Exercises 3

1. The data in the accompanying R output relate to a study of the quantity of vitamin B_2 in turnip green (from Anderson R.L. and Bancroft T.L. (1959), Statistical Theory in Research, McGraw-Hill). Three explanatory variables are:

 x_1 = radiation in relative gram claeries per minute during the preceding half day of sunlight (coded by dividing by 100),

 x_2 = average soil moisture tension (coded by dividing by 100),

 $x_3 = \text{air temperature in degrees Farenheit (coded by dividing by 10)},$

and the response variable is

 $Y = \text{milligrams of vitamin } B_2 \text{ per gram of turnip green.}$

Go through the R output and explain what you can deduce from it as follows:

- (a) Comment on the matrix plot of the data.
- (b) State algebraically in terms of unknown parameters the form of model 1.
- (c) What do you deduce from the P-value associated with the 'F-statistic' for model 1?
- (d) From the value R^2 , and the residuals vs. fitted and normal plot of standardised residuals only, comment on whether model 1 is an adequate fit to the data. Explain what output prompted the fitting of model 2.
- (e) Proceeding as in (d), comment on the fit of model 2.
- (f) What can you deduce from the t-test associated with the coefficient of $I(x2^2)$ in the output for model 2? ($I(x2^2)$ in R means that variable x_2^2 has been included.)
- (g) Is there any variable that you could drop from model 2? Explain your answer.
- (h) Write down the *fitted* form of model 3 and give reasons why you could choose model 3 as an adequate model (for this model, also comment on the other residual plots).
- 2. Let

$$Z_i = \mathbf{u}_i^T \boldsymbol{\beta}_Z + d_i, \ i = 1, \dots, N,$$

 d_i iid with $Ed_i = 0$, $var(d_i) = \sigma_Z^2$.

Let $Y_i = aZ_i + \mathbf{u}_i^T \mathbf{b}$, $\mathbf{x}_i = \mathbf{A}^T \mathbf{u}_i$, where $a \in \mathbb{R}$, $\mathbf{b} \in \mathbb{R}^p$, \mathbf{A} invertible $p \times p$ -matrix.

(a) Show that the linear model

$$Y_i = \mathbf{x}_i^T \boldsymbol{\beta}_Y + e_i, \ i = 1, \dots, N,$$

holds with

$$\boldsymbol{\beta}_Y = \mathbf{A}^{-1}(a\boldsymbol{\beta}_Z + \mathbf{b}), \ Ee_i = 0, \ var(e_i) = \sigma_Y^2 = a^2\sigma_Z^2.$$

(b) Show that for the LS-estimators $\hat{\boldsymbol{\beta}}_{Y},~\hat{\boldsymbol{\beta}}_{Z}$ of $\boldsymbol{\beta}_{Y},~\boldsymbol{\beta}_{Z}$:

$$\hat{\boldsymbol{\beta}}_Y = \mathbf{A}^{-1}(a\hat{\boldsymbol{\beta}}_Z + \mathbf{b}).$$

Hint: using the matrix notation introduced for linear regression in the notes, and defining ${\bf U}$ and ${\bf Z}$ by analogy, you get

$$X = UA, Y = aZ + Ub.$$

(Why?)

(c) Show that for $\hat{\sigma}_Y^2$, $\hat{\sigma}_Z^2$ estimating σ_Y^2 , σ_Z^2 :

$$\hat{\sigma}_V^2 = a^2 \hat{\sigma}_Z^2.$$

These results are called "linear equivariance" (or "affine equivariance") and mean that the LS-estimator behaves automatically correctly if the response and predictors are linearly transformed.

```
> #
      exercises 3, question 1, R output
> # Data frame turnip contains data on x1,x2,x3,y
> turnip
    x1
          x2 x3
1 1.76 0.070 7.8 110.4
2 1.55 0.070 8.9 102.8
3 2.73 0.070 8.9 101.0
4 2.73 0.070 7.2 108.4
5 2.56 0.070 8.4 100.7
6 2.80 0.070 8.7 100.3
7 2.80 0.070 7.4 102.0
8 1.84 0.070 8.7 93.7
9 2.16 0.070 8.8 98.9
10 1.98 0.020 7.6 96.6
11 0.59 0.020 6.5 99.4
12 0.80 0.020 6.7 96.2
13 0.80 0.020 6.2 99.0
14 1.05 0.020 7.0 88.4
15 1.80 0.020 7.3 75.3
16 1.80 0.020 6.5 92.0
17 1.77 0.020 7.6 82.4
18 2.30 0.020 8.2 77.1
19 2.03 0.474 7.6 74.0
20 1.91 0.474 8.3 65.7
21 1.91 0.474 8.2 56.8
22 1.91 0.474 6.9 62.1
23 0.76 0.474 7.4 61.0
24 2.13 0.474 7.6 53.2
25 2.13 0.474 6.9 59.4
26 1.51 0.474 7.5 58.7
27 2.05 0.474 7.6 58.0
> # Model 1
> turnip.lm1<-lm(y~x1+x2+x3, turnip)</pre>
> summary(turnip.lm1)
lm(formula = y ~ x1 + x2 + x3, data = turnip)
Residuals:
   Min
            1Q Median
                            3Q
                                   Max
-22.097 -3.790 1.956 5.486 16.980
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 82.069 19.831 4.138 0.000399 ***
x1
              2.276
                        3.657 0.623 0.539736
                         9.354 -8.321 2.17e-08 ***
x2
            -77.831
             1.640
                         2.933 0.559 0.581466
xЗ
Residual standard error: 9.876 on 23 degrees of freedom
Multiple R-Squared: 0.7549,
                             Adjusted R-squared: 0.7229
F-statistic: 23.61 on 3 and 23 DF, p-value: 3.306e-07
> # Residual plots attached (the commands have been edited out)
```

```
> # Model 2
> turnip.lm2<-update(turnip.lm1, .~.+I(x2^2), turnip)</pre>
> summary(turnip.lm2)
Call:
lm(formula = y ~ x1 + x2 + x3 + I(x2^2), data = turnip)
```

Residuals:

1Q Median Min 3Q Max -11.889 -3.490 -0.632 2.772 13.957

Coefficients:

000111010100					
	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	119.571	13.676	8.743	1.31e-08	***
x1	-3.367	2.438	-1.381	0.1811	
x2	542.504	100.526	5.397	2.03e-05	***
x3	-5.026	2.109	-2.383	0.0263	*
$I(x2^2) -$	-1209.047	195.603	-6.181	3.20e-06	***

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

Residual standard error: 6.104 on 22 degrees of freedom Multiple R-Squared: 0.9104, Adjusted R-squared: 0.8941 F-statistic: 55.9 on 4 and 22 DF, p-value: 3.282e-11

- > # Residual plots attached (commands have been edited out)
- > # Model 3
- > turnip.lm3<-update(turnip.lm2, .~.-x1, turnip)</pre>
- > summary(turnip.lm3)

 $lm(formula = y ~ x2 + x3 + I(x2^2), data = turnip)$

Residuals:

Min 1Q Median 3Q Max -12.9663 -3.4432 -0.8141 4.2950 13.2652

Coefficients:

Estimate Std. Error t value Pr(>|t|) (Intercept) 120.627 13.922 8.665 1.06e-08 *** 490.414 95.006 5.162 3.12e-05 *** x2-5.716 2.089 -2.736 0.0118 * xЗ -1107.853 184.910 -5.991 4.14e-06 *** $I(x2^2)$

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

Residual standard error: 6.223 on 23 degrees of freedom Multiple R-Squared: 0.9027, Adjusted R-squared: 0.89 F-statistic: 71.09 on 3 and 23 DF, p-value: 8.747e-12

> # Residual plots attached (commands have been edited out)

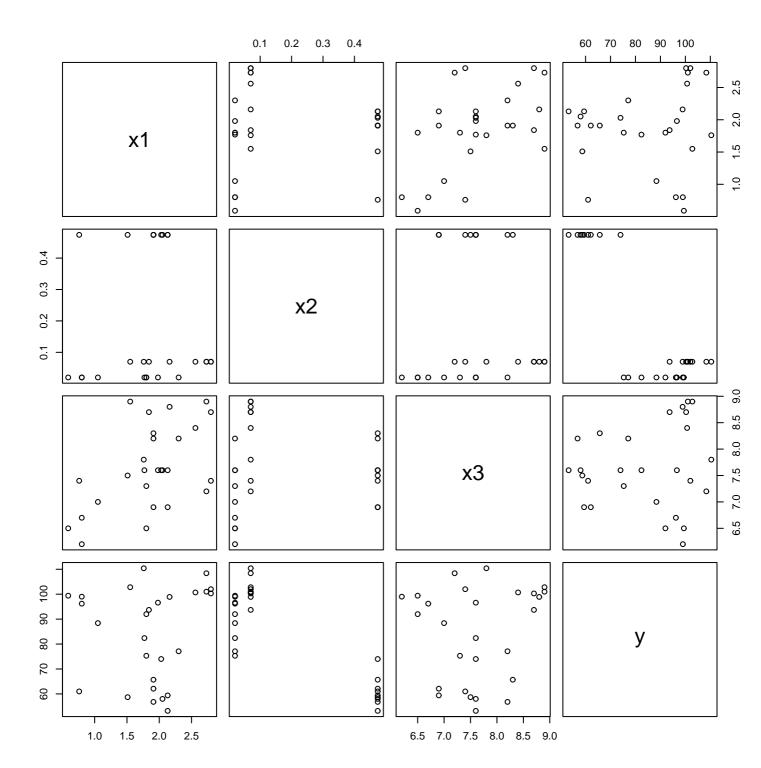


Figure 1: Matrix plot for turnip data.

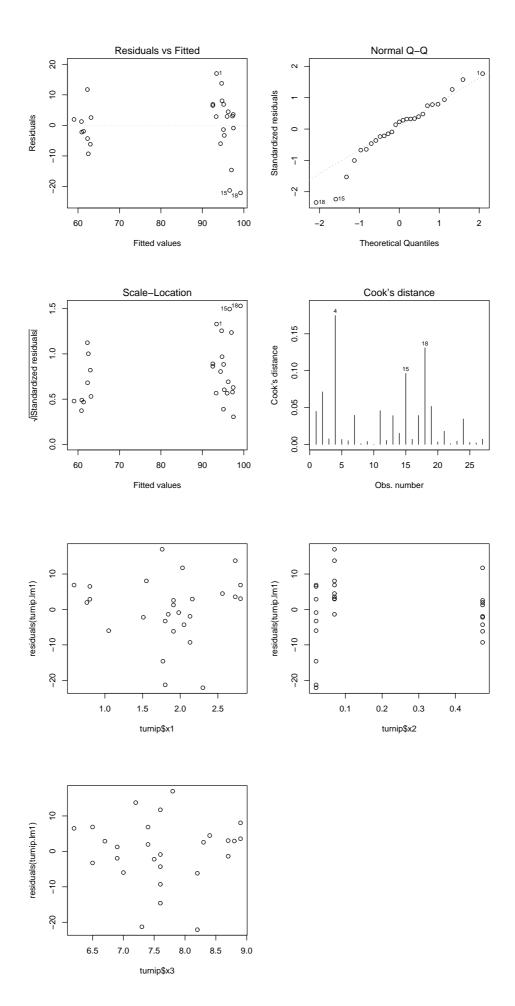


Figure 2: Residual plots for model 1.

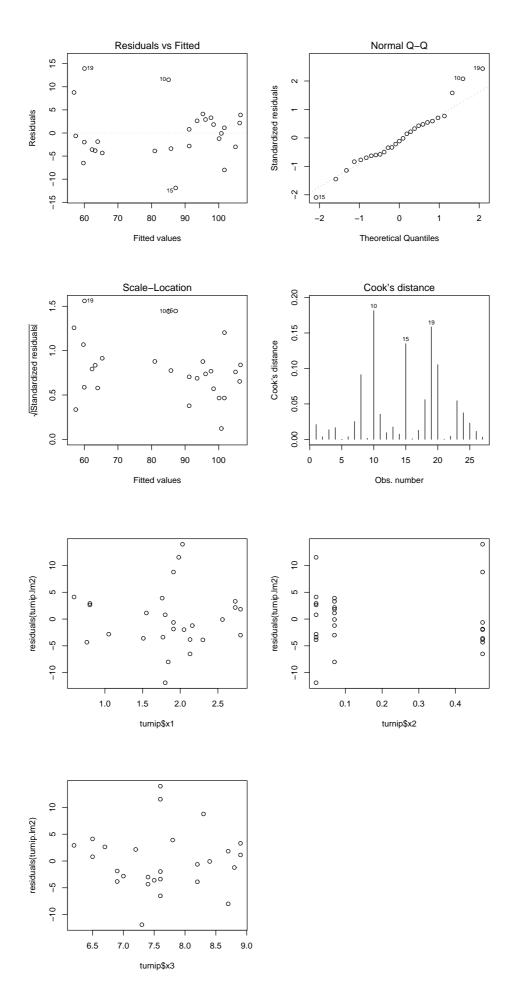


Figure 3: Residual plots for model 2.

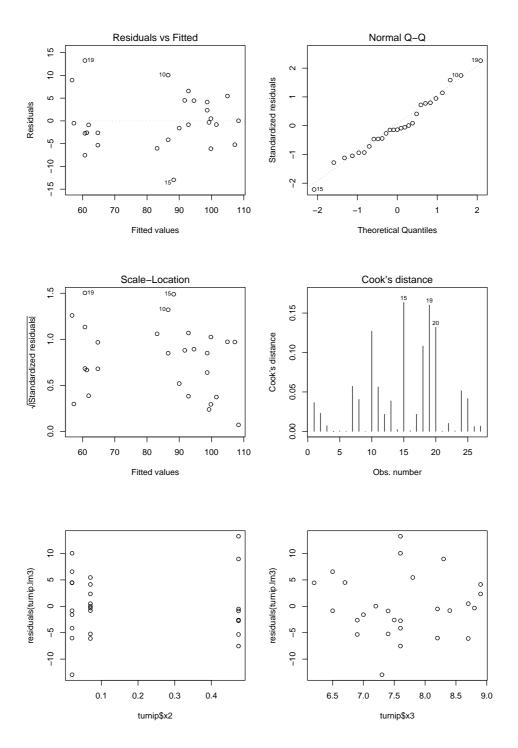


Figure 4: Residual plots for model 3.