

# EDDA - Assignment 2 - Group 77

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## Exercise 1

If left alone bread will become moldy, rot or decay otherwise. To investigate the influence of temperature and humidity on this process, the time to decay was measured for 18 slices of white bread, which were placed in 3 different environments and humidified or not. The data are given in the file bread.txt, with the first column time to decay in hours, the second column the environment (cold, warm or intermediate temperature) and the third column the humidity.

a) The 18 slices came from a single loaf, but were randomized to the 6 combinations of conditions. Present an R-code for this randomization process.

```
data_bread <- read.table(file="data/bread.txt",header=TRUE)

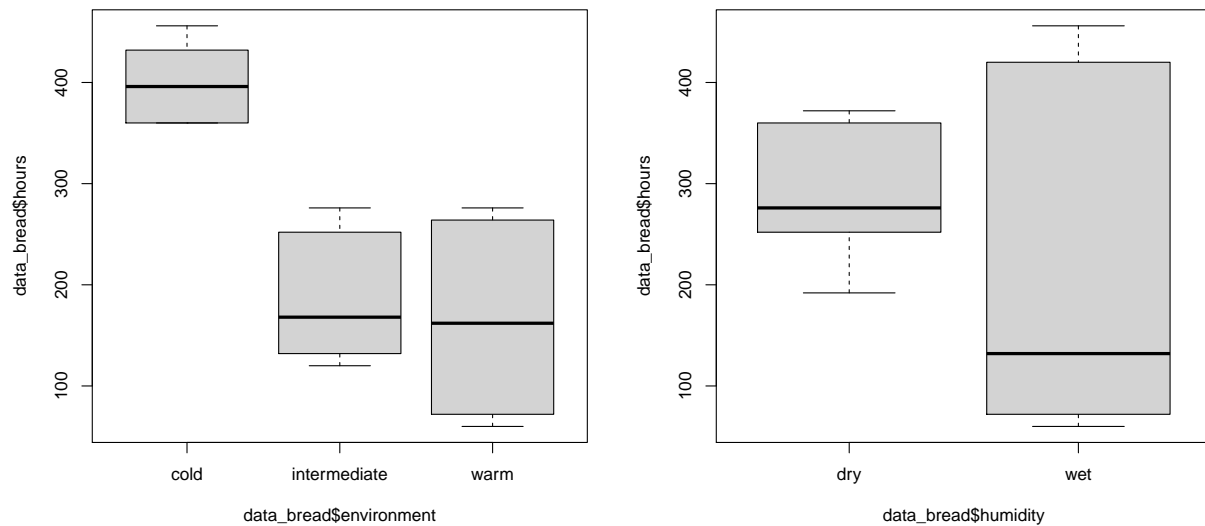
humid <- factor(rep(c("dry","wet"),each = 9))
temp <- factor(rep(c("cold", "intermediate","warm"),times = 6))

data.frame(humid,temp,slices = sample(1:18))
```

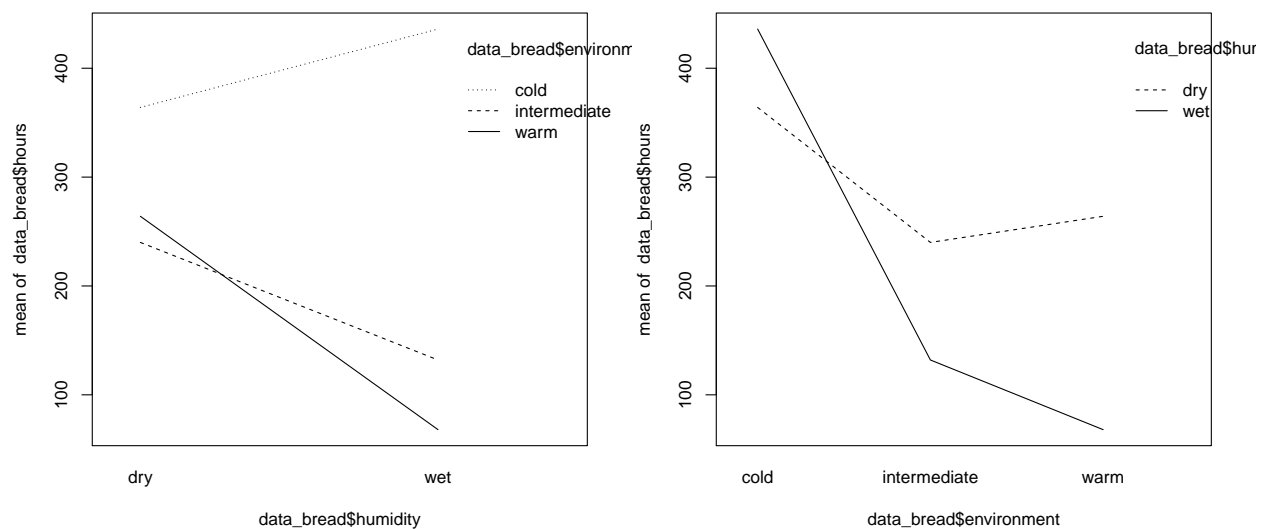
##	humid	temp	slices
## 1	dry	cold	16
## 2	dry	intermediate	12
## 3	dry	warm	2
## 4	dry	cold	10
## 5	dry	intermediate	8
## 6	dry	warm	14
## 7	dry	cold	1
## 8	dry	intermediate	9
## 9	dry	warm	3
## 10	wet	cold	11
## 11	wet	intermediate	13
## 12	wet	warm	18
## 13	wet	cold	17
## 14	wet	intermediate	15
## 15	wet	warm	5
## 16	wet	cold	4
## 17	wet	intermediate	6
## 18	wet	warm	7

b) Make two boxplots of hours versus the two factors and two interaction plots (keeping the two factors fixed in turn).

```
par(mfrow=c(1,2))
boxplot(data_bread$hours~data_bread$environment)
boxplot(data_bread$hours~data_bread$humidity)
```



```
interaction.plot(data_bread$humidity,data_bread$environment,data_bread$hours)
interaction.plot(data_bread$environment,data_bread$humidity,data_bread$hours)
```



c) Perform an analysis of variance to test for effect of the factors temperature, humidity, and the interaction. Describe the interaction effect in words.

```
attach(data_bread)
environment=as.factor(environment)
humidity=as.factor(humidity)
dataaov=lm(hours~humidity*environment,data=data_bread)
anova(dataaov)

## Analysis of Variance Table
##
## Response: hours
##
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
humidity	1	26912	26912	62.3	4.3e-06 ***
environment	2	201904	100952	233.7	2.5e-10 ***
humidity:environment	2	55984	27992	64.8	3.7e-07 ***
Residuals	12	5184	432		

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(dataaov)

##
## Call:
## lm(formula = hours ~ humidity * environment, data = data_bread)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-48	-7	0	11	36

```
##
## Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	364	12	30.33	1.0e-12 ***
humiditywet	72	17	4.24	0.0011 **
environmentintermediate	-124	17	-7.31	9.4e-06 ***
environmentwarm	-100	17	-5.89	7.3e-05 ***
humiditywet:environmentintermediate	-180	24	-7.50	7.2e-06 ***
humiditywet:environmentwarm	-268	24	-11.17	1.1e-07 ***

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.8 on 12 degrees of freedom
## Multiple R-squared:  0.982, Adjusted R-squared:  0.975
## F-statistic: 132 on 5 and 12 DF, p-value: 4.68e-10
```

When looking at the two-way anova model we see that it consists of the following terms:  $Y_{ijk} = \mu_{ij} + e_{ijk}$   
 $= \mu + \alpha_i + \beta_j + \gamma_{ij} + e_{ijk}$  We decompose the formula in this way such that  $\mu$  is the overall mean,  
 $\alpha_i$  and  $\beta_j$  are the main effect of level  $i$  and  $j$  of the first factor and second factor respectively and  $\gamma_{ij}$  the  
interaction effect.

In order to test the effect of the temperature, humidity, and the interaction we set up 3 hypotheses which  
are:  $H_{AB}$ :  $\gamma_{ij} = 0$  for every  $(i, j)$  (no interactions between factor A and B)

$H_A$ :  $\alpha_i = 0$  for every  $i$  (no main effect of factor A)

$H_B$ :  $\beta_j = 0$  for every  $j$  (no main effect of factor B)

We use the test statistics  $F_{AB}$  for  $H_{AB}$ ,  $F_A$  for  $H_A$  and  $F_B$  for  $H_B$  where F is the F-distribution.

To see if the Hypotheses can be rejected we want to look at the probability that  $P(F > f_{AB})$ ,  $P(F > f_A)$  and  $P(F > f_B)$ , the bigger the F value the lower the probability that the Hypothesis lays under a F-distribution and therefore the Hypothesis can be rejected.

We see that the humidity has a p-value of 4.3e-06, environment a p-value of 2.5e-10 and the interaction between the two (humidity:environment) shows a p-value of 3.7e-07. This means that humidity, environment and the interaction effect between humidity and environment have a significant influence on the hours, which means we can reject  $H_A$ ,  $H_B$  and  $H_{AB}$ .

The interaction effect looks at the difference of differences, for example: it looks at the difference in hours for environment = cold and environment = warm for humidity = wet. Then it looks the difference between environment = cold and environment = warm for humidity = dry. It then looks at the difference between those differences and when this difference is high it shows that there is indeed interaction.

d) Which of the two factors has the greatest (numerical) influence on the decay? Is this a good question?

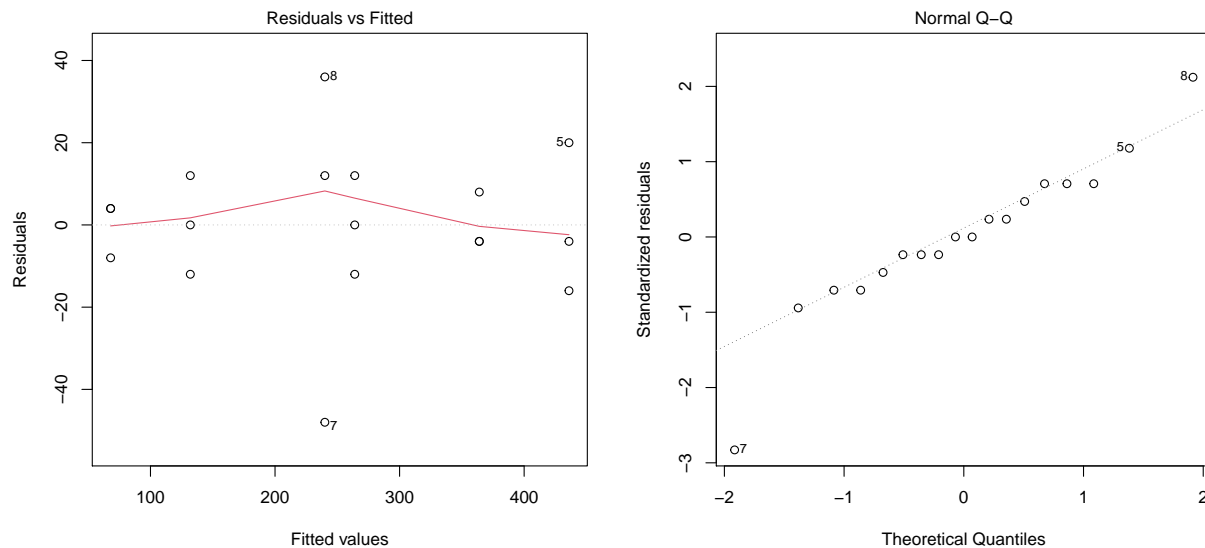
```
# Without interaction
humidity=as.factor(humidity)
environment=as.factor(environment)
dataaov=lm(hours~humidity+environment)
anova(dataaov)

## Analysis of Variance Table
##
## Response: hours
##          Df Sum Sq Mean Sq F value    Pr(>F)
## humidity    1  26912   26912     6.16   0.026 *
## environment  2 201904  100952    23.11 3.7e-05 ***
## Residuals   14   61168    4369
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

When we want to know which factor has the greatest influence we want to use the additive model as used above. This shows a p-value of 0.026 for humidity and a p-value of 3.7e-05 for environment. This means that the environment has the greatest influence.

e) Check the model assumptions by using relevant diagnostic tools. Are there any outliers?

```
par(mfrow=c(1,2))
dataaov2=lm(hours~humidity*environment,data=data_bread);
plot(dataaov2, 1)
plot(dataaov2, 2)
```



The qqplot shows a somewhat linear line which means that based on the qqplot we can state that the data is normally distributed. We also looked at the spread of the residuals, which showed that there are three outliers which are number 5, 7 and 8 which can be observed in both plot.

## Exercise 2

A researcher is interested in the time it takes a student to find a certain product on the internet using a search engine. There are three different types of interfaces with the search engine and especially the effect of these interfaces is of importance. There are five different types of students, indicating their level of computer skill (the lower the value of this indicator, the better the computer skill of the corresponding student). Fifteen students are selected; three from each group with a certain level of computer skill. The data is given in the file search.txt. Assume that the experiment was run according to a randomized block design which you make in a). (Beware that the levels of the factors are coded by numbers.)

a) Number the selected students 1 to 15 and show how (by using R) the students could be randomized to the interfaces in a randomized block design.

```
interface <- factor(rep(c(1,2,3),each = 5))
skill <- factor(rep(c(1,2,3,4,5),times = 3))
students <- c(1:15)
block <- data.frame(students,skill,interface); block
```

```
##      students skill interface
## 1           1     1          1
## 2           2     2          1
## 3           3     3          1
## 4           4     4          1
## 5           5     5          1
## 6           6     1          2
## 7           7     2          2
## 8           8     3          2
## 9           9     4          2
## 10          10     5          2
```

```
## 11      11      1      3
## 12      12      2      3
## 13      13      3      3
## 14      14      4      3
## 15      15      5      3
```

b) Test the null hypothesis that the search time is the same for all interfaces. What type of interface does require the longest search time? For which combination of skill level and type of interface is the search time the shortest? Estimate the time it takes a typical user of skill level 3 to find the product on the website if the website uses interface 3.

```
data_search <- read.table(file="data/search.txt",header=TRUE)
data_search$skill <- as.factor(data_search$skill)
data_search$interface <- as.factor(data_search$interface)

aovsearch = lm(time~interface+skill, data= data_search)

anova(aovsearch)
```

```
## Analysis of Variance Table
##
## Response: time
##          Df Sum Sq Mean Sq F value Pr(>F)
## interface  2   50.5   25.23    7.82  0.013 *
## skill      4   80.1   20.01    6.21  0.014 *
## Residuals  8   25.8    3.23
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(aovsearch)
```

```
##
## Call:
## lm(formula = time ~ interface + skill, data = data_search)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.573 -0.697  0.387  1.057  1.787
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    15.01      1.23    12.24 1.8e-06 ***
## interface2      2.70      1.14     2.38  0.0447 *
## interface3      4.46      1.14     3.93  0.0044 **
## skill12         1.30      1.47     0.89  0.4012
## skill13         3.03      1.47     2.07  0.0724 .
## skill14         5.30      1.47     3.61  0.0068 **
## skill15         6.10      1.47     4.16  0.0032 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.8 on 8 degrees of freedom
## Multiple R-squared:  0.835, Adjusted R-squared:  0.711
## F-statistic: 6.74 on 6 and 8 DF, p-value: 0.0084
```

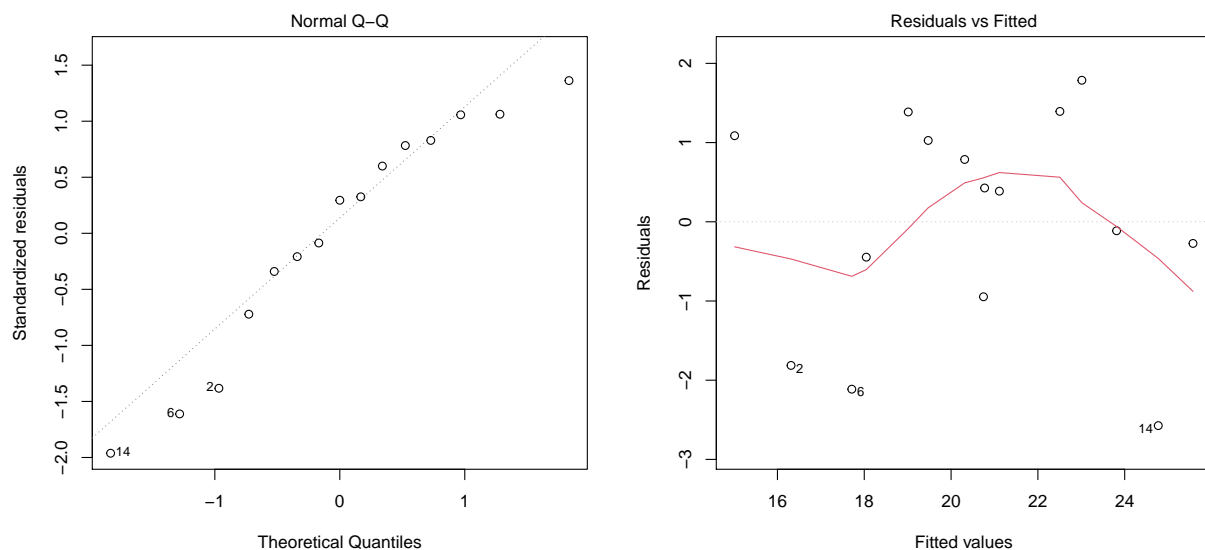
```
# Estimate interface 3 and skill 3:
Y = 15.01+4.46+3.03+1.8
Y
```

```
## [1] 24.3
```

Looking at the additive ANOVA test we can conclude that there is a significant main effect of the interface. Furthermore, the summary shows that interface three gives the highest alpha parameter value, making the time it takes for this interface the longest. For the shortest search time, interface 1 can be combined with skill levels 1,2 or 3 since all three have the lowest alpha parameter values without being significant. For the estimation of time it takes a typical user of skill level 3 using interface 3 we can calculate  $\hat{Y}$  by summing the estimates and adding the error, giving a time of 24.3 units.

c) Check the model assumptions by using relevant diagnostic tools.

```
par(mfrow=c(1,2))
plot(aovsearch,2)
plot(aovsearch,1)
```



As shown in the above QQ-plot and the residuals-fitted plot there are some outliers that raises some doubt about the normality of the data.

d) Perform the Friedman test to test whether there is an effect of interface.

```
friedman.test(data_search$time, data_search$interface, data_search$skill)
```

```
##
## Friedman rank sum test
##
## data: data_search$time, data_search$interface and data_search$skill
## Friedman chi-squared = 6, df = 2, p-value = 0.04
```

P-value is significant thus  $H_0$  is not rejected and therefore there is a significant effect of the interface.

e) Test the null hypothesis that the search time is the same for all interfaces by a one-way ANOVA test, ignoring the variable skill. Is it right/wrong or useful/not useful to perform this test on this dataset?

```
aovsearch = lm(data_search$time~data_search$interface)
anova(aovsearch)

## Analysis of Variance Table
##
## Response: data_search$time
##              Df Sum Sq Mean Sq F value Pr(>F)
## data_search$interface  2    50.5    25.23    2.86  0.096 .
## Residuals              12   105.9     8.82
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

is it not useless also to ignore skill since the time is clearly also depended on this variable, you can not simply ignore such a variable right?

Looking at the p-value of the one-way ANOVA test, we see that is not significant. We could therefore conclude that the interfaces does not have a significant effect on the search time. However, since the data originates from a random block design, it is not correct to use this test since it leaves out important interactions.

## Excercise 3

In a study on the effect of feedingstuffs on lactation a sample of nine cows were fed with two types of food, and their milk production was measured. All cows were fed both types of food, during two periods, with a neutral period in-between to try and wash out carry-over effects. The order of the types of food was randomized over the cows. The observed data can be found in the file cow.txt, where A and B refer to the types of feedingstuffs.

a) Test whether the type of feedingstuffs influences milk production using an ordinary “fixed effects” model, fitted with lm. Estimate the difference in milk production.

```
# read data
data <- read.table(file="data/cow.txt",header=TRUE)
data$treatment <- as.factor(data$treatment); data$order <- as.factor(data$order)
data$id <- as.factor(data$id); data$per <- as.factor(data$per)

# perform fixed effects model analysis
fixed_aov <- lm(milk ~ order + id + per + treatment, data = data)
summary(fixed_aov)

##
## Call:
## lm(formula = milk ~ order + id + per + treatment, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.260 -0.438  0.000  0.438  2.260
##
## Coefficients: (1 not defined because of singularities)
```



```
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  30.300      1.244   24.35  5.0e-08 ***
## orderBA     -11.200      1.574   -7.12  0.00019 ***
## id2         23.000      1.574   14.61  1.7e-06 ***
## id3         11.150      1.574    7.08  0.00020 ***
## id4         -1.350      1.574   -0.86  0.41948
## id5          4.150      1.574    2.64  0.03360 *
## id6         34.650      1.574   22.01  1.0e-07 ***
## id7         24.750      1.574   15.72  1.0e-06 ***
## id8         16.100      1.574   10.23  1.8e-05 ***
## id9          NA         NA      NA      NA
## per2        -2.390      0.747   -3.20  0.01505 *
## treatmentB  -0.510      0.747   -0.68  0.51654
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.57 on 7 degrees of freedom
## Multiple R-squared:  0.993, Adjusted R-squared:  0.983
## F-statistic: 101 on 10 and 7 DF, p-value: 1.35e-06
```

b)

```
attach(data)
mixed_avo <- lmer(milk ~ treatment + order + per + (1|id),REML=FALSE)
mixed_avo_1 <- lmer(milk ~ order + per + (1|id),REML=FALSE)
anova(mixed_avo_1, mixed_avo)
```

```
## Data: NULL
## Models:
## mixed_avo_1: milk ~ order + per + (1 | id)
## mixed_avo: milk ~ treatment + order + per + (1 | id)
##           npar AIC BIC logLik deviance Chisq Df Pr(>Chisq)
## mixed_avo_1    5 118 122  -53.9      108
## mixed_avo      6 119 125  -53.7      107  0.58  1      0.45
```

c)

```
attach(data)
```

```
## The following objects are masked from data (pos = 3):
##
##      id, milk, order, per, treatment
```

```
t.test(milk[treatment=="A"],milk[treatment=="B"],paired=TRUE)
```

```
##
## Paired t-test
##
## data:  milk[treatment == "A"] and milk[treatment == "B"]
## t = 0.2, df = 8, p-value = 0.8
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
```

```
## -2.27 2.76
## sample estimates:
## mean of the differences
## 0.244
```

## Exercise 4

Stochastic models for word counts are used in quantitative studies on literary styles. Statistical analysis of the counts can, for example, be used to solve controversies about true author ships. Another example is the analysis of word frequencies in relation to Jane Austen's novel Sanditon. At the time Austen died, this novel was only partly completed. Austen, however, had made a summary for the remaining part. An admirer of Austen's work finished the novel, imitating Austen's style as much as possible. The file `austen.txt` contains counts of different words in some of Austen's novels: chapters 1 and 3 of *Sense and Sensibility* (stored in the *Sense* column), chapters 1, 2 and 3 of *Emma* (column *Emma*), chapters 1 and 6 of *Sanditon* (both written by Austen herself, column *Sand1*) and chapters 12 and 24 of *Sanditon* (both written by the admirer, *Sand2*)

a) Discuss whether a contingency table test for independence or for homogeneity is most appropriate here.

The contingency table test for homogeneity is appropriate because we want to know if the fan writer imitates Austen in a good way. This means that we want to test whether or not the different columns of data in the table come from the same population (writer) or not, which would be the case if the fan imitated Austen correctly. The  $H_0$  of the contingency table test for homogeneity states that the distribution of the words is the same for the stories.

b) Using the given data set, investigate whether Austen herself was consistent in her different novels. Where are the main inconsistencies?

```
data=read.table(file="data/austen.txt",header=TRUE)
austen = data[,1:3]
z = chisq.test(austen)
z
```

```
##
## Pearson's Chi-squared test
##
## data: austen
## X-squared = 12, df = 10, p-value = 0.3
```

```
residuals(z)
```

```
##      Sense  Emma Sand1
## a      -1.0300 -0.129  1.594
## an      0.4473 -0.159 -0.375
## this    0.0513  0.294 -0.504
## that    0.7482  0.287 -1.442
## with   -0.0475  0.521 -0.704
## without  1.0654 -1.588  0.893
```

She is not inconsistent as the p-value is above 0.05. This means that we cannot reject the  $H_0$ . She does however have some main inconsistency, which where the words "a", "that" and "without". As can be seen in the residual table above.

```
z = chisq.test(data)
z
```

```
##
## Pearson's Chi-squared test
##
## data: data
## X-squared = 46, df = 15, p-value = 6e-05
```

```
residuals(z)
```

```
##      Sense      Emma  Sand1   Sand2
## a      -1.015 -0.112093  1.606 -0.0589
## an     -0.591 -1.219955 -1.067  3.7282
## this    0.139  0.390490 -0.444 -0.3267
## that    1.594  1.179849 -0.910 -3.0493
## with   -0.512  0.000192 -1.025  1.7482
## without 1.392 -1.341196  1.137 -1.0696
```

The fan is inconsistent as the p-value of the test is below 0.05. Therefore we have to reject the  $H_0$  and accept that the distribution of the words in the stories are not the same. Because Austen herself did not have this inconsistency we can say that the inconsistency is caused by the fan writer. The main inconsistencies were for the words “that” and “an”. As can be seen in the residual table above.

## Exercise 5

The data in `expenses crime.txt` were obtained to determine factors related to state expenditures on criminal activities (courts, police, etc.) The variables are: `state` (indicating the state in the USA), `expend` (state expenditures on criminal activities in \$1000), `bad` (crime rate per 100000), `crime` (number of persons under criminal supervision), `lawyers` (number of lawyers in the state), `employ` (number of persons employed in the state) and `pop` (population of the state in 1000). In the regression analysis, take `expend` as response variable and `bad`, `crime`, `lawyers`, `employ` and `pop` as explanatory variables.

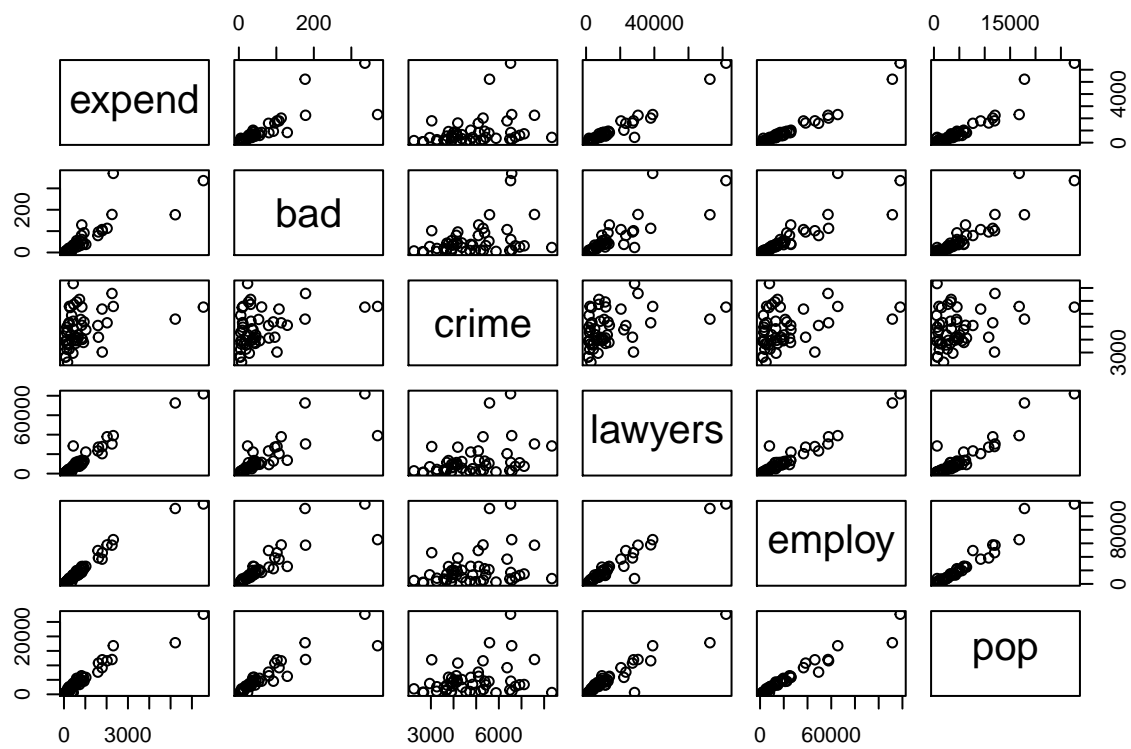
a) Make some graphical summaries of the data. Investigate the problem of potential and influence points, and the problem of collinearity.

```
data_crime = read.table(file="data/expensescrime.txt",header=TRUE)
data_crime
```

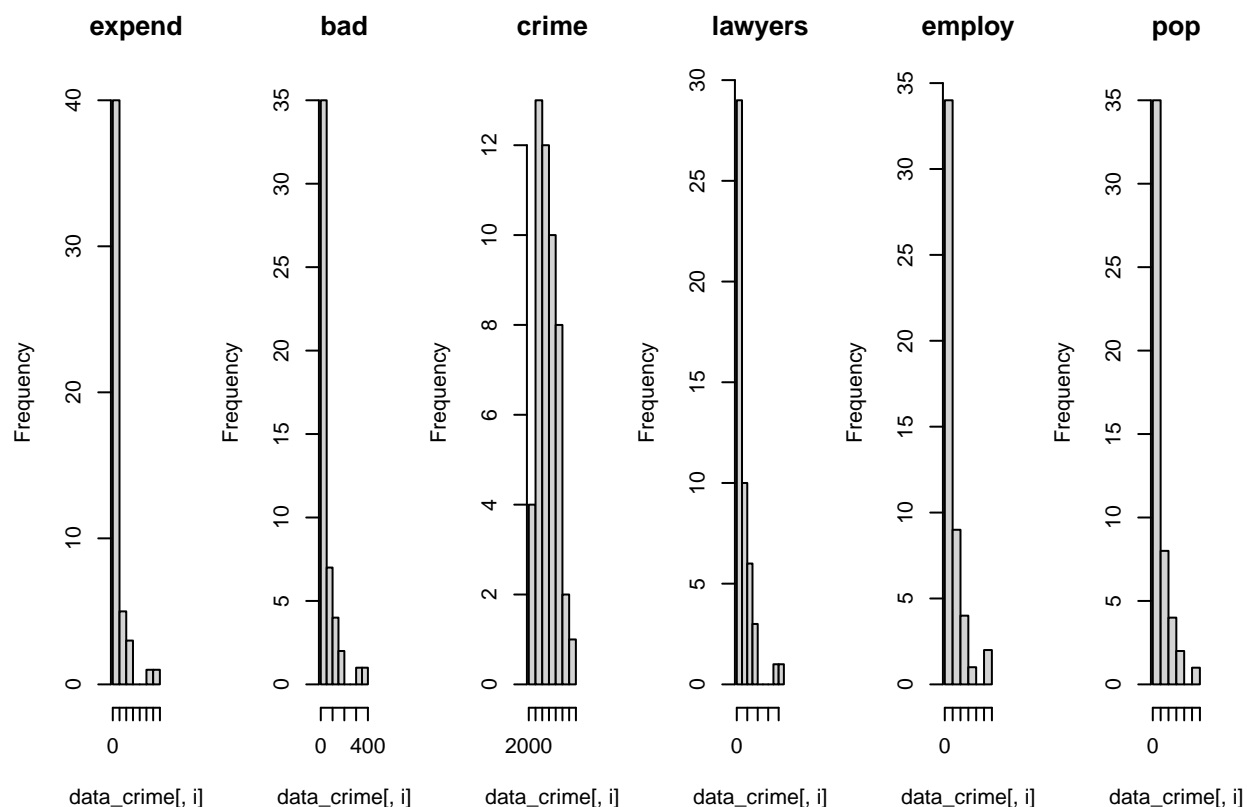
```
##      state expend    bad crime lawyers employ   pop
## 1      AK    360    5.1  5877   1749   2796   525
## 2      AL    498   34.4  3942   6679  13999  4083
## 3      AR    219   19.2  3585   3741   7227  2388
## 4      AZ    728   31.3  7116   7535  14755  3386
## 5      CA   6539  336.2  6518  82001 118149 27663
## 6      CO    602   25.7  6919  11174  12556  3296
## 7      CT    544   43.5  3705  11397  14798  3211
## 8      DC    435   23.3  8339  28399   7925   622
## 9      DE    130   10.6  4961   1597   3230   644
## 10     FL   2252  177.9  7574  30444  57310 12023
## 11     GA    835  129.2  5110  13652  25848  6222
```

## 12	HI	210	10.8	5201	2787	3886	1083
## 13	IA	368	17.7	3943	6182	9309	2834
## 14	ID	120	5.8	3908	2031	3363	998
## 15	IL	2023	113.0	5303	37873	57748	11582
## 16	IN	593	55.3	3914	9499	19647	5531
## 17	KS	324	23.8	4375	5555	9726	2476
## 18	KY	417	27.9	2947	7017	13480	3727
## 19	LA	785	52.7	5564	10569	21184	4461
## 20	MA	1024	37.8	4758	22154	26048	5855
## 21	MD	940	92.0	5373	12866	22541	4535
## 22	ME	128	6.3	3672	2528	4340	1187
## 23	MI	1788	107.2	6366	20445	36632	9200
## 24	MN	665	38.6	4134	11343	13159	4246
## 25	MO	660	44.9	4366	12439	20260	5103
## 26	MS	245	18.9	3266	4270	8463	2625
## 27	MT	123	4.9	4549	2006	3211	809
## 28	NC	821	80.2	4121	9265	24843	6413
## 29	ND	75	2.4	2679	1290	1997	672
## 30	NE	206	13.7	3695	4289	5820	1594
## 31	NH	140	4.8	3252	2139	4034	1057
## 32	NJ	1592	79.2	5094	23301	49346	7672
## 33	NM	296	8.9	6486	3164	7413	1500
## 34	NV	256	11.4	6575	2276	5528	1007
## 35	NY	5220	176.7	5589	72575	111518	17825
## 36	OH	1617	96.0	4187	27191	38404	10784
## 37	OK	432	32.4	5425	8302	13167	3272
## 38	OR	463	31.2	6730	7385	9858	2724
## 39	PA	1796	101.9	3037	27798	46200	11936
## 40	RI	164	9.2	4723	2527	3774	986
## 41	SC	427	34.5	4841	5021	13177	3425
## 42	SD	79	3.9	2641	1230	2396	709
## 43	TN	568	45.2	4167	8782	18190	4855
## 44	TX	2313	370.1	6569	39028	65488	16789
## 45	UT	244	10.0	5317	3446	5715	1680
## 46	VA	914	40.5	3779	13390	25720	5904
## 47	VT	74	6.2	3888	1372	1969	548
## 48	WA	838	60.7	6529	11507	17020	4538
## 49	WI	863	36.6	4017	10316	19911	4807
## 50	WV	168	7.2	2253	2835	5079	1897

```
plot(data_crime[,c(2,3,4, 5, 6, 7)])
```



```
par(mfrow=c(1,6))
for (i in c(2,3,4, 5, 6, 7)) hist(data_crime[,i],main=names(data_crime)[i])
```



```
regression_data = data_crime[2:7]

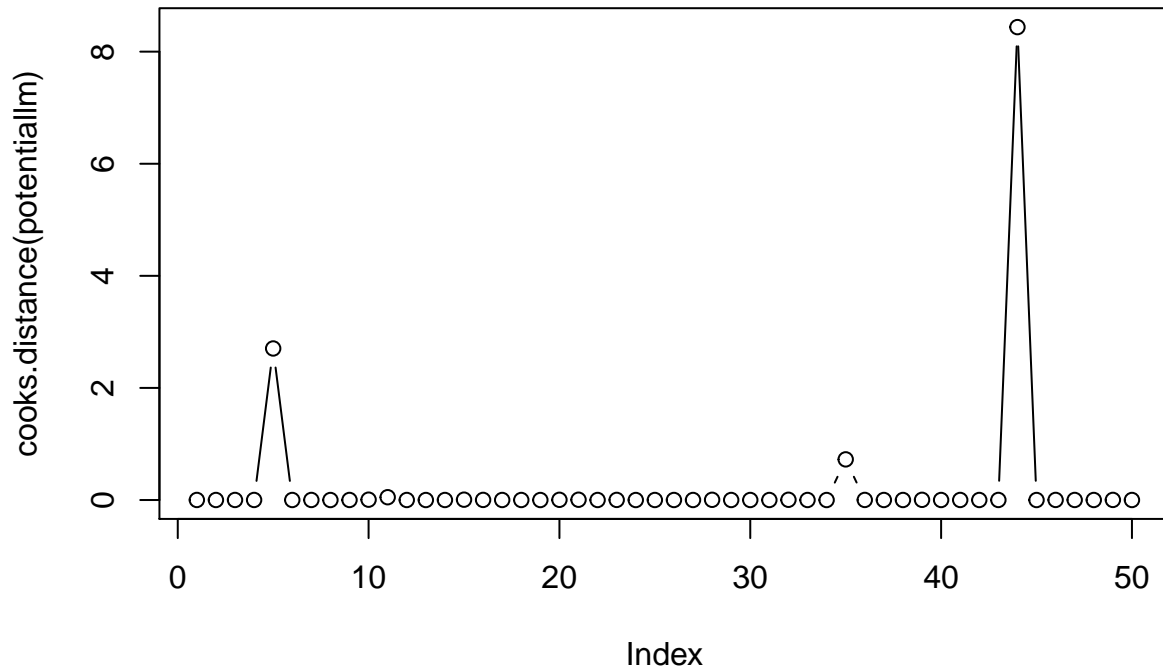
par(mfrow=c(1,1))
potentiallm = lm(expend~bad, data = regression_data)
potentiallm
```

```
##
## Call:
## lm(formula = expend ~ bad, data = regression_data)
##
## Coefficients:
## (Intercept)      bad
##      128.3      13.3
```

```
round(cooks.distance(potentiallm),2)
```

```
##      1      2      3      4      5      6      7      8      9     10     11     12     13     14     15     16
## 0.00 0.00 0.00 0.00 2.70 0.00 0.00 0.00 0.00 0.01 0.05 0.00 0.00 0.00 0.01 0.00
##     17     18     19     20     21     22     23     24     25     26     27     28     29     30     31     32
## 0.00 0.00 0.00 0.00 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##     33     34     35     36     37     38     39     40     41     42     43     44     45     46     47     48
## 0.00 0.00 0.73 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 8.44 0.00 0.00 0.00 0.00
##     49     50
## 0.00 0.00
```

```
plot(cooks.distance(potentiallm), type="b")
```



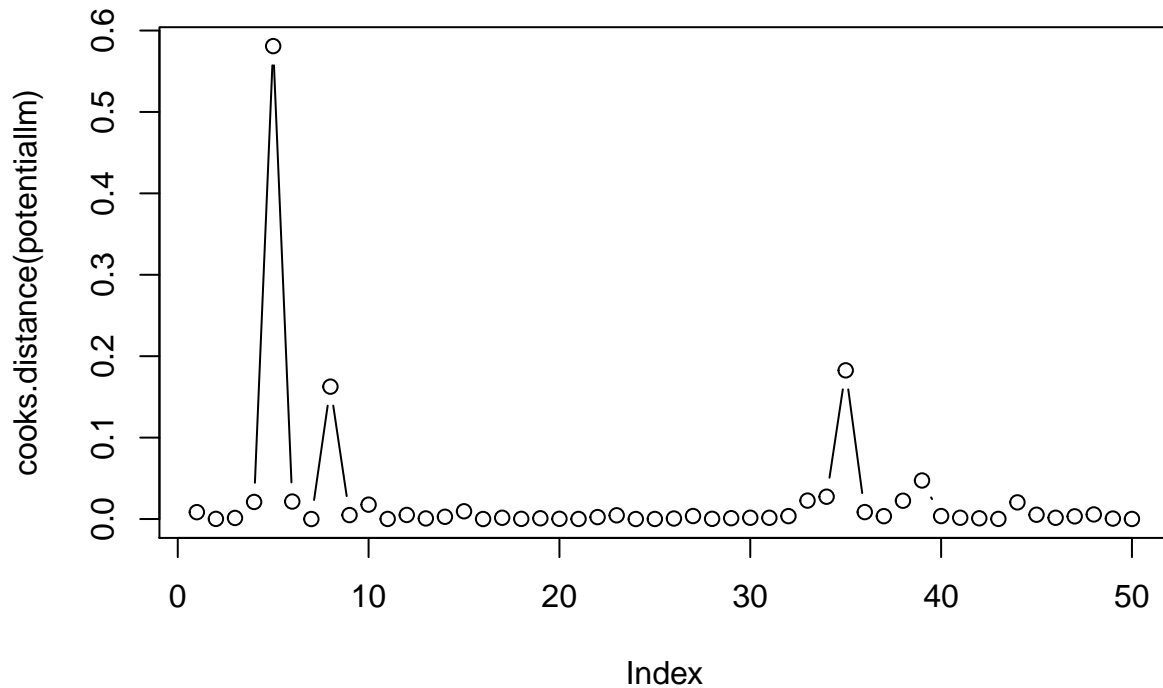
```
potentiallm = lm(expend~crime, data = regression_data)
potentiallm
```

```
##
## Call:
## lm(formula = expend ~ crime, data = regression_data)
##
## Coefficients:
## (Intercept)      crime
##   -500.284      0.283
```

```
round(cooks.distance(potentiallm),2)
```

```
##   1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 0.01 0.00 0.00 0.02 0.58 0.02 0.00 0.16 0.00 0.02 0.00 0.01 0.00 0.00 0.01 0.00
## 17   18   19   20   21   22   23   24   25   26   27   28   29   30   31   32
## 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
## 33   34   35   36   37   38   39   40   41   42   43   44   45   46   47   48
## 0.02 0.03 0.18 0.01 0.00 0.02 0.05 0.00 0.00 0.00 0.00 0.02 0.01 0.00 0.00 0.01
## 49   50
## 0.00 0.00
```

```
plot(cooks.distance(potentiallm), type="b")
```



```
potentiallm = lm(expend~lawyers, data = regression_data)
potentiallm
```

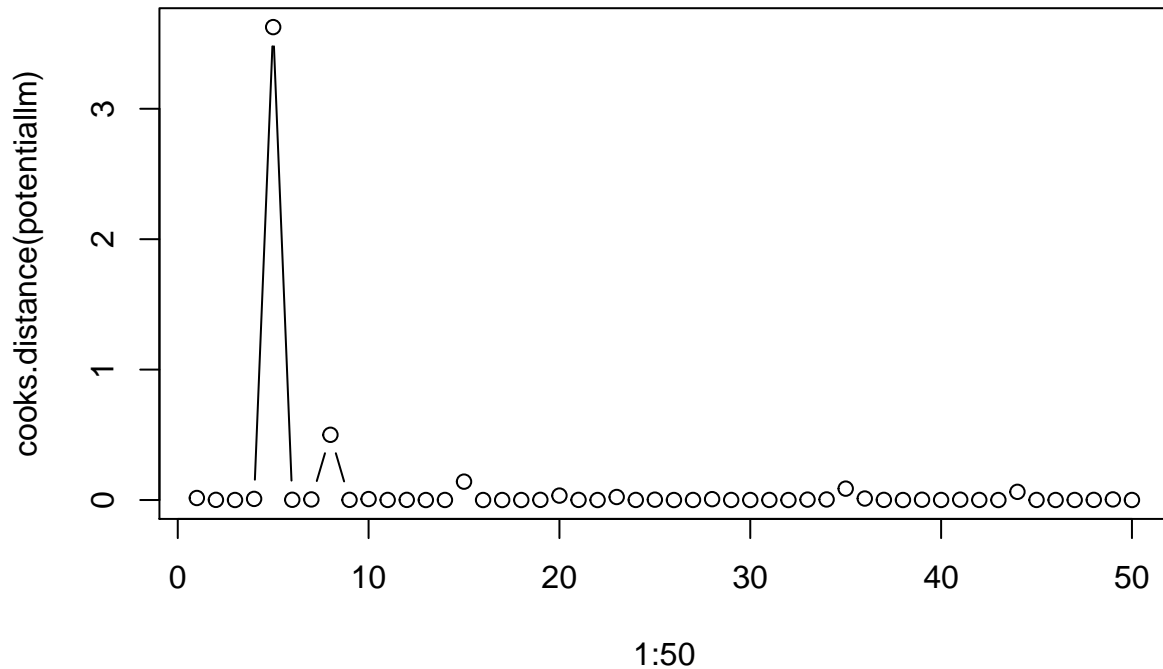
```
##
## Call:
## lm(formula = expend ~ lawyers, data = regression_data)
##
## Coefficients:
## (Intercept)      lawyers
##    -62.6806      0.0705
```

```
round(cooks.distance(potentiallm),2)
```

```
##   1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 0.02 0.00 0.00 0.01 3.63 0.00 0.00 0.50 0.00 0.01 0.00 0.00 0.00 0.00 0.14 0.00
##  17   18   19   20   21   22   23   24   25   26   27   28   29   30   31   32
## 0.00 0.00 0.00 0.03 0.00 0.00 0.02 0.00 0.00 0.00 0.00 0.01 0.00 0.00 0.00 0.00
##  33   34   35   36   37   38   39   40   41   42   43   44   45   46   47   48
## 0.00 0.00 0.09 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.06 0.00 0.00 0.00 0.00
##   49   50
## 0.00 0.00
```



```
plot(1:50,cooks.distance(potentiallm), type="b")
```



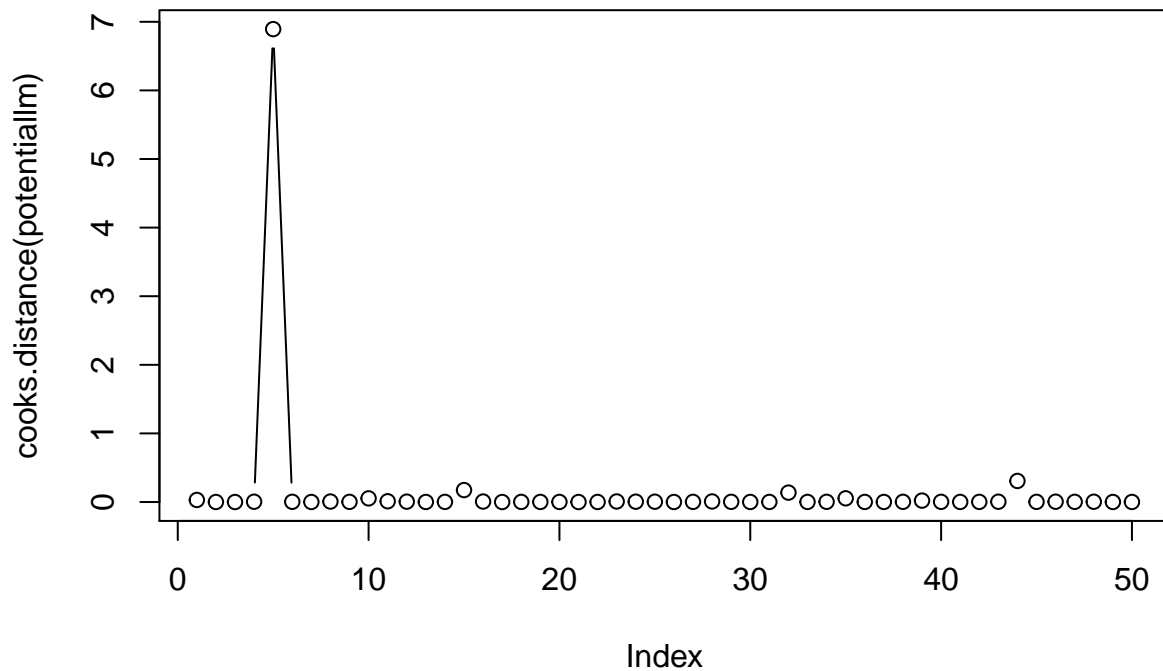
```
potentiallm = lm(expend~employ, data = regression_data)
potentiallm
```

```
##
## Call:
## lm(formula = expend ~ employ, data = regression_data)
##
## Coefficients:
## (Intercept)      employ
##   -120.3669      0.0469
```

```
round(cooks.distance(potentiallm),2)
```

```
##   1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 0.03 0.00 0.00 0.00 6.89 0.00 0.00 0.01 0.00 0.05 0.01 0.01 0.00 0.00 0.17 0.01
##  17   18   19   20   21   22   23   24   25   26   27   28   29   30   31   32
## 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.00 0.00 0.00 0.00 0.01 0.00 0.00 0.00 0.14
##  33   34   35   36   37   38   39   40   41   42   43   44   45   46   47   48
## 0.00 0.00 0.05 0.00 0.00 0.00 0.02 0.00 0.00 0.00 0.00 0.31 0.00 0.00 0.00 0.00
##   49   50
## 0.00 0.00
```

```
plot(cooks.distance(potentiallm), type="b")
```



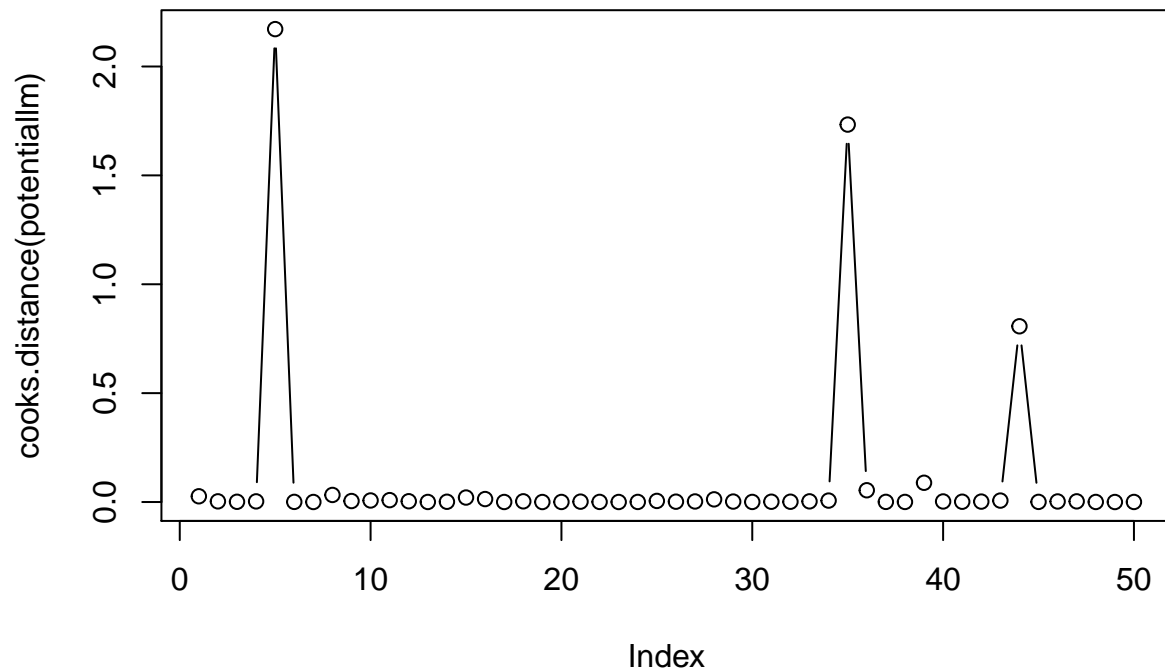
```
potentiallm = lm(expend~pop, data = regression_data)
potentiallm
```

```
##
## Call:
## lm(formula = expend ~ pop, data = regression_data)
##
## Coefficients:
## (Intercept)      pop
##   -195.844      0.218
```

```
round(cooks.distance(potentiallm),2)
```

```
##   1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 0.03 0.00 0.00 0.00 2.17 0.00 0.00 0.03 0.00 0.01 0.01 0.00 0.00 0.00 0.02 0.01
##  17   18   19   20   21   22   23   24   25   26   27   28   29   30   31   32
## 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.00 0.00 0.01 0.00 0.00 0.00 0.00
##  33   34   35   36   37   38   39   40   41   42   43   44   45   46   47   48
## 0.00 0.01 1.73 0.05 0.00 0.00 0.09 0.00 0.00 0.00 0.01 0.81 0.00 0.00 0.00 0.00
##   49   50
## 0.00 0.00
```

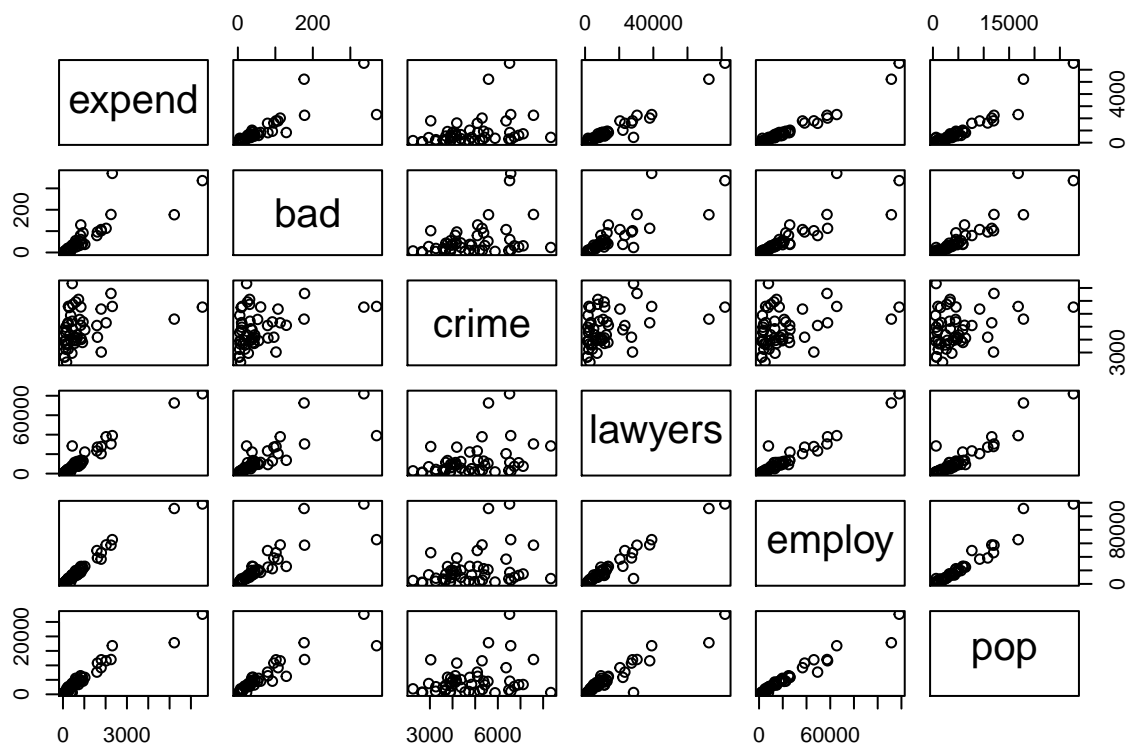
```
plot(cooks.distance(potentiallm), type="b")
```



```
# Collinearity
round(cor(regression_data),2)
```

```
##      expend  bad crime lawyers employ pop
## expend  1.00 0.83 0.33  0.97  0.98 0.95
## bad     0.83 1.00 0.37  0.83  0.87 0.92
## crime   0.33 0.37 1.00  0.37  0.30 0.27
## lawyers 0.97 0.83 0.37  1.00  0.97 0.93
## employ  0.98 0.87 0.30  0.97  1.00 0.97
## pop     0.95 0.92 0.27  0.93  0.97 1.00
```

```
pairs(regression_data)
```



```
# We see that employee and lawyers are strongly correlated(0.97)
# We see that employee and crime rate per 100000 are strongly correlated(0.87)
# We see that lawyers and crime rate per 100000 are strongly correlated(0.83)
# We see a correlation between pop and bad and pop and lawyers and pop and employ
```

```
regressionlm=lm(expend~bad+crime+lawyers+employ, data=regression_data)
car::vif(regressionlm)
```

```
## Registered S3 methods overwritten by 'car':
```

```
## method from
## influence.merMod lme4
## cooks.distance.influence.merMod lme4
## dfbeta.influence.merMod lme4
## dfbetas.influence.merMod lme4
```

```
## bad crime lawyers employ
## 4.42 1.30 16.58 20.87
```

```
# We see a value above 5 for lawyers and employees which means we need to take one out
```

```
regressionlm=lm(expend~bad+crime+lawyers, data=regression_data)
car::vif(regressionlm)
```

```
## bad crime lawyers
## 3.26 1.17 3.27
```

```
# Now it looks good
```

b) Fit a linear regression model to the data. Use both the step-up and the step-down method to find the best model. If step-up and step-down yield two different models, choose one and motivate your choice.

```
# Step-up method
```

```
summary(lm(expend~bad, data=regression_data)) #0.694
```

```
##
## Call:
## lm(formula = expend ~ bad, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2742.7  -133.1   -75.6   110.9  2739.2
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   128.34     117.77    1.09   0.28
## bad           13.31       1.28   10.43 6.2e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 668 on 48 degrees of freedom
## Multiple R-squared:  0.694, Adjusted R-squared:  0.688
## F-statistic: 109 on 1 and 48 DF, p-value: 6.17e-14
```

```
summary(lm(expend~crime, data=regression_data)) #0.1
```

```
##
## Call:
## lm(formula = expend ~ crime, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1423    -583    -181     138     5196
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -500.284     585.908  -0.85   0.397
## crime         0.283       0.117    2.42   0.019 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1140 on 48 degrees of freedom
## Multiple R-squared:  0.109, Adjusted R-squared:  0.0901
## F-statistic: 5.85 on 1 and 48 DF, p-value: 0.0194
```

```
summary(lm(expend~lawyers, data=regression_data)) #0.9369
```

```
##
## Call:
## lm(formula = expend ~ lawyers, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1503.7   -28.9    36.3    94.5   822.9
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -62.68063   55.13018   -1.14    0.26
## lawyers      0.07047    0.00264   26.70 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 303 on 48 degrees of freedom
## Multiple R-squared:  0.937, Adjusted R-squared:  0.936
## F-statistic: 713 on 1 and 48 DF, p-value: <2e-16
```

```
summary(lm(expend~employ, data=regression_data))#0.954
```

```
##
## Call:
## lm(formula = expend ~ employ, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -636.8   -85.0    50.1   106.1  1120.3
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.20e+02  4.82e+01   -2.5    0.016 *
## employ       4.69e-02  1.49e-03   31.5 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 260 on 48 degrees of freedom
## Multiple R-squared:  0.954, Adjusted R-squared:  0.953
## F-statistic: 991 on 1 and 48 DF, p-value: <2e-16
```

```
summary(lm(expend~pop, data=regression_data)) # 0.907
```

```
##
## Call:
## lm(formula = expend ~ pop, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1148.3  -161.1    26.1   138.1  1533.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -195.8440   71.3698   -2.74  0.0085 **
```

```
## pop          0.2178      0.0101   21.66   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 368 on 48 degrees of freedom
## Multiple R-squared:  0.907, Adjusted R-squared:  0.905
## F-statistic: 469 on 1 and 48 DF, p-value: <2e-16
```

```
summary(lm(expend~employ+bad, data=regression_data))
```

```
##
## Call:
## lm(formula = expend ~ employ + bad, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -655.3 -100.0   39.1  102.3 1149.7
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.20e+02  4.81e+01  -2.49   0.016 *
## employ       4.97e-02  3.01e-03  16.49  <2e-16 ***
## bad         -1.08e+00  1.00e+00  -1.08   0.286
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 259 on 47 degrees of freedom
## Multiple R-squared:  0.955, Adjusted R-squared:  0.953
## F-statistic: 498 on 2 and 47 DF, p-value: <2e-16
```

```
summary(lm(expend~employ+crime, data=regression_data))
```

```
##
## Call:
## lm(formula = expend ~ employ + crime, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -666.9  -84.3   56.7  101.4 1119.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.56e+02  1.33e+02  -1.92   0.061 .
## employ       4.64e-02  1.56e-03  29.71  <2e-16 ***
## crime        3.03e-02  2.79e-02   1.09   0.282
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 259 on 47 degrees of freedom
## Multiple R-squared:  0.955, Adjusted R-squared:  0.953
## F-statistic: 498 on 2 and 47 DF, p-value: <2e-16
```

```
summary(lm(expend~employ+pop, data=regression_data))
```

```
##
## Call:
## lm(formula = expend ~ employ + pop, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -689.4   -96.3    46.2   113.2  1065.1
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.31e+02   5.15e+01  -2.55   0.014 *
## employ       4.31e-02   6.21e-03   6.94   1e-08 ***
## pop          1.84e-02   2.96e-02   0.62   0.538
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 261 on 47 degrees of freedom
## Multiple R-squared:  0.954, Adjusted R-squared:  0.952
## F-statistic: 489 on 2 and 47 DF, p-value: <2e-16
```

```
summary(lm(expend~employ+lawyers, data=regression_data)) #0.9631 ==> only significant model
```

```
##
## Call:
## lm(formula = expend ~ employ + lawyers, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -599.8   -93.4    38.4    94.8   931.6
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.15e+02   4.36e+01  -2.63   0.0115 *
## employ       2.98e-02   5.15e-03   5.77   5.9e-07 ***
## lawyers      2.69e-02   7.82e-03   3.44   0.0012 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 234 on 47 degrees of freedom
## Multiple R-squared:  0.963, Adjusted R-squared:  0.962
## F-statistic: 613 on 2 and 47 DF, p-value: <2e-16
```

```
# expend = -1.146e+02 + 2.690e-02*lawyers + 2.976e-02*employ + error
# Step-down
```

```
summary(lm(expend~bad+crime+lawyers+employ + pop, data=regression_data))
```

```
##
## Call:
## lm(formula = expend ~ bad + crime + lawyers + employ + pop, data = regression_data)
```



```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -638.7   -92.6    23.1   117.7   792.5
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.14e+02   1.42e+02  -2.21   0.0322 *
## bad          -2.90e+00   1.25e+00  -2.32   0.0251 *
## crime         3.42e-02   2.84e-02   1.21   0.2345
## lawyers       2.31e-02   8.08e-03   2.86   0.0064 **
## employ        2.27e-02   7.50e-03   3.03   0.0041 **
## pop           8.06e-02   3.55e-02   2.27   0.0281 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 227 on 44 degrees of freedom
## Multiple R-squared:  0.968, Adjusted R-squared:  0.964
## F-statistic: 264 on 5 and 44 DF, p-value: <2e-16
```

```
summary(lm(expend~lawyers+employ+bad + pop, data=regression_data))
```

```
##
## Call:
## lm(formula = expend ~ lawyers + employ + bad + pop, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -635.8   -79.6    19.7   116.5   799.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.52e+02   4.65e+01  -3.27   0.0020 **
## lawyers       2.65e-02   7.62e-03   3.48   0.0011 **
## employ        2.26e-02   7.54e-03   3.00   0.0044 **
## bad          -2.27e+00   1.14e+00  -1.99   0.0529 .
## pop           6.54e-02   3.33e-02   1.96   0.0560 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 228 on 45 degrees of freedom
## Multiple R-squared:  0.967, Adjusted R-squared:  0.964
## F-statistic: 326 on 4 and 45 DF, p-value: <2e-16
```

```
summary(lm(expend~lawyers+employ + bad, data=regression_data))
```

```
##
## Call:
## lm(formula = expend ~ lawyers + employ + bad, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -631.8   -94.9    32.2    92.4   958.6
```

```
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.14e+02  4.36e+01  -2.62  0.0118 *
## lawyers      2.63e-02  7.85e-03   3.36  0.0016 **
## employ       3.23e-02  5.85e-03   5.53  1.5e-06 ***
## bad          -8.55e-01  9.12e-01  -0.94  0.3530
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 235 on 46 degrees of freedom
## Multiple R-squared:  0.964, Adjusted R-squared:  0.961
## F-statistic: 408 on 3 and 46 DF, p-value: <2e-16
```

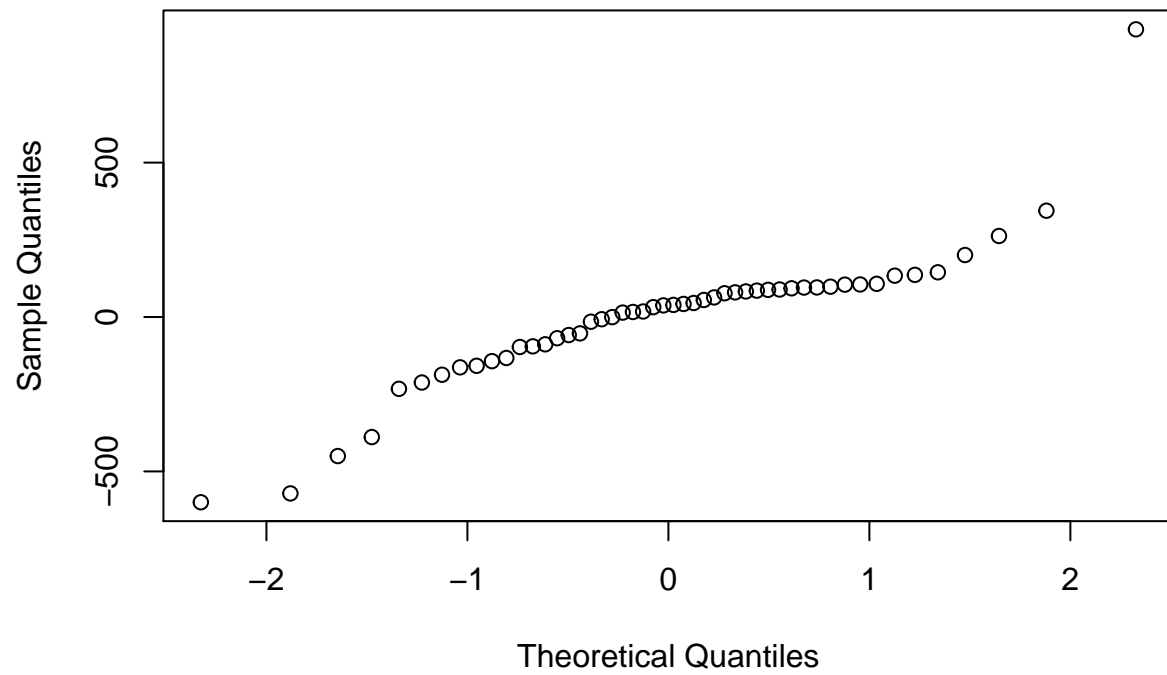
```
summary(lm(expend~lawyers+employ , data=regression_data))
```

```
##
## Call:
## lm(formula = expend ~ lawyers + employ, data = regression_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -599.8  -93.4   38.4   94.8  931.6
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.15e+02  4.36e+01  -2.63  0.0115 *
## lawyers      2.69e-02  7.82e-03   3.44  0.0012 **
## employ       2.98e-02  5.15e-03   5.77  5.9e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 234 on 47 degrees of freedom
## Multiple R-squared:  0.963, Adjusted R-squared:  0.962
## F-statistic: 613 on 2 and 47 DF, p-value: <2e-16
```

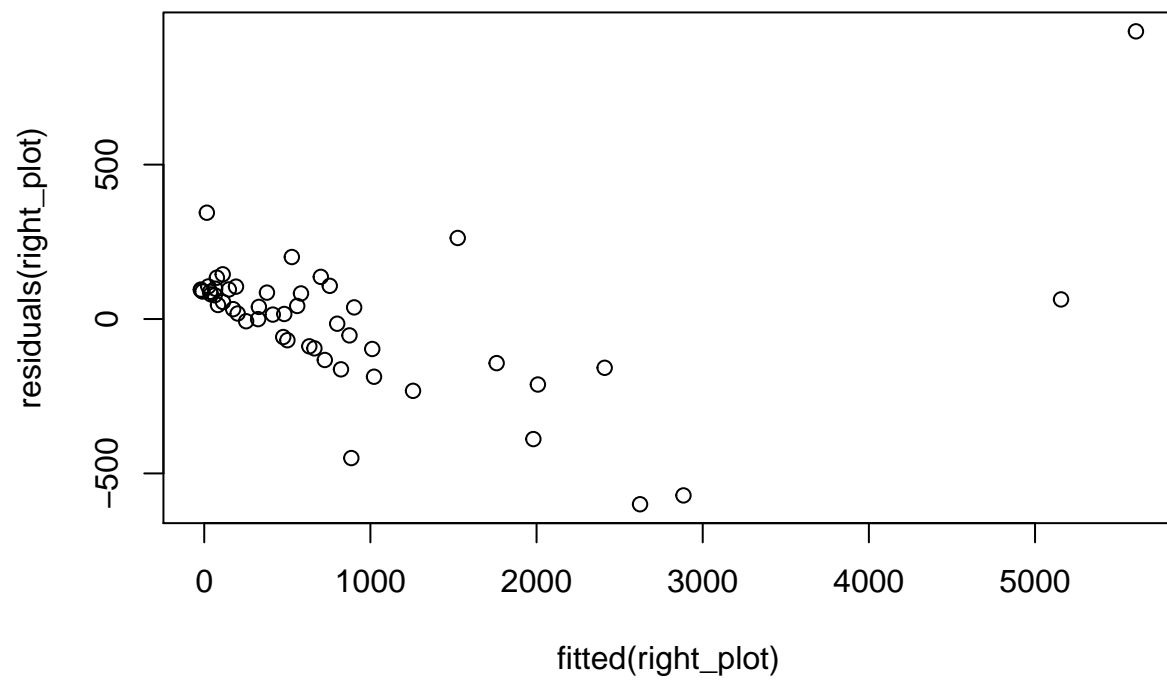
c) Check the model assumptions (of the resulting model from b)) by using relevant diagnostic tools.

```
right_plot = lm(expend~lawyers+employ , data=regression_data)
qqnorm(residuals(right_plot))
```

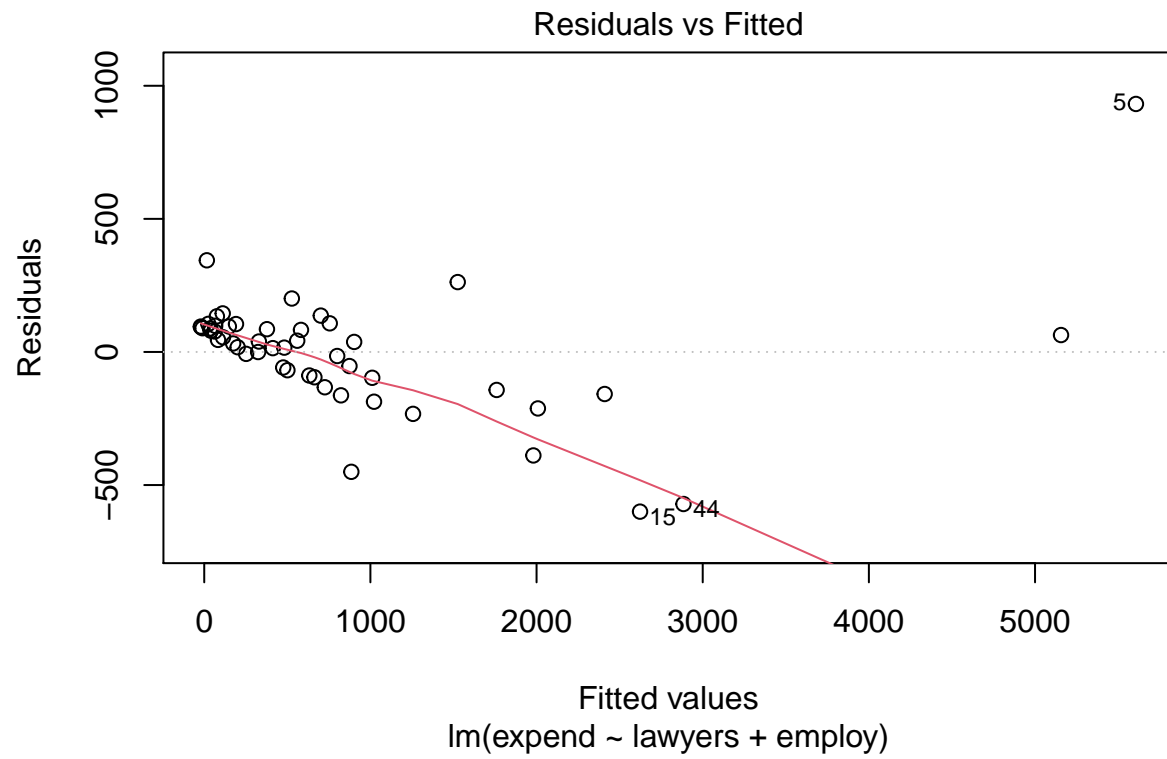
**Normal Q-Q Plot**



```
plot(fitted(right_plot), residuals(right_plot))
```



```
plot(right_plot, 1)
```



```
plot(right_plot, 2)
```

