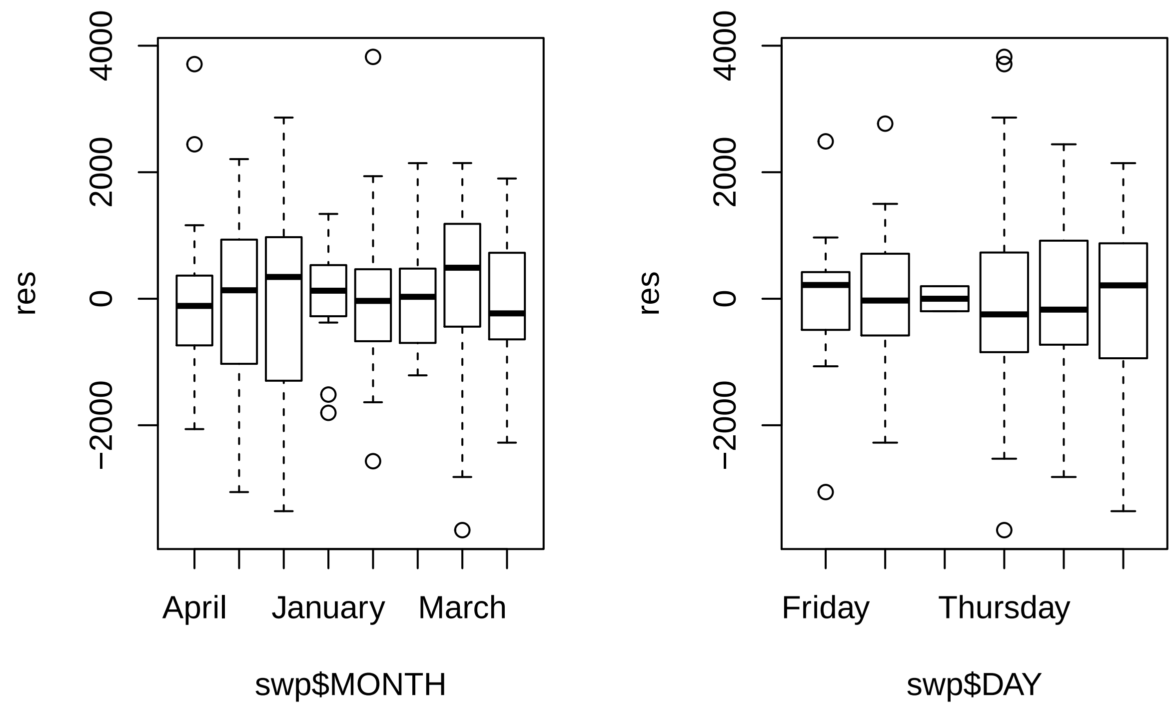

```
#There is heteroscedasticity.
#There is definatly a trend.
#For some the middle the variance increases.
#it starts low gets high and then gets low.
#For some there is an increase in variance
#with an increase in level.

#This does not effect estimates
#but it does effect estimated variances (and hence p-values.)
#Our p-values may be lower than they should be.

plot(fitted(swlm)~swp$Total_Production);abline(c(0,1))
plot(fitted(swlm1)~swp$Total_Production);abline(c(0,1))
plot(fitted(swlm2)~swp$Total_Production);abline(c(0,1))
plot(fitted(swlm3)~swp$Total_Production);abline(c(0,1))
```



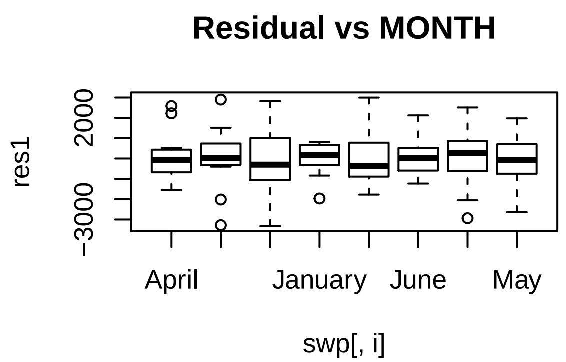

```
#Actual vs fitted looks good, on the whole.
#there is some slight non-linearity.
#but it is small.

plot(res);abline(h=0)
plot(res1);abline(h=0)
plot(res2);abline(h=0)
plot(res3);abline(h=0)
```

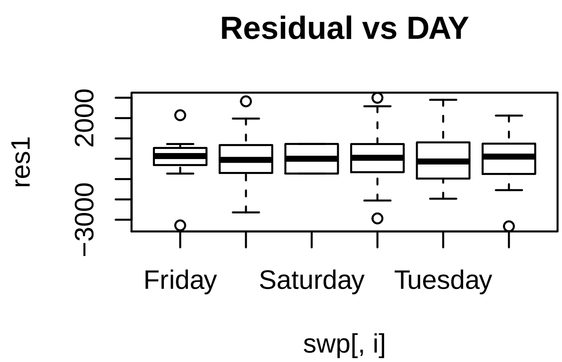


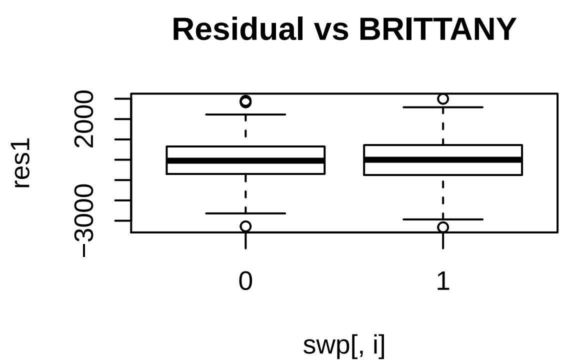

```
#Not serially correlated.

#Lets check residuals vs each factor.

par(mfrow=c(1,2))
plot(res~swp$MONTH)
plot(res~swp$DAY)
```

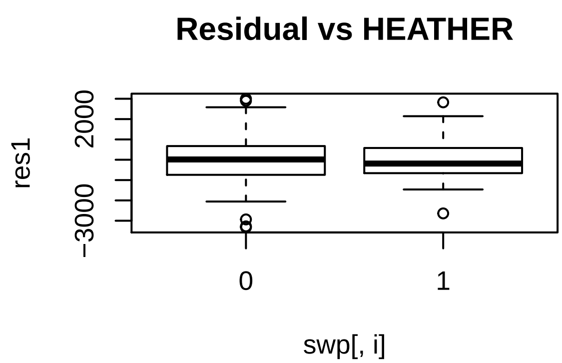


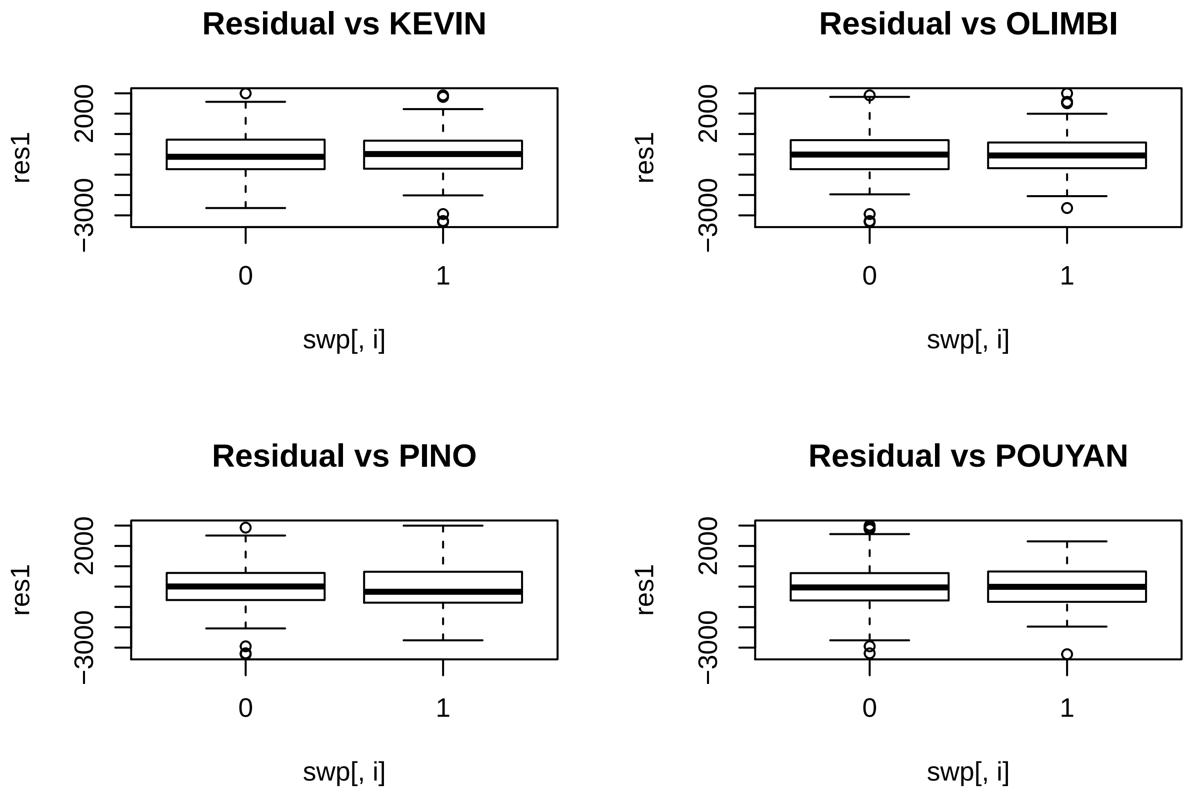

```r
#Some heteroscedasticity.

par(mfrow=c(2,2))
for(i in attr(swlm1$terms,"term.labels")[1:11]){
  plot(res1~swp[,i],main=paste0("Residual vs ",i))
}
```


Residual vs MONTH
res1
2000
−3000
April
January
June
May
swp[, i]

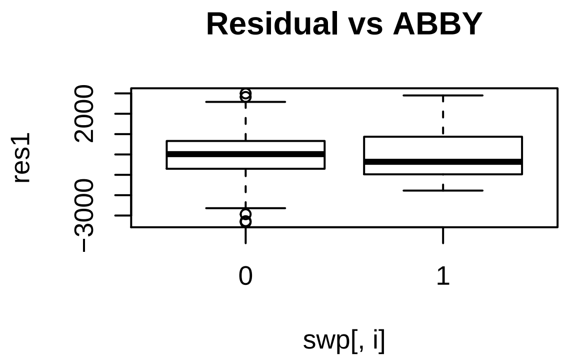

Residual vs DAY
res1
2000
−3000
Friday
Saturday
Tuesday
swp[, i]

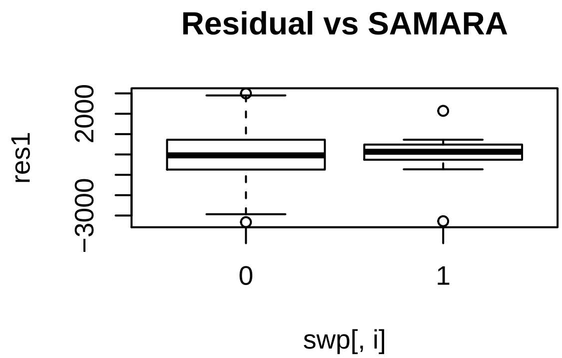

Residual vs BRITTANY
res1
2000
−3000
0
1
swp[, i]

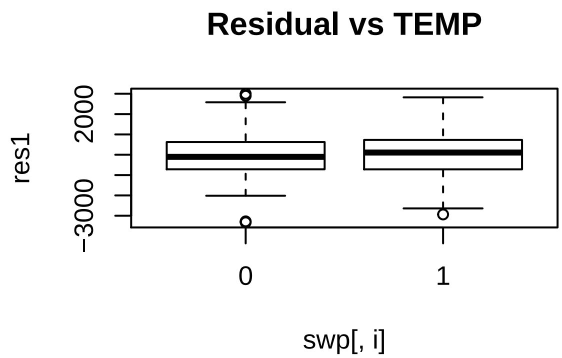

Residual vs HEATHER
res1
2000
−3000
0
1
swp[, i]



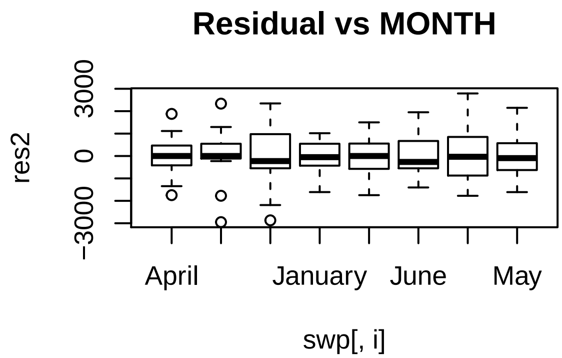

```
#Some heteroscedasticity.
par(mfrow=c(2,2))
```

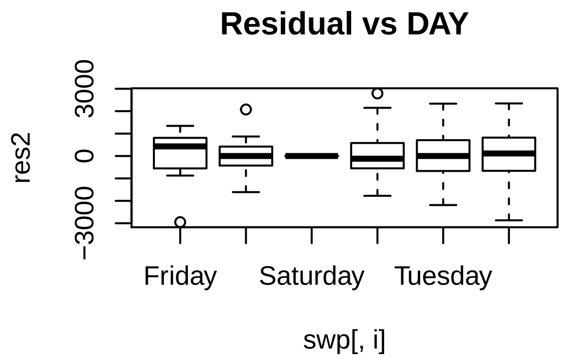


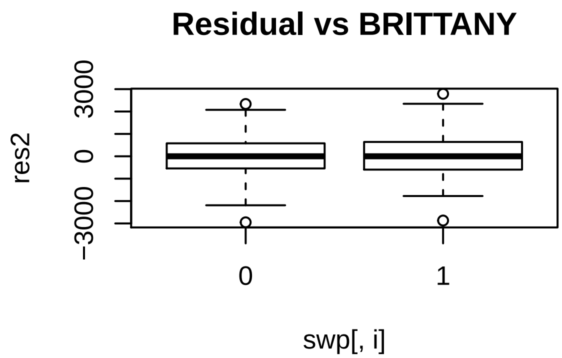


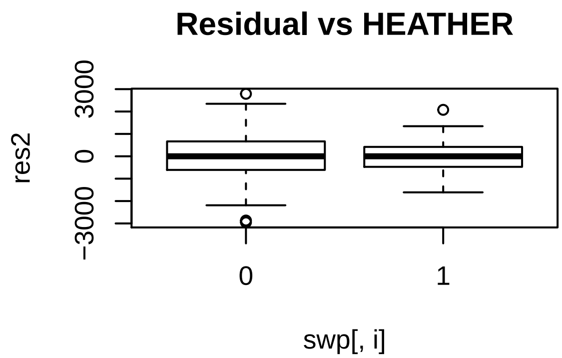


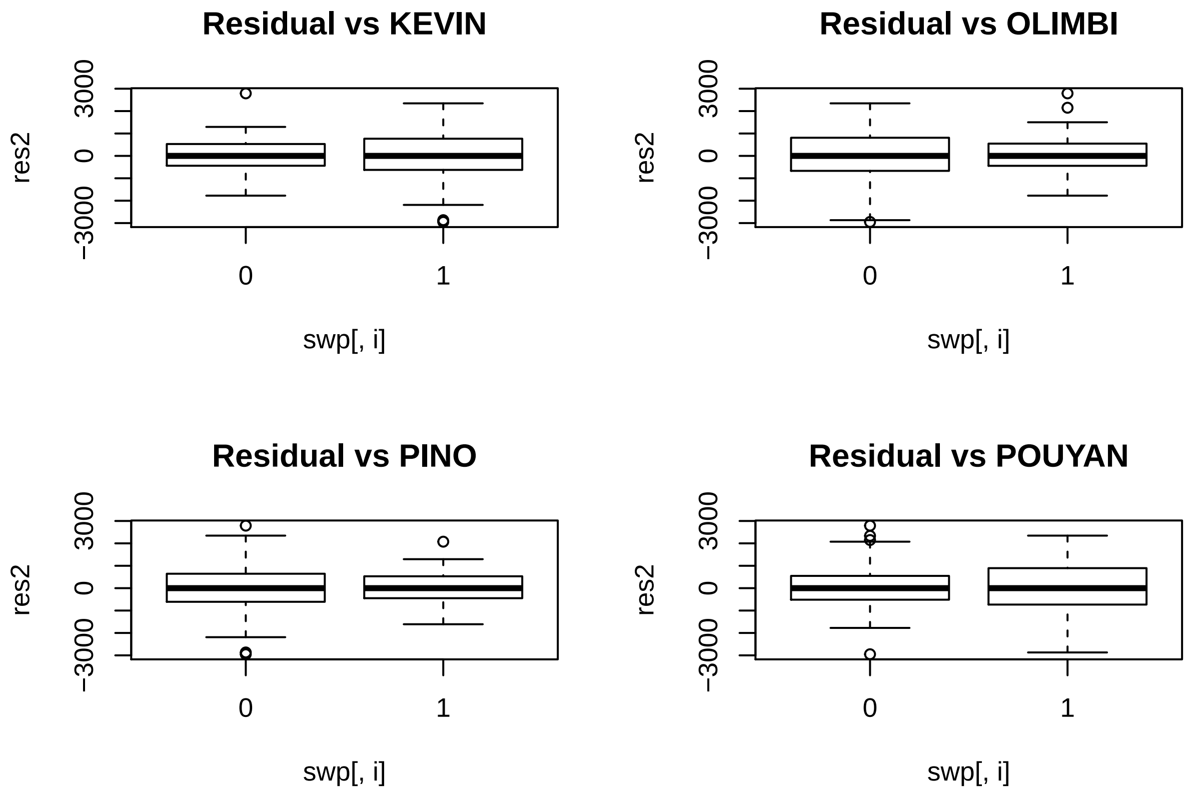

```
for(i in attr(swlm2$terms,"term.labels")[1:11]){
  plot(res2~swp[,i],main=paste0("Residual vs ",i))
}
```


Residual vs MONTH
res2
3000
0
−3000
April
January
June
May
swp[, i]

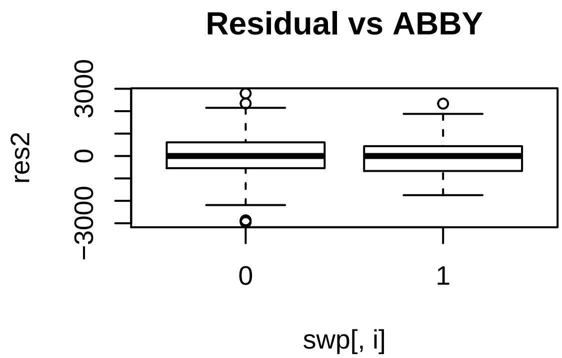

Residual vs DAY
res2
3000
0
−3000
Friday
Saturday
Tuesday
swp[, i]

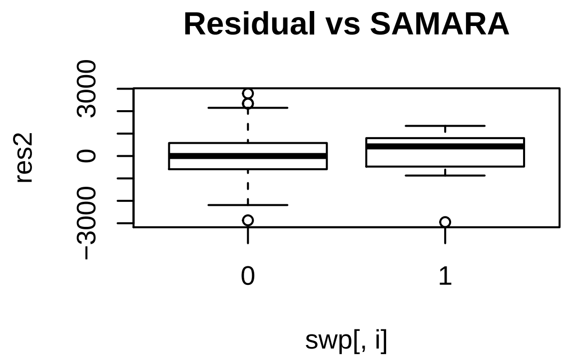

Residual vs BRITTANY
res2
3000
0
−3000
0
1
swp[, i]

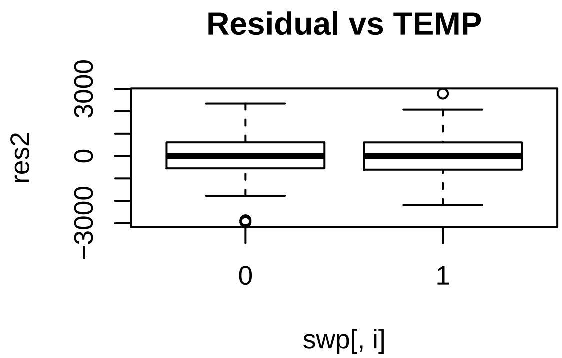

Residual vs HEATHER
res2
3000
0
−3000
0
1
swp[, i]



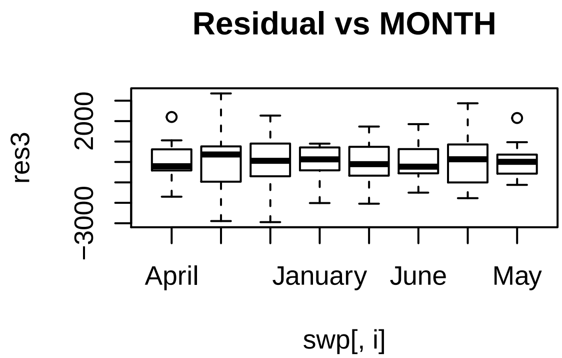

```r
#Some heteroscedasticity.
par(mfrow=c(2,2))
```

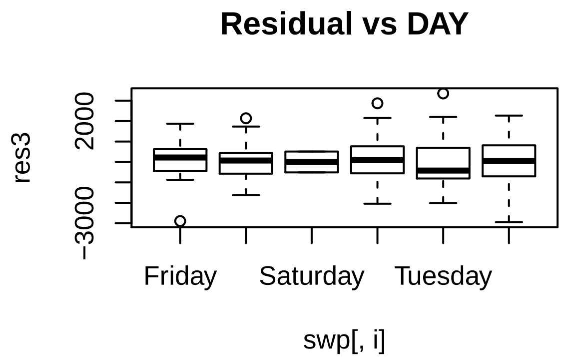


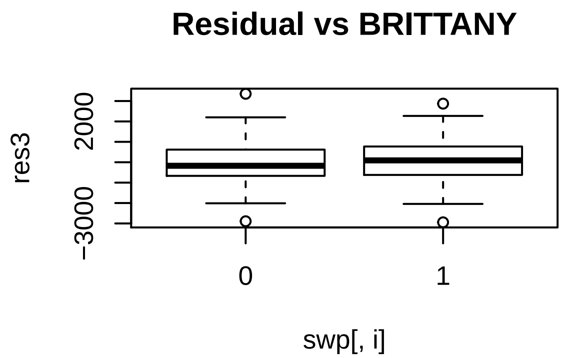


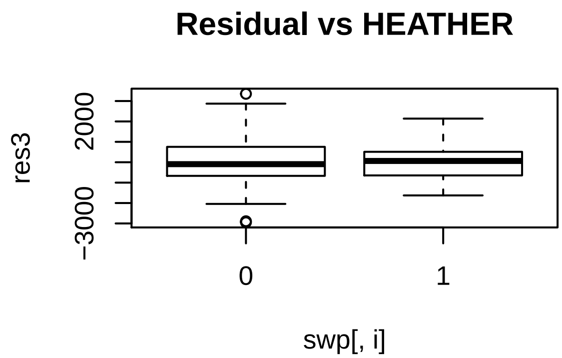


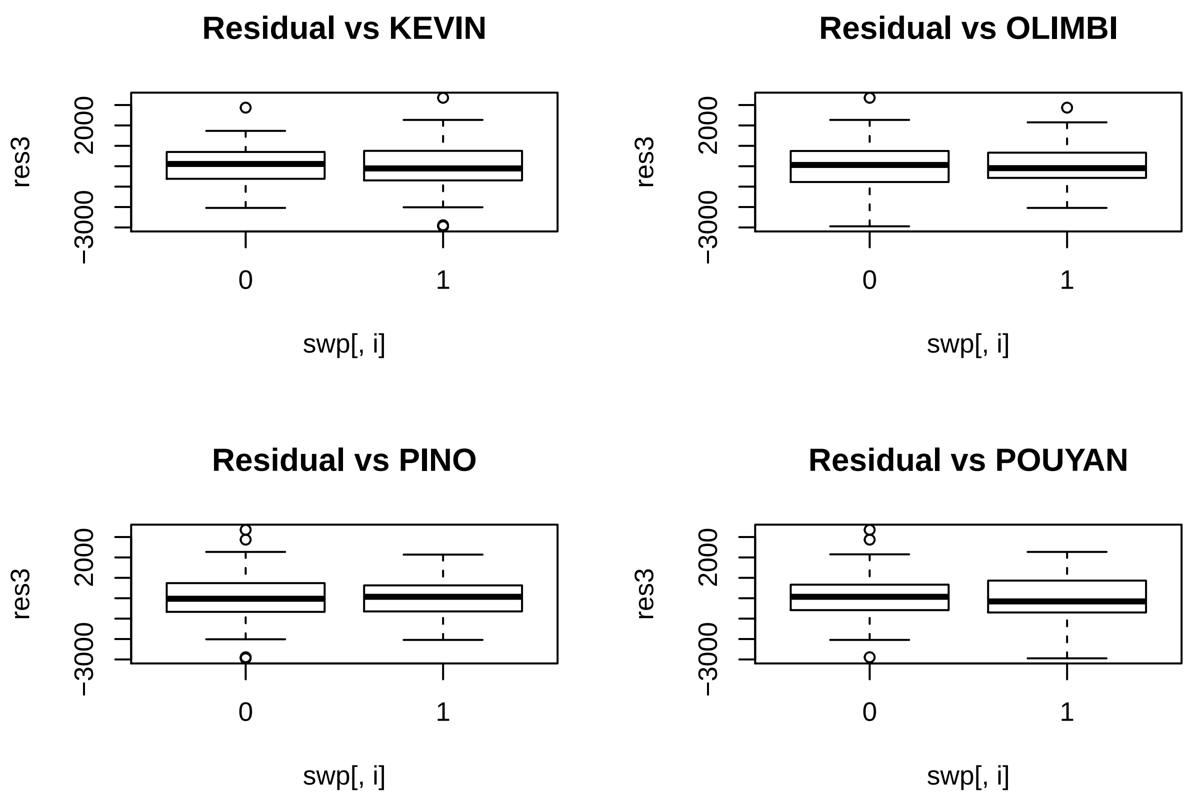

```
for(i in attr(swlm3$terms,"term.labels")[1:11]){
  plot(res3~swp[,i],main=paste0("Residual vs ",i))
}
```


Residual vs MONTH
res3
2000
−3000
April
January
June
May
swp[, i]

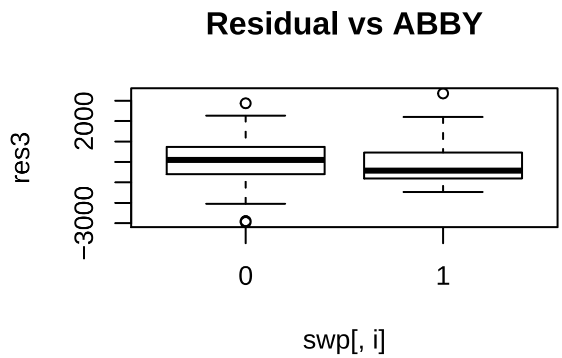

Residual vs DAY
res3
2000
−3000
Friday
Saturday
Tuesday
swp[, i]

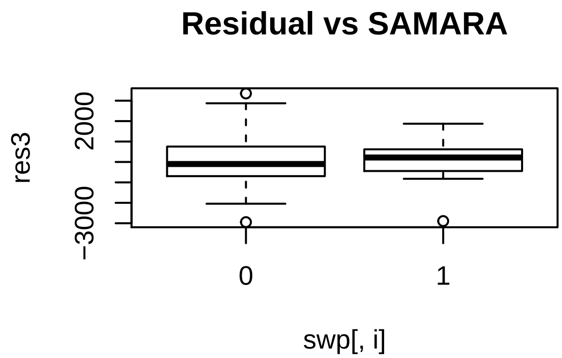

Residual vs BRITTANY
res3
2000
−3000
0
1
swp[, i]

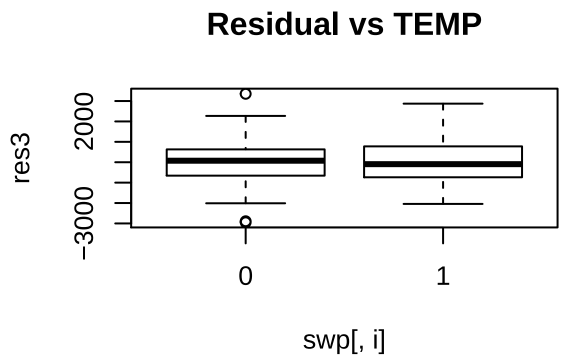

Residual vs HEATHER
res3
2000
−3000
0
1
swp[, i]




```r
#Some heteroscedasticity.

par(mfrow=c(1,1)) #put settings back to default.
```








```r
#Some heteroscadiscty means that there may be significance
#when there isn't any. Estimates remain accurate though.
#We press forward with this in mind.
##############################################################
##############################################################
#4) Interpretation and Discussion.

#Lets look at all the models together.

anova(swlm,swlm1,swlm2,swlm3)
```

```
## Analysis of Variance Table
##
## Model 1: Total_Production ~ DAY + MONTH
## Model 2: Total_Production ~ MONTH + DAY + (BRITTANY + HEATHER + KEVIN +
##     OLIMBI + PINO + POUYAN + ABBY + SAMARA + TEMP)
## Model 3: Total_Production ~ MONTH + DAY + (BRITTANY + HEATHER + KEVIN +
##     OLIMBI + PINO + POUYAN + ABBY + SAMARA + TEMP + BRITTANY *
##     HEATHER + BRITTANY * KEVIN + BRITTANY * OLIMBI + BRITTANY *
##     PINO + BRITTANY * POUYAN + BRITTANY * ABBY + BRITTANY * SAMARA +
##     BRITTANY * TEMP + HEATHER * KEVIN + HEATHER * OLIMBI + HEATHER *
##     PINO + HEATHER * POUYAN + HEATHER * ABBY + HEATHER * SAMARA +
##     HEATHER * TEMP + KEVIN * OLIMBI + KEVIN * PINO + KEVIN *
##     POUYAN + KEVIN * ABBY + KEVIN * SAMARA + KEVIN * TEMP + OLIMBI *
##     PINO + OLIMBI * POUYAN + OLIMBI * ABBY + OLIMBI * SAMARA +
##     OLIMBI * TEMP + PINO * POUYAN + PINO * ABBY + PINO * SAMARA +
```

```
##     PINO * TEMP + POUYAN * ABBY + POUYAN * SAMARA + POUYAN *
##     TEMP + ABBY * SAMARA + ABBY * TEMP + SAMARA * TEMP)
## Model 4: Total_Production ~ MONTH + DAY + (BRITTANY + HEATHER + KEVIN +
##     OLIMBI + PINO + POUYAN + ABBY + SAMARA + TEMP + KEVIN * TEMP +
##     HEATHER * KEVIN + BRITTANY * TEMP + BRITTANY * PINO + BRITTANY *
##     KEVIN)
##   Res.Df       RSS  Df Sum of Sq      F   Pr(>F)
## 1    122 241831139
## 2    113 199672926   9  42158213 2.9978 0.003692 **
## 3     87 135944724  26  63728202 1.5686 0.063170 .
## 4    108 157073438 -21 -21128714 0.6439 0.873981
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#The absolutly most significant model compared to our
#blocking factors (Month and Day) is the model with
#the main effects of the doctors alone (with blocked factors.)

#The reduced F-Test shows that the interaction model
#is somewhat significant at .06 compared to blocked factors.
#All the interaction terms together are significant

anova(swlm2)
```

```
## Analysis of Variance Table
##
## Response: Total_Production
##                  Df    Sum Sq  Mean Sq F value    Pr(>F)
## MONTH             7  39155687  5593670  3.5798 0.0019729 **
## DAY               5 151922573 30384515 19.4451 5.965e-13 ***
## BRITTANY          1   1325897  1325897  0.8485 0.3595162
## HEATHER           1   6856670  6856670  4.3880 0.0390997 *
## KEVIN             1    672235   672235  0.4302 0.5136182
## OLIMBI            1    111817   111817  0.0716 0.7897131
## PINO              1  20566109 20566109 13.1616 0.0004813 ***
## POUYAN            1  11528687 11528687  7.3780 0.0079644 **
## ABBY              1     93299    93299  0.0597 0.8075329
## SAMARA            1    212346   212346  0.1359 0.7132930
## TEMP              1    791152   791152  0.5063 0.4786440
## BRITTANY:HEATHER  1    569140   569140  0.3642 0.5477364
## BRITTANY:KEVIN    1  14215675 14215675  9.0975 0.0033552 **
## BRITTANY:OLIMBI   1    387182   387182  0.2478 0.6198960
## BRITTANY:PINO     1   8741360  8741360  5.5942 0.0202436 *
## BRITTANY:POUYAN   1      2579     2579  0.0017 0.9676842
## BRITTANY:ABBY     1     62710    62710  0.0401 0.8416894
## BRITTANY:TEMP     1   6618671  6618671  4.2357 0.0425740 *
## HEATHER:KEVIN     1   6406779  6406779  4.1001 0.0459462 *
## HEATHER:OLIMBI    1    813746   813746  0.5208 0.4724485
## HEATHER:PINO      1    783535   783535  0.5014 0.4807628
## HEATHER:POUYAN    1    126585   126585  0.0810 0.7766093
## HEATHER:ABBY      1    639749   639749  0.4094 0.5239468
## HEATHER:SAMARA    1    976285   976285  0.6248 0.4314224
## HEATHER:TEMP      1      7583     7583  0.0049 0.9446239
## KEVIN:OLIMBI      1   1741903  1741903  1.1148 0.2939731
```

```
## KEVIN:PINO        1   4146718  4146718  2.6538 0.1069213
## KEVIN:POUYAN      1     58913    58913  0.0377 0.8464951
## KEVIN:ABBY        1     35330    35330  0.0226 0.8808238
## KEVIN:TEMP        1  12342277 12342277  7.8986 0.0061106 **
## OLIMBI:POUYAN     1    222283   222283  0.1423 0.7069690
## OLIMBI:TEMP       1    272456   272456  0.1744 0.6772924
## PINO:POUYAN       1    293090   293090  0.1876 0.6660209
## PINO:ABBY         1    577918   577918  0.3698 0.5446715
## PINO:TEMP         1    343279   343279  0.2197 0.6404512
## POUYAN:TEMP       1   1449057  1449057  0.9273 0.3382223
## ABBY:TEMP         1   1893399  1893399  1.2117 0.2740299
## Residuals        87 135944724  1562583
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#The last model is just the significant interaction terms
#and the main effects (and blocked factors)

#Lets look at the significant doctor pairs.
#Kevin and Temp
#Heather and Kevin
#Brittany and Temp
#Brittany and Pino
#Brittany and Kevin

#Lets look more closely at those

summary(swlm3)
```

```
##
## Call:
## lm(formula = form, data = swp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2944.7  -657.4    55.7   731.0  3353.6
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)        7119.4     1205.2   5.907  4.1e-08 ***
## MONTHAugust        1043.2      515.2   2.025  0.04535 *
## MONTHFebruary     -1254.4      446.5  -2.809  0.00589 **
## MONTHJanuary      -1049.8      519.4  -2.021  0.04574 *
## MONTHJuly           219.4      423.3   0.518  0.60530
## MONTHJune           107.5      403.4   0.266  0.79047
## MONTHMarch         -795.9      487.5  -1.633  0.10547
## MONTHMay           -453.4      402.2  -1.127  0.26213
## DAYMonday          3891.2     1173.1   3.317  0.00124 **
## DAYSaturday        4514.6     1570.4   2.875  0.00487 **
## DAYThursday        3314.0     1344.0   2.466  0.01525 *
## DAYTuesday         3112.2     1202.8   2.587  0.01100 *
## DAYWednesday       3406.5     1335.4   2.551  0.01214 *
## BRITTANY1          1056.2      970.1   1.089  0.27869
## HEATHER1           -484.6      677.2  -0.716  0.47578
```

```
## KEVIN1              -505.9      663.6  -0.762  0.44753
## OLIMBI1              699.5      563.6   1.241  0.21722
## PINO1                425.7      523.5   0.813  0.41792
## POUYAN1             1377.9      533.0   2.585  0.01107 *
## ABBY1               -192.7      516.7  -0.373  0.70986
## SAMARA1              801.8     1028.3   0.780  0.43728
## TEMP1              -1237.2      566.5  -2.184  0.03111 *
## KEVIN1:TEMP1        1536.4      631.0   2.435  0.01653 *
## HEATHER1:KEVIN1     2048.7      748.5   2.737  0.00725 **
## BRITTANY1:TEMP1     -920.8      578.2  -1.593  0.11417
## BRITTANY1:PINO1     1130.9      908.4   1.245  0.21586
## BRITTANY1:KEVIN1  -1381.6      744.7  -1.855  0.06628 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1206 on 108 degrees of freedom
## Multiple R-squared:  0.6372, Adjusted R-squared:  0.5498
## F-statistic: 7.295 on 26 and 108 DF,  p-value: 4.209e-14
```

```
#Heather and Kevin appears to be a good team.
#But Brittany and kevin aren't too good.

#I believe that these interaction terms are not
#important enough to consider when scheduling doctors.
#Not when considering the main effects.

#Lets look at the individual doctor main effects.

summary(swlm1)
```

```
##
## Call:
## lm(formula = form, data = swp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3323.5  -717.8   -34.3   672.7  2997.7
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    6681.53    1257.47   5.313 5.47e-07 ***
## MONTHAugust    1409.60     532.46   2.647  0.00927 **
## MONTHFebruary  -718.17     459.93  -1.561  0.12121
## MONTHJanuary   -810.66     529.86  -1.530  0.12882
## MONTHJuly       257.78     458.88   0.562  0.57539
## MONTHJune        -5.53     441.49  -0.013  0.99003
## MONTHMarch     -172.35     492.35  -0.350  0.72695
## MONTHMay       -340.20     438.07  -0.777  0.43903
## DAYMonday      2457.49    1153.30   2.131  0.03527 *
## DAYSaturday    1869.27    1490.99   1.254  0.21253
## DAYThursday    2850.57    1378.38   2.068  0.04092 *
## DAYTuesday     2442.42    1228.41   1.988  0.04920 *
## DAYWednesday   2754.90    1324.63   2.080  0.03981 *
## BRITTANY1      -215.98     698.09  -0.309  0.75760
```

```
## HEATHER1        738.06     504.95   1.462  0.14661
## KEVIN1          427.10     452.57   0.944  0.34733
## OLIMBI1         674.77     565.99   1.192  0.23568
## PINO1          1489.99     461.48   3.229  0.00163 **
## POUYAN1        1267.48     568.94   2.228  0.02787 *
## ABBY1            69.98     545.51   0.128  0.89815
## SAMARA1         325.97    1109.23   0.294  0.76939
## TEMP1          -223.37     333.82  -0.669  0.50478
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1329 on 113 degrees of freedom
## Multiple R-squared:  0.5388, Adjusted R-squared:  0.453
## F-statistic: 6.285 on 21 and 113 DF,  p-value: 3.002e-11
```

```r
#If we just look at significace:
#Pino, Pouyan are significant. But we know that Pino
#Is signifinant because he is a pediatric doctor and
#charges more. So that doesn't help.
#The others are then "average" and should be considered equal.

#The estimated impact on prodution of Pino and Pouyan is:
#Pouyan: +$1267
#Pino: +$1490

#But this doesn't help very much.

#Unfortinuatly there isn't much to help for scheduling.
#It turns out that there isn't much to get from the data.
#Except for pino, which it is known that he produces more.
#Pouyan seems to be good too.

#Lets look at the base, blocked model.

summary(swlm)
```

```
##
## Call:
## lm(formula = Total_Production ~ DAY + MONTH, data = swp)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3657.5  -702.2    53.4   711.1  3823.0
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      7570.4      470.9  16.076  < 2e-16 ***
## DAYMonday        3800.5      448.7   8.470 6.53e-14 ***
## DAYSaturday      2454.0     1088.0   2.256   0.0259 *
## DAYThursday      2784.6      446.4   6.238 6.63e-09 ***
## DAYTuesday       3100.3      443.8   6.986 1.61e-10 ***
## DAYWednesday     3121.9      452.4   6.901 2.47e-10 ***
## MONTHAugust      1051.8      516.2   2.038   0.0437 *
## MONTHFebruary    -460.9      467.5  -0.986   0.3262
```

```
## MONTHJanuary   -1113.8      532.0  -2.094   0.0384 *
## MONTHJuly        558.3      454.4   1.229   0.2216
## MONTHJune        196.3      454.6   0.432   0.6666
## MONTHMarch      -285.6      468.6  -0.610   0.5433
## MONTHMay        -256.7      449.5  -0.571   0.5690
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1408 on 122 degrees of freedom
## Multiple R-squared:  0.4414, Adjusted R-squared:  0.3864
## F-statistic: 8.033 on 12 and 122 DF,  p-value: 6.236e-11
```

```
#It is likely that is best to just schedule based on the day.
#Lets make a quick model with just the day. And it appears that
#Friday is terrible and monday is great for
#for production, but this makes lots of sense.
#Also, August is good and January isn't.
##############################################################################
##############################################################################
#5) Final words.

#We determined that the data doesn't really have much to help.
#The most signifince came from known points.

#Pino makes a lot of money, (he is a pediatric doctor so we knew this.)
#Friday is terrible, monday is better. So the advice is to try to
#schedule more on friday to make more even, or schdule more
#doctors on monday.

#The doctor pairs don't have much significance. Heather and Kevin seem to be
#a good pair and Brittany and Kevin aren't too good.

#August makes a lot of money and January doesn't make a lot. This might
#help in determing the best days to take a vacation.

#There is some information that can be sussed out from this data set
#but not much of it is too helpful. The initial question was to determine
#doctor effectivness in order to better schedule. The most I can confidently
#say is that the presence of Pouyan correlates with high net profit.

#It is important to realize that data does not always answer every question.
#Sometimes the data doesn't tell a very nuanced story. Sometimes the data
#has all the answers and sometimes the data doesn't say anything. In this case,
#the data doesn't speak very loudly. It says most strongly that Pino makes the
#company the most money, which isn't something you didn't already know.

#Besides that, it says that Pouyan also makes a lot of money for the
#company, which you might not have known.

#There were a few significant doctor pairs, but the complications entailed in
#scheduling them together or away from each other might not be worth the work.

#If you want to try to use significant doctor pairs in scheduling we could automate
#a process that does so. This is known in Operations Reaseach as an "assignment problem"
```

```
#and there are many algorithms that we can use to do it. Just let me know what you
#want to do.  ---Wayne Kenney
```