

# MATH3714 Linear Regression and Robustness

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## Preface

From previous modules we know how to fit a regression line through points  $(x_1, y_1), \dots, (x_n, y_n) \in \mathbb{R}^2$ . The underlying model here is described by the equation

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

for all  $i \in \{1, 2, \dots, n\}$ , and the aim is to find values for the intercept  $\alpha$  and the slope  $\beta$  such that the fitted line is as close as possible to the data points. This procedure, called simple linear regression, is illustrated in figure 1. The variables  $x_i$  are called **input**, “features”, “predictors”, or sometimes also “explanatory variables” or “independent variables”. The variables  $y_i$  are called **output** or “response”, or sometimes the “dependent variables”. The values  $\varepsilon_i$  are called the **errors** or **noise terms**.

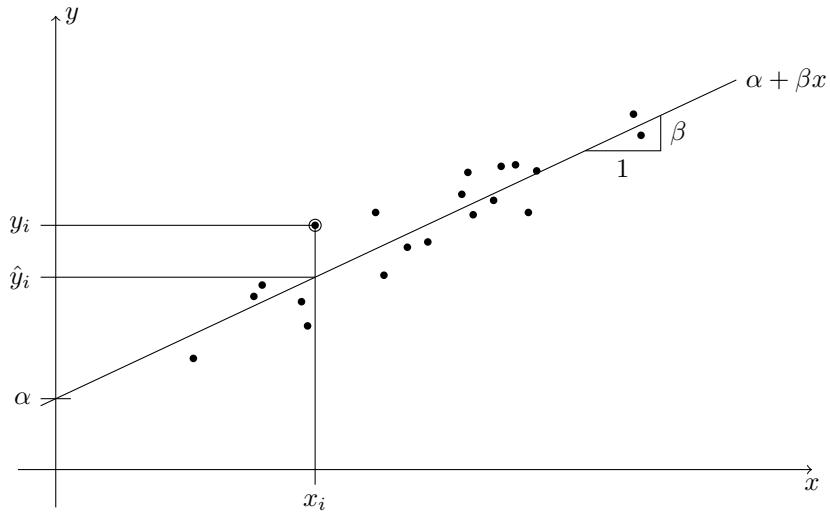


Figure 1: An illustration of linear regression. Each of the black circles in the plot stands for one paired sample  $(x_i, y_i)$ . The regression line  $x \mapsto \alpha + \beta x$ , with intercept  $\alpha$  and slope  $\beta$ , aims to predict the value of  $y$  using the observed value  $x$ . For the marked sample  $(x_i, y_i)$ , the predicted  $y$ -value is  $\hat{y}_i$ .

Extending the situation of simple linear regression, here we will consider multiple linear regression, where the response  $y$  is allowed to depend on several input variables. The corresponding model is now

$$y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip} + \varepsilon_i$$

for all  $i \in \{1, 2, \dots, n\}$ , where  $n$  is still the number of observations, and  $p$  is now the number of inputs we observe for each sample. The aim is now to find values for the intercept  $\beta_0$  and the slopes  $\beta_1, \dots, \beta_p$  such that the fitted hyperplane is as close as possible to the data points. Note that for multiple linear regression, we still consider a single response for each sample, only the number of inputs has been increased.

We will discuss multiple linear regression in much detail; our discussion will answer questions like the following:

1. Given a new input  $x$ , how can we predict the corresponding output  $y$ ?
2. By studying a fitted regression model, sometimes better understanding of the data can be achieved. For example, one could ask whether all of the  $p$  input variables carry information about the response  $y$ . We will use statistical hypothesis tests to answer such questions.
3. How well does the model fit the data?
4. How to deal with outliers in the data?

In the next section, we will begin by reviewing simple linear regression in detail, before moving on to the multiple regression case.

# 1 Simple Linear Regression

As a reminder, we consider simple linear regression in this section. My hope is that all of you have seen this material before at some stage, *e.g.* in school or in some first or second year modules.

In preparation for notation introduced in the next section, we rename the parameters  $\alpha$  and  $\beta$  from the introduction to the new names  $\beta_0$  for the intercept and  $\beta_1$  for the slope.

## 1.1 Residual Sum of Squares

In simple linear regression, the aim is to find a regression line  $y = \beta_0 + \beta_1 x$ , such that the line is “close” to given data points  $(x_1, y_1), \dots, (x_n, y_n) \in \mathbb{R}^2$  for  $i \in \{1, 2, \dots, n\}$ . The usual way to find  $\beta_0$  and  $\beta_1$ , and thus the regression line, is by minimising the **residual sum of squares**:

$$r(\beta_0, \beta_1) = \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2. \quad (1)$$

For given  $\beta_0$  and  $\beta_1$ , the value  $r(\beta_0, \beta_1)$  measures how close (in vertical direction) the given data points  $(x_i, y_i)$  are to the regression line  $\beta_0 + \beta_1 x$ . By minimising  $r(\beta_0, \beta_1)$  we find the regression line which is “closest” to the data. The solution of this minimisation problem is usually expressed in terms of the sample variance  $s_x$  and the sample covariance  $s_{xy}$ .

**Definition 1.1.** The **sample covariance** of  $x_1, \dots, x_n \in \mathbb{R}$  and  $y_1, \dots, y_n \in \mathbb{R}$  is given by

$$s_{xy} := \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}),$$

where  $\bar{x}$  and  $\bar{y}$  are the sample means.

The **sample variance** of  $x_1, \dots, x_n \in \mathbb{R}$  is given by

$$s_x^2 := s_{xx} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2,$$

where, again,  $\bar{x}$  is the sample mean of the  $x_i$ .

**Lemma 1.1.** Assume that  $s_x^2 > 0$ . Then the function  $r(\beta_0, \beta_1)$  from (1) takes its minimum at the point  $(\hat{\beta}_0, \hat{\beta}_1)$  given by

$$\hat{\beta}_1 = \frac{s_{xy}}{s_x^2}, \quad \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x},$$

where  $\bar{x}, \bar{y}$  are the sample means,  $s_{xy}$  is the sample covariance and  $s_x^2$  is the sample variance.

*Proof.* We could find the minimum of  $r$  by differentiating and setting the derivatives to zero. Here we follow a different approach which uses a “trick” to simplify the algebra: Let  $\tilde{x}_i = x_i - \bar{x}$  and  $\tilde{y}_i = y_i - \bar{y}$  for all  $i \in \{1, \dots, n\}$ . Then we have

$$\sum_{i=1}^n \tilde{x}_i = \sum_{i=1}^n x_i - n\bar{x} = 0$$

and, similarly,  $\sum_{i=1}^n \tilde{y}_i = 0$ . Using the new coordinates  $\tilde{x}_i$  and  $\tilde{y}_i$  we find

$$\begin{aligned} r(\beta_0, \beta_1) &= \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2 \\ &= \sum_{i=1}^n (\tilde{y}_i + \bar{y} - \beta_0 - \beta_1 \tilde{x}_i - \beta_1 \bar{x})^2 \\ &= \sum_{i=1}^n ((\tilde{y}_i - \beta_1 \tilde{x}_i) + (\bar{y} - \beta_0 - \beta_1 \bar{x}))^2 \\ &= \sum_{i=1}^n (\tilde{y}_i - \beta_1 \tilde{x}_i)^2 + 2(\bar{y} - \beta_0 - \beta_1 \bar{x}) \sum_{i=1}^n (\tilde{y}_i - \beta_1 \tilde{x}_i) + n(\bar{y} - \beta_0 - \beta_1 \bar{x})^2 \end{aligned}$$

Since  $\sum_{i=1}^n \tilde{x}_i = \sum_{i=1}^n \tilde{y}_i = 0$ , the second term on the right-hand side vanishes and we get

$$r(\beta_0, \beta_1) = \sum_{i=1}^n (\tilde{y}_i - \beta_1 \tilde{x}_i)^2 + n(\bar{y} - \beta_0 - \beta_1 \bar{x})^2. \quad (2)$$

Both of these terms are positive and we can minimise the second term (without changing the first term) by setting  $\beta_0 = \bar{y} - \beta_1 \bar{x}$ .

To find the value of  $\beta_1$  which minimises the first term on the right-hand side of (2) we now set the (one-dimensional) derivative w.r.t.  $\beta_1$  equal to 0. We get the condition

$$\begin{aligned} 0 &\stackrel{!}{=} \frac{d}{d\beta_1} \sum_{i=1}^n (\tilde{y}_i - \beta_1 \tilde{x}_i)^2 \\ &= \sum_{i=1}^n 2(\tilde{y}_i - \beta_1 \tilde{x}_i) \frac{d}{d\beta_1} (\tilde{y}_i - \beta_1 \tilde{x}_i) \\ &= -2 \sum_{i=1}^n (\tilde{y}_i - \beta_1 \tilde{x}_i) \tilde{x}_i \\ &= -2 \sum_{i=1}^n \tilde{x}_i \tilde{y}_i + 2\beta_1 \sum_{i=1}^n \tilde{x}_i^2. \end{aligned}$$

The only solution to this equation is

$$\begin{aligned} \beta_1 &= \frac{\sum_{i=1}^n \tilde{x}_i \tilde{y}_i}{\sum_{i=1}^n \tilde{x}_i^2} \\ &= \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \\ &= \frac{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \\ &= \frac{s_{xy}}{s_x^2}. \end{aligned}$$

Since the second derivative is  $2 \sum_{i=1}^n \tilde{x}_i^2 > 0$ , this is indeed a minimum and the proof is complete.  $\square$

## 1.2 Linear Regression as a Parameter Estimation Problem

In statistics, any analysis starts by making a statistical model of the data. This is done by writing random variables which have the same structure as the data, and which are chosen so that the data “looks like” a random sample from these random variables.

To construct a model for the data used in a simple linear regression problem, we consider fixed  $x_1, \dots, x_n$  and then define random variables  $Y_1, \dots, Y_n$  as follows:

$$Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i \quad (3)$$

for all  $i \in \{1, 2, \dots, n\}$ , where  $\varepsilon_1, \dots, \varepsilon_n$  are i.i.d. random variables with  $\mathbb{E}(\varepsilon_i) = 0$  and  $\text{Var}(\varepsilon_i) = \sigma^2$ .

- Here the  $x$ -values are fixed and known. The only random quantities in the model are  $\varepsilon_i$  and  $Y_i$ . (There are more complicated models which also allow for randomness of  $x$ , but we won't consider such models here.)
- The random variables  $\varepsilon_i$  are errors or noise terms. In a scatter plot, the errors correspond to the vertical distance between the samples and the true regression line. Often one assumes that  $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$  for all  $i \in \{1, 2, \dots, n\}$ .
- The values  $\beta_0$ ,  $\beta_1$  and  $\sigma^2$  are parameters of the model. To fit the model to data, we need to estimate these parameters.

This model is more complex than the models considered in some introductory statistics courses:

- The data consists now of pairs of numbers, instead of just single numbers.
- We have

$$\mathbb{E}(Y_i) = \mathbb{E}(\beta_0 + \beta_1 x_i + \varepsilon_i) = \beta_0 + \beta_1 x_i + \mathbb{E}(\varepsilon_i) = \beta_0 + \beta_1 x_i.$$

Thus, the expectation of  $Y_i$  depends on  $x_i$  and, at least for  $\beta_1 \neq 0$ , the random variables  $Y_i$  are not identically distributed.

In this setup, we can consider the estimates  $\hat{\beta}_0$  and  $\hat{\beta}_1$  from the previous subsection as statistical parameter estimates for the model parameters  $\beta_0$  and  $\beta_1$ .

In order to fit a linear model we also need to estimate the error variance  $\sigma^2$ . We can't use the usual formula for estimating a variance, since the errors  $\varepsilon_i$  are not observed. Instead we consider the **residuals**

$$\hat{\varepsilon}_i = y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i).$$

These are the vertical distances between the data points  $(x_i, y_i)$  and the fitted regression line. (In contrast, the errors  $\varepsilon_i$  are the vertical distances between the data points and the unknown, true regression line). Using the residuals, we can estimate  $\sigma^2$  by

$$\hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^n \hat{\varepsilon}_i^2 = \frac{1}{n-2} \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2. \quad (4)$$

To understand the form of this estimator, we have to remember that  $\sigma^2$  is the variance of the  $\varepsilon_i$ . Thus, using the standard estimator for the variance, we could estimate  $\sigma^2$  as

$$\sigma^2 \approx \frac{1}{n-1} \sum_{i=1}^n (\varepsilon_i - \bar{\varepsilon})^2 \approx \frac{1}{n-1} \sum_{i=1}^n (\hat{\varepsilon}_i - \bar{\hat{\varepsilon}})^2, \quad (5)$$

where  $\bar{\varepsilon}$  and  $\bar{\hat{\varepsilon}}$  are the averages of the  $\varepsilon_i$  and the  $\hat{\varepsilon}_i$ , respectively. We will later see that  $\bar{\hat{\varepsilon}} = 0$ . The estimates of  $\beta_0$  and  $\beta_1$  are sensitive to fluctuations in the data, with the effect that the estimated regression line is, on average, slightly closer to the data points than the true regression line would be. This causes the sample variance of the  $\hat{\varepsilon}_i$ , on average, to be slightly smaller than the true error variance  $\sigma^2$  and thus the estimator (5) is slightly biased. A more detailed analysis reveals that an unbiased estimator can be obtained if one replaces the pre-factor  $1/(n-1)$  in equation (5) with  $1/(n-2)$ . This leads to the estimator (4).

The main advantage gained by considering a statistical model is, that we now can consider how close the estimators  $\hat{\beta}_0$ ,  $\hat{\beta}_1$  and  $\hat{\sigma}^2$  are to the true values. Results one can obtain include the following:

- The estimators  $\hat{\beta}_0$ ,  $\hat{\beta}_1$  and  $\hat{\sigma}^2$  are unbiased: This means that when we plug in random data  $(x_i, Y_i)$  from the model (3), on average we get the correct answer:  $\mathbb{E}(\hat{\beta}_0) = \beta_0$ ,  $\mathbb{E}(\hat{\beta}_1) = \beta_1$ ,  $\mathbb{E}(\hat{\sigma}^2) = \sigma^2$ .
- One can ask about the average distance between the estimated parameters  $\hat{\beta}_0$ ,  $\hat{\beta}_1$  and  $\hat{\sigma}^2$  and the (unknown) true values  $\beta_0$ ,  $\beta_1$  and  $\sigma^2$ . One measure for these distances is the root mean squared error of the estimators.
- One can consider confidence intervals for the parameters  $\beta_0$ ,  $\beta_1$  and  $\sigma^2$ .
- One can consider statistical hypothesis tests to answer yes/no questions about the parameters. For example, one might ask whether the data could have come from the model with  $\beta_0 = 0$ .
- One can consider whether the data is compatible with the model at all, irrespective of parameter values. If there is a non-linear relationship between  $x$  and  $y$ , the model (3) will no longer be appropriate.

We will consider most of these topics over the course of the module.

### 1.3 Matrix Notation

To conclude this section, we will rewrite the results using matrix notation. This approach simplifies our equations and will be extensively used for multiple linear regression in the rest of this module. The idea here is to arrange all quantities in the problem as matrices and vectors. We write

$$X = \begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix} \in \mathbb{R}^{n \times 2}, \quad y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \in \mathbb{R}^n, \quad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} \in \mathbb{R}^n, \quad \beta = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix} \in \mathbb{R}^2$$

Using this notation, we can rewrite the  $n$  equations  $y_i = \beta_0 + x_i\beta_1 + \varepsilon_i$  for  $i \in \{1, \dots, n\}$  as one vector-valued equation in  $\mathbb{R}^n$ : we get

$$y = X\beta + \varepsilon,$$

and we want to “solve” this vector-valued equation for  $\beta$ . The sum of squares can now be written as

$$r(\beta) = \sum_{i=1}^n \varepsilon_i^2 = \varepsilon^\top \varepsilon = (y - X\beta)^\top (y - X\beta) = y^\top y - 2\beta^\top X^\top y + \beta^\top X^\top X\beta.$$

In the next section we will see that the minimum of  $r$  is attained for

$$\hat{\beta} = (X^\top X)^{-1} X^\top y$$

and one can check that the components of this vector  $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1)$  coincide with the estimates we obtained above.

#### Summary

- Simple linear regression is the case where there is only one input.
- A regression line is fitted by minimising the residual sum of squares.
- Linear regression is a statistical parameter estimation problem.
- The problem can be conveniently written in matrix/vector notation.

# **Part I**

# **Theory**

## 2 Least Squares Estimates

### 2.1 Data and Models

For multiple linear regression we assume that there are  $p$  inputs and one output. If we have a sample of  $n$  observations, we have  $np$  inputs and  $n$  outputs in total. Here we denote the  $i$ th observation of the  $j$ th input by  $x_{ij}$  and the corresponding output by  $y_i$ .

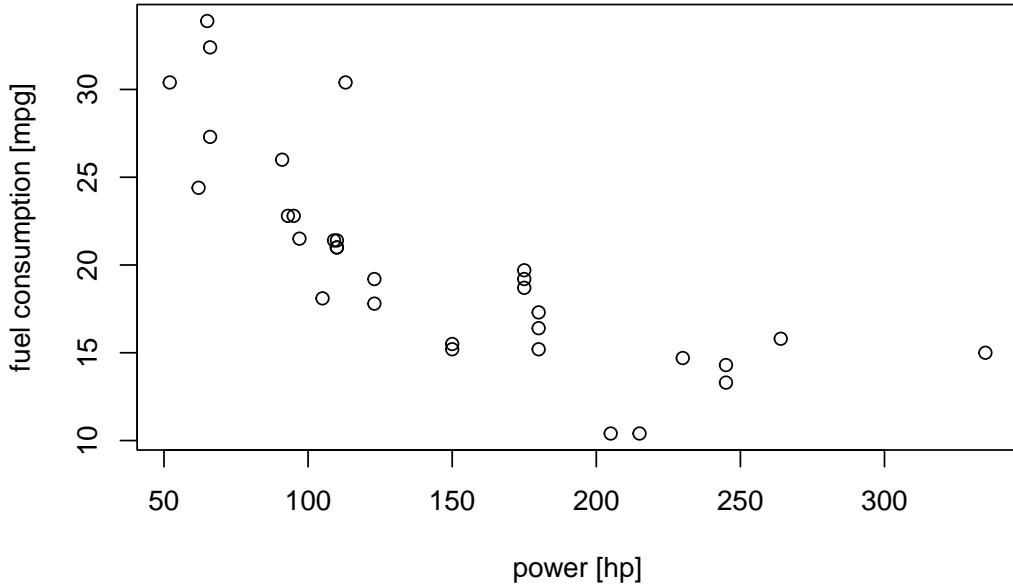
As an example, we consider the `mtcars` dataset built into R. This is a small dataset, which contains information about 32 automobiles (1973-74 models). The table lists fuel consumption `mpg`, gross horsepower `hp`, and 9 other aspects of these cars. Here we consider `mpg` to be the output, and the other listed aspects to be inputs. Type `help(mtcars)` in R to learn more about this dataset:

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
# Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
# Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
# Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
# Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
# Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
# Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
# Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
# Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
# Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
# Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4
# Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4
# Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
# Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
# Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3
# Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3	4
# Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3	4
# Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3	4
# Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
# Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
# Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
# Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
# Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0	3	2
# AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
# Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
# Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
# Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
# Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
# Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
# Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
# Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
# Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
# Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

For this dataset we have  $n = 32$  (number of cars), and  $p = 10$  (number of predictors, excluding `mpg`). The values  $y_1, \dots, y_{32}$  are listed in the first column of the table, the values  $x_{i,1}$  for  $i \in \{1, \dots, 32\}$  are shown in the second column, and the values  $x_{i,10}$  are shown in the last column.

It is easy to make scatter plots which show how a single input affects the output. For example, we can show how the engine power affects fuel consumption:

```
plot(mtcars$hp, mtcars$mpg,
     xlab = "power [hp]", ylab = "fuel consumption [mpg]")
```



We can see that cars with stronger engines tend to use more fuel (*i.e.* a gallon of fuel lasts for fewer miles; the curve goes down), but leaving out the other inputs omits a lot of information. It is not easy to make a plot which takes all inputs into account. It is also not immediately obvious which of the variables are most important.

In linear regression, we assume that the output depends on the inputs in a linear way. We write this as

$$y_i = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_p x_{i,p} + \varepsilon_i \quad (6)$$

where the errors  $\varepsilon_i$  are assumed to be “small”. Here,  $i$  ranges over all  $n$  samples, so (6) represents  $n$  simultaneous equations. The parameters  $\beta_j$  can be interpreted as the expected change in the response  $y$  per unit change in  $x_j$  when all other inputs are held fixed.

This model describes a hyperplane in the  $(p+1)$ -dimensional space of the inputs  $x_j$  and the output  $y$ . The hyperplane is easily visualized when  $p=1$  (as a line in  $\mathbb{R}^2$ ), and visualisation can be attempted for  $p=2$  (as a plane in  $\mathbb{R}^3$ ) but is hard for  $p>2$ .

## 2.2 The Normal Equations

Similar to what we did in Section 1.3, we rewrite the model using matrix notation. We define the vectors

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \in \mathbb{R}^n, \quad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} \in \mathbb{R}^n, \quad \beta = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{pmatrix} \in \mathbb{R}^{1+p}$$

as well as the matrix

$$X = \begin{pmatrix} 1 & x_{1,1} & \cdots & x_{1,p} \\ 1 & x_{2,1} & \cdots & x_{2,p} \\ \vdots & \vdots & & \vdots \\ 1 & x_{n,1} & \cdots & x_{n,p} \end{pmatrix} \in \mathbb{R}^{n \times (1+p)}.$$

The parameters  $\beta_i$  are called the **regression coefficients** and the matrix  $X$  is called the **design matrix**.

Using this notation, the model (6) can be written as

$$y = X\beta + \varepsilon, \quad (7)$$

where again  $X\beta$  is a matrix-vector multiplication which “hides” the sums in equation (6), and (7) is an equation of vectors of size  $n$ , which combines the  $n$  individual equations from (6).

To simplify notation, we index the columns of  $X$  by  $0, 1, \dots, p$  (instead of the more conventional  $1, \dots, p+1$ ), so that we can for example write

$$(X\beta)_i = \sum_{j=0}^p x_{i,j}\beta_j = \beta_0 + \sum_{j=1}^p x_{i,j}\beta_j.$$

As before, we find the regression coefficients by minimising the residual sum of squares:

$$\begin{aligned} r(\beta) &= \sum_{i=1}^n \varepsilon_i^2 \\ &= \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_{i,1} + \dots + \beta_p x_{i,p}))^2. \end{aligned}$$

In practice, this notation turns out to be cumbersome, and we will use matrix notation in the following proof.

**Lemma 2.1.** *Assume that the matrix  $X^\top X \in \mathbb{R}^{(1+p) \times (1+p)}$  is invertible. Then the function  $r(\beta)$  takes its minimum at the vector  $\hat{\beta} \in \mathbb{R}^{p+1}$  given by*

$$\hat{\beta} = (X^\top X)^{-1} X^\top y.$$

*Proof.* Using the vector equation  $\varepsilon = y - X\beta$ , we can also write the residual sum of squares as

$$\begin{aligned} r(\beta) &= \sum_{i=1}^n \varepsilon_i^2 \\ &= \varepsilon^\top \varepsilon \\ &= (y - X\beta)^\top (y - X\beta) \\ &= y^\top y - y^\top X\beta - (X\beta)^\top y + (X\beta)^\top (X\beta). \end{aligned}$$

Using the linear algebra rules from Appendix A.2 we find that  $y^\top X\beta = (X\beta)^\top y = \beta^\top X^\top y$  and  $(X\beta)^\top (X\beta) = \beta^\top X^\top X\beta$ . Thus we get

$$r(\beta) = y^\top y - 2\beta^\top X^\top y + \beta^\top X^\top X\beta.$$

Note that in this equation  $X$  is a matrix,  $y$  and  $\beta$  are vectors, and  $r(\beta)$  is a number.

To find the minimum of this function, we set all partial derivatives  $\frac{\partial}{\partial \beta_i} r(\beta)$  equal to 0. Going through the terms in the formula for  $r(\beta)$  we find: (1)  $y^\top y$  does not depend on  $\beta$ , so we have  $\frac{\partial}{\partial \beta_i} y^\top y = 0$  for all  $i$ , (2) we have

$$\frac{\partial}{\partial \beta_i} \beta^\top X^\top y = \frac{\partial}{\partial \beta_i} \sum_{j=0}^p \beta_j (X^\top y)_j = (X^\top y)_i$$

and (3) finally

$$\frac{\partial}{\partial \beta_i} \beta^\top X^\top X\beta = \frac{\partial}{\partial \beta_i} \sum_{j,k=0}^p \beta_j (X^\top X)_{j,k} \beta_k = 2 \sum_{k=0}^p (X^\top X)_{i,k} \beta_k = 2((X^\top X)\beta)_i.$$

(Some care is needed, when checking that the middle equality sign in the previous equation is correct.) Combining these derivatives, we find

$$\frac{\partial}{\partial \beta_i} r(\beta) = 0 - 2(X^\top y)_i + 2(X^\top X\beta)_i \quad (8)$$

for all  $i \in \{0, 1, \dots, p\}$ . At a local minimum of  $r$ , all of these partial derivatives must be zero and using a vector equation we find that a necessary condition for a minimum is

$$X^\top X\beta = X^\top y. \quad (9)$$

Since we assumed that  $X^\top X$  is invertible, there is exactly one vector  $\beta$  which solves (9). This vector is given by

$$\hat{\beta} := (X^\top X)^{-1} X^\top y.$$

As for one-dimensional minimisation, there is a condition on the second derivatives which must be checked to see which local extrema are local minima. Here we are only going to sketch this argument: A sufficient condition for  $\hat{\beta}$  to be a minimum is for the second derivative matrix (the Hessian matrix) to be positive definite (see appendix A.2.8). Using equation (8) we find

$$\frac{\partial^2}{\partial \beta_i \partial \beta_j} r(\beta) = 2(X^\top X)_{i,j}$$

And thus the Hessian matrix is  $H = 2X^\top X$ . Using results from linear algebra, one can show that this matrix is indeed positive definite and thus  $\hat{\beta}$  is the unique minimum of  $r$ .  $\square$

Equation (9) gives a system of  $p+1$  linear equations with  $p+1$  unknowns. This system of linear equations,  $X^\top X\beta = X^\top y$  is called the **normal equations**. If  $X^\top X$  is invertible, as assumed in the lemma, this system of equations has  $\hat{\beta}$  as its unique solution. Otherwise, there may be more than one  $\beta$  which leads to the same value  $r(\beta)$  and the minimum will no longer be unique. This happens for example, if two of the inputs are identical to each other (or, more generally, one input is linearly dependent on one or more other inputs).

The condition that  $X^\top X$  must be invertible in lemma 2.1 corresponds to the condition  $s_x^2 > 0$  in lemma 1.1.

The value  $\hat{\beta}$  found in the lemma is called the **least squares estimator** for  $\beta$ .

## 2.3 Fitted Values

Let us again consider our model

$$y = X\beta + \varepsilon,$$

using the matrix notation introduced above. Here we can think of  $X\beta$  as the **true values**, while  $\varepsilon$  are the errors. Using the least squares estimate  $\hat{\beta}$  we can estimate the true values as

$$\hat{y} = X\hat{\beta}. \quad (10)$$

These estimates are called the **fitted values**. Using the definition of  $\hat{\beta}$  we get

$$\hat{y} = X(X^\top X)^{-1} X^\top y =: Hy.$$

The matrix  $H = X(X^\top X)^{-1} X^\top$  is commonly called the **hat matrix** (because it “puts the hat on  $y$ ”).

Finally, we can estimate the errors using the residuals

$$\hat{\varepsilon} = y - X\hat{\beta} = y - \hat{y} = y - Hy = (I - H)y, \quad (11)$$

where  $I$  is the  $n \times n$  identity matrix.

## 2.4 Example

To conclude this section, we demonstrate how these methods can be used in R. For this we consider the `mtcars` example from the beginning of the section again. We will first see how to do the analysis “by hand”, and later show how the same result can be obtained using R’s built-in functions.

We first split `mtcars` into the response column `y` (the first column) and the design matrix `X` (a column of ones, followed by columns 2 to 11 of `mtcars`):

```
y <- mtcars[, 1]
X <- cbind(1, data.matrix(mtcars[, 2:11]))
```

Next we compute  $X^T X$  and solve the normal equations. Often it is faster, easier, and has smaller numerical errors to solve the normal equations rather than inverting the matrix  $X^T X$ .

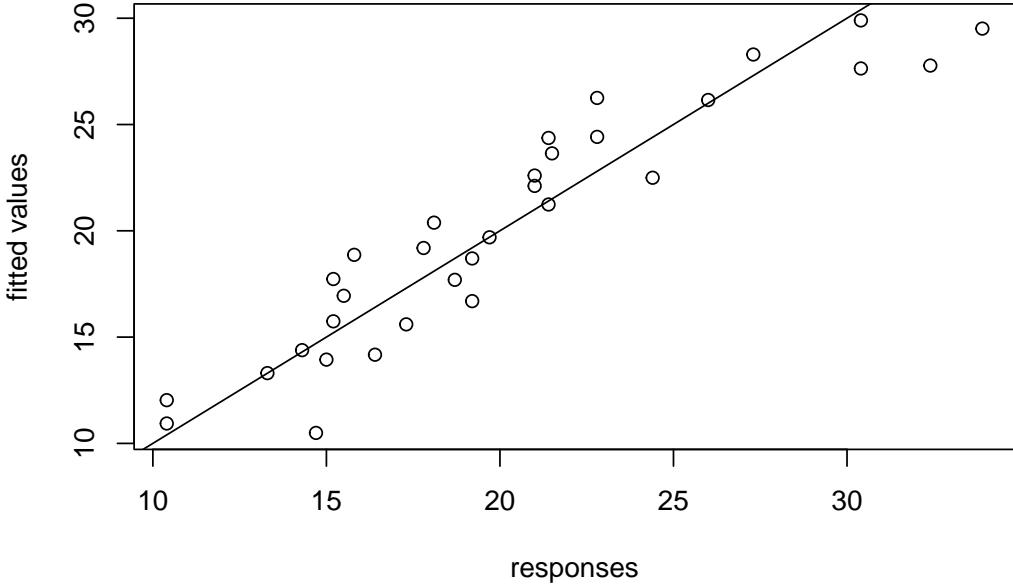
```
XtX <- t(X) %*% X
beta.hat <- solve(XtX, t(X) %*% y)
beta.hat

# [,1]
#      12.30337416
# cyl -0.11144048
# disp  0.01333524
# hp    -0.02148212
# drat   0.78711097
# wt    -3.71530393
# qsec   0.82104075
# vs     0.31776281
# am     2.52022689
# gear   0.65541302
# carb  -0.19941925
```

Without further checks it is hard to know whether the result is correct, or whether we made a mistake somewhere. One good sign is that we argued earlier that higher `hp` should lead to lower `mpg`, and indeed the corresponding coefficient `-0.02148212` is negative.

Finally, compute the fitted values and generate a plot of fitted values against responses. If everything worked, we would expect the points in this plot to be close to the diagonal.

```
y.hat <- X %*% beta.hat
plot(y, y.hat, xlab = "responses", ylab = "fitted values")
abline(a = 0, b = 1) # plot the diagonal
```



For comparison we now re-do the analysis using built-in R commands. In the `lm()` command below, we use `data=mtcars` to tell R where the data is stored, and the formula `mpg ~ .` states that we want to model `mpg` as a function of all other variable (this is the meaning of `.`).

```
m <- lm(mpg ~ ., data = mtcars) # fit a linear model
coef(m) # get the estimated coefficients
```

```
# (Intercept)          cyl         disp         hp        drat         wt
# 12.30337416 -0.11144048  0.01333524 -0.02148212  0.78711097 -3.71530393
#       qsec          vs          am         gear         carb
#  0.82104075  0.31776281  2.52022689  0.65541302 -0.19941925
```

Comparing these coefficients to the vector `beta.hat` from above shows that we got the same result using both methods. The fitted values can be computed using `fitted.values(m)`. Here we just check that we get the same result as above:

```
max(abs(fitted.values(m) - y.hat))
```

```
# [1] 3.979039e-13
```

This result  $3.410605 \cdot 10^{-13}$  stands for the number  $3.410605 \cdot 10^{-13}$ , which is extremely small. The difference between our results and R's result is caused by rounding errors.

## 2.5 Models Without Intercept

Sometimes, it is useful to fit a model without an intercept. This means that we assume that the output  $y$  is a linear function of the inputs  $x_1, \dots, x_p$  but that the output is zero when all inputs are zero. We write this as

$$y_i = \beta_1 x_{i,1} + \dots + \beta_p x_{i,p} + \varepsilon_i$$

for all  $i \in \{1, \dots, n\}$ .

When we write this model in matrix notation, we need to leave out the intercept column in the design matrix  $X$ . For this case we get

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \in \mathbb{R}^n, \quad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} \in \mathbb{R}^n, \quad \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix} \in \mathbb{R}^p$$

as well as the matrix

$$X = \begin{pmatrix} x_{1,1} & \cdots & x_{1,p} \\ x_{2,1} & \cdots & x_{2,p} \\ \vdots & & \vdots \\ x_{n,1} & \cdots & x_{n,p} \end{pmatrix} \in \mathbb{R}^{n \times p}.$$

The vectors  $y$  and  $\varepsilon$  are unchanged, but the vector  $\beta$  is now shorter and the matrix  $X$  is narrower.

Most of the results in this module carry over to this case, for example the least squares estimate for  $\beta$  is still given by

$$\hat{\beta} = (X^\top X)^{-1} X^\top y.$$

However, some results need to be adjusted and to be sure one has to carefully check the details of the derivations when results are needed for models without intercept.

### Summary

- Multiple linear regression allows for more than one input, but still has only one output.
- The least squared estimate for the coefficients is found by minimising the residual sum of squares.
- The least squares estimate can be computed by solving the normal equations.
- The hat matrix transforms responses into fitted values.
- Residuals estimate the errors as  $\hat{\varepsilon} = y - \hat{y}$ .
- Models can be fitted without an intercept term when appropriate.

## Interlude: Linear Regression in R

### Fitting a Model

The function `lm()` is used to fit a linear model in R. There are different ways to specify the form of the model and the data to be used for fitting the model.

- The most basic way to call `lm()` is the case where the explanatory variables and the response variable are stored as separate vectors. Assuming, for example, that the explanatory variables are `x1`, `x2`, `x3` and that the response variable is `y` in R, we can tell R to fit the linear model  $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon$  by using the following command:

```
lm(y ~ x1 + x2 + x3)
```

Note that R automatically added the intercept term  $\beta_0$  to this model. If we want to fit a model without an intercept, *i.e.* the model  $y = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon$ , we have to add `0 +` in front of the explanatory variables:

```
lm(y ~ 0 + x1 + x2 + x3)
```

The general form of a model specification is the response variable, followed by `~`, followed by a plus-separated list of explanatory variables. For this form of calling `lm()`, the variables `y`, `x1`, `x2`, and `x3` in the examples above must be already defined before `lm()` is called. It may be a good idea to double-check that the variables have the correct values before trying to call `lm()`.

- Both for the response and for explanatory variables we can specify arbitrary R expressions to compute the numeric values to be used. For example, to fit the model  $\log(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$  (assuming that all  $y_i$  are positive) we can use the following command:

```
lm(log(y) ~ x1 + x2)
```

Some care is needed, because `+`, `*` and `^` have a special meaning inside the first argument of `lm()`; any time we want to compute a variable for `lm()` using these operations, we need to surround the corresponding expression with `I()`, to tell R that `+`, `*` or `^` should have their usual, arithmetic meaning. For example, to fit a model of the form  $y \sim \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon$ , we can use the following R command:

```
lm(y ~ x + I(x^2))
```

Here, the use of `I()` tells R that `x^2` is to be interpreted as the vector  $(x_1^2, \dots, x_n^2)$ . Similarly, we can fit a model of the form  $y = \beta_0 + \beta_1(x_1 + x_2) + \varepsilon$ :

```
lm(y ~ I(x1+x2))
```

Here, the use of `I()` tells R that `x1+x2` indicates the vector  $(x_{1,1} + x_{2,1}, \dots, x_{1,n} + x_{2,n})$  instead of two separate explanatory variables.

Details about how to specify models in calls to `lm()` can be found by using the command `help(formula)` in R.

- If the response and the explanatory variables are stored in the columns of a data frame, we can use the `data=...` argument to `lm()` to specify this data frame and then just use the column names to specify the regression model. For example, the `stackloss` dataset built into R consists of a data frame with columns `Air.Flow`, `Water.Temp`, `Acid.Conc.`, `stack.loss`. To predict `stackloss$stack.loss` from `stackloss$Air.Flow` we can write

```
lm(stack.loss ~ Air.Flow, data=stackloss)
```

As a special case, a single dot “.” can be used in place of the explanatory variables in the model to indicate that all columns except for the given response should be used. Thus, the following two commands are equivalent:

```
lm(stack.loss ~ ., data=stackloss)
lm(stack.loss ~ Air.Flow + Water.Temp + Acid.Conc., data=stackloss)
```

## Understanding the Model

The output of the `lm()` function is an R object which can be used to extract information about the fitted model. A good way to work with this object is to store it in a variable and then use commands like the ones listed below to work with this variable. For example, the following R command fits a model for the `stackloss` dataset and stores it in the variable `m`:

```
m <- lm(stack.loss ~ ., data=stackloss)
```

Many operations are available to use with this object `m`:

- Printing `m` to the screen:

```
m
#
# Call:
# lm(formula = stack.loss ~ ., data = stackloss)
#
# Coefficients:
# (Intercept)      Air.Flow    Water.Temp    Acid.Conc.
# -39.9197        0.7156       1.2953       -0.1521
```

This shows the estimated values for the regression coefficient.

- The command `summary()` can be used to print additional information about the fitted model:

```
summary(m)
#
# Call:
# lm(formula = stack.loss ~ ., data = stackloss)
#
# Residuals:
#      Min      1Q Median      3Q      Max
# -7.2377 -1.7117 -0.4551  2.3614  5.6978
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) -39.9197   11.8960  -3.356  0.00375 ***
# Air.Flow      0.7156    0.1349   5.307  5.8e-05 ***
# Water.Temp    1.2953    0.3680   3.520  0.00263 **
# Acid.Conc.   -0.1521    0.1563  -0.973  0.34405
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 3.243 on 17 degrees of freedom
# Multiple R-squared:  0.9136, Adjusted R-squared:  0.8983
# F-statistic: 59.9 on 3 and 17 DF,  p-value: 3.016e-09
```

We will learn over the course of this module how to interpret all of this output.

- The coefficient vector  $\beta$  can be obtained using `coef(m)`:

```
coef(m)

# (Intercept) Air.Flow Water.Temp Acid.Conc.
# -39.9196744 0.7156402 1.2952861 -0.1521225
```

- The fitted values  $\hat{y}_i$  can be obtained using the command `fitted(m)`:

```
fitted(m)

#      1       2       3       4       5       6       7       8
# 38.765363 38.917485 32.444467 22.302226 19.711654 21.006940 21.389491 21.389491
#      9      10      11      12      13      14      15      16
# 18.144379 12.732806 11.363703 10.220540 12.428561 12.050499 5.638582 6.094949
#     17      18      19      20      21
# 9.519951 8.455093 9.598257 13.587853 22.237713
```

- The estimated residuals  $\hat{\varepsilon}_i = y_i - \hat{y}_i$  can be obtained using the command `resid(m)`:

```
resid(m)

#      1       2       3       4       5       6
# 3.23463723 -1.91748529 4.55553300 5.69777417 -1.71165358 -3.00693970
#      7       8       9      10      11      12
# -2.38949071 -1.38949071 -3.14437890 1.26719408 2.63629676 2.77946036
#     13      14      15      16      17      18
# -1.42856088 -0.05049929 2.36141836 0.90505080 -1.51995059 -0.45509295
#     19      20      21
# -0.59825656 1.41214728 -7.23771286
```

- The design matrix  $X$  can be found using `model.matrix(m)`:

```
model.matrix(m)

# (Intercept) Air.Flow Water.Temp Acid.Conc.
# 1           1      80       27      89
# 2           1      80       27      88
# 3           1      75       25      90
# 4           1      62       24      87
# 5           1      62       22      87
# 6           1      62       23      87
# 7           1      62       24      93
# 8           1      62       24      93
# 9           1      58       23      87
# 10          1      58       18      80
# 11          1      58       18      89
# 12          1      58       17      88
# 13          1      58       18      82
# 14          1      58       19      93
# 15          1      50       18      89
# 16          1      50       18      86
# 17          1      50       19      72
# 18          1      50       19      79
# 19          1      50       20      80
# 20          1      56       20      82
# 21          1      70       20      91
# attr(,"assign")
# [1] 0 1 2 3
```

Instead of giving a fitted model `m`, we can also just give the data and formula as

in the call to `lm()`, e.g. `model.matrix(y ~ x1 + x2 + x3)`.

## Making Predictions

One of the main aims of fitting a linear model is to use the model to make predictions for new, not previously observed  $x$ -values, *i.e.* to compute  $y_{\text{new}} = X_{\text{new}}\hat{\beta}$ . The general form of the command for prediction is `predict(m, newdata)`, where `m` is the model previously fitted using `lm()`, and `newdata` specifies the new  $x$ -values to predict responses for. The argument `newdata` should be a `data.frame` and for each variable in the original model there should be a column in `newdata` which has the name of the original variable and contains the new values. For example, if the model was fitted using

```
m <- lm(y ~ x + I(x^2))
```

and if the new samples are stored in `x.new`, then responses for the  $x$ -values in `x.new` can be predicted using the following command:

```
predict(m, data.frame(x=x.new))
```

As a second example, for the `stackloss` dataset, the following commands can be used to predict `stack.loss` for two new  $x$ -values:

```
m <- lm(stack.loss ~ ., data = stackloss)
newdata <- data.frame(Air.Flow=c(70, 73), Water.Temp=c(25,24), Acid.Conc.=c(78,90))
predict(m, newdata)

#      1      2
# 30.69174 29.71790
```

More information about `predict()` can be found by reading the output of `help(predict.lm)`.

### 3 Random Vectors and Covariance

A **random vector** is a vector  $Z = (Z_1, \dots, Z_n)$  where each component  $Z_i$  is a random variable.

When we introduce a statistical model for multiple linear regression in the following section, we will assume that the errors are random variables. As in (7), the model can be written in vector form as

$$Y = X\beta + \varepsilon. \quad (12)$$

This vector-valued equation contains two random vectors,  $Y$  and  $\varepsilon$ .

#### 3.1 Expectation

The expectation of a random vector is taken for each component separately. This is formalised in the following definition.

**Definition 3.1.** Let  $Z = (Z_1, \dots, Z_n) \in \mathbb{R}^n$  be a random vector. Then the expectation of  $Z$  is the (non-random) vector

$$\mathbb{E}(Z) = \begin{pmatrix} \mathbb{E}(Z_1) \\ \vdots \\ \mathbb{E}(Z_n) \end{pmatrix} \in \mathbb{R}^n.$$

**Example 3.1.** The random vector  $\varepsilon$  in (12) has

$$\mathbb{E}(\varepsilon)_i = \mathbb{E}(\varepsilon_i) = 0$$

for all  $i \in \{1, \dots, n\}$  and thus  $\mathbb{E}(\varepsilon) = 0 \in \mathbb{R}^n$ , where 0 here denotes the zero-vector  $(0, \dots, 0) \in \mathbb{R}^n$ .

Since the expectation of a random vector is defined in terms of the usual expectation, most rules we know for expectations still hold. For example, if  $Y$  and  $Z$  are two random vectors, we have  $\mathbb{E}(Y + Z) = \mathbb{E}(Y) + \mathbb{E}(Z)$ .

**Example 3.2.** The random vector  $Y$  in (12) has

$$\mathbb{E}(Y)_i = \mathbb{E}(Y_i) = \mathbb{E}((X\beta)_i + \varepsilon_i) = (X\beta)_i + \mathbb{E}(\varepsilon_i) = (X\beta)_i$$

for all  $i \in \{1, \dots, n\}$  and thus  $\mathbb{E}(Y) = X\beta \in \mathbb{R}^n$ . We often will write the above derivation in vector form as

$$\mathbb{E}(Y) = \mathbb{E}(X\beta + \varepsilon) = X\beta + \mathbb{E}(\varepsilon) = X\beta.$$

**Example 3.3.** If  $A \in \mathbb{R}^{m \times n}$  is a matrix and  $Z \in \mathbb{R}^n$  is a random vector, then we find the expectation of  $AZ \in \mathbb{R}^m$  as

$$\mathbb{E}(AZ)_i = \mathbb{E}((AZ)_i) = \mathbb{E}\left(\sum_{j=1}^n a_{ij}Z_j\right) = \sum_{j=1}^n \mathbb{E}(a_{ij}Z_j) = \sum_{j=1}^n a_{ij}\mathbb{E}(Z_j) = \sum_{j=1}^n a_{ij}\mathbb{E}(Z)_j$$

for all  $i \in \{1, \dots, m\}$  and thus we have  $\mathbb{E}(AZ) = A\mathbb{E}(Z)$ .

#### 3.2 Covariance Matrix

The variance of random variables is replaced with the concept of a “covariance matrix” for random vectors.

**Definition 3.2.** Let  $Z = (Z_1, \dots, Z_n) \in \mathbb{R}^n$  be a random vector. Then the covariance matrix of  $Z$  is the matrix  $\text{Cov}(Z) \in \mathbb{R}^{n \times n}$  given by

$$\text{Cov}(Z)_{ij} = \text{Cov}(Z_i, Z_j),$$

for all  $i, j \in \{1, \dots, n\}$ , where  $\text{Cov}(Z_i, Z_j)$  denotes the usual covariance between random variables.

We collect some basic properties of covariance matrices here. Most of these arguments use concepts and rules from linear algebra, as summarised in section A in the appendix.

- Since  $\text{Cov}(Z_i, Z_j) = \text{Cov}(Z_j, Z_i)$ , covariance matrices are symmetric.
- The diagonal elements of  $\text{Cov}(Z)$  are

$$\text{Cov}(Z)_{ii} = \text{Cov}(Z_i, Z_i) = \text{Var}(Z_i). \quad (13)$$

- If the elements  $Z_i$  of  $Z$  are (statistically) independent, we have  $\text{Cov}(Z_i, Z_j) = 0$  and thus  $\text{Cov}(Z)_{ij} = 0$  for  $i \neq j$ . Hence, if  $Z$  is a vector of independent random variables, the covariance matrix of  $Z$  is diagonal.
- Let  $\mu = \mathbb{E}(Z) \in \mathbb{R}^n$ . If we interpret  $\mu$  as a column vector, then  $M = (Z - \mu)(Z - \mu)^\top$  is an  $n \times n$  matrix and we have

$$M_{ij} = ((Z - \mu)(Z - \mu)^\top)_{ij} = (Z - \mu)_i(Z - \mu)_j.$$

Taking expectations gives  $\mathbb{E}(M_{ij}) = \mathbb{E}((Z - \mu)_i(Z - \mu)_j) = \text{Cov}(Z_i, Z_j)$  and thus we can write

$$\text{Cov}(Z) = \mathbb{E}((Z - \mu)(Z - \mu)^\top). \quad (14)$$

- Covariance matrices are positive semi-definite. To see this, let  $C = \text{Cov}(Z)$  and  $u \in \mathbb{R}^n$  be a vector. We have to show that  $u^\top Cu \geq 0$ . Writing  $\bar{Z} := Z - \mathbb{E}(Z)$  as an abbreviation, we get

$$\begin{aligned} u^\top Cu &= u^\top \mathbb{E}(\bar{Z}\bar{Z}^\top)u \\ &= \mathbb{E}(u^\top \bar{Z}\bar{Z}^\top u) \\ &= \mathbb{E}((\bar{Z}^\top u)^\top \bar{Z}^\top u) \\ &= \mathbb{E}(\|\bar{Z}^\top u\|^2), \end{aligned}$$

where  $\|\bar{Z}^\top u\|$  denotes the Euclidean length of the vector  $\bar{Z}^\top u$ . Since  $\|\bar{Z}^\top u\|^2 \geq 0$  we find  $u^\top Cu \geq 0$ . This shows that the covariance matrix  $C$  is positive semi-definite. (Note that, nevertheless, individual *elements* of the matrix  $C$  can be negative numbers.)

**Example 3.4.** The random vector  $\varepsilon$  in equation (12) has  $\mathbb{E}(\varepsilon) = 0$ . We have  $\text{Cov}(\varepsilon)_{ii} = \text{Var}(\varepsilon_i) = \sigma^2$  for all  $i \in \{1, \dots, n\}$ . Since we assumed the  $\varepsilon_i$  to be independent, the covariance matrix is diagonal and we find

$$\text{Cov}(\varepsilon) = \sigma^2 I,$$

where  $I$  is the  $n \times n$  identity matrix.

An important result about covariance matrices is given in the following lemma, which describes how the covariance matrix changes under affine transformations.

**Lemma 3.1.** *Let  $Z \in \mathbb{R}^n$  be a random vector,  $A \in \mathbb{R}^{m \times n}$  a matrix and  $b \in \mathbb{R}^m$  a vector. Then*

$$\text{Cov}(AZ + b) = A \text{Cov}(Z) A^\top.$$

*Proof.* As in equation (14), we can write  $\text{Cov}(AZ + b)$  as

$$\text{Cov}(AZ + b) = \mathbb{E}((AZ + b - \mu)(AZ + b - \mu)^\top),$$

where  $\mu = \mathbb{E}(AZ + b) = \mathbb{E}(AZ) + b$ . Thus,  $AZ + b - \mu = AZ - \mathbb{E}(AZ)$  and we find

$$\begin{aligned} \text{Cov}(AZ + b) &= \mathbb{E}((AZ - \mathbb{E}(AZ))(AZ - \mathbb{E}(AZ))^\top) \\ &= \text{Cov}(AZ). \end{aligned}$$

This shows that the covariance matrix ignores non-random shifts.

Furthermore, we have  $AZ - \mathbb{E}(AZ) = AZ - A\mathbb{E}(Z) = A(Z - \mathbb{E}(Z))$ . Using equation (14) again, we find

$$\begin{aligned}\text{Cov}(AZ) &= \mathbb{E}((AZ - \mathbb{E}(AZ))(AZ - \mathbb{E}(AZ))^\top) \\ &= \mathbb{E}(A(Z - \mathbb{E}(Z))(Z - \mathbb{E}(Z))^\top A^\top) \\ &= A\mathbb{E}((Z - \mathbb{E}(Z))(Z - \mathbb{E}(Z))^\top)A^\top \\ &= A\text{Cov}(Z)A^\top.\end{aligned}$$

This completes the proof.  $\square$

### 3.3 The Multivariate Normal Distribution

With the concepts of expectation and covariance in hand, we can now turn to the distribution of random vectors. Since we assume that the random errors  $\varepsilon_i$  are normally distributed, we will need to understand how vectors of normally distributed random variables behave.

**Definition 3.3.** A random vector  $Z \in \mathbb{R}^n$  follows a **multivariate normal distribution**, if  $u^\top Z \in \mathbb{R}$  is normally distributed or constant for every vector  $u \in \mathbb{R}^n$ .

This definition takes its slightly surprising form to avoid some boundary cases which we will discuss in an example, below. To understand the definition, a good start is to consider the cases where  $u$  is one of the standard basis vectors, say  $u_i = 1$  and  $u_j = 0$  for all  $j \neq i$ . In this case we have

$$u^\top Z = \sum_{k=1}^n u_k Z_k = Z_i.$$

Thus, if  $Z$  follows a multivariate normal distribution, each of the components  $Z_i$  is normally distributed. Example 3.8, below, shows that the converse is not true.

One can show that a multivariate normal distribution is completely determined by the mean  $\mu = \mathbb{E}(Z)$  and the covariance  $\Sigma = \text{Cov}(Z)$ . The distribution of such a  $Z$  is denoted by  $\mathcal{N}(\mu, \Sigma)$ . Also, for every  $\mu \in \mathbb{R}^n$  and every positive semi-definite matrix  $\Sigma \in \mathbb{R}^{n \times n}$  there is a random vector  $Z$  which follows a multivariate normal distribution with this mean and covariance.

**Example 3.5.** Consider the vector  $\varepsilon$  from the model (12). This vector has components  $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$  and by assumption, the components  $\varepsilon_i$  are independent. For  $u \in \mathbb{R}^n$  we have

$$u^\top \varepsilon = \sum_{i=1}^n u_i \varepsilon_i.$$

Using the fact that a sum of independent, one-dimensional, normally distributed random variables is also normally distributed, we see that  $u^\top \varepsilon$  is normally distributed for every  $u$ . Thus,  $\varepsilon$  is a normally distributed random vector. We have already seen  $\mathbb{E}(\varepsilon) = 0$  and  $\text{Cov}(\varepsilon) = \sigma^2 I$ , and thus  $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$ .

Without proof we state here some properties of the multivariate normal distribution:

- If  $Z \sim \mathcal{N}(\mu, \Sigma)$  and  $a \in \mathbb{R}^n$ , then  $Z + a \sim \mathcal{N}(\mu + a, \Sigma)$ .
- If  $Z \sim \mathcal{N}(\mu, \Sigma)$  and  $A \in \mathbb{R}^{m \times n}$ , then  $AZ \sim \mathcal{N}(A\mu, A\Sigma A^\top)$ .
- If  $Z_1 \sim \mathcal{N}(\mu_1, \Sigma_1)$  and  $Z_2 \sim \mathcal{N}(\mu_2, \Sigma_2)$  are independent, then  $Z_1 + Z_2 \sim \mathcal{N}(\mu_1 + \mu_2, \Sigma_1 + \Sigma_2)$ .

**Example 3.6.** Let  $Z = (Z_1, Z_2)$  where  $Z_1$  and  $Z_2$  are independently standard normal distributed. Let

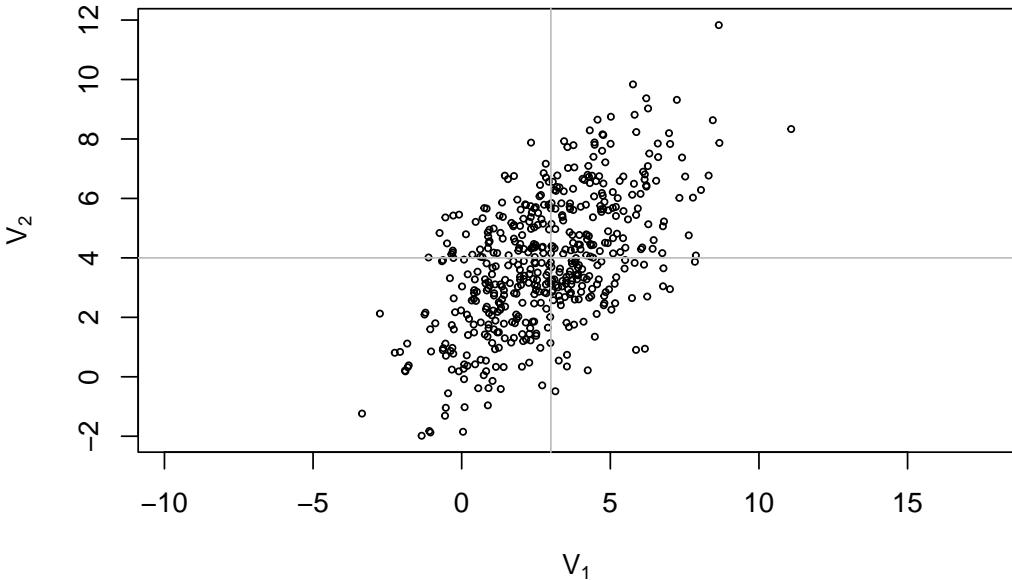
$$A := \begin{pmatrix} 2 & -1 \\ 2 & 1 \end{pmatrix} \quad \text{and} \quad b := \begin{pmatrix} 3 \\ 4 \end{pmatrix}.$$

Then  $AZ + b \sim \mathcal{N}(b, \Sigma)$  where

$$\Sigma = A \text{Cov}(Z) A^\top = \begin{pmatrix} 2 & -1 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 2 & 2 \\ -1 & 1 \end{pmatrix} = \begin{pmatrix} 5 & 3 \\ 3 & 5 \end{pmatrix}$$

We can use R to plot a sample of this two-dimensional normal distribution. (The grey cross indicates the mean.)

```
N <- 500
Z <- rbind(rnorm(N), rnorm(N))
A <- matrix(c(2, 2, -1, 1), 2, 2)
b <- c(3, 4)
V <- A %*% Z + b
plot(V[1,], V[2,], asp = 1, cex = .5,
      xlab = expression(V[1]),
      ylab = expression(V[2]))
abline(v = 3, col = "grey")
abline(h = 4, col = "grey")
```



**Example 3.7.** The random vector  $Y$  in (12) satisfies  $Y = X\beta + \varepsilon$  and since  $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$  we have  $Y \sim \mathcal{N}(X\beta, \sigma^2 I)$ .

**Example 3.8.** Let  $Y \sim \mathcal{N}(0, 1)$  be a random variable. Define a random vector  $Z = (Z_1, Z_2)$  as  $Z_1 = Y$  and

$$Z_2 = \begin{cases} Y & \text{if } |Y| < 1, \text{ and} \\ -Y & \text{otherwise.} \end{cases}$$

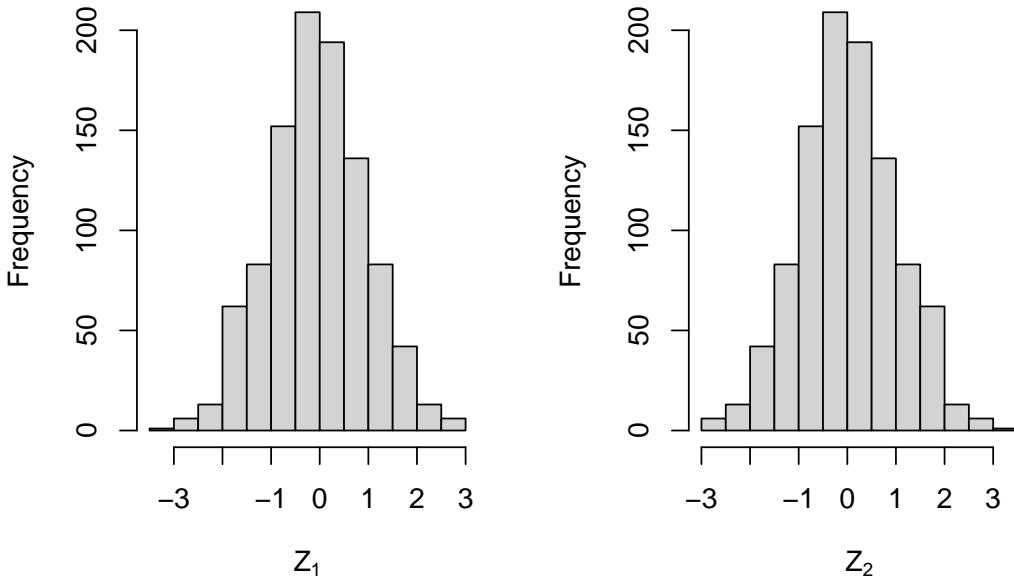
Clearly  $Z_1$  is standard normally distributed. Since  $\mathcal{N}(0, 1)$  is symmetric, both  $Y$  and  $-Y$  are standard normally distributed and it follows that  $Z_2$  is also standard normally distributed. Nevertheless, the random vector  $Z$  does not follow a multivariate normal distribution. Instead of giving a proof of this fact, we illustrate this here using an R experiment. We start by verifying that  $Z_1$  and  $Z_2$  are normally distributed.

```

N <- 1000
Y <- rnorm(N)
Z1 <- Y
Z2 <- ifelse(abs(Y)<1, Y, -Y)

par(mfrow=c(1,2))
hist(Z1, main=NULL, xlab=expression(Z[1]))
hist(Z2, main=NULL, xlab=expression(Z[2]))

```

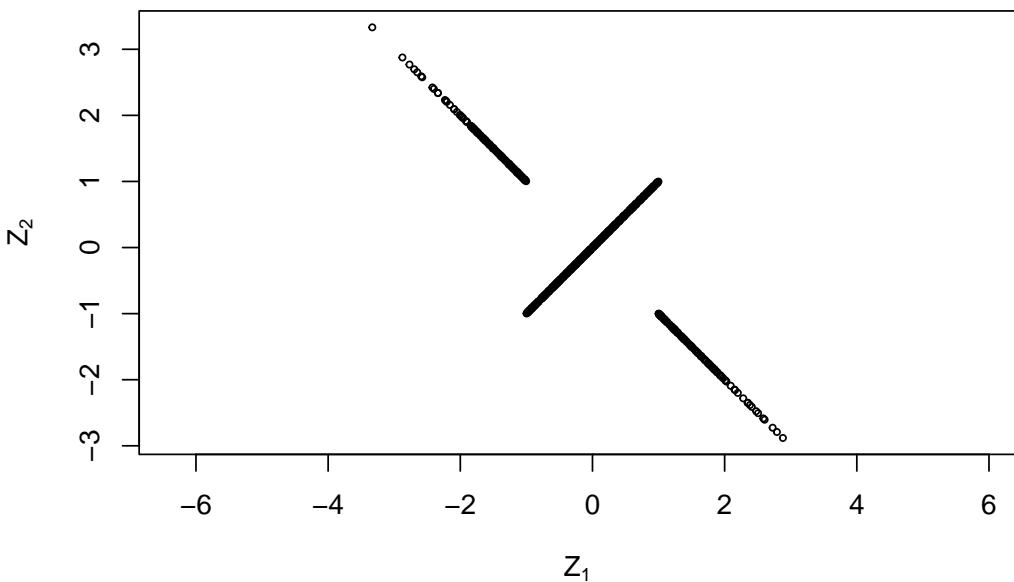


The histograms make it plausible that the components are indeed normally distributed.  
Now we use a scatter plot to show the joint distribution of  $Z_1$  and  $Z_2$ :

```

plot(Z1, Z2, cex=0.5,
      xlab=expression(Z[1]),
      ylab=expression(Z[2]))

```



This plot looks peculiar! Most people would not call this a normal distribution and the formal definition of a multivariate normal distribution is made to exclude cases like this.

### Summary

- The expectation of a random vector is computed component-wise.
- The covariance matrix of a random vector plays the role of the variance for scalar random variables.
- For linear transformations we have  $\mathbb{E}(AZ) = A\mathbb{E}(Z)$  and  $\text{Cov}(AZ + b) = A\text{Cov}(Z)A^\top$ .
- A multivariate normal distribution is determined by its mean  $\mu$  and covariance matrix  $\Sigma$ , and denoted by  $\mathcal{N}(\mu, \Sigma)$ .

## Problem Sheet 1

This problem sheet covers material from Sections 1-3 of the course. You should attempt all these questions and write up your solutions in advance of the workshop in week 2. Your solutions are not assessed. Instead, the answers will be discussed in the workshop and will be made available online afterwards.

You may find it helpful to review the following key concepts:

- Simple linear regression model:  $y_i = \beta_0 + x_i\beta_1 + \varepsilon_i$
- Least squares estimation for regression coefficients
- Matrix notation for linear regression:  $y = X\beta + \varepsilon$
- Properties of the design matrix  $X$  and the hat matrix  $H = X(X^\top X)^{-1}X^\top$
- Expectation and covariance of random vectors
- Basic properties of the multivariate normal distribution

1. Consider a simple linear regression model fitted to a dataset with  $n$  pairs of observations  $(x_1, y_1), \dots, (x_n, y_n)$ . Let  $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1)$  be the least squares estimate of the coefficients in the model.

- a. Show that if we shift all  $y$ -values by a constant  $c$  (*i.e.*, replace each  $y_i$  with  $y_i + c$ ), the new least squares estimate for the slope  $\hat{\beta}_1$  remains unchanged, while the new estimate for the intercept becomes  $\hat{\beta}_0 + c$ .

Solution: Let us denote the new  $y$ -values as  $y'_i = y_i + c$ . Then the new RSS is

$$\begin{aligned}\text{RSS}'(\beta_0, \beta_1) &= \sum_{i=1}^n (y'_i - (\beta_0 + \beta_1 x_i))^2 \\ &= \sum_{i=1}^n ((y_i + c) - (\beta_0 + \beta_1 x_i))^2 \\ &= \sum_{i=1}^n (y_i - (\beta_0 - c + \beta_1 x_i))^2.\end{aligned}$$

This is equivalent to the original RSS with  $\beta_0$  replaced by  $\beta_0 - c$ . Therefore, the value of  $\beta_1$  that minimises this will be the same as before, while the value of  $\beta_0$  that minimises it will be  $\hat{\beta}_0 + c$ .

- b. Now consider shifting all  $x$ -values by a constant  $d$  (*i.e.*, replace each  $x_i$  with  $x_i + d$ ). How does this affect the least squares estimates  $\hat{\beta}_0$  and  $\hat{\beta}_1$ ? Express the new estimates in terms of the original estimates and the constant  $d$ .

Solution: Let us denote the new  $x$ -values as  $x'_i = x_i + d$ . Then the new RSS is

$$\begin{aligned}\text{RSS}'(\beta_0, \beta_1) &= \sum_{i=1}^n (y_i - (\beta_0 + \beta_1(x_i + d)))^2 \\ &= \sum_{i=1}^n (y_i - (\beta_0 + \beta_1d + \beta_1 x_i))^2.\end{aligned}$$

This is equivalent to the original RSS with  $\beta_0$  replaced by  $\beta_0 + \beta_1 d$ . Therefore, the new estimates will be

$$\begin{aligned}\hat{\beta}'_1 &= \hat{\beta}_1, \\ \hat{\beta}'_0 &= \hat{\beta}_0 - \hat{\beta}_1 d.\end{aligned}$$

The slope remains unchanged, but the intercept changes to maintain the same fitted line in the shifted coordinate system.

2. Consider the simple linear regression model  $y_i = \beta_0 + x_i\beta_1 + \varepsilon_i$  for  $i \in \{1, 2, \dots, n\}$  and let  $X$  be the design matrix.

a. Show that  $X^\top X = \begin{pmatrix} n & \sum_{i=1}^n x_i \\ \sum_{i=1}^n x_i & \sum_{i=1}^n x_i^2 \end{pmatrix} \in \mathbb{R}^{2 \times 2}$ .

Solution: For simple linear regression, we have  $p = 1$  and the design matrix is

$$X = \begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix}.$$

Thus we have

$$\begin{aligned} X^\top X &= \begin{pmatrix} 1 & 1 & \cdots & 1 \\ x_1 & x_2 & \cdots & x_n \end{pmatrix} \begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix} \\ &= \left( \frac{\sum_{i=1}^n 1}{\sum_{i=1}^n x_i \cdot 1}, \frac{\sum_{i=1}^n 1 \cdot x_i}{\sum_{i=1}^n x_i^2} \right) \\ &= \left( \frac{n}{\sum_{i=1}^n x_i}, \frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n x_i^2} \right). \end{aligned}$$

b. Using the formula

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{ad - bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix},$$

find  $(X^\top X)^{-1}$ .

Solution: Using the formula for the inverse of a  $2 \times 2$ -matrix, we find

$$\begin{aligned} (X^\top X)^{-1} &= \left( \frac{n}{\sum_{i=1}^n x_i}, \frac{\sum_{i=1}^n x_i}{\sum_{i=1}^n x_i^2} \right)^{-1} \\ &= \frac{1}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2} \begin{pmatrix} \sum_{i=1}^n x_i^2 & -\sum_{i=1}^n x_i \\ -\sum_{i=1}^n x_i & n \end{pmatrix}. \end{aligned}$$

c. Find  $X^\top y$  and use this to derive an explicit formula for the least squares estimate  $\hat{\beta} = (X^\top X)^{-1} X^\top y$ .

Solution: Omitting the indices in the sums for brevity, we have

$$X^\top y = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ x_1 & x_2 & \cdots & x_n \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} \sum y_i \\ \sum x_i y_i \end{pmatrix}$$

and thus

$$\begin{aligned} \hat{\beta} &= (X^\top X)^{-1} X^\top y \\ &= \frac{1}{n \sum x_i^2 - (\sum x_i)^2} \begin{pmatrix} \sum x_i^2 & -\sum x_i \\ -\sum x_i & n \end{pmatrix} \begin{pmatrix} \sum y_i \\ \sum x_i y_i \end{pmatrix} \\ &= \frac{1}{n \sum x_i^2 - (\sum x_i)^2} \begin{pmatrix} \sum x_i^2 \sum y_i - \sum x_i \sum x_i y_i \\ -\sum x_i \sum y_i + n \sum x_i y_i \end{pmatrix} \\ &= \frac{1}{\frac{1}{n} \sum_{i=1}^n x_i^2 - (\frac{1}{n} \sum_{i=1}^n x_i)^2} \begin{pmatrix} \frac{1}{n} \sum_{i=1}^n x_i^2 \cdot \frac{1}{n} \sum_{i=1}^n y_i - \frac{1}{n} \sum_{i=1}^n x_i \cdot \frac{1}{n} \sum_{i=1}^n x_i y_i \\ -\frac{1}{n} \sum_{i=1}^n x_i \cdot \frac{1}{n} \sum_{i=1}^n y_i + \frac{1}{n} \sum_{i=1}^n x_i y_i \end{pmatrix}. \end{aligned}$$

This completes the answer.

Inspection of the final result shows that we have recovered the traditional formula for the coefficients in simple linear regression, only written in slightly unusual form. For example, the term  $\frac{1}{n} \sum_{i=1}^n x_i^2 - (\frac{1}{n} \sum_{i=1}^n x_i)^2$  equals the sample variance of the  $x_i$  (up to a factor of  $n/(n-1)$ ). The algebra in this answer could be slightly simplified by changing to new coordinates  $\tilde{x}_i = x_i - \bar{x}$  and  $\tilde{y}_i = y_i - \bar{y}$  before fitting the regression model.

3. Let  $X$  be the design matrix of a model including an intercept, and let  $H = X(X^\top X)^{-1}X^\top \in \mathbb{R}^{n \times n}$  be the hat matrix. Finally, let  $\mathbf{1} = (1, 1, \dots, 1) \in \mathbb{R}^n$ . Show that  $H\mathbf{1} = \mathbf{1}$ .

Solution: We already know that  $HX = X(X^\top X)^{-1}X^\top X = X$ . Since the first column of  $X$  equals  $\mathbf{1}$ , the first column of the matrix equation  $HX = X$  is  $H\mathbf{1} = \mathbf{1}$ . This completes the proof.

4. For the `stackloss` dataset built into R, predict a value for `stack.loss` when the inputs are `Air.Flow = 60`, `Water.Temp = 21` and `Acid.Conc = 87`.

Solution: We can fit the model using `lm()` as usual:

```
m <- lm(stack.loss ~ ., data = stackloss)
m

#
# Call:
# lm(formula = stack.loss ~ ., data = stackloss)
#
# Coefficients:
# (Intercept)      Air.Flow     Water.Temp     Acid.Conc.
# -39.9197        0.7156       1.2953       -0.1521
```

To predict a new value, we use the `predict()` command. Note that `Acid.Conc.` is spelled with a trailing dot, which we need to include in the name when we supply the new input values here.

```
predict(m, data.frame(Air.Flow = 60, Water.Temp = 21, Acid.Conc. = 87))
#
#           1
# 16.98509
```

Thus, the predicted value for `stack.loss` is 16.98509.

5. Let  $\varepsilon_1, \dots, \varepsilon_n \sim \mathcal{N}(\mu, \sigma^2)$  be independent. Then  $\varepsilon = (\varepsilon_1, \dots, \varepsilon_n)$  is a random vector. Determine  $\mathbb{E}(\varepsilon)$ ,  $\text{Cov}(\varepsilon)$  and  $\mathbb{E}(\|\varepsilon\|^2)$ .

Solution: We immediately find  $\mathbb{E}(\varepsilon) = \mu\mathbf{1}$  where  $\mathbf{1} = (1, \dots, 1) \in \mathbb{R}^n$ . Since the  $\varepsilon_i$  are independent, we have  $\text{Cov}(\varepsilon) = \sigma^2 I$ . Finally we have

$$\begin{aligned}\mathbb{E}(\|\varepsilon\|^2) &= \mathbb{E}\left(\sum_{i=1}^n \varepsilon_i^2\right) \\ &= \sum_{i=1}^n \mathbb{E}(\varepsilon_i^2) \\ &= n\mathbb{E}(\varepsilon_1^2).\end{aligned}$$

Since  $\mathbb{E}(\varepsilon_1^2) = \text{Var}(\varepsilon_1) + \mathbb{E}(\varepsilon_1)^2 = \sigma^2 + \mu^2$  we get  $\mathbb{E}(\|\varepsilon\|^2) = n(\sigma^2 + \mu^2)$ .

## 4 Properties of the Least Squares Estimate

In the previous section we introduced random vectors and the multivariate normal distribution. We now use these tools to build a statistical model for multiple linear regression. As in the one-dimensional case, we assume that the errors are random. More precisely we have

$$Y = X\beta + \varepsilon. \quad (15)$$

where  $\varepsilon = (\varepsilon_1, \dots, \varepsilon_n)$  is a random error. The individual errors  $\varepsilon_1, \dots, \varepsilon_n$  are assumed to be i.i.d. random variables with  $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$ .

Remarks:

- The parameters in this model are the regression coefficients  $\beta = (\beta_0, \beta_1, \dots, \beta_p) \in \mathbb{R}^{p+1}$  and the error variance  $\sigma^2$ .
- Using the notation from the previous section, we have  $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$  and  $Y \sim \mathcal{N}(X\beta, \sigma^2 I)$ .
- The model assumes that the  $x$ -values are fixed and known. The only random quantities in the model are  $\varepsilon_i$  and  $Y_i$ . This is a modelling assumption, there are more general models where the  $x$ -values are also random.

Having defined the model, our next task is to understand the properties of the least squares estimator  $\hat{\beta}$  when applied to data from this model. We study these properties by treating the estimates as random variables.

### 4.1 Mean and Covariance

We begin by examining the bias of the estimator. To find  $\text{bias}(\hat{\beta}) = \mathbb{E}(\hat{\beta}) - \beta$  we need to determine the expectation of  $\hat{\beta} = (X^\top X)^{-1} X^\top Y$ , where  $Y$  is the random vector from the model (15).

**Lemma 4.1.** *We have*

- 1)  $\hat{\beta} = \beta + (X^\top X)^{-1} X^\top \varepsilon$  and
- 2)  $\hat{\beta} \sim \mathcal{N}(\beta, \sigma^2 (X^\top X)^{-1})$ .

*Proof.* From lemma 2.1 we know

$$\hat{\beta} = (X^\top X)^{-1} X^\top Y,$$

Using the definition of  $Y$  we can write this as

$$\begin{aligned} \hat{\beta} &= (X^\top X)^{-1} X^\top Y \\ &= (X^\top X)^{-1} X^\top (X\beta + \varepsilon) \\ &= (X^\top X)^{-1} X^\top X\beta + (X^\top X)^{-1} X^\top \varepsilon \\ &= \beta + (X^\top X)^{-1} X^\top \varepsilon. \end{aligned}$$

This proves the first claim.

Since  $\varepsilon$  follows a multivariate normal distribution,  $\beta + (X^\top X)^{-1} X^\top \varepsilon$  is also normally distributed. Taking expectations we get

$$\begin{aligned} \mathbb{E}(\hat{\beta}) &= \mathbb{E}(\beta + (X^\top X)^{-1} X^\top \varepsilon) \\ &= \beta + (X^\top X)^{-1} X^\top \mathbb{E}(\varepsilon) \\ &= \beta, \end{aligned}$$

since  $\mathbb{E}(\varepsilon) = 0$ .

For the covariance we find

$$\begin{aligned}\text{Cov}(\hat{\beta}) &= \text{Cov}(\beta + (X^\top X)^{-1} X^\top \varepsilon) \\ &= \text{Cov}((X^\top X)^{-1} X^\top \varepsilon) \\ &= (X^\top X)^{-1} X^\top \text{Cov}(\varepsilon) ((X^\top X)^{-1} X^\top)^\top \\ &= (X^\top X)^{-1} X^\top \text{Cov}(\varepsilon) X (X^\top X)^{-1}.\end{aligned}$$

Since  $\text{Cov}(\varepsilon) = \sigma^2 I$ , this simplifies to

$$\begin{aligned}\text{Cov}(\hat{\beta}) &= (X^\top X)^{-1} X^\top \sigma^2 I X (X^\top X)^{-1} \\ &= \sigma^2 (X^\top X)^{-1} X^\top X (X^\top X)^{-1} \\ &= \sigma^2 (X^\top X)^{-1}.\end{aligned}$$

This completes the proof.  $\square$

The lemma implies that  $\mathbb{E}(\hat{\beta}) = \beta$ , i.e. the estimator  $\hat{\beta}$  is unbiased. Note that for this statement we only used  $\mathbb{E}(\varepsilon) = 0$  to compute the expectation of  $\hat{\beta}$ . Thus, the estimator will still be unbiased for correlated noise or for noise which is not normally distributed.

We have seen earlier in equation (13) that the diagonal elements of a covariance matrix give the variances of the elements of the random vector. Setting  $C := (X^\top X)^{-1}$  as a shorthand here, we find that the individual estimated coefficients  $\hat{\beta}_j$  satisfy

$$\hat{\beta}_j \sim \mathcal{N}(\beta_j, \sigma^2 C_{jj}) \quad (16)$$

for  $j \in \{0, \dots, p\}$ .

Before we can use these results in practice, we need to address a problem: the error variance  $\sigma^2$  is usually unknown. We will return to estimating  $\sigma^2$  in section 4.4 below.

## 4.2 Properties of the Hat Matrix

Before we can estimate the error variance  $\sigma^2$ , we need to establish some important properties of the hat matrix  $H = X(X^\top X)^{-1} X^\top$ . These properties will be essential tools for deriving the distribution of our variance estimator.

**Lemma 4.2.** *The hat matrix  $H$  has the following properties:*

- 1)  $H^\top = H$
- 2)  $(I - H)^\top = I - H$
- 3)  $H^2 = H$
- 4)  $(I - H)^2 = I - H$
- 5)  $HX = X$
- 6)  $(I - H)X = 0$

*Proof.* For property 1 we have

$$\begin{aligned}H^\top &= (X(X^\top X)^{-1} X^\top)^\top \\ &= (X^\top)^\top ((X^\top X)^{-1})^\top X^\top \\ &= X(X^\top X)^{-1} X^\top \\ &= H,\end{aligned}$$

where we used that the inverse of a symmetric matrix is symmetric.

Property 2 follows from property 1, since

$$(I - H)^\top = I^\top - H^\top = I - H.$$

For property 3 we have

$$\begin{aligned} H^2 &= (X(X^\top X)^{-1}X^\top)(X(X^\top X)^{-1}X^\top) \\ &= X((X^\top X)^{-1}X^\top X)(X^\top X)^{-1}X^\top \\ &= X(X^\top X)^{-1}X^\top \\ &= H. \end{aligned}$$

Property 4 follows from property 3, since

$$(I - H)^2 = I - 2H + H^2 = I - 2H + H = I - H.$$

For property 5 we have

$$HX = X(X^\top X)^{-1}X^\top X = XI = X.$$

Property 6 follows from property 5, since

$$(I - H)X = IX - HX = X - X = 0.$$

This completes the proof.  $\square$

*Remark.* Properties 1 and 2 state that  $H$  and  $I - H$  are **symmetric**. Properties 3 and 4 state that  $H$  and  $I - H$  are **idempotent**.

Before proceeding to further properties of  $H$ , we note without proof that geometrically,  $H$  can be interpreted as the orthogonal projection onto the subspace of  $\mathbb{R}^n$  which is spanned by the columns of  $X$ . This subspace contains the possible output vectors of the linear system and the least squares procedure finds the point  $\hat{y}$  in this subspace which is closest to the observed data  $y \in \mathbb{R}^n$ .

We can now use the transformation properties of the multivariate normal distribution to find the distributions of the fitted values and residuals.

**Lemma 4.3.** *Under the model (15), the fitted values and residuals satisfy*

$$\hat{Y} \sim \mathcal{N}(X\beta, \sigma^2 H) \tag{17}$$

and

$$\hat{\varepsilon} \sim \mathcal{N}(0, \sigma^2(I - H)). \tag{18}$$

*Proof.* Since  $Y \sim \mathcal{N}(X\beta, \sigma^2 I)$ , we have  $\hat{Y} = HY \sim \mathcal{N}(HX\beta, H\sigma^2 IH^\top)$  by lemma 3.1. Using properties 3 and 5 of lemma 4.2, we find  $\hat{Y} \sim \mathcal{N}(X\beta, \sigma^2 H)$ . Similarly,  $\hat{\varepsilon} = (I - H)Y \sim \mathcal{N}((I - H)X\beta, \sigma^2(I - H))$ , and using lemma 4.2 again, we obtain  $\hat{\varepsilon} \sim \mathcal{N}(0, \sigma^2(I - H))$ .  $\square$

The distributions of  $\hat{Y}$  and  $\hat{\varepsilon}$  reveal a deeper geometric structure, described in the next lemma.

**Lemma 4.4.** *For every vector  $v \in \mathbb{R}^n$  we have*

$$\|v\|^2 = \|Hv\|^2 + \|(I - H)v\|^2. \tag{19}$$

In particular, for the data vector  $y$  we have  $\|y\|^2 = \|\hat{y}\|^2 + \|\hat{\varepsilon}\|^2$ .

*Proof.* We can write  $v$  as

$$\begin{aligned} v &= (H + I - H)v \\ &= Hv + (I - H)v. \end{aligned}$$

The inner product between these two components is

$$\begin{aligned} (Hv)^\top(I - H)v &= v^\top H^\top(I - H)v \\ &= v^\top H(I - H)v \\ &= v^\top(H - H^2)v \\ &= v^\top(H - H)v \\ &= 0, \end{aligned}$$

so the two vectors are orthogonal. As a result we get

$$\begin{aligned} \|v\|^2 &= v^\top v \\ &= (Hv + (I - H)v)^\top(Hv + (I - H)v) \\ &= (Hv)^\top Hv + 2(Hv)^\top(I - H)v + ((I - H)v)^\top(I - H)v \\ &= \|Hv\|^2 + \|(I - H)v\|^2 \end{aligned}$$

for any vector  $v \in \mathbb{R}^n$ . (This is Pythagoras' theorem in  $\mathbb{R}^n$ .) Since  $\hat{y} = Hy$  and  $\hat{\varepsilon} = (I - H)y$ , we can apply this idea to the vector  $v = y$  to get  $\|y\|^2 = \|\hat{y}\|^2 + \|\hat{\varepsilon}\|^2$ . This completes the proof.  $\square$

Some authors define:

- $SS_T = \sum_{i=1}^n y_i^2$  (where “T” stands for “total”)
- $SS_R = \sum_{i=1}^n \hat{y}_i^2$  (where “R” stands for “regression”)
- $SS_E = \sum_{i=1}^n \hat{\varepsilon}_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2$  (where “E” stands for “error”)

Using this notation, our equation  $\|y\|^2 = \|\hat{y}\|^2 + \|\hat{\varepsilon}\|^2$  turns into

$$SS_T = SS_R + SS_E.$$

A final algebraic property of the hat matrix concerns its trace.

**Lemma 4.5.** *We have*

$$\text{tr}(H) = p + 1. \quad (20)$$

*Proof.* Using the property of the trace that  $\text{tr}(ABC) = \text{tr}(BCA)$  (see section A.2.5), we find

$$\begin{aligned} \text{tr}(H) &= \text{tr}(X(X^\top X)^{-1}X^\top) \\ &= \text{tr}((X^\top X)^{-1}X^\top X) \\ &= \text{tr}(I) \\ &= p + 1. \end{aligned}$$

This completes the proof.  $\square$

### 4.3 Cochran's theorem

To prove that our variance estimator is unbiased, we need to understand the distribution of certain expressions involving the error vector. These expressions are of the form  $\varepsilon^\top A\varepsilon$  for suitable matrices  $A$ . Such expressions are called **quadratic forms**.

**Definition 4.1.** For  $x \in \mathbb{R}^n$  and  $A \in \mathbb{R}^{n \times n}$ , the expression  $x^\top Ax$  is called a **quadratic form**.

We use a simplified version of Cochran's theorem as our main tool in this and the following section:

**Theorem 4.1.** *The following statements are true:*

- 1)  $\frac{1}{\sigma^2} \varepsilon^\top H \varepsilon \sim \chi^2(p+1)$
- 2)  $\frac{1}{\sigma^2} \varepsilon^\top (I - H) \varepsilon \sim \chi^2(n-p-1)$
- 3)  $H\varepsilon$  and  $(I - H)\varepsilon$  are independent.

*Proof.* We transform the error vector  $\varepsilon$  to a coordinate system where  $H$  becomes diagonal. In this new coordinate system, the quadratic forms  $\varepsilon^\top H \varepsilon$  and  $\varepsilon^\top (I - H) \varepsilon$  become sums of squares of independent standard normals, making their distributions easy to determine.

We start by diagonalising  $H$ . Since  $H$  is symmetric, we can diagonalise  $H$  (see A.2 in the appendix): there is an orthogonal matrix  $U$  such that  $D := UHU^\top$  is diagonal, and the diagonal elements of  $D$  are the eigenvalues of  $H$ .

Next we determine the eigenvalues of  $H$ . Since  $H$  is idempotent, we have  $H^2 = H$ . This implies that every eigenvalue  $\lambda$  of  $H$  satisfies  $\lambda^2 = \lambda$ , and thus  $\lambda \in \{0, 1\}$ . Therefore, the diagonal elements of  $D$  can only be 0 or 1.

Since  $U$  is orthogonal, we have  $U^\top U = I$  and thus

$$U^\top DU = U^\top UHU^\top U = H.$$

The same matrix  $U$  also diagonalises  $I - H$ , since

$$U(I - H)U^\top = UU^\top - UHU^\top = I - D.$$

Note that exactly one of the diagonal elements  $D_{ii}$  and  $(I - D)_{ii}$  is 1 and the other is 0 for every  $i$ . This partitions the index set  $\{1, \dots, n\}$  into two disjoint subsets: the set  $\mathcal{J}_1 = \{i : D_{ii} = 1\}$  contains exactly  $p+1$  elements (corresponding to  $\text{rank}(H) = p+1$ ), and the set  $\mathcal{J}_0 = \{i : D_{ii} = 0\}$  contains the remaining  $n-p-1$  elements. This partition is the key to understanding both the degrees of freedom in the  $\chi^2$  distributions and the independence of the two quadratic forms.

Since  $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$  we find that  $\eta := U\varepsilon$  is normally distributed with mean  $U0 = 0$  and covariance matrix  $\sigma^2 UIU^\top = \sigma^2 UU^\top = \sigma^2 I$ . Thus  $\eta$  has the same distribution as  $\varepsilon$  does:  $\eta \sim \mathcal{N}(0, \sigma^2 I)$  and the components  $\eta_i$  are independent of each other. We have

$$H\varepsilon = U^\top DU\varepsilon = U^\top D\eta,$$

and

$$(I - H)\varepsilon = U^\top (I - D)U\varepsilon = U^\top (I - D)\eta.$$

To prove the independence statement, we examine how the components of  $\eta$  contribute to  $D\eta$  and  $(I - D)\eta$ . Since  $D$  is diagonal, we have

$$(D\eta)_i = D_{ii}\eta_i = \begin{cases} \eta_i & \text{if } i \in \mathcal{J}_1 \\ 0 & \text{if } i \in \mathcal{J}_0. \end{cases}$$

Similarly,

$$((I - D)\eta)_i = (1 - D_{ii})\eta_i = \begin{cases} 0 & \text{if } i \in \mathcal{J}_1 \\ \eta_i & \text{if } i \in \mathcal{J}_0. \end{cases}$$

This shows that each component  $\eta_i$  contributes to exactly one of the two vectors  $D\eta$  and  $(I - D)\eta$ : it contributes to  $D\eta$  if  $i \in \mathcal{J}_1$ , and to  $(I - D)\eta$  if  $i \in \mathcal{J}_0$ . Since the sets  $\mathcal{J}_1$  and  $\mathcal{J}_0$

are disjoint, the vectors  $D\eta$  and  $(I - D)\eta$  depend on disjoint subsets of the independent random variables  $\eta_1, \dots, \eta_n$ . Therefore,  $D\eta$  and  $(I - D)\eta$  are independent. Finally, since  $H\varepsilon = U^\top D\eta$  and  $(I - H)\varepsilon = U^\top (I - D)\eta$  are deterministic linear transformations of  $D\eta$  and  $(I - D)\eta$ , it follows that  $H\varepsilon$  and  $(I - H)\varepsilon$  are also independent. This proves the third statement of the theorem.

For the first statement, we note that

$$\begin{aligned}\varepsilon^\top H\varepsilon &= \varepsilon^\top U^\top DU\varepsilon \\ &= \eta^\top D\eta \\ &= \sum_{\substack{i=1 \\ D_{ii}=1}}^n \eta_i^2.\end{aligned}$$

Since  $(X^\top X) \in \mathbb{R}^{(p+1) \times (p+1)}$  is invertible, one can show that  $\text{rank}(H) = p + 1$  and thus that there are  $p + 1$  terms contributing to the sum (we skip the proof of this statement here). Thus,

$$\frac{1}{\sigma^2} \varepsilon^\top H\varepsilon = \sum_{\substack{i=1 \\ D_{ii}=1}}^n (\eta_i/\sigma)^2$$

is the sum of the squares of  $p + 1$  independent standard normals, and thus is  $\chi^2(p + 1)$ -distributed. This completes the proof of the first statement.  $\square$

Finally, the second statement follows in much of the same way as the first one, except that  $H$  is replaced with  $I - H$  and the sum is over the  $n - p - 1$  indices  $i$  where  $D_{ii} = 0$ . This completes the proof.  $\square$

Since  $\varepsilon^\top H\varepsilon = (H\varepsilon)^\top (H\varepsilon)$  is a function of  $H\varepsilon$ , and similarly for  $I - H$ , the independence in part 3 of the theorem extends to the quadratic forms in parts 1 and 2.

#### 4.4 Estimating the Error Variance

Recall from equation (16) that the variance of each coefficient estimate is  $\sigma^2 C_{jj}$ . To use this result in practice—for constructing confidence intervals or performing hypothesis tests—we need to estimate the unknown parameter  $\sigma^2$ . A natural approach is to examine the residuals  $y_i - \hat{y}_i$ , which estimate the unobserved errors  $\varepsilon_i$ .

Having established the necessary properties of the hat matrix and Cochran's theorem, we can now show that an unbiased estimator for  $\sigma^2$  is given by

$$\hat{\sigma}^2 := \frac{1}{n - p - 1} \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \frac{1}{n - p - 1} \sum_{i=1}^n \hat{\varepsilon}_i^2. \quad (21)$$

As for the case of simple linear regression, in (4), the estimate does not have the prefactor  $1/n$ , which one might expect, but the denominator is decreased by one for each component of the vector  $\beta$ . Using Cochran's theorem, we can now show that the estimator  $\hat{\sigma}^2$  is unbiased.

**Lemma 4.6.** *We have*

$$\mathbb{E}(\hat{\sigma}^2) = \sigma^2.$$

*Proof.* We first note that for data from the model we have

$$\hat{\varepsilon} = (I - H)y = (I - H)(X\beta + \varepsilon) = (I - H)\varepsilon,$$

where we used property 6 of lemma 4.2 to see that  $(I - H)X\beta = 0$ . Using this relation, we get

$$\begin{aligned}(n - p - 1)\hat{\sigma}^2 &= \hat{\varepsilon}^\top \hat{\varepsilon} \\ &= \varepsilon^\top (I - H)^\top (I - H)\varepsilon \\ &= \varepsilon^\top (I - H)\varepsilon.\end{aligned}$$

Now we can apply Cochran's theorem. This shows that

$$\frac{1}{\sigma^2}(n - p - 1)\hat{\sigma}^2 = \frac{1}{\sigma^2}\varepsilon^\top (I - H)\varepsilon \sim \chi^2(n - p - 1). \quad (22)$$

Since the expectation of a  $\chi^2(\nu)$  distribution equals  $\nu$  (see appendix B.5.1), we find

$$\frac{1}{\sigma^2}(n - p - 1)\mathbb{E}(\hat{\sigma}^2) = n - p - 1$$

and thus

$$\mathbb{E}(\hat{\sigma}^2) = \sigma^2.$$

This completes the proof.  $\square$

The lemma shows that  $\hat{\sigma}^2$  is an unbiased estimator for  $\sigma^2$ .

This concludes our study of the statistical properties of the least squares estimator. In the next section we will use these properties to construct confidence intervals and hypothesis tests for the regression coefficients.

### Summary

- The least squares estimator for the regression coefficients is unbiased.
- The hat matrix is idempotent and symmetric.
- Cochran's theorem allows us to understand the distribution of some quadratic forms involving the hat matrix.
- $\hat{\sigma}^2$  is an unbiased estimator for  $\sigma^2$ .

## 5 Uncertainty for Individual Regression Coefficients

In this section we will consider different ways to study the uncertainty in the estimates  $\hat{\beta}_i$  for the regression coefficient  $\beta_i$ , individually. In the following sections we will then consider the problem of simultaneously estimating several or all coefficients.

### 5.1 Measuring the Estimation Error

We have seen that  $\hat{\beta} \sim \mathcal{N}(\beta, \sigma^2 C)$ , where  $C := (X^\top X)^{-1}$ . Restricting this to a single coefficient, we find

$$\hat{\beta}_i \sim \mathcal{N}(\beta_i, \sigma^2 C_{ii}),$$

since the diagonal elements of the covariance matrix contain the variances of the elements of a random vector. In practice we will not know the value of  $\sigma^2$ , so we have to estimate this from data, using the estimator

$$\hat{\sigma}^2 = \frac{1}{n-p-1} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

from equation (21). As a first application of Cochran's theorem we showed in equation (22) that

$$\frac{1}{\sigma^2} (n-p-1) \hat{\sigma}^2 \sim \chi^2(n-p-1).$$

Note that in the equations above, we index the rows and columns of  $C$  using  $i, j \in \{0, 1, \dots, p\}$ , i.e. the first row and column are using the index 0 each. This is to match the convention for the components of  $\beta = (\beta_0, \beta_1, \dots, \beta_p)$ .

**Lemma 5.1.** *The random vector  $\hat{\beta}$  and the random number  $\hat{\sigma}^2$  are independent of each other.*

*Proof.* We will show that  $\hat{\beta}$  can be written as a function of  $H\varepsilon$  and that  $\hat{\sigma}^2$  can be written as a function of  $(I-H)\varepsilon$ . The result then follows from Cochran's theorem.

From lemma 4.1 we know that the least squares estimate  $\hat{\beta}$  can be written as

$$\hat{\beta} = \beta + (X^\top X)^{-1} X^\top \varepsilon$$

and that  $H = X(X^\top X)^{-1} X^\top$ . Thus we can write  $\hat{\beta}$  as

$$\begin{aligned} \hat{\beta} &= \beta + (X^\top X)^{-1} X^\top X (X^\top X)^{-1} X^\top \varepsilon \\ &= \beta + (X^\top X)^{-1} X^\top H \varepsilon, \end{aligned}$$

which is a function of  $H\varepsilon$ .

Similar to the argument at the end of the previous section, we can write  $\hat{\sigma}^2$  as

$$\begin{aligned} (n-p-1) \hat{\sigma}^2 &= (Y - \hat{Y})^\top (Y - \hat{Y}) \\ &= (Y - HY)^\top (Y - HY) \\ &= Y^\top (I - H)^\top (I - H) Y \\ &= \|(I - H)Y\|^2. \end{aligned}$$

Since  $Y = X\beta + \varepsilon$  and since we know  $(I - H)X = 0$  from lemma 4.2, we find

$$\begin{aligned} \hat{\sigma}^2 &= \frac{1}{n-p-1} \|(I - H)(X\beta + \varepsilon)\|^2 \\ &= \frac{1}{n-p-1} \|(I - H)\varepsilon\|^2, \end{aligned}$$

which is a function of  $(I - H)\varepsilon$ .

From Cochran's theorem we know that  $H\varepsilon$  and  $(I - H)\varepsilon$  are independent and thus we can conclude that  $\hat{\beta}$  and  $\hat{\sigma}^2$  are also independent of each other. This completes the proof.  $\square$

We now construct a quantity  $T$  which measures the distance between the estimated value  $\hat{\beta}_i$  and the unknown true value  $\beta_i$ :

$$T := \frac{\hat{\beta}_i - \beta_i}{\sqrt{\hat{\sigma}^2 C_{ii}}}. \quad (23)$$

While there are many ways to measure this distance, the  $T$  constructed here has two main advantages:

- The value of  $T$  can be computed from the given data, without any reference to unknown quantities (except for  $\beta_i$ ).
- Below, we will be able to find the distribution of  $T$ . This will allow us to use  $T$  to construct confidence intervals and statistical tests.

**Lemma 5.2.** *Assume that the data follows the model (15). Then  $T \sim t(n - p - 1)$ , i.e.  $T$  follows a  $t$ -distribution with  $n - p - 1$  degrees of freedom (see appendix B.5.2).*

*Proof.* We have

$$\begin{aligned} T &= \frac{(\hat{\beta}_i - \beta_i)/\sqrt{C_{ii}}}{\sqrt{\hat{\sigma}^2}} \\ &= \frac{(\hat{\beta}_i - \beta_i)/\sqrt{\sigma^2 C_{ii}}}{\sqrt{\hat{\sigma}^2/\sigma^2}} \\ &= \frac{(\hat{\beta}_i - \beta_i)/\sqrt{\sigma^2 C_{ii}}}{\sqrt{((n-p-1)\hat{\sigma}^2/\sigma^2)/(n-p-1)}} \\ &=: \frac{Z}{\sqrt{Y/(n-p-1)}}, \end{aligned}$$

where  $Z = (\hat{\beta}_i - \beta_i)/\sqrt{\sigma^2 C_{ii}} \sim \mathcal{N}(0, 1)$  and  $Y = (n - p - 1)\hat{\sigma}^2/\sigma^2 \sim \chi^2(n - p - 1)$  are independent, by lemma 5.1. Thus,  $T \sim t(n - p - 1)$  as required.  $\square$

The quantity  $\sqrt{\sigma^2 C_{ii}}$  is sometimes called the **standard error** of the estimator  $\hat{\beta}_i$ , denoted by  $\text{se}(\hat{\beta}_i)$ .

## 5.2 Confidence Intervals

Using the scaled distance  $T$ , it is easy to construct a confidence interval for  $\hat{\beta}_i$ : For  $\alpha \in (0, 1)$ , say  $\alpha = 5\%$ , lemma 5.2 shows that

$$P(T \in [-t_{n-p-1}(\alpha/2), +t_{n-p-1}(\alpha/2)]) = 1 - \alpha,$$

where  $t_{n-p-1}(\alpha/2)$  is the  $(1 - \alpha/2)$ -quantile of the  $t(n - p - 1)$ -distribution. Rewriting this expression as a condition on  $\hat{\beta}_i$  instead of on  $T$  gives a confidence interval for  $\beta_i$ .

**Lemma 5.3.** *The interval*

$$[U, V] := \left[ \hat{\beta}_i - \sqrt{\hat{\sigma}^2 C_{ii}} t_{n-p-1}(\alpha/2), \hat{\beta}_i + \sqrt{\hat{\sigma}^2 C_{ii}} t_{n-p-1}(\alpha/2) \right]$$

*is a  $(1 - \alpha)$ -confidence interval for  $\beta_i$ .*

*Proof.* We have to show that  $P(\beta_i \in [U, V]) \geq 1 - \alpha$ . We have

$$\begin{aligned} \beta_i &\in [U, V] \\ \iff |\hat{\beta}_i - \beta_i| &\leq \sqrt{\hat{\sigma}^2 C_{ii}} t_{n-p-1}(\alpha/2) \\ \iff \left| \frac{\hat{\beta}_i - \beta_i}{\sqrt{\hat{\sigma}^2 C_{ii}}} \right| &\leq t_{n-p-1}(\alpha/2) \\ \iff T &\in [-t_{n-p-1}(\alpha/2), +t_{n-p-1}(\alpha/2)] \end{aligned}$$

and thus  $P(\beta_i \in [U, V]) = 1 - \alpha$ . This completes the proof.  $\square$

### 5.3 Hypothesis Tests

Very similar to the argument for confidence intervals, we can derive a hypothesis test to test the hypothesis

$$H_0: \beta_i = b$$

against the alternative

$$H_1: \beta_i \neq b.$$

If we use  $b = 0$  in the test, we can test whether  $\beta_i = 0$ . If  $\beta_i = 0$  is true, the corresponding input  $x_i$  has no influence on the output.

Here we redefine  $T$  as

$$T := \frac{\hat{\beta}_i - b}{\sqrt{\hat{\sigma}^2 C_{ii}}}, \quad (24)$$

using  $b$  in place of the  $\beta_i$  above. When  $H_0$  is true, this new definition of  $T$  is the same as (23).

**Lemma 5.4.** *The test which rejects  $H_0$  if and only if  $|T| > t_{n-p-1}(\alpha/2)$  has significance level  $\alpha$ .*

*Proof.* We have to show that the probability of type I errors (*i.e.* of wrongly rejecting  $H_0$  when it is true) is less than or equal to  $\alpha$ . Assume that  $H_0$  is true. Then we have  $\beta_i = b$  and thus the  $T$  defined in this section coincides with the expression from equation (23). From lemma 5.2 we know that  $T \sim t(n - p - 1)$ . Thus we have

$$\begin{aligned} P(\text{type I error}) &= P(|T| > t_{n-p-1}(\alpha/2)) \\ &= P(T < -t_{n-p-1}(\alpha/2)) + P(T > t_{n-p-1}(\alpha/2)) \\ &= 2P(T > t_{n-p-1}(\alpha/2)) \\ &= 2 \frac{\alpha}{2} \\ &= \alpha. \end{aligned}$$

This completes the proof.  $\square$

As usual with statistical tests, one needs to be extremely careful when performing several tests on the same data. In particular, it would be unwise to test more than one component of  $\beta$  using this procedure for the same data. Instead, in the next section we will consider how to perform tests for several components of  $\beta$  simultaneously. Before we do this, we will perform some experiments with R.

### 5.4 R Experiments

#### 5.4.1 Fitting the model

```

m <- lm(stack.loss ~ ., data = stackloss)
summary(m)

#
# Call:
# lm(formula = stack.loss ~ ., data = stackloss)
#
# Residuals:
#   Min     1Q Median     3Q    Max
# -7.2377 -1.7117 -0.4551  2.3614  5.6978
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) -39.9197    11.8960  -3.356  0.00375 ***
# Air.Flow      0.7156     0.1349   5.307  5.8e-05 ***
# Water.Temp    1.2953     0.3680   3.520  0.00263 **
# Acid.Conc.   -0.1521     0.1563  -0.973  0.34405
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 3.243 on 17 degrees of freedom
# Multiple R-squared:  0.9136, Adjusted R-squared:  0.8983
# F-statistic:  59.9 on 3 and 17 DF,  p-value: 3.016e-09

```

#### 5.4.2 Estimating the Variance of the Error

We can get the design matrix  $X$  and the covariance matrix  $C$  as follows:

```

X <- model.matrix(m)
C <- solve(t(X) %*% X)
round(C, 4)

#           (Intercept) Air.Flow Water.Temp Acid.Conc.
# (Intercept) 13.4527   0.0273   -0.0620   -0.1594
# Air.Flow     0.0273   0.0017   -0.0035   -0.0007
# Water.Temp   -0.0620  -0.0035    0.0129    0.0000
# Acid.Conc.   -0.1594  -0.0007    0.0000    0.0023

```

Next we need to estimate the variance  $\sigma^2$ :

```

y <- stackloss$stack.loss
n <- nrow(stackloss)
p <- ncol(stackloss) - 1
hat.sigma2 <- sum((y - fitted(m))^2) / (n - p - 1)
hat.sigma2

# [1] 10.51941

```

The square root of this number, so the estimated standard deviation of the  $\varepsilon_i$  is shown as **Residual standard error** in the summary output above. We check that we get the same result:

```

sqrt(hat.sigma2)

# [1] 3.243364

```

This result is also listed as the **Residual standard error** near the bottom of the **summary(m)** output, above.

### 5.4.3 Estimating the Standard Errors

We can estimate the standard errors, *i.e.* the standard deviations  $\text{stdev}(\hat{\beta})_i$  as  $\sqrt{\hat{\sigma}^2 C_{ii}}$ :

```
se <- sqrt(hat.sigma2 * diag(C))
se

# (Intercept) Air.Flow Water.Temp Acid.Conc.
# 11.8959969 0.1348582 0.3680243 0.1562940
```

These values are also listed in the `Std. Error` column of the `summary(m)` output.

### 5.4.4 Hypothesis tests

Let us now test the hypothesis  $H_0: \beta_i = 0$ . The test statistic for this case is the following:

```
T <- coef(m) / se
T

# (Intercept) Air.Flow Water.Temp Acid.Conc.
# -3.3557234 5.3066130 3.5195672 -0.9733098
```

These values are also listed in the `t value` column of the `summary(m)` output.

Before we can perform the test, we need to choose  $\alpha$  and to find the corresponding critical value:

```
alpha <- 0.05
t <- qt(1 - alpha/2, n - p - 1)
t

# [1] 2.109816
```

Using the critical value  $t$  we can decide whether  $H_0$  should be accepted or rejected. For example, looking at the intercept  $\beta_0$ , we find  $|T_0| = |-3.3557234| > 2.109816 = t_{n-p-1}(1-\alpha/2)$  and thus we can reject the hypothesis  $H_0: \beta_0 = 0$ . This means that the intercept is significantly different from 0.

### 5.4.5 Confidence Intervals

Using the quantile  $t$  we can also get confidence intervals. Here we only show the confidence interval for the intercept  $\beta_0$ :

```
c(coef(m)[1] - se[1] * t, coef(m)[1] + se[1] * t)

# (Intercept) (Intercept)
# -65.01803 -14.82131
```

Confidence intervals for the remaining coefficients can be obtained similarly.

## Summary

- We know how to scale the distance between individual parameter estimates and the truth.
- We have seen how to construct confidence intervals for  $\beta_i$ .
- We have seen how to construct statistical tests for  $\beta_i$ .
- We have understood some more of the summary output for the `lm()` function in R.

## 6 Estimating Coefficients Simultaneously

In section 5, we learnt how to construct confidence intervals and hypothesis tests for individual regression coefficients using the  $t$ -distribution. However, as noted there, it would be unwise to apply that procedure to test multiple coefficients on the same data. In this section we will study how to assess the uncertainty in two or more regression coefficients simultaneously. This is needed since the estimates for different coefficients will usually not be independent.

### 6.1 Linear Combinations of Coefficients

As a general setup which allows to describe which coefficients we are interested in, we consider the image  $K\beta$ , where  $K \in \mathbb{R}^{k \times (p+1)}$  with  $k \leq p + 1$ .

**Example 6.1.** If  $p = 3$  and

$$K = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix},$$

then

$$K\beta = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}.$$

Thus, this choice of  $K$  would be appropriate if we are interested in  $\beta_1$  and  $\beta_2$  only.

The setup allows for more general questions than just selecting components of  $\beta$ . We can also derive statements about linear combinations of the  $\beta_i$ , e.g. we will be able to derive confidence intervals for quantities like  $\beta_1 - \beta_2$ .

Since  $\hat{\beta}$  is an estimator for  $\beta$ , we can use  $K\hat{\beta}$  as an estimator for  $K\beta$ . From lemma 4.1 we know that  $\hat{\beta} \sim \mathcal{N}(\beta, \sigma^2(X^\top X)^{-1})$  and thus we get

$$K\hat{\beta} \sim \mathcal{N}(K\beta, \sigma^2 K(X^\top X)^{-1} K^\top).$$

Given an invertible, positive definite matrix  $Q$ , we define the shorthand notation

$$\|v\|_Q^2 := v^\top Q^{-1} v.$$

This is called the **Mahalanobis norm** when  $Q$  is a covariance matrix. Using this notation for  $Q = K(X^\top X)^{-1} K^\top$ , we define

$$F := \frac{\|K\hat{\beta} - K\beta\|_{K(X^\top X)^{-1} K^\top}^2}{k\hat{\sigma}^2} \tag{25}$$

as a measure for the distance between  $K\hat{\beta}$  and  $K\beta$ . This quantity plays the role of  $T$  (or more precisely,  $T^2$ ) from the previous section. We also need to introduce the  $F$ -distribution, which will take the place of the  $t$ -distribution from the previous section.

**Definition 6.1.** The  **$F$ -distribution** with  $\nu_1$  and  $\nu_2$  degrees of freedom is the distribution of

$$X = \frac{S_1/\nu_1}{S_2/\nu_2},$$

where  $S_1$  and  $S_2$  are independent random variables with chi-square distributions with  $\nu_1$  and  $\nu_2$  degrees of freedom, respectively.

With these preparations in place, we can state the main result.

**Lemma 6.1.** Assume that the data follows the model (15) and that  $Q := K(X^\top X)^{-1} K^\top$  is invertible. Then  $F \sim F_{k, n-p-1}$ , i.e.  $F$  follows a  $F$ -distribution with  $k$  and  $n-p-1$  degrees of freedom.

*Proof.* We have

$$\begin{aligned}
& \|K\hat{\beta} - K\beta\|_Q^2 \\
&= \|K(\hat{\beta} - \beta)\|_Q^2 \\
&= \|K(X^\top X)^{-1}X^\top \varepsilon\|_Q^2 \\
&= \varepsilon^\top X(X^\top X)^{-1}K^\top Q^{-1}K(X^\top X)^{-1}X^\top \varepsilon \\
&=: \varepsilon^\top R\varepsilon.
\end{aligned}$$

It is tedious but easy to check that  $R$  is idempotent:

$$\begin{aligned}
R^2 &= \left( X(X^\top X)^{-1}K^\top Q^{-1}K(X^\top X)^{-1}X^\top \right) \left( X(X^\top X)^{-1}K^\top Q^{-1}K(X^\top X)^{-1}X^\top \right) \\
&= X(X^\top X)^{-1}K^\top Q^{-1}K(X^\top X)^{-1} \left( X^\top X(X^\top X)^{-1} \right) K^\top Q^{-1}K(X^\top X)^{-1}X^\top \\
&= X(X^\top X)^{-1}K^\top \left( Q^{-1}K(X^\top X)^{-1}K^\top \right) Q^{-1}K(X^\top X)^{-1}X^\top \\
&= X(X^\top X)^{-1}K^\top Q^{-1}K(X^\top X)^{-1}X^\top \\
&= R.
\end{aligned}$$

When we checked in the proof of Cochran's theorem (theorem 4.1) that  $\varepsilon^\top H\varepsilon$  was chi-squared distributed, the only property of  $H$  we used was that  $H$  is idempotent. (If you don't remember the details, it would be a good idea to re-read the proof before continuing.) Thus, the same argument gives that  $\varepsilon^\top R\varepsilon/\sigma^2$  is chi-squared distributed, and as before the number of degrees of freedom of this chi-squared distribution equals the rank of  $R$ . Using the assumption that  $Q$  is invertible, one can show (we skip this part of the proof again) that the rank of  $Q$  equals  $\min(k, p+1) = k$  and thus we find that

$$S_1 := \frac{1}{\sigma^2} \|K\hat{\beta} - K\beta\|_Q^2 \sim \chi^2(k).$$

Similarly, from the direct application of Cochran's theorem in equation (22), we know

$$S_2 := \frac{1}{\sigma^2} (n-p-1)\hat{\sigma}^2 \sim \chi^2(n-p-1).$$

Since  $S_1$  is a function of  $\hat{\beta}$  and  $S_2$  is a function of  $\hat{\sigma}^2$ , we can use lemma 5.1 to conclude that  $S_1$  and  $S_2$  are independent. Combining these results we find

$$\begin{aligned}
F &= \frac{\|K\hat{\beta} - K\beta\|_{K(X^\top X)^{-1}K^\top}^2}{k\hat{\sigma}^2} \\
&= \frac{\frac{1}{\sigma^2} \|K\hat{\beta} - K\beta\|_Q^2 / k}{\frac{1}{\sigma^2} (n-p-1)\hat{\sigma}^2 / (n-p-1)} \\
&= \frac{S_1/k}{S_2/(n-p-1)} \\
&\sim F_{k, n-p-1}.
\end{aligned}$$

This completes the proof.  $\square$

## 6.2 Confidence Regions

Using  $F$  as a distance between the unknown true  $K\beta$  and the estimator  $\hat{\beta}$ , it is easy to find a region of  $\mathbb{R}^k$  which covers  $K\beta$  with high probability. Since we now have a  $k$ -dimensional parameter vector, this region will no longer be an interval. Instead, we will get a  $k$ -dimensional ellipsoid.

### 6.2.1 Result

Define

$$E := \left\{ z \in \mathbb{R}^k \mid \|z - K\hat{\beta}\|_{K(X^\top X)^{-1}K^\top} \leq \sqrt{k\hat{\sigma}^2 f_{k,n-p-1}(\alpha)} \right\},$$

where  $f_{k,n-p-1}(\alpha)$  is the  $(1 - \alpha)$ -quantile of the  $F_{k,n-p-1}$ -distribution. This is a “ball” around  $K\hat{\beta}$  in  $\mathbb{R}^k$ , where distance is measured using the norm  $\|\cdot\|_{K(X^\top X)^{-1}K^\top}$  introduced above. The following lemma shows that  $\sqrt{k\hat{\sigma}^2 f_{k,n-p-1}(\alpha)}$  is the correct choice of “radius” to make the ball cover the true value  $K\beta$  with probability  $1 - \alpha$ .

**Lemma 6.2.** *We have*

$$P(K\beta \in E) = 1 - \alpha,$$

i.e. the set  $E$  is a  $(1 - \alpha)$ -confidence region for  $K\beta$ .

*Proof.* We have

$$\begin{aligned} K\beta \in E \\ \iff \|K\beta - K\hat{\beta}\|_{K(X^\top X)^{-1}K^\top} \leq \sqrt{k\hat{\sigma}^2 f_{k,n-p-1}(\alpha)} \\ \iff \|K\hat{\beta} - K\beta\|_{K(X^\top X)^{-1}K^\top}^2 \leq k\hat{\sigma}^2 f_{k,n-p-1}(\alpha) \\ \iff \frac{\|K\hat{\beta} - K\beta\|_{K(X^\top X)^{-1}K^\top}^2}{k\hat{\sigma}^2} \leq f_{k,n-p-1}(\alpha) \\ \iff F \leq f_{k,n-p-1}(\alpha) \end{aligned}$$

Now the claim follows, since  $f_{k,n-p-1}(\alpha)$  is the  $(1 - \alpha)$ -quantile of  $F$ .  $\square$

### 6.2.2 Numerical Experiments

We start by fitting a linear model to the `stackloss` dataset as before:

```
m <- lm(stack.loss ~ ., data = stackloss)
summary(m)

#
# Call:
# lm(formula = stack.loss ~ ., data = stackloss)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -7.2377 -1.7117 -0.4551  2.3614  5.6978
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) -39.9197    11.8960  -3.356  0.00375 **
# Air.Flow      0.7156     0.1349   5.307  5.8e-05 ***
# Water.Temp    1.2953     0.3680   3.520  0.00263 **
# Acid.Conc.   -0.1521     0.1563  -0.973  0.34405
#
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 3.243 on 17 degrees of freedom
# Multiple R-squared:  0.9136, Adjusted R-squared:  0.8983
# F-statistic: 59.9 on 3 and 17 DF,  p-value: 3.016e-09
```

Here I want to consider the two regression coefficients  $\beta_1$  (`Air.Flow`) and  $\beta_2$  (`Water.Temp`). For this we need to construct a matrix  $K$  with two rows, where each row selects one of the two coefficients:

```
X <- model.matrix(m)
n <- nrow(X)
p <- ncol(X) - 1

K <- matrix(c(0, 1, 0, 0,    # indices in R start at 1, so beta_1 is col. 2
            0, 0, 1, 0),   # ... and beta_2 is column 3.
            byrow = TRUE,
            nrow = 2, ncol = 4)
k <- nrow(K)
K.beta.hat <- as.vector(K %*% coef(m))
```

As we have seen in the previous section, for this  $K$  the covariance matrix for the ellipse is  $Q = K(X^\top X)^{-1}K^\top$ :

```
Q <- K %*% solve(t(X) %*% X) %*% t(K)
```

**6.2.2.1 A Single Point** To try out the method, we first consider the test point  $m = K\beta = (1, 1)$  and we compute the  $F$  value for this point to see whether the point is inside or outside the ellipse:

```
a <- c(1, 1)

sigma.hat <- summary(m)$sigma
d <- a - K.beta.hat
F <- t(d) %*% solve(Q, d) / (k * sigma.hat^2)
F

#           [,1]
# [1,] 2.834083
```

The  $F$  value, measuring the distance from the centre of the ellipse is 2.834 for this test point. This has to be compared to the critical value:

```
alpha <- 0.05
f.crit <- qf(1 - alpha, k, n - p - 1)
f.crit

# [1] 3.591531
```

Since the  $F$  value is less than the critical value, the point  $(1, 1)$  is inside the ellipse. As the next step, we will plot a picture of the full ellipse.

**6.2.2.2 Points on a Grid** An easy way to show the ellipse is to repeat the above procedure for all points on a rectangular grid, and then colour the points depending on whether they are inside or outside the ellipse. We start by making a list of grid points.

```
x.min <- -1
x.max <- 3
y.min <- -0.5
y.max <- 3
L <- 200

xx <- seq(x.min, x.max, length.out = L)
yy <- seq(y.min, y.max, length.out = L)

Z <- as.matrix(expand.grid(x = xx - K.beta.hat[1],
```

```

y = yy - K.beta.hat[2],
KEEP.OUT.ATTRS = FALSE))
dim(Z)
# [1] 40000      2

```

The matrix  $Z$  now has two columns, containing the  $x$  and  $y$  coordinates respectively of the  $200 \times 200$  points in our grid. Now we need to compute the  $F$  value for every grid point:

```

F <- rowSums(Z * t(solve(Q, t(Z)))) / (k * sigma.hat^2)
F <- matrix(F, byrow = TRUE, L, L)
dim(F)
# [1] 200 200

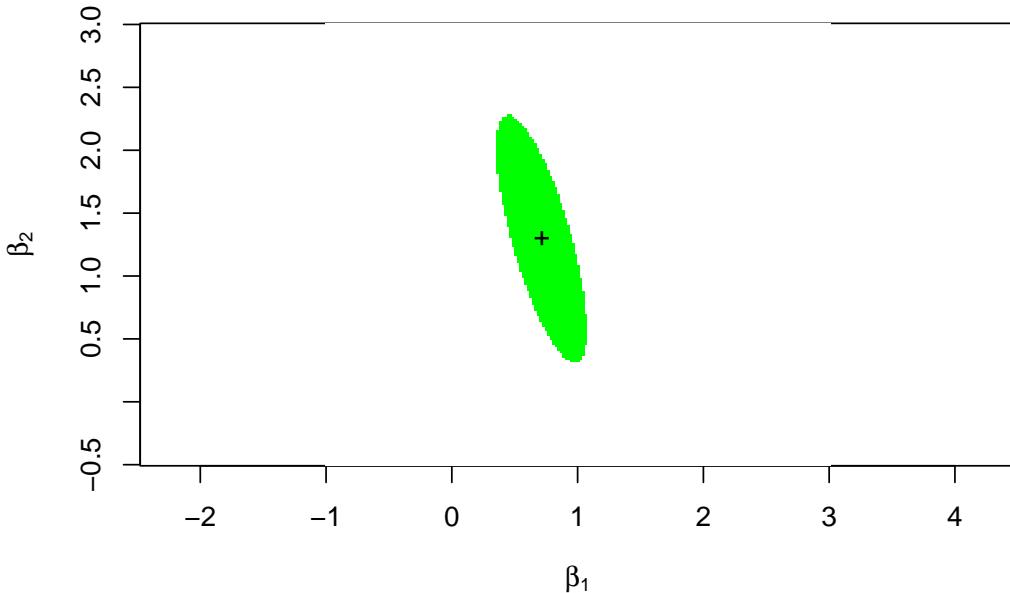
```

The resulting matrix contains the  $F$  value for every grid point. Finally, we can mark all the points where  $F$  exceeds the critical value in a plot:

```

image(x = xx, y = yy, t(F > f.crit), asp = 1,
      col = c("green", "white"),
      xlab = expression(beta[1]), ylab = expression(beta[2]))
points(K.beta.hat[1], K.beta.hat[2], pch = "+")

```



The green ellipse in this plot is the 95% confidence ellipse for the vector  $(\beta_1, \beta_2)$ .

#### 6.2.2.3 Coordinates of the Outline This sub-section is non-examinable (but hopefully interesting).

Using some more linear algebra, we can find a formula for the coordinates of the points on the ellipse which forms the boundary of the confidence region. For this, we use the Singular Value Decomposition of the matrix  $Q$ . This allows to write  $Q$  as

$$Q = UDV^\top$$

where  $U$  and  $V$  are orthogonal matrices and  $D$  is a diagonal matrix:

```

svd <- La.svd(Q)
svd

```

```

# $d
# [1] 0.0138678012 0.0007364967
#
# $u
# [,1]      [,2]
# [1,] -0.2749061 0.9614711
# [2,]  0.9614711 0.2749061
#
# $vt
# [,1]      [,2]
# [1,] -0.2749061 0.9614711
# [2,]  0.9614711 0.2749061

```

The R output shows the diagonal elements  $d_{ii}$  of  $D$  and the matrices  $U$  and  $V^\top$ . Since  $Q$  is symmetric, we have  $U = V$  and thus  $Q = UDU^\top$  in this case, *i.e.* we have found a diagonalisation of  $Q$ .

Using the SVD we can simplify the norm used in the definition of the ellipse. We write  $D^{-1/2}$  for the matrix which has  $1/\sqrt{d_{ii}}$  on the diagonal. Then we have

$$\begin{aligned}
Q(D^{-1/2}U^\top)^\top(D^{-1/2}U^\top) &= QUD^{-1/2}D^{-1/2}U^\top \\
&= UDU^\top UD^{-1}U^\top \\
&= UDD^{-1}U^\top \\
&= UU^\top \\
&= I.
\end{aligned}$$

Thus,  $(D^{-1/2}U^\top)^\top(D^{-1/2}U^\top)$  is the inverse of  $Q$  and we get

$$\begin{aligned}
\|z - K\hat{\beta}\|_Q^2 &= (z - K\hat{\beta})^\top Q^{-1}(z - K\hat{\beta}) \\
&= (z - K\hat{\beta})^\top (D^{-1/2}U^\top)^\top (D^{-1/2}U^\top)(z - K\hat{\beta}) \\
&= \|D^{-1/2}U^\top(z - K\hat{\beta})\|^2,
\end{aligned}$$

where the norm on the right-hand side is the usual Euclidean norm. Thus, the boundary of the ellipse consists of all points of the form  $K\hat{\beta} + d$ , where  $e := D^{-1/2}U^\top d$  is a vector of length

$$\|e\| = \sqrt{k\hat{\sigma}^2 f_{k,n-p-1}(\alpha)}.$$

Finally, using polar coordinates, we find the points on the boundary to be

$$d = UD^{1/2}e = UD^{1/2}\sqrt{k\hat{\sigma}^2 f_{k,n-p-1}(\alpha)} \begin{pmatrix} \cos(\varphi) \\ \sin(\varphi) \end{pmatrix}$$

with  $\varphi \in [0, 2\pi]$ . This allows to plot the boundary line in R.

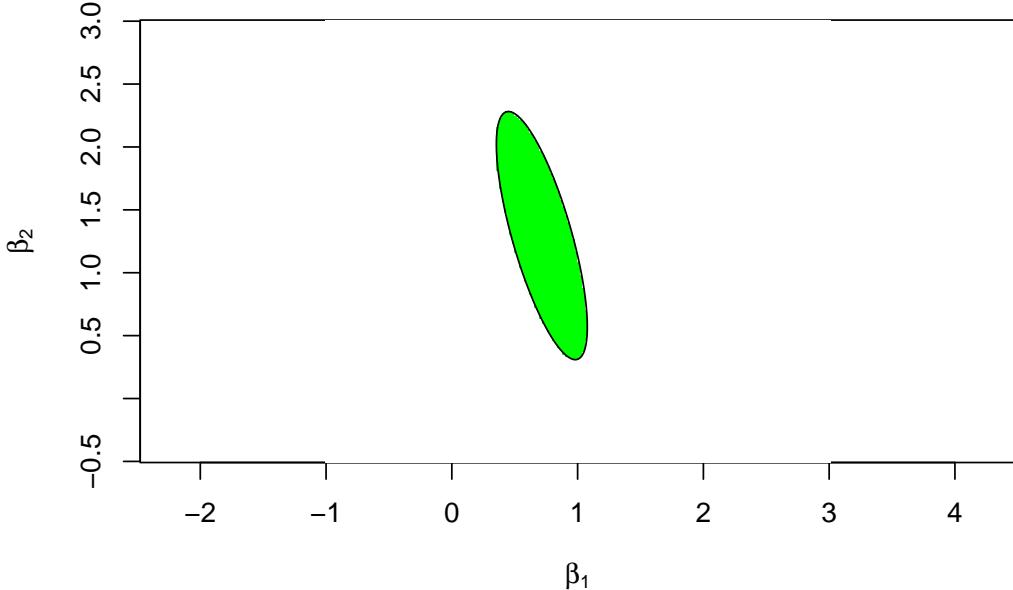
```

phi <- seq(0, 2*pi, length.out = 201)
circ <- rbind(cos(phi), sin(phi)) * sqrt(f.crit * k * sigma.hat^2)

ellipse <- svd$u %*% (circ * sqrt(svd$d)) + K.beta.hat

image(x = xx, y = yy, t(F > f.crit), asp = 1,
      col = c("green", "white"),
      xlab = expression(beta[1]), ylab = expression(beta[2]))
lines(ellipse[1,], ellipse[2,])

```



To verify that everything is consistent, we have plotted the line on top of the image from the previous subsection. Since the black line perfectly surrounds the green area, both approaches are consistent.

### 6.3 Hypothesis Tests

We can easily derive a hypothesis test to test the hypothesis

$$H_0: K\beta = m$$

against the alternative

$$H_1: K\beta \neq m,$$

where  $m \in \mathbb{R}^k$ .

We redefine  $F$  as

$$F := \frac{\|K\hat{\beta} - m\|_{K(X^\top X)^{-1}K^\top}^2}{k\hat{\sigma}^2}$$

using  $m$  in place of the  $K\beta$  above. Then the new definition of  $F$  is the same as (25) if  $H_0$  is true.

**Lemma 6.3.** *The test which rejects  $H_0$  if and only if  $|F| > f_{k,n-p-1}(\alpha)$  has significance level  $\alpha$ .*

*Proof.* Assume that  $H_0$  is true. Then we have  $K\beta = m$  and thus the  $F$  defined in this section coincides with the expression from equation (25). From lemma 6.1 we know that  $F \sim F_{k,n-p-1}$ . Thus we have

$$\begin{aligned} P(\text{type I error}) &= P(F > f_{k,n-p-1}(\alpha)) \\ &= 1 - P(F \leq f_{k,n-p-1}(\alpha)) \\ &= 1 - (1 - \alpha) \\ &= \alpha. \end{aligned}$$

This completes the proof. □

#### Summary

- We have learned how to measure the distance between a subset of coefficients and the corresponding estimates.
- We have introduced the  $F$ -distribution.
- We have learned how to compute confidence regions for subsets of the regression coefficients.
- We have learned how to perform hypothesis tests for subsets of the regression coefficients.

## Interlude: Loading Data into R

Before we can analyse data using R, we have to “import” the data into R. How exactly this is done depends on how the data is stored, and more specifically on which file format is used. Here we consider two commonly used formats: comma-separated values (`.csv`) and Microsoft Excel files (`.xls` or `.xlsx`).

### Importing CSV Files

The `read.csv()` command can be used to import `.csv` files into R: if we use the command

```
x <- read.csv("file.csv")
```

then the contents of the file `file.csv` will be stored in the variable `x`. Optional arguments to `read.csv()` can be used to specify whether or not the file includes column names, and allow to deal with variations of how the data may be stored in the file. Some of these are explained below.

The most important things to know about the function `read.csv()` are:

- The filename can either denote a file on the local computer, or a file available for download from the internet. If you want R to read the file directly from the internet, replace the file name with the web address (starting with `http://` or `https://`).
- If the input file is on the local computer, you may need to change R’s current directory to the directory where the file is stored before calling `read.csv()`. In RStudio you can use the menu “Session > Set Working Directory > Choose Directory ...” to do this. If you are not sure what the filename for a given input file is, you can use the command `file.choose()` in place of the file name, to choose a file interactively.
- By default, R uses the first row of the `.csv` file to set the column names of the data frame and assumes that the actual data starts in row 2 of the `.csv` file. If the file does not contain column names, you can use the `header=FALSE` option with `read.csv()` to tell R that the column names are not included in the data:

```
x <- read.csv("file.csv", header=FALSE)
```

You can see whether this option is needed by opening the file in Excel and looking whether the first row contains headers or not. Alternatively you can inspect the column names and the contents of the first data row in R to see whether everything looks right after importing the data.

- R uses a special data type called `Factor` to represent categorical data. If the `.csv` file contains such data, the option `stringsAsFactors=TRUE` can be used to automatically convert text to factors. (This option used to be the default for R versions before 4.0.0.)
- Sometimes, the columns in a `.csv` file are separated not by a comma, but using a semicolon instead. In this case you need to use the option `sep=";"` when you import the data:

```
x <- read.csv("file.csv", sep=";")
```

- Missing values should be represented by empty cells in the `.csv` file and are represented as special `NA` values in the data frame. If the `.csv` file uses a different encoding for missing values, the `na.strings` option can be used to tell `read.csv()` which cell values should be interpreted as missing values. For example, `read.csv("file.csv", na.strings=c("", "-"))` can be used for a file

where missing values are indicated by either empty cells or cells containing a hyphen.

Further details about the function `read.csv()` can be found using the command `help(read.csv)` in R.

**Example 6.2.** In the 2016 version of the MATH1712 module, I performed a small questionnaire in the first lecture. The following R command can be used to load the data from the questionnaire into R

```
x <- read.csv("https://teaching.seehuhn.de/rintro/Q2016.csv")
```

The variable `x` now contains the questionnaire results. Instead of directly downloading the data from the internet into R, you can alternatively first download the data using a web browser, and then import the data directly from your computer:

```
x <- read.csv("Q2016.csv")
```

Both approaches give the same result.

## Importing Microsoft Excel Files

The easiest way to import Excel files into R is to first convert these files to `.csv` format. To do this:

- Open the file with the data in Excel.
- Open a new, empty file (choosing “Blank workbook” in Excel).
- Copy and paste the relevant cells into the empty file. It is important to just copy the required data and to leave out any explanatory text and empty rows/columns. The data must form a tidy rectangle, with one sample per row and one variate per column. Optionally, you can put column headers into the first row.
- Save the new file in `.csv` format in a folder where you will find it again.
- Read the resulting `.csv` into R as explained above.

Alternatively, you can try the `read_excel()` function from the `readxl` package. (You may need to install this R package first.) You can learn how to use this function at <https://readxl.tidyverse.org/> or using the command `help(read_excel)`. Note that these functions return a “tibble” instead of a data frame, so some additional knowledge is required to use the result.

## Checking the Imported Data

The following commands can be used to get a quick overview over the data:

- `dim(x)` gives the number of rows and columns of the data frame. Similarly, `nrow(x)` shows the number of rows and `ncol(x)` shows the number of columns in the data frame.
- `str(x)` shows the structure of any R object. This command is often an excellent way to understand the nature of any problems one may encounter while importing data into R.
- `summary(x)` prints, for each variate, the values of various summary statistics. For variates with numeric values, these are the minimum, first quartile, median, mean, third quartile, maximum, and the number of missing values. For attribute data this gives the counts for each observed value.
- `head(x)` shows the first few rows of the data.

Every time you import a dataset into R, you should use some of these commands to check that everything went well. In case you discover problems, you should either fix the data file (*e.g.* using Microsoft Excel) or by using the correct options for the `read.csv()` command.

**Example 6.3.** Continuing with the dataset from example above, we can try the following commands: We first check that the data has plausible dimensions:

```
dim(x)
```

```
# [1] 220 5
```

This tells us that the data has  $n = 220$  rows and  $p = 5$  columns, as expected. Next, we get some details about the five columns of the data frame:

```
str(x)
```

```
# 'data.frame': 220 obs. of 5 variables:
# $ gender      : chr "M" "M" "M" "M" ...
# $ height      : num 180 183 183 182 164 ...
# $ handedness : chr "R" "R" "R" "R" ...
# $ travel.time: int 20 25 20 12 5 20 15 10 11 7 ...
# $ R.skills    : chr "basic" "basic" "basic" "basic" ...
```

This shows, for each column, the “data type” and the first few values. The “data type” is a good indicator to detect problems; it should read `int` for integer valued numeric data, `num` for all other numeric data, and `Factor` for attribute data. For attribute data, the range of observed values is also shown. For our dataset, we see that the fields `$gender`, `$handedness` and `$R.skills` are represented as text data (type `chr`) instead of categorical data. To fix this, we re-import the data using the `stringsAsFactors=TRUE` option:

```
x <- read.csv("data/Q2016.csv", stringsAsFactors=TRUE)
str(x)
```

```
# 'data.frame': 220 obs. of 5 variables:
# $ gender      : Factor w/ 2 levels "F","M": 2 2 2 2 1 1 1 1 1 2 ...
# $ height      : num 180 183 183 182 164 ...
# $ handedness : Factor w/ 3 levels "L","R","both": 2 2 2 2 2 2 2 2 2 2 ...
# $ travel.time: int 20 25 20 12 5 20 15 10 11 7 ...
# $ R.skills    : Factor w/ 4 levels "basic","good",...: 1 1 1 1 1 1 1 3 1 1 ...
```

Now the output is as expected, and the correct “levels” are shown for the categorical variables.

Finally, we can print summary statistics for all columns:

```
summary(x)
```

	gender	height	handedness	travel.time	R.skills
# F:102	Min. :147.0	L : 18	Min. : 0.00	basic :157	
# M:118	1st Qu.:167.0	R :201	1st Qu.: 5.00	good : 4	
	Median :175.0	both: 1	Median : 15.00	medium: 28	
	Mean :173.7		Mean : 19.15	none : 31	
	3rd Qu.:180.3		3rd Qu.: 25.00		
	Max. :195.6		Max. :150.00		
	NA's :23				

None of these commands showed any remaining problems, so we are now ready to use the data.

## Common Problems

There are many things which can go wrong when importing data. Some commonly encountered problems are the following:

- If the data file contains no line with headers, but the `header=FALSE` option for `read.csv()` has been omitted, the first row of data will be used in place of the column names. This can, for example, be seen in the `str()` output. The solution to this problem is to correctly use the `header=FALSE` option.
- If the data in a `.csv` file is not separated by commas but by some other character like a semicolon, R will be unable to separate the columns. When this is the case, the imported data will appear to only have one column, where each entry shows as some garbled version of the data for the whole row. The solution to this problem is to use the `sep=...` option.
- If attribute values are encoded inconsistently, *e.g.* if a mix of `m` and `M` is used to encode the gender “male”, this will be visible in the `str()` output. One solution to this problem is to fix the `.csv` file using Microsoft Excel, before trying to import it into R again.
- If a numeric column in the input file contains one or more entries which are neither numbers nor empty, R will interpret the whole column as attribute data. This problem can be detected in the `str()` output, when a numeric column is listed as having data type `Factor`. One solution to this problem is to use Microsoft Excel to remove or fix the offending entry.

## 7 Examples

To illustrate the results of the last two sections, we consider a series of examples.

### 7.1 Simple Confidence Interval

In this subsection we will illustrate how to compute a simple confidence interval for a single regression coefficient. We use a dataset about toxicity of chemicals towards aquatic life from the UCI Machine Learning Repository. The data are available at

- <https://archive.ics.uci.edu/ml/datasets/QSAR+aquatic+toxicity>

There are nine different variables. (The web page explains the interpretation of these variables.) We will fit a model which describes LC50 as a function of the remaining variables:

```
# data from https://archive.ics.uci.edu/ml/datasets/QSAR+aquatic+toxicity
qsar <- read.csv("data/qsar_aquatic_toxicity.csv", sep = ";", header = FALSE)
names(qsar) <- c(
  "TPSA",
  "SAacc",
  "H050",
  "MLOGP",
  "RDCHI",
  "GATS1p",
  "nN",
  "C040",
  "LC50"
)
m <- lm(LC50 ~ ., data = qsar)
summary(m)

#
# Call:
# lm(formula = LC50 ~ ., data = qsar)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.4934 -0.7579 -0.1120  0.5829  4.9778
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 2.698887  0.244554 11.036 < 2e-16 ***
# TPSA        0.027201  0.002661 10.220 < 2e-16 ***
# SAacc      -0.015081  0.002091 -7.211 1.90e-12 ***
# H050        0.040619  0.059787  0.679 0.497186
# MLOGP       0.446108  0.063296  7.048 5.60e-12 ***
# RDCHI       0.513928  0.135565  3.791 0.000167 ***
# GATS1p     -0.571313  0.153882 -3.713 0.000227 ***
# nN         -0.224751  0.048301 -4.653 4.12e-06 ***
# C040        0.003194  0.077972  0.041 0.967340
#
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.203 on 537 degrees of freedom
# Multiple R-squared:  0.4861,  Adjusted R-squared:  0.4785
# F-statistic: 63.5 on 8 and 537 DF,  p-value: < 2.2e-16
```

Our aim is to find a 95% confidence interval for GATS1p.

### 7.1.1 From First Principles

To compute the confidence interval from first principles, we can use Lemma 5.3. The centre of the confidence interval is given by  $\hat{\beta}_i$ :

```
mid <- coef(m)[7]
mid

#      GATS1p
# -0.5713131
```

To find the half-width of the interval, we need to first construct the covariance matrix  $C$  and the estimated error variance  $\hat{\sigma}^2$ . We will also need the corresponding quantile of the  $t$ -distribution.

```
X <- model.matrix(m)
y <- qsar$LC50
n <- nrow(X)
p <- ncol(X) - 1

Cii <- solve(t(X) %*% X)[7, 7]
cat("Cii =", Cii, "\n")

# Cii = 0.01637454

sigma.hat.squared <- sum((fitted(m) - y)^2) / (n - p - 1)
cat("hat.sigma.square =", sigma.hat.squared, "\n")

# hat.sigma.square = 1.446134

alpha <- 0.05
t <- qt(1 - alpha/2, n - p - 1)
cat("t =", t, "\n")

# t = 1.964391
```

With this information in place, we can easily find the confidence interval:

```
d <- sqrt(Cii * sigma.hat.squared) * t
cat("[", mid - d, ", ", mid + d, "] \n", sep = "")

# [-0.8735983, -0.2690279]
```

### 7.1.2 From the lm() Output

We can obtain the same result using only the quantile  $t$  and numbers shown in the `summary(m)` output. We focus on the row corresponding to GATS1p in the output shown above:

```
GATS1p      -0.571313  0.153882 -3.713 0.000227 ***
```

The first number in this row is the centre of the confidence interval, the second number corresponds to  $\sqrt{\hat{\sigma}^2 C_{ii}}$ :

```
alpha <- 0.05
t <- qt(1 - alpha/2, n - p - 1)
cat("[", -0.571313 - 0.153882*t, ", ", -0.571313 + 0.153882*t, "] \n", sep = "")

# [-0.8735975, -0.2690285]
```

This is the same result as above.

## 7.2 Confidence Intervals for the Mean

So far we have only seen how to compute confidence intervals for the regression coefficients  $\beta_i$ . Using the same techniques we can also compute confidence intervals for the model mean corresponding to an input  $(\tilde{x}_1, \dots, \tilde{x}_p)$ . If we write

$$\tilde{x} = (1, \tilde{x}_1, \dots, \tilde{x}_p),$$

then the model mean corresponding to this input is

$$\tilde{y} = \beta_0 + \tilde{x}_1\beta_1 + \dots + \tilde{x}_p\beta_p = \tilde{x}^\top \beta,$$

To derive a confidence interval for this quantity, we follow the same steps as we did when we derived a confidence interval for  $\hat{\beta}_i$ .

Our estimator for this  $\tilde{y}$  is

$$\hat{y} = \tilde{x}^\top \hat{\beta} \sim \mathcal{N}(\tilde{x}^\top \beta, \sigma^2 \tilde{x}^\top (X^\top X)^{-1} \tilde{x}).$$

Thus,

$$\begin{aligned} T &:= \frac{\tilde{x}^\top \hat{\beta} - \tilde{x}^\top \beta}{\sqrt{\hat{\sigma}^2 \tilde{x}^\top (X^\top X)^{-1} \tilde{x}}} \\ &= \frac{\frac{1}{\sqrt{\sigma^2 \tilde{x}^\top (X^\top X)^{-1} \tilde{x}}} (\tilde{x}^\top \hat{\beta} - \tilde{x}^\top \beta)}{\sqrt{\frac{1}{\sigma^2} \hat{\sigma}^2}} \end{aligned}$$

is  $t(n - p - 1)$ -distributed, since the numerator is  $\mathcal{N}(0, 1)$ , the denominator is  $\sqrt{\chi^2(n - p - 1)/(n - p - 1)}$  and  $\hat{\beta}$  is independent of  $\hat{\sigma}^2$ . Let  $t_{n-p-1}(\alpha/2)$  be the  $(1 - \alpha/2)$ -quantile of the  $t(n - p - 1)$ -distribution. Then we can solve the inequality  $|T| \leq t_{n-p-1}(\alpha/2)$  for  $\tilde{x}^\top \beta$  to find the required confidence interval:

$$[\tilde{x}^\top \hat{\beta} - \sqrt{\hat{\sigma}^2 \tilde{x}^\top (X^\top X)^{-1} \tilde{x}} t_{n-p-1}(\alpha/2), \tilde{x}^\top \hat{\beta} + \sqrt{\hat{\sigma}^2 \tilde{x}^\top (X^\top X)^{-1} \tilde{x}} t_{n-p-1}(\alpha/2)].$$

We illustrate this using a numerical example. For the `stackloss` dataset with input values `Air.Flow = 60`, `Water.Temp = 21` and `Acid.Conc = 87`, we can get the following results:

```
m <- lm(stack.loss ~ ., data = stackloss)
X <- model.matrix(m)
n <- nrow(X)
p <- ncol(X) - 1

tilde.x <- c(1, 60, 21, 87)
hat.beta <- coef(m)

c <- t(tilde.x) %*% solve(t(X) %*% X, tilde.x)
sigma.hat.squared <- sum((fitted(m) - stackloss$stack.loss)^2) / (n - p - 1)
t <- qt(0.975, n - p - 1)

mid <- t(tilde.x) %*% hat.beta
d <- sqrt(c * sigma.hat.squared) * t
cat("[", mid - d, ", ", mid + d, "]\\n", sep = "")

# [15.46463, 18.50554]
```

## 7.3 Testing a Single Coefficient

Continuing with the dataset from the previous example, we can test whether the regression coefficient corresponding to the water temperature might equal zero. We will perform a test at 5%-level.

### 7.3.1 From First Principles

We can compute the test statistic manually, using the formula from equation (24) with  $b = 0$ :

```
T <- hat.beta[3] / sqrt(sigma.hat.squared * solve(t(X) %*% X)[3, 3])
T
# Water.Temp
# 3.519567

t.crit <- qt(0.975, n - p - 1)
abs(T) > t.crit

# Water.Temp
# TRUE
```

Since the test statistic is larger than the critical value, we reject the hypothesis that  $\beta_2 = 0$ .

### 7.3.2 Using the lm() Output, I

We can also find the test statistic in the `lm()` output:

```
summary(m)

#
# Call:
# lm(formula = stack.loss ~ ., data = stackloss)
#
# Residuals:
#   Min     1Q Median     3Q    Max
# -7.2377 -1.7117 -0.4551  2.3614  5.6978
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) -39.9197    11.8960  -3.356  0.00375 **
# Air.Flow      0.7156     0.1349   5.307  5.8e-05 ***
# Water.Temp    1.2953     0.3680   3.520  0.00263 **
# Acid.Conc.   -0.1521     0.1563  -0.973  0.34405
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 3.243 on 17 degrees of freedom
# Multiple R-squared:  0.9136, Adjusted R-squared:  0.8983
# F-statistic: 59.9 on 3 and 17 DF,  p-value: 3.016e-09
```

The column `t value` shows the value of the test statistic  $T$  for the hypothesis that  $\beta_i = 0$ . For  $\beta_2$  we find the value 3.520, which is a rounded version of the 3.519567 we found above.

Again, we can use the command `qt(0.975, 17)` to get the critical value, where we can find the degrees of freedom in the `Residual standard error` row near the bottom. Alternatively, we can use the so called “p-value” listed in the `Pr(>|t|)` column. This value is the smallest significance level at which  $H_0$  is still rejected. Here we find 0.00263 and since we have  $\alpha = 0.05 > 0.00263$ , we can see that  $H_0$  is rejected.

If we wanted to test  $\beta_2 = 1$  instead, we could use the value  $\hat{\beta}_2 = 1.2953$  from the `Estimate` column and  $\sqrt{\hat{\sigma}^2 C_{ii}} = 0.3680$  from the `Std. Error` column, to get  $T = (1.2953 - 1)/0.3680$  and then we would accept or reject the hypothesis  $\beta_2 = 1$  by comparing the result to the critical value `qt(0.975, 17)`.

### 7.3.3 Using the `lm()` Output, II

For the hypotheses  $\beta_i = 0$ , we can also use the stars (or sometimes dots) shown in the right margin to perform the test. Since the `Water.Temp` row ends in `**`, we would reject  $\beta_2 = 0$  even at the stricter  $\alpha = 0.01$  level, and thus we would also reject this hypothesis at  $\alpha = 0.05$  level.

## 7.4 Testing Multiple Coefficients

This section illustrates how a group of coefficients can be tested simultaneously. We consider a small, synthetic dataset:

```
# data from https://teaching.seehuhn.de/data/small/small.csv
small <- read.csv("data/small.csv")
m <- lm(y ~ ., data = small)
summary(m)

#
# Call:
# lm(formula = y ~ ., data = small)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -0.64664 -0.09369 -0.03420  0.07768  0.63353
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 5.53329   0.12360 44.768 6.92e-12 ***
# x1          0.18903   0.12059  1.568  0.1514
# x2         -0.30731   0.18011 -1.706  0.1221
# x3          -0.12382   0.05639 -2.196  0.0557 .
# x4          -0.11731   0.12619 -0.930  0.3768
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 0.3822 on 9 degrees of freedom
# Multiple R-squared:  0.6404, Adjusted R-squared:  0.4806
# F-statistic: 4.007 on 4 and 9 DF, p-value: 0.03891
```

From the R output it is clear that the intercept is non-zero, but none of the remaining regression coefficients are significantly different from zero when testing at 5% level. This poses the question whether the inputs have any effect on the output at all. To answer this question, we test the hypothesis

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0,$$

omitting only  $\beta_0$  in the hypothesis. We use the method from section 6.3 to perform this test.

### 7.4.1 From First Principles

The matrix  $K$  which selects the regression coefficients is

$$K = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \in \mathbb{R}^{4 \times 5}.$$

The test statistic is

$$F = \frac{\|K\hat{\beta} - 0\|_{K(X^\top X)^{-1}K^\top}^2}{4\hat{\sigma}^2},$$

where  $K\hat{\beta} = (\hat{\beta}_1, \dots, \hat{\beta}_4)$  and  $K(X^\top X)^{-1}K^\top$  is obtained by removing the first row and column from  $(X^\top X)^{-1}$ :

```
b <- coef(m)[2:5]
X <- model.matrix(m)
C <- solve(t(X) %*% X)[2:5, 2:5]
F <- t(b) %*% solve(C, b) / (4 * summary(m)$sigma^2)
F

#           [,1]
# [1,] 4.007393
```

From lemma 6.3 we know that under  $H_0$  the test statistic is  $F_{k,n-p-1}$ -distributed, and the critical value is the  $1 - \alpha$  quantile of this distribution:

```
n <- nrow(X)      # 14
p <- ncol(X) - 1  # 4
k <- 4
f <- qf(0.95, k, n - p - 1)
f

# [1] 3.633089
```

Since the test statistic is larger than the critical value, we can reject  $H_0$  and conclude at significance level 5% that not all regression coefficients can be zero.

#### 7.4.2 Using the `lm()` output

The information required to perform this  $F$  test is contained in the last row of the `summary(m)` output:

```
F-statistic: 4.007 on 4 and 9 DF,  p-value: 0.03891
```

Here we can see that the test statistic is 4.007 (a rounded version of the value we found above) and the degrees of freedom for the  $F$ -test are  $k = 4$  and  $n - p - 1 = 9$ . The “p-value” listed is the smallest significance level at which the test still rejects  $H_0$ . We see that  $H_0$  is rejected at significance level 0.03891, and thus also at  $\alpha = 0.05$ .

#### Summary

- We have illustrated the results of sections 5 and 6 with the help of examples.
- We have learned how to use the `lm()` output to compute confidence intervals and to perform hypothesis tests.

## Problem Sheet 2

This problem sheet covers material from Sections 4-7 of the course. You should attempt all these questions and write up your solutions in advance of the workshop in week 4. Your solutions are not assessed. Instead, the answers will be discussed in the workshop and will be made available online afterwards.

- 5.** Assume that  $X \sim \mathcal{N}(0, 1)$ ,  $Y \sim \chi^2(2)$  and  $Z \sim \chi^2(3)$  are independent. What are the distributions of the following random variables?

- $X^2$ ,
- $X^2 + Y + Z$ ,
- $\frac{\sqrt{2}X}{\sqrt{Y}}$ ,
- $\frac{2X^2}{Y}$ , and
- $1.5 Y/Z$ .

Solution:

The distributions involved in this question are the normal distribution, the  $\chi^2$ -dis-tri-bu-tion, the  $t$ -distribution and the  $F$ -distribution. The general rules are: (1) the sum of squares of  $d$  independent, standard normally distributed random variables follows a  $\chi^2(d)$ -distribution. (2) If  $Z \sim \mathcal{N}(0, 1)$  and  $V \sim \chi^2(d)$  are independent, then  $Z/\sqrt{V/d} \sim t(d)$ , and finally (3) If  $V_1 \sim \chi^2(d_1)$  and  $V_2 \sim \chi^2(d_2)$  are independent, then  $(V_1/d_1)/(V_2/d_2) \sim F(d_1, d_2)$ . Using these rules:

- $X^2 \sim \chi^2(1)$ ,
- $X^2 + Y + Z \sim \chi^2(1+2+3) = \chi^2(6)$ ,
- $\frac{\sqrt{2}X}{\sqrt{Y}} = \frac{X}{\sqrt{Y/2}} \sim t(2)$ ,
- $\frac{2X^2}{Y} = \frac{X^2/1}{Y/2} \sim F(1, 2)$ ,
- $1.5 Y/Z = \frac{Y/2}{Z/3} \sim F(2, 3)$ .

- 6.** Let  $\mathbf{1} = (1, 1, \dots, 1) \in \mathbb{R}^n$  and let  $X \sim \mathcal{N}(\mu, \sigma^2 I)$  be a normally-distributed random vector, where  $I$  is the  $n \times n$  identity matrix. Define  $A = \frac{1}{n}\mathbf{1}\mathbf{1}^\top \in \mathbb{R}^{n \times n}$ .

- Show that  $(AX)_i = \bar{X}$  for all  $i \in \{1, \dots, n\}$ , where  $\bar{X} = \frac{1}{n} \sum_{j=1}^n X_j$ .
- Show that  $A$  is symmetric.
- Show that  $A$  is idempotent.
- Use results from lectures to conclude that the random variables  $AX$  and  $X^\top(I - A)X$  are independent.
- Using the previous parts of the question, show that  $\bar{X}$  and  $\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$  are independent.

Solution:

The matrix  $A = (a_{ij})$  has entries  $a_{ij} = 1/n$  for all  $i, j \in \{1, \dots, n\}$ . Using this observation, the statements of the first few questions follow easily:

- We have

$$(Ax)_i = \sum_{j=1}^n a_{ij}x_j = \sum_{j=1}^n \frac{1}{n}x_j = \frac{1}{n} \sum_{j=1}^n x_j = \bar{x}$$

for all  $i \in \{1, \dots, n\}$ .

- We have

$$a_{ij} = \frac{1}{n} = a_{ji}$$

for all  $i, j \in \{1, \dots, n\}$  and thus  $A$  is symmetric.

- We have  $\mathbf{1}^\top \mathbf{1} = \sum_{i=1}^n 1 \cdot 1 = n$  and thus

$$A^2 = \left(\frac{1}{n}\mathbf{1}\mathbf{1}^\top\right)\left(\frac{1}{n}\mathbf{1}\mathbf{1}^\top\right) = \frac{1}{n^2}\mathbf{1}(\mathbf{1}^\top \mathbf{1})\mathbf{1}^\top = \frac{1}{n}\mathbf{1}\mathbf{1}^\top = A.$$

(Alternatively, we could use the fact that we know the entries of  $A$  and compute  $A^2$  explicitly.)

- For the remaining statements we will use the fact that  $X$  is normally distributed. We will repeatedly use the result that if two random variables  $X$  and  $Y$  are independent, that then any function of  $X$  is independent of any function of  $Y$ .

In lectures we learned that, if  $A$  is symmetric and idempotent and if  $\varepsilon \sim \mathcal{N}(0, I)$ , then  $A\varepsilon$  and  $(I - A)\varepsilon$  are independent. Applying this result with  $\varepsilon = (X - \mu\mathbf{1})/\sigma$  we find that  $AX = \sigma A\varepsilon + \mu A\mathbf{1}$  and  $(I - A)X = \sigma(I - A)\varepsilon + \mu(I - A)\mathbf{1}$  are independent, since they are functions of  $A\varepsilon$  and  $(I - A)\varepsilon$ .

Since  $(I - A)^\top(I - A) = I^2 - IA - AI + A^2 = I - A - A + A = I - A$  we have

$$X^\top(I - A)X = X^\top(I - A)^\top(I - A)X = \left((I - A)X\right)^\top \left((I - A)X\right).$$

Thus,  $X^\top(I - A)X$  is a function of  $(I - A)X$  and as such is also independent of  $AX$ .

- We have seen  $(AX)_i = \bar{X}$  and thus  $((I - A)X)_i = X_i - \bar{X}$ . This gives

$$\begin{aligned} X^\top(I - A)X &= \left((I - A)X\right)^\top \left((I - A)X\right) \\ &= \sum_{i=1}^n \left((I - A)X\right)_i^2 \\ &= \sum_{i=1}^n (X_i - \bar{X})^2 \end{aligned}$$

Thus we can write the sample mean as  $\bar{X} = (AX)_i$ , and the sample variance as  $s_X^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 = X^\top(I - A)X/(n-1)$ , and if  $X$  is normally distributed the two values  $\bar{X}$  and  $s_X^2$  are independent.

## 7. Consider the following R commands:

```
m <- lm(stack.loss ~ ., data=stackloss)
summary(m)

#
# Call:
# lm(formula = stack.loss ~ ., data = stackloss)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -14.500  -3.825  -1.250   3.325  23.500
```

```

# -7.2377 -1.7117 -0.4551  2.3614  5.6978
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) -39.9197    11.8960  -3.356  0.00375 **
# Air.Flow      0.7156     0.1349   5.307  5.8e-05 ***
# Water.Temp    1.2953     0.3680   3.520  0.00263 **
# Acid.Conc.   -0.1521     0.1563  -0.973  0.34405
#
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 3.243 on 17 degrees of freedom
# Multiple R-squared:  0.9136, Adjusted R-squared:  0.8983
# F-statistic:  59.9 on 3 and 17 DF,  p-value: 3.016e-09

```

Either using this output, or using R to further inspect the built-in `stackloss` dataset, find a 99%-confidence interval for the parameter  $\beta_{\text{Acid.Conc.}}$ .

Solution: From lectures, we know that a confidence interval for a single coefficient  $\beta_j$  is given by

$$[U, V] = \left[ \hat{\beta}_j - t_{n-p-1}(\alpha/2) \sqrt{\hat{\sigma}^2 C_{jj}}, \hat{\beta}_j + t_{n-p-1}(\alpha/2) \sqrt{\hat{\sigma}^2 C_{jj}} \right],$$

where  $t_{n-p-1}$  is the  $(1 - \alpha/2)$ -quantile of the  $t$ -distribution,  $C_{jj} = (X^\top X)^{-1}_{jj}$ , and  $X$  is the design matrix.

We can read off the required values for computing the confidence interval from the output of `summary(m)`: the centre of the confidence interval can be found in the column `Estimate`, the standard error  $\sqrt{\hat{\sigma}^2 C_{jj}}$  is given in column `Std. Error`, and the value  $n - p - 1$  for the  $t$ -quantile can be found as the `degrees of freedom` for the residual standard error, near the bottom of the output. Using these values, we can find a 95%-confidence interval for `Acid.Conc.` as follows:

```

c(-0.1521 - qt(0.995, 17) * 0.1563, -0.1521 + qt(0.995, 17) * 0.1563)
# [1] -0.6050934  0.3008934

```

Thus, the confidence interval is  $[-0.605, 0.301]$ .

## 8. The file 20211020.csv from

- <https://teaching.seehuhn.de/data/20211020.csv>

contains pairs of  $(x, y)$  values. Fit the following models to the data:

- $y = \beta_0 + \beta_1 x + \varepsilon$
- $y = \beta_0 + \beta_1 x + \beta_2 x^2 + \varepsilon$
- $y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \varepsilon$

For each model, create a “residual plot”, *i.e.* a scatter plot which has the fitted values on the horizontal axis and the residuals on the vertical axis. Comment on the resulting plots.

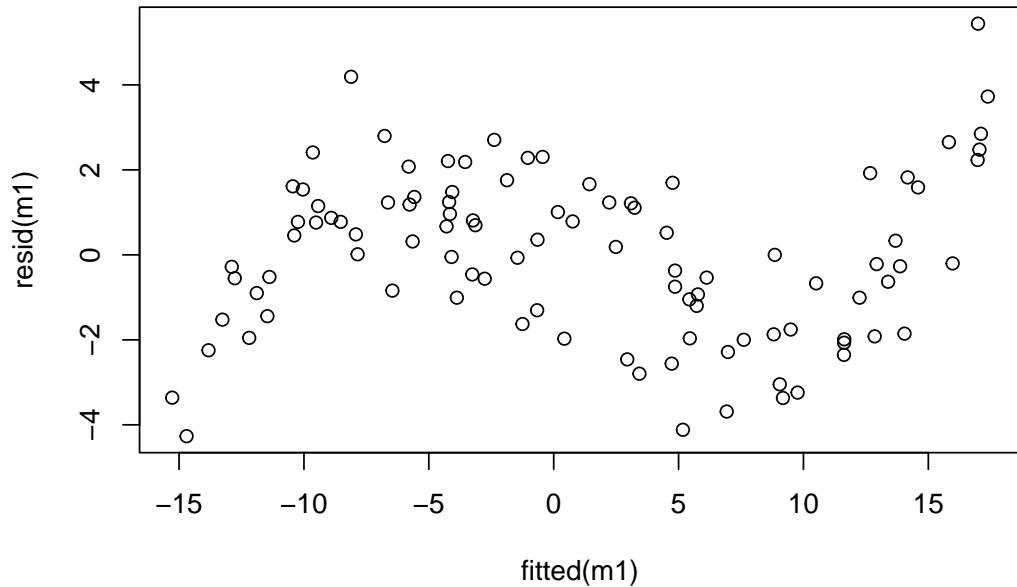
Solution:

```

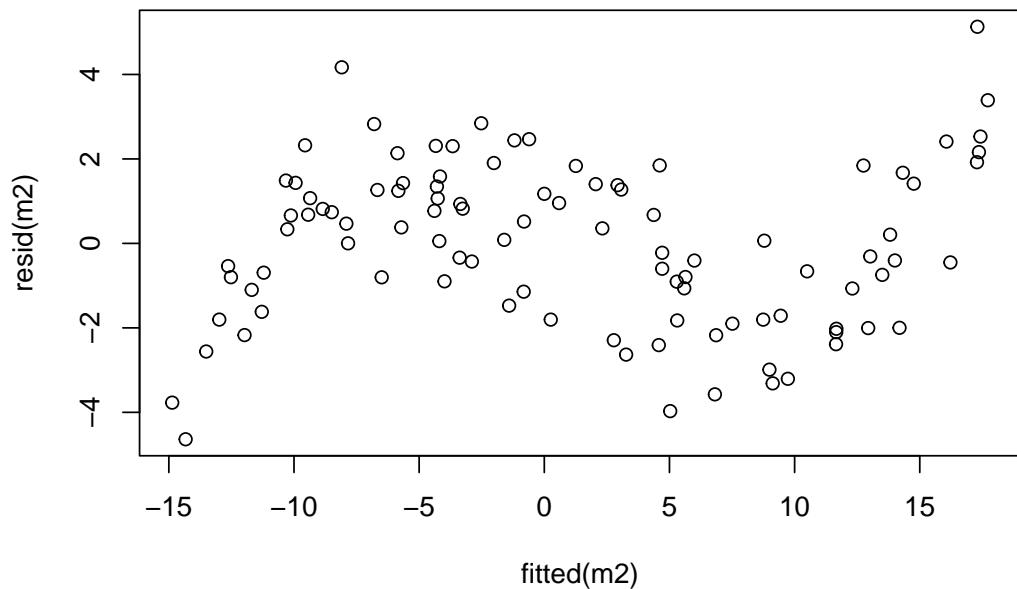
# data from https://teaching.seehuhn.de/data/20211020.csv
d <- read.csv("data/20211020.csv")

```

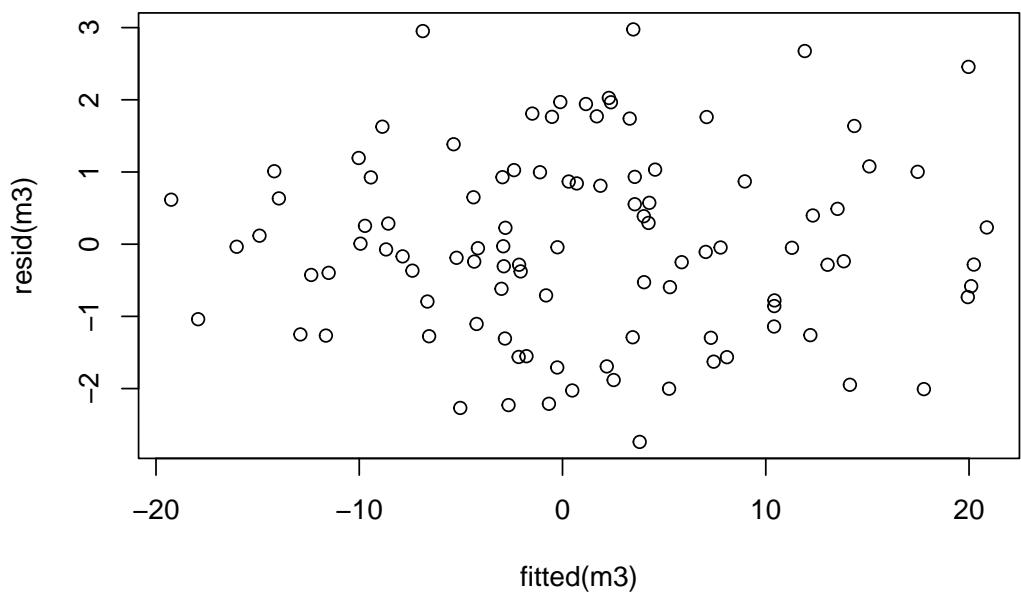
```
m1 <- lm(y ~ x, data = d)
plot(fitted(m1), resid(m1))
```



```
m2 <- lm(y ~ x + I(x^2), data = d)
plot(fitted(m2), resid(m2))
```



```
m3 <- lm(y ~ x + I(x^2) + I(x^3), data = d)
plot(fitted(m3), resid(m3))
```



## 8 The Influence of Observations

Having learned how to estimate parameters and perform hypothesis tests in sections 5–7, a natural question arises: how reliable are these estimates? In particular, do individual observations have an undue influence on our results? In this section we consider the influence which individual observations have on the estimate. Observations with a large influence may be outliers, and are worth checking for validity.

### 8.1 Deleting Observations

The most direct way to check for the influence of an observation is to compute the parameter estimate  $\hat{\beta}$  both with and without the observation in question, and to see how much the two results differ.

**Definition 8.1.** For  $I \subset \{1, \dots, n\}$  we write  $\hat{\beta}^{(I)}$  for the estimate where all observations  $i \in I$  have been removed. As a shorthand we write  $\hat{\beta}^{(i)}$  instead of  $\hat{\beta}^{\{i\}}$  for the case where only a single observation has been removed.

This approach is very different from what we used in section 6. There, we selected a subset of regression coefficients, corresponding to columns in the design matrix  $X$ , whereas here we are considering a subset of the observations, corresponding to rows of  $X$ .

Using the formula for the least squares estimate, we know that

$$\hat{\beta}^{(I)} = (X_{(I)}^\top X_{(I)})^{-1} X_{(I)}^\top y_{(I)}, \quad (26)$$

where now  $y^{(I)}$  is  $y$  with all  $y_i$  for  $i \in I$  removed and  $X_{(I)}$  is  $X$  with all rows  $i \in I$  removed. (We write the “ $(I)$ ” as a subscript, to make space for the transpose sign.) Our first aim is to find an explicit formula for the difference between  $\hat{\beta}$  and  $\hat{\beta}^{(I)}$ .

We have

$$\begin{aligned} (X_{(I)}^\top y_{(I)})_k &= \sum_{j \notin I} X_{jk} y_j \\ &= \sum_{j=1}^n X_{jk} y_j - \sum_{j \in I} X_{jk} y_j \end{aligned}$$

for all  $k \in \{0, \dots, p\}$ , and thus

$$X_{(I)}^\top y_{(I)} = X^\top y - X_I^\top y_I, \quad (27)$$

where  $X_I$  stands for the matrix which only contains the rows  $i \in I$  of the matrix  $X$ , and  $y_I = (y_i)_{i \in I}$ . Before we substitute this result into equation (26), we first consider how we can write the inverse  $(X_{(I)}^\top X_{(I)})^{-1}$  in terms of  $(X^\top X)^{-1}$ .

**Lemma 8.1.** Let  $A \in \mathbb{R}^{(p+1) \times (p+1)}$  and let  $U, V \in \mathbb{R}^{m \times (p+1)}$ . Then

$$(A - U^\top V)^{-1} = A^{-1} + A^{-1}U^\top(I - VA^{-1}U^\top)^{-1}VA^{-1}.$$

*Proof.* This statement is proved by multiplying by  $A - U^\top V$ . Expanding all brackets and using the relation  $AA^{-1} = I$ , we find

$$(A - U^\top V)(A^{-1} + A^{-1}U^\top(I - VA^{-1}U^\top)^{-1}VA^{-1}) = \dots = I.$$

This shows that we have indeed found the inverse of  $A - U^\top V$ .  $\square$

Using this result, we can now derive a formula for the change in  $\hat{\beta}$  when some observations are omitted.

**Lemma 8.2.** *We have*

$$\hat{\beta}^{(I)} - \hat{\beta} = -(X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} \hat{\varepsilon}_I,$$

where  $H_{II} := X_I(X^\top X)^{-1} X_I^\top = (h_{ij})_{i,j \in I}$  is the matrix which contains the elements of the hat matrix  $H$  where both row and column are in  $I$ , and  $\hat{\varepsilon}_I = (\hat{\varepsilon}_i)_{i \in I} = (y_i - \hat{y}_i)_{i \in I}$  is the vector of residuals at the omitted samples.

The vector  $\hat{\varepsilon}_I$  consists of a subset of the original residuals, computed using the original  $\hat{y}$  and  $\hat{\beta}$ . It does not refer to the modified estimate  $\hat{\beta}^{(I)}$  which was computed with some observations omitted. Similarly,  $H_{II}$  is a submatrix of the original hat matrix.

*Proof.* Similar to equation (27), we have

$$(X_{(I)}^\top X_{(I)})_{ik} = \sum_{j \notin I} X_{ji} X_{jk} = \sum_{j=1}^n X_{ji} X_{jk} - \sum_{j \in I} X_{ji} X_{jk}$$

and thus

$$X_{(I)}^\top X_{(I)} = X^\top X - X_I^\top X_I.$$

Now we can use the lemma with  $U = V = X_I$  to get

$$\begin{aligned} (X_{(I)}^\top X_{(I)})^{-1} &= (X^\top X)^{-1} + (X^\top X)^{-1} X_I^\top (I - X_I(X^\top X)^{-1} X_I^\top)^{-1} X_I(X^\top X)^{-1} \\ &= (X^\top X)^{-1} + (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} X_I(X^\top X)^{-1}. \end{aligned}$$

Using equations (26) and (27) and lemma 8.1 we get

$$\begin{aligned} \hat{\beta}^{(I)} &= (X_{(I)}^\top X_{(I)})^{-1} X_{(I)}^\top y \\ &= (X_{(I)}^\top X_{(I)})^{-1} (X^\top y - X_I^\top y_I) \\ &= \left( (X^\top X)^{-1} + (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} X_I(X^\top X)^{-1} \right) (X^\top y - X_I^\top y_I) \\ &= (X^\top X)^{-1} X^\top y \\ &\quad + (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} X_I \hat{\beta} \\ &\quad - (X^\top X)^{-1} X_I^\top y_I \\ &\quad - (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} X_I (X^\top X)^{-1} X_I^\top y_I \\ &= \hat{\beta} + (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} X_I \hat{\beta} \\ &\quad - (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} (I - H_{II}) y_I \\ &\quad - (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} H_{II} y_I \\ &= \hat{\beta} + (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} X_I \hat{\beta} \\ &\quad - (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} y_I \\ &= \hat{\beta} - (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} (y_I - X_I \hat{\beta}) \\ &= \hat{\beta} - (X^\top X)^{-1} X_I^\top (I - H_{II})^{-1} \hat{\varepsilon}_I. \end{aligned}$$

This completes the proof.  $\square$

We can also find the change in estimated error variance, when samples are omitted from the estimate. The estimated variance in the modified model is

$$\begin{aligned} \hat{\sigma}_{(I)}^2 &:= \frac{1}{n-m-p-1} \sum_{i \notin I} (y_i - (X \hat{\beta}^{(I)})_i)^2 \\ &= \frac{1}{n-m-p-1} \|y_{(I)} - X_{(I)} \hat{\beta}^{(I)}\|^2 \end{aligned}$$

where  $m = |I|$  so that  $n - m$  is the number of observations used in the estimate. We want to compare this quantity to the original estimate

$$\begin{aligned}\hat{\sigma}^2 &= \frac{1}{n-p-1} \sum_{i=1}^n (y_i - (X\hat{\beta})_i)^2 \\ &= \frac{1}{n-p-1} \|y - X\hat{\beta}\|^2.\end{aligned}$$

Here we used again the Euclidean norm as a shorthand for the sum of squares used in these estimates. The following lemma shows how the residual sum of squares decreases when the observations  $I$  are omitted from the estimate.

**Lemma 8.3.** *We have*

$$\|y_{(I)} - X_{(I)}\hat{\beta}^{(I)}\|^2 - \|y - \hat{y}\|^2 = -\hat{\varepsilon}_I^\top (I - H_{II})^{-1} \hat{\varepsilon}_I.$$

The proof of this lemma is similar to the proof of lemma 8.2, but we omit the tedious calculations here.

**Example 8.1.** To illustrate the results of this subsection, we give a numerical example. In the example we consider the `stackloss` dataset, and study what happens when the first two observations are omitted:

```
m1 <- lm(stack.loss ~ ., data = stackloss)
m2 <- lm(stack.loss ~ ., data = stackloss[-c(1,2),])
coef(m2) - coef(m1)

# (Intercept) Air.Flow Water.Temp Acid.Conc.
# 0.86331016 -0.03780761 -0.02706305 0.02124533
```

Using the result of lemma 8.2, we can get the difference between the two estimates without using the model `m2`:

```
X <- model.matrix(m1)
H <- X %*% solve(t(X) %*% X, t(X))
XI <- X[1:2,]
hII <- H[1:2, 1:2]
hat.epsI <- resid(m1)[1:2]

-as.vector(solve(t(X) %*% X) %*% t(XI) %*% solve(diag(2) - hII, hat.epsI))

# [1] 0.86331016 -0.03780761 -0.02706305 0.02124533
```

This is the same result as we obtained above. (I used `as.vector()` to convert the result from a  $4 \times 1$  matrix into a vector.)

Similarly, we can compare the residual sum of squares: A direct comparison gives

```
sum(resid(m2)^2) - sum(resid(m1)^2)

# [1] -15.41758
```

Using the result of lemma 8.3, we get the same result without requiring `m2`:

```
-t(hat.epsI) %*% solve(diag(2) - hII, hat.epsI)

# [,1]
# [1,] -15.41758
```

Again, the results using both methods agree.

In the special case of  $m = 1$ , where  $I = \{i\}$  for some  $i \in \{1, \dots, n\}$ , our results simplify to

$$\hat{\beta}^{(i)} - \hat{\beta} = -(X^\top X)^{-1} x_i \frac{\hat{\varepsilon}_i}{1 - h_{ii}} \quad (28)$$

and

$$\|y_{(i)} - x_i^\top \hat{\beta}^{(i)}\|^2 - \|y - \hat{y}\|^2 = -\frac{\hat{\varepsilon}_i^2}{1 - h_{ii}},$$

where  $x_i \in \mathbb{R}^{p+1}$  is the  $i$ th row of  $X$  as a vector,  $\hat{\varepsilon}_i$  is the usual  $i$ th residual, and  $h_{ii}$  is the  $i$ th diagonal element of the hat matrix. Using the correct prefactors the second result gives

$$(n - p - 2)\hat{\sigma}_{(i)}^2 = (n - p - 1)\hat{\sigma}^2 - \frac{\hat{\varepsilon}_i^2}{1 - h_{ii}}.$$

We can find numerical values for these quantities using the function `influence()`:

```
x <- c(1, 2, 3, 10)
y <- c(0, 0, 1, 3)
m <- lm(y ~ x)
influence(m)

# $hat
#   1     2     3     4
# 0.43  0.33  0.27  0.97
#
# $coefficients
#   (Intercept)          x
# 1  0.01719298 -0.002105263
# 2 -0.19582090  0.019104478
# 3  0.15369863 -0.009315068
# 4  0.30666667 -0.160000000
#
# $sigma
#   1         2         3         4
# 0.4682929 0.2591605 0.2482818 0.4082483
#
# $wt.res
#   1     2     3     4
# 0.02 -0.32  0.34 -0.04
```

The output lists the diagonal elements  $h_{ii}$  of the hat matrix as `$hat`, the vectors  $\hat{\beta}^{(i)} - \hat{\beta}$  for each  $i$  as `$coefficients`, the standard deviations  $\hat{\sigma}_{(i)}$  for each  $i$  as `$sigma`, and the residuals  $\hat{\varepsilon}_i$  as `$wt.res`.

## 8.2 Cook's Distance

In section 6 we learned how to measure distances of estimated parameter vectors: To compare  $K\hat{\beta}$  to a vector  $K\beta$  we used the norm

$$\|K\hat{\beta} - K\beta\|_{K(X^\top X)^{-1}K^\top}^2 = (K\hat{\beta} - K\beta)^\top (K(X^\top X)^{-1}K^\top)^{-1} (K\hat{\beta} - K\beta).$$

If we consider the full parameter vector, we can use  $K = I$  to get

$$\|\hat{\beta} - \beta\|_{(X^\top X)^{-1}}^2 = (\hat{\beta} - \beta)^\top X^\top X (\hat{\beta} - \beta).$$

From lemma 6.1 we know that

$$F = \frac{\|\hat{\beta} - \beta\|_{(X^\top X)^{-1}}^2}{(p + 1)\hat{\sigma}^2}$$

follows an  $F_{p+1,n-p-1}$ -distribution. We can use this measure to quantify when the difference  $\hat{\beta}^{(i)} - \hat{\beta}$  should be considered “large”.

**Definition 8.2. Cook's distance** for observation  $i$  is defined as

$$D_i = \frac{(\hat{\beta}^{(i)} - \hat{\beta})^\top X^\top X (\hat{\beta}^{(i)} - \hat{\beta})}{(p+1)\hat{\sigma}^2}.$$

We will consider observation  $i$  to be **influential** if  $D_i$  is large. Since this “lives on the scale” of an  $F_{p+1,n-p-1}$ -distribution, we should compare  $D_i$  to typical values of such a distribution. For example, we could consider the median. Here is a sample of median values for different  $n$  and  $p$ :

```
n <- c(10, 30, 100)
p <- c(1, 3, 5)
xx <- expand.grid(n = n, p = p)
cbind(xx, median = qf(0.5, xx$p + 1, xx$n - xx$p - 1))

#      n p    median
# 1 10 1 0.7568285
# 2 30 1 0.7105929
# 3 100 1 0.6980730
# 4 10 3 0.9419133
# 5 30 3 0.8614530
# 6 100 3 0.8451308
# 7 10 5 1.0616689
# 8 30 5 0.9168687
# 9 100 5 0.8977754
```

In practice, some authors suggest that an observation is “influential” if  $D_i > 1$ , instead of using an exact quantile of the  $F$ -distribution.

The following lemma provides two additional ways to compute Cook's distance.

**Lemma 8.4.** *We have*

$$\begin{aligned} D_i &= \frac{(\hat{y}^{(i)} - \hat{y})^\top (\hat{y}^{(i)} - \hat{y})}{(p+1)\hat{\sigma}^2} \\ &= \frac{\hat{\varepsilon}_i^2}{(p+1)\hat{\sigma}^2} \cdot \frac{h_{ii}}{(1-h_{ii})^2}. \end{aligned}$$

where  $\hat{y}^{(i)} := X\hat{\beta}^{(i)}$  is the fitted value which is predicted for observation  $i$  when this observation is not used to fit the model,  $\hat{\varepsilon}_i$  are the usual residuals, and  $h_{ii}$  are the diagonal elements of the hat matrix.

*Proof.* We have  $\hat{y}^{(i)} - \hat{y} = X\hat{\beta}^{(i)} - X\hat{\beta}$  and thus

$$(\hat{y}^{(i)} - \hat{y})^\top (\hat{y}^{(i)} - \hat{y}) = (\hat{\beta}^{(i)} - \hat{\beta})^\top X^\top X (\hat{\beta}^{(i)} - \hat{\beta}).$$

This proves the first equality. From equation (28) we know

$$\hat{\beta}^{(i)} - \hat{\beta} = -(X^\top X)^{-1} x_i \frac{\hat{\varepsilon}_i}{1-h_{ii}}$$

and thus we find

$$\begin{aligned} (\hat{\beta}^{(i)} - \hat{\beta})^\top X^\top X (\hat{\beta}^{(i)} - \hat{\beta}) &= \frac{\hat{\varepsilon}_i^2}{(1-h_{ii})^2} x_i^\top (X^\top X)^{-1} X^\top X (X^\top X)^{-1} x_i \\ &= \frac{\hat{\varepsilon}_i^2}{(1-h_{ii})^2} x_i^\top (X^\top X)^{-1} x_i \\ &= \frac{\hat{\varepsilon}_i^2}{(1-h_{ii})^2} h_{ii} \end{aligned}$$

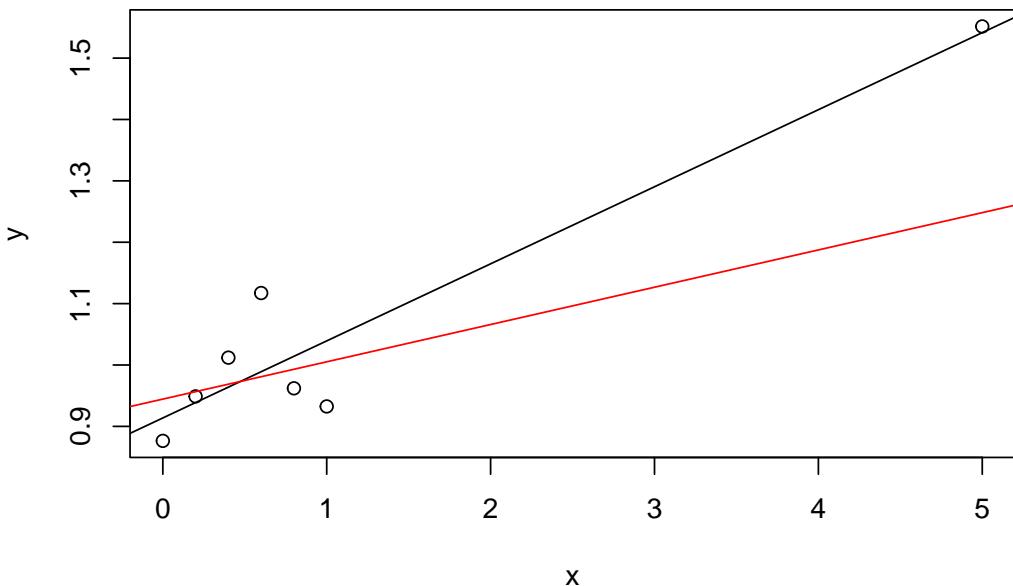
and dividing by  $(p + 1)\hat{\sigma}^2$  completes the proof.  $\square$

**Example 8.2.** To illustrate how Cook's  $D$  is computed, we use a small dataset with simulated data. We include an  $x$ -space outlier:

```
set.seed(20211026)
x <- c(5, seq(0, 1, length.out = 6))
y <- 1 + 0.1 * x + 0.1 * rnorm(7)
plot(x, y)

m <- lm(y ~ x)
abline(m)

m2 <- lm(y[-1] ~ x[-1])
abline(m2, col = "red")
```



The black line in the plot is the regression line using all data, the red line is the regression line fitted using only the left-most six points and leaving out the “outlier” at  $x = 5$ . The difference between the two lines makes it clear that the point at  $x = 5$  has a large effect on the estimated regression line. An easy way to compute the  $D$ -values is the second formula from lemma 8.4:

```
X <- model.matrix(m)
H <- X %*% solve(t(X) %*% X, t(X))
hii <- diag(H)
D <- resid(m)^2 * hii / 2 / summary(m)$sigma^2 / (1 - hii)^2
D

#           1            2            3            4            5            6
# 6.456405260 0.035318182 0.002129694 0.042504418 0.268374731 0.040765842
#           7
# 0.162580015
```

The results show as expected a very large value for the first observation,  $D_1 = 6.456$ , and small values for the remaining  $D_i$ . We can also find Cook's  $D$ -values in the output of the `influence.measures()` function:

```
influence.measures(m)
```

```

# Influence measures of
#   lm(formula = y ~ x) :
#
#   dfb.1_   dfb.x   dffit cov.r cook.d   hat inf
# 1 -0.7475  3.1083  3.3670 39.046 6.45641 0.967   *
# 2 -0.2441  0.1415 -0.2441  1.791 0.03532 0.215
# 3  0.0583 -0.0296  0.0585  1.920 0.00213 0.192
# 4  0.2674 -0.1142  0.2720  1.596 0.04250 0.173
# 5  0.9536 -0.3189  0.9959  0.348 0.26837 0.159
# 6 -0.2461  0.0560 -0.2681  1.512 0.04077 0.149
# 7 -0.5620  0.0577 -0.6512  0.687 0.16258 0.144

```

The table also shows the diagonal elements of the hat matrix, in the column `hat`, and some additional measures which we will not discuss here. A star in the last column, titled `inf`, marks influential observations. The star is placed if *any* of the measures shown in the table is significantly large.

Having completed the theoretical development of influence measures, the remainder of this module focuses on more practical aspects of model diagnostics. We begin in the next section by using visual tools to assess whether our modelling assumptions are satisfied.

### Summary

- The influence of an observation can be measured by how much the estimated parameters change when that observation is deleted.
- Efficient formulas allow us to compute these changes without having to refit the model  $n$  times.
- Cook's distance combines is a single measure, which can be compared to an  $F$ -distribution to identify influential observations.

## Part II

# Linear Regression in Practice

## 9 Diagnostic Plots

(The following video refers to an older version of this section.)

When we developed the theory for linear models, we used the following assumptions:

- Linear relationship between inputs and outputs:  $y \approx x^\top \beta$
- Independence of errors: the  $\varepsilon_i = y_i - (X\beta)_i$  are independent of each other.
- Normally distributed errors:  $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$  for all  $i$ . In particular, the variance of the  $\varepsilon_i$  does not depend on  $i$ .

Sometimes, plotting the data can reveal when these assumptions are violated. Here we discuss different plot types which can be used for this purpose.

### 9.1 Residual Plots

A plot of  $\hat{\varepsilon}_i$  against  $\hat{y}_i$  is often called a **residual plot**. If the modelling assumptions are correct, the errors will be independent and normally distributed with mean zero and constant variance. The fitted residuals are estimates of the errors, so they should approximately satisfy these two properties.

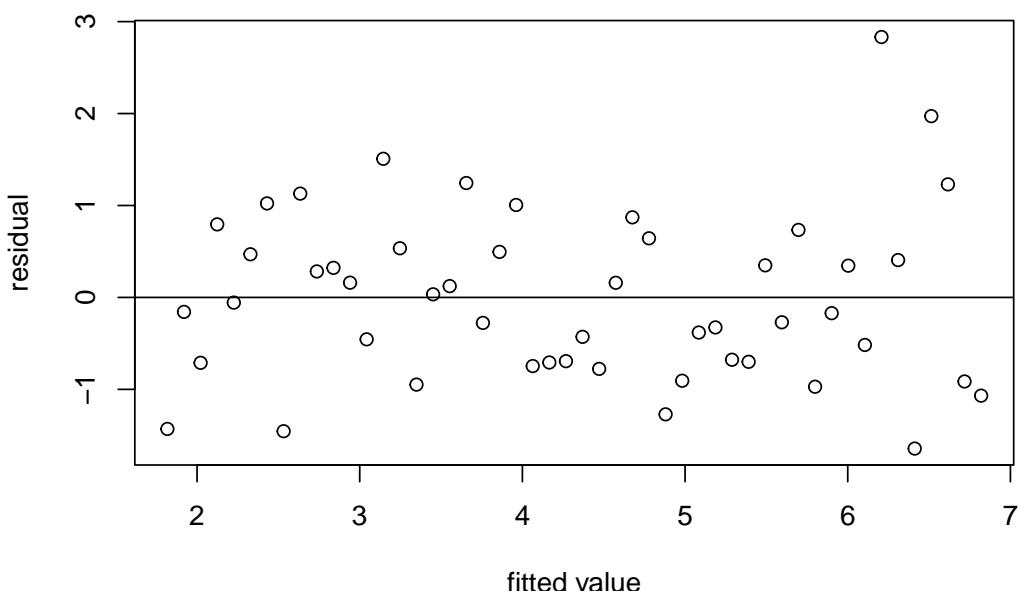
If the variance of the residuals seems to increase with  $\hat{y}$  then a transformation may be necessary. The presence of a curvilinear relationship in this plot suggests a non-linear relationship between inputs and outputs.

**Example 9.1.** To demonstrate the use of residual plots, we first produce such a plot for simulated data, where we know that the modelling assumptions are satisfied.

```
n <- 50
x <- seq(0, 10, length.out = n)
y <- 2 + 0.5 * x + rnorm(n)

m <- lm(y ~ x)
plot(fitted(m), resid(m),
      xlab = "fitted value", ylab = "residual",
      main = "modelling assumptions satisfied")
abline(h = 0)
```

**modelling assumptions satisfied**



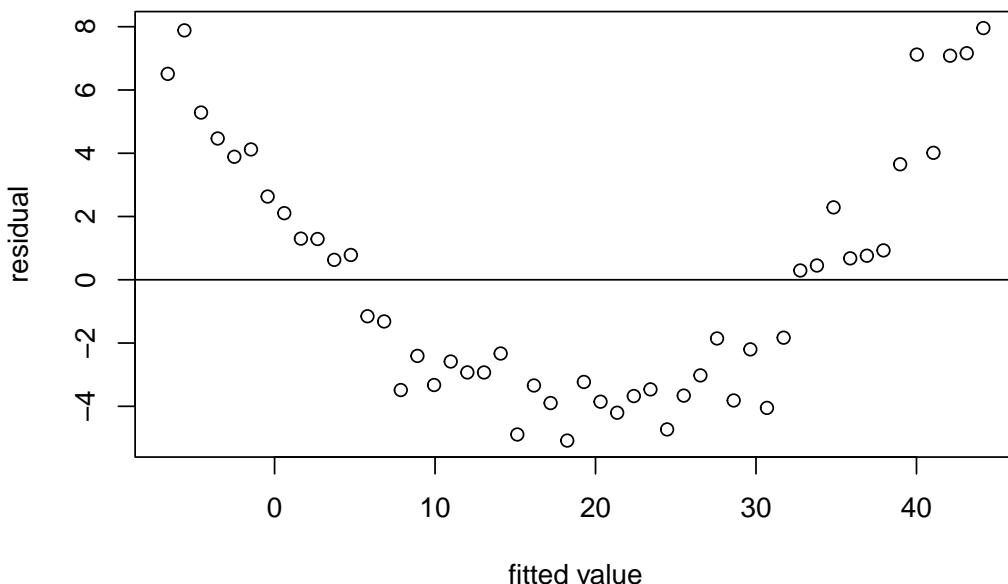
We can see that the residuals are clustered around zero as expected.

**Example 9.2.** Next we consider a residual plot where the modelling assumptions are known to be violated. Here we generate data using a quadratic dependency (instead of linear) of the output on the input:

```
n <- 50
x <- seq(0, 10, length.out = n)
y <- 2 + 0.5 * x^2 + rnorm(n)

m <- lm(y ~ x)
plot(fitted(m), resid(m),
      xlab = "fitted value", ylab = "residual",
      main = "modelling assumptions violated")
abline(h = 0)
```

**modelling assumptions violated**



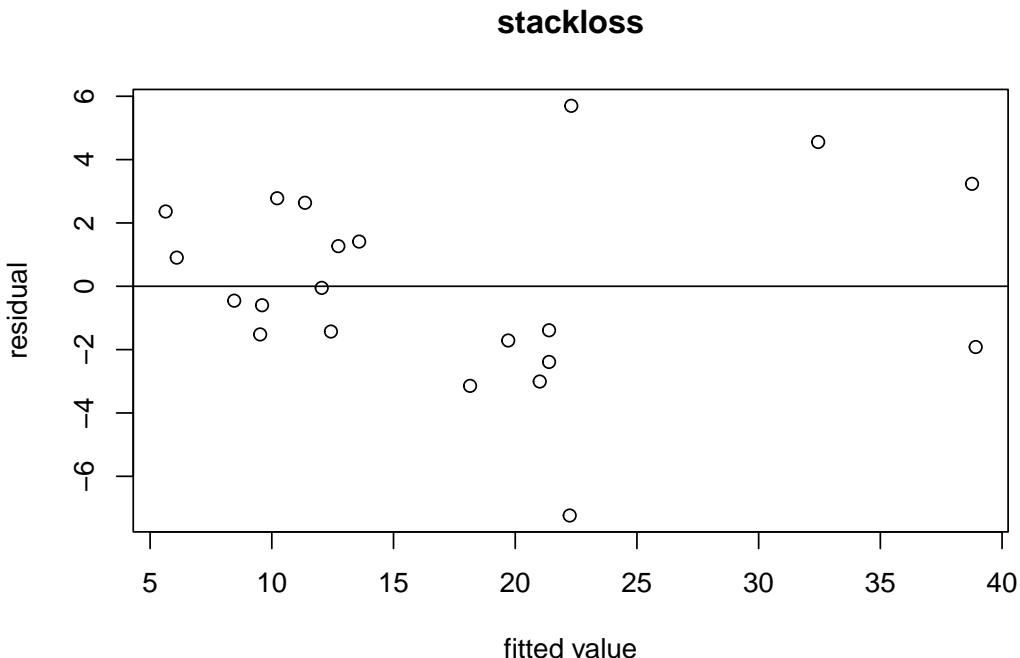
It is clear that the residuals are not centred around the horizontal zero line, but form a parabola instead.

The structure of the  $x$ -values can affect the visual appearance of this type of plot, even if the modelling assumptions are exactly satisfied. For example, if the  $x$ -values “thin out” towards the edges of the range, the “band” of residuals may appear narrower there, just because there are fewer chances for large residuals to occur near the edges.

The following example shows a residual plot for real data, where it is unknown whether or not the modelling assumptions are satisfied.

**Example 9.3.** A residual plot for the `stackloss` dataset can be produced as follows:

```
m <- lm(stack.loss ~ ., data = stackloss)
plot(fitted(m), resid(m),
      xlab = "fitted value", ylab = "residual",
      main = "stackloss")
abline(h = 0)
```



The residuals are well-centred around zero with no obvious patterns visible. Since there are no systematic trends, the plot does not indicate any problems with model fit.

## 9.2 Q-Q Plots

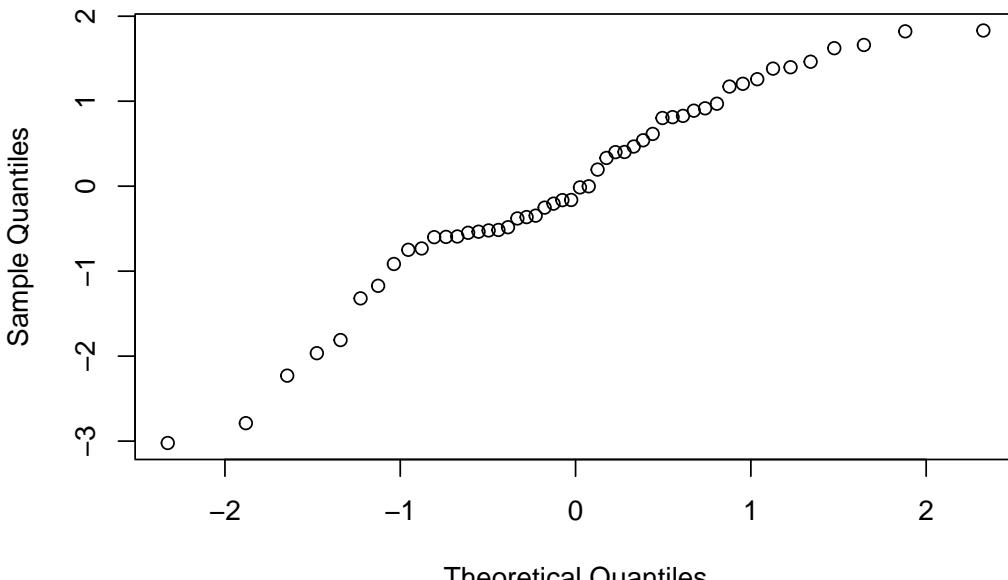
A Q-Q plot of the residuals can be used to assess whether the residuals are normally distributed. These plots plot quantiles of the data against quantiles of a normal distribution. If the residuals are normally distributed, both sets of quantiles come from the same distribution, causing the points to lie on a straight line. The R command to produce Q-Q plots for the normal distribution is `qqnorm()`.

**Example 9.4.** We first show an example with simulated data, where the modelling assumptions are known to be satisfied.

```
n <- 50
x <- seq(0, 10, length.out = n)
y <- 2 + 0.5 * x + rnorm(n)

m <- lm(y ~ x)
qqnorm(resid(m), main = "modelling assumptions satisfied")
```

### modelling assumptions satisfied



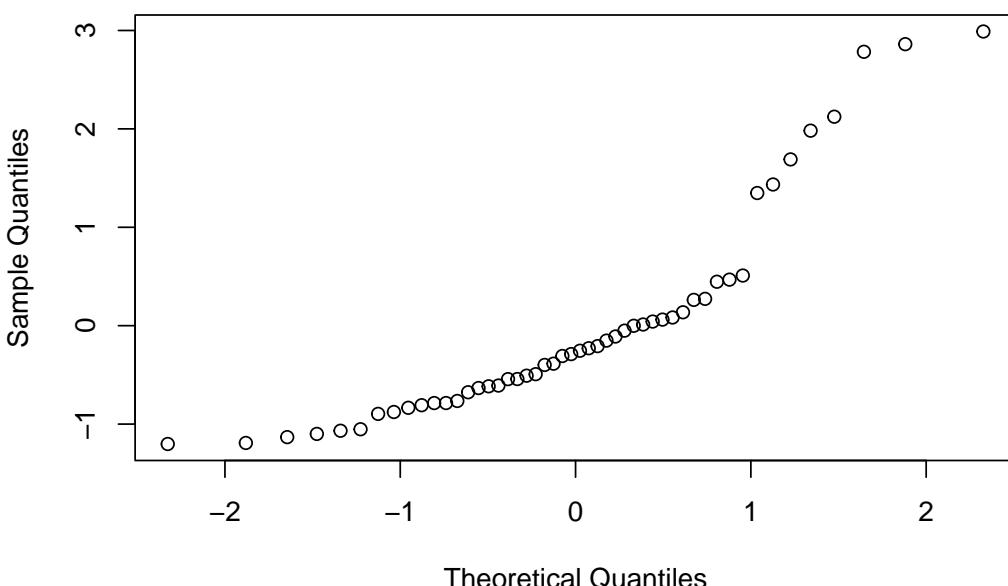
As expected, the points lie approximately on a straight line.

**Example 9.5.** Next we consider an example where the errors are exponentially instead of normally distributed.

```
n <- 50
x <- seq(0, 10, length.out = n)
eps <- rexp(n) - 1 # we subtract 1, so that the errors still have mean zero
y <- 2 + x + eps

m <- lm(y ~ x)
qqnorm(resid(m), main = "modelling assumptions violated")
```

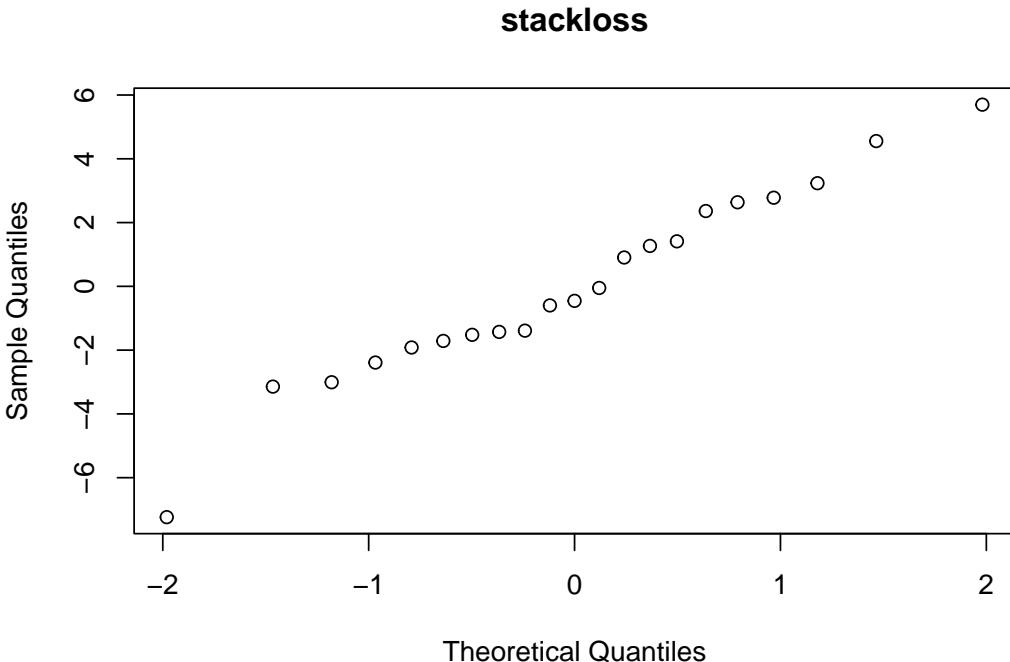
### modelling assumptions violated



Now the points of the Q-Q plot lie on a curved line, indicating that the residuals are not normally distributed.

**Example 9.6.** A Q-Q plot for the `stackloss` dataset can be produced as follows:

```
m <- lm(stack.loss ~ ., data = stackloss)
qqnorm(resid(m), main = "stackloss")
```



The points in this Q-Q plot lie more or less on a straight line, so it seems reasonable to assume that the errors were normally distributed.

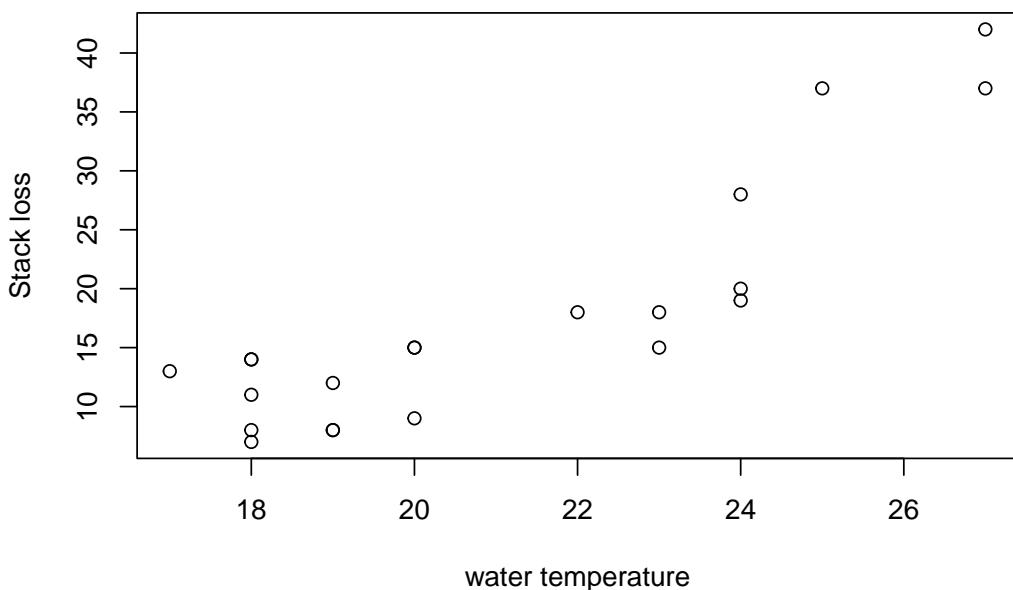
### 9.3 Other Plot Types

Sometimes, different plot types are also used.

1. A scatter plot of the response  $y$  against each of the explanatory variables  $x_j$  for  $j \in \{1, \dots, p\}$ . Great care is needed when interpreting such plots: even if the full model is linear, the dependency of the output on individual inputs may appear non-linear. This can be caused by non-linear structures in the input data (which don't violate the modelling assumptions).
2. A scatter plot of  $\hat{\varepsilon}$  against each of the explanatory variables  $x_j$  for  $j \in \{1, \dots, p\}$ . Again, care is needed when trying to interpret such plots.
3. A plot of  $x_j$  against  $x_k$  for  $j \neq k$  can also be useful. For example, if two or more regressors are highly correlated, we say that multicollinearity is present. When this occurs, the least squares estimate  $\hat{\beta}$  becomes numerically unstable. (We will learn more about this effect in chapter 15.)
4. Data are often collected in time order. Even if time is not an explanatory variable, a plot of  $y$  against time can be of interest. It can reveal serial correlation in the data. Similarly, plotting the residuals against time can reveal temporal patterns in the model fit.

**Example 9.7.** We can plot `stack.loss` against `Water.Temp` for the `stackloss` dataset:

```
plot(stackloss$Water.Temp, stackloss$stack.loss,
     xlab = "water temperature", ylab = "Stack loss")
```



## 10 Measures for Model Fit

### 10.1 The Coefficient of Multiple Determination

A widely used measure of model fit is the coefficient of multiple determination, commonly denoted  $R^2$ . This measure is not specific to linear regression, but can be used for any regression model which produces fitted values  $\hat{y}_i$  and residuals  $\hat{\varepsilon}_i$ .

**Definition 10.1.** The **coefficient of multiple determination** is defined as

$$R^2 := 1 - \frac{s_{\hat{\varepsilon}}^2}{s_y^2} = 1 - \frac{\frac{1}{n-1} \sum_{i=1}^n (\hat{\varepsilon}_i - \bar{\hat{\varepsilon}})^2}{\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2}.$$

The coefficient of multiple determination provides a numerical measure of how well the model fits the data. The numerator  $s_{\hat{\varepsilon}}^2$  is the sample variance of the residuals, while the denominator  $s_y^2$  is the sample variance of the response variable  $y$ . Thus,  $R^2$  measures the proportion of total variance in  $y$  which is explained by the regression model. Large values of  $R^2$  indicate good model fit.

We will use the following lemma to simplify the formula for  $R^2$  for the special case of linear regression models.

**Lemma 10.1.** *For multiple linear regression models with an intercept term, the following relations hold:*

1. We have

$$\sum_{i=1}^n \hat{\varepsilon}_i = 0,$$

and thus  $\bar{\hat{\varepsilon}} = 0$ .

2. We have

$$\sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2 + \sum_{i=1}^n (\hat{\varepsilon}_i - \bar{\hat{\varepsilon}})^2.$$

*Proof.* Define  $\mathbf{1} = (1, \dots, 1) \in \mathbb{R}^n$ . From exercise 2 on problem sheet 1 we know that  $H\mathbf{1} = \mathbf{1}$  and since  $H$  is symmetric we also have  $\mathbf{1}^\top H = \mathbf{1}^\top$ . This gives

$$\mathbf{1}^\top (I - H) = \mathbf{1}^\top - \mathbf{1}^\top H = \mathbf{1}^\top - \mathbf{1}^\top = 0. \quad (29)$$

We first show that the residuals sum to zero. Using equation (29) we have

$$\sum_{i=1}^n \hat{\varepsilon}_i = \mathbf{1}^\top \hat{\varepsilon} = \mathbf{1}^\top (I - H)y = 0,$$

which proves part 1 of the lemma. Thus we have  $\bar{\hat{\varepsilon}} = 0$ . Since  $y = \hat{y} + \hat{\varepsilon}$ , taking sample means we also find

$$\bar{y} = \bar{\hat{y}} + \bar{\hat{\varepsilon}} = \bar{\hat{y}}. \quad (30)$$

For part 2, we note that as shown previously, the fitted values and residuals are orthogonal:

$$\hat{y}^\top \hat{\varepsilon} = (Hy)^\top (I - H)y = y^\top H(I - H)y = 0.$$

Combining this with  $\mathbf{1}^\top \hat{\varepsilon} = 0$ , we find that  $(\hat{y} - \bar{y}\mathbf{1})^\top \hat{\varepsilon} = 0$ . Using Pythagoras' theorem as in section 4.2, we obtain

$$\begin{aligned} \|y - \bar{y}\mathbf{1}\|^2 &= \|(y - \hat{y}) + (\hat{y} - \bar{y}\mathbf{1})\|^2 \\ &= \|\hat{\varepsilon}\|^2 + \|\hat{y} - \bar{y}\mathbf{1}\|^2, \end{aligned}$$

which proves the first equality in part 2. The second equality follows by noting that  $\bar{\hat{\varepsilon}} = 0$  and using equation (30).  $\square$

Note that in equation (19) we have seen that

$$\|y\|^2 = \|\hat{y}\|^2 + \|\hat{\varepsilon}\|^2.$$

The lemma shows that a similar relation also holds after the sample means are subtracted.

We can express the terms in the statement of lemma 10.1 as sample variances. For example, we write

$$s_y^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$$

for the sample variance of  $y$ . Using this notation, the statement of the lemma can be written as

$$s_y^2 = s_{\hat{y}}^2 + s_{\hat{\varepsilon}}^2.$$

Unlike equation (19), this relation is only true for models which include an intercept.

Some authors define

- $\text{SS}_{\text{tot}} = \sum_{i=1}^n (y_i - \bar{y})^2$  (where “tot” stands for “total”)
- $\text{SS}_{\text{reg}} = \sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2$  (where “reg” stands for “regression”)
- $\text{SS}_{\text{res}} = \sum_{i=1}^n (y_i - \hat{y}_i)^2$  (where “res” stands for “residual”)

Using this notation, the statement of lemma 10.1 becomes

$$\text{SS}_{\text{tot}} = \text{SS}_{\text{reg}} + \text{SS}_{\text{res}}.$$

Using the result of lemma 10.1, for linear regression models we can also express  $R^2$  as

$$R^2 = s_{\hat{y}}^2 / s_y^2.$$

Since both numerator and denominator are positive, we have  $R^2 \geq 0$ . Similarly, from the definition it is clear that  $R^2 \leq 1$ , so that  $R^2 \in [0, 1]$  always holds.

**Example 10.1.** We can easily compute the  $R^2$  value for the `stackloss` dataset manually:

```
m <- lm(stack.loss ~ ., data = stackloss)
R.squared <- 1 - var(resid(m)) / var(stackloss$stack.loss)
R.squared
# [1] 0.9135769
```

We can also find this value near the bottom of the output of `summary(m)`, listed as **Multiple R-squared**:

```
summary(m)

#
# Call:
# lm(formula = stack.loss ~ ., data = stackloss)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -7.2377 -1.7117 -0.4551  2.3614  5.6978
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) -39.9197    11.8960  -3.356  0.00375 **
# Air.Flow      0.7156     0.1349   5.307  5.8e-05 ***
#
```

```

# Water.Temp     1.2953      0.3680   3.520  0.00263 **
# Acid.Conc.    -0.1521      0.1563  -0.973  0.34405
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 3.243 on 17 degrees of freedom
# Multiple R-squared:  0.9136, Adjusted R-squared:  0.8983
# F-statistic:  59.9 on 3 and 17 DF,  p-value: 3.016e-09

```

Note that the alternative formula  $R^2 = s_y^2/s_{\hat{y}}^2$  and the variance decomposition in lemma 10.1 require the model to include an intercept term.

## 10.2 Adjusted $R^2$

One problem with the  $R^2$  value is that it always increases when another input variable is added to the model. Thus, the  $R^2$  value cannot be used to compare model fit for models with different numbers of variables. An attempt to compensate for this effect is the adjusted  $R^2$  value.

**Definition 10.2.** The adjusted  $R^2$  value is given by

$$R_{\text{adj}}^2 := 1 - \frac{\frac{1}{n-p-1} S_{\hat{y}}^2}{\frac{1}{n-1} S_y^2} = 1 - \frac{n-1}{n-p-1} (1 - R^2).$$

The value  $R_{\text{adj}}^2$  is always smaller than the  $R^2$  value, and  $R_{\text{adj}}^2$  can be (slightly) negative.

**Example 10.2.** The adjusted  $R^2$  value for the stackloss dataset can be found as follows:

```

n <- nrow(stackloss)
p <- ncol(stackloss) - 1
R.squared.adj <- 1 - (n - 1) / (n - p - 1) * (1 - R.squared)
R.squared.adj
# [1] 0.8983258

```

We can also find this value near the bottom of the output of `summary(m)`, listed as Adjusted R-squared.

**Example 10.3.** As suggested in example 9.7, we may want to include a new quadratic term in the stackloss dataset:

```

m2 <- lm(stack.loss ~ . + I(Water.Temp^2), data = stackloss)
summary(m2)

```

```

#
# Call:
# lm(formula = stack.loss ~ . + I(Water.Temp^2), data = stackloss)
#
# Residuals:
#       Min     1Q Median     3Q    Max
# -4.1217 -1.5205 -0.3091  0.9753  6.0554
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 57.73727   46.08487   1.253  0.22826
# Air.Flow     0.53683    0.14708   3.650  0.00216 ***
# Water.Temp   -7.62030   4.10441  -1.857  0.08188 .
# Acid.Conc.   -0.09697   0.14371  -0.675  0.50946

```

```

# I(Water.Temp^2)  0.21224    0.09738   2.179  0.04459 *
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 2.936 on 16 degrees of freedom
# Multiple R-squared:  0.9334, Adjusted R-squared:  0.9167
# F-statistic: 56.02 on 4 and 16 DF, p-value: 3.293e-09

```

As expected, the  $R^2$  value has increased here (from 0.9136 to 0.9334). Since the adjusted  $R^2$  value has also increased (from 0.8983 to 0.9167), the extended model may be better than the original model.

### 10.3 Error Variance

Another measure for model fit is the estimated error variance,

$$\hat{\sigma}^2 = \frac{1}{n-p-1} \sum_{i=1}^n (y_i - \hat{y}_i)^2.$$

Good models have small  $\hat{\sigma}^2$ . This measure is closely related to the adjusted  $R^2$  value. We have

$$\begin{aligned} R_{\text{adj}}^2 &= 1 - \frac{\frac{1}{n-p-1} s_{\hat{\varepsilon}}^2}{\frac{1}{n-1} s_y^2} \\ &= 1 - \frac{\frac{n-1}{n-p-1} s_{\hat{\varepsilon}}^2}{s_y^2} \\ &= 1 - \frac{\frac{1}{n-p-1} \sum_{i=1}^n (y_i - \hat{y}_i)^2}{s_y^2} \\ &= 1 - \frac{\hat{\sigma}^2}{s_y^2}, \end{aligned}$$

where  $s_{\hat{\varepsilon}}^2$  and  $s_y^2$  are the sample variances as before. Thus, minimising  $\hat{\sigma}^2$  is equivalent to maximising  $R_{\text{adj}}^2$ .

### 10.4 Prediction Error Sum of Squares

The **Prediction Error Sum of Squares (PRESS)** compares each output  $y_i$  to the fitted value  $\hat{y}_i^{(i)}$  for observation  $i$ , computed without using sample  $i$ :

$$\text{PRESS} := \sum_{i=1}^n (y_i - \hat{y}_i^{(i)})^2.$$

By using  $\hat{y}_i^{(i)}$  instead of  $\hat{y}_i$  in the comparison, we avoid overoptimistic estimates that would arise from overfitting in models with too many parameters. Good models have small PRESS. The following lemma provides a convenient formula for computing PRESS without having to fit  $n$  separate models.

**Lemma 10.2.** *We have*

$$\text{PRESS} = \sum_{i=1}^n \left( \frac{\hat{\varepsilon}_i}{1 - h_{ii}} \right)^2,$$

where  $h_{ii}$  denotes the diagonal elements of the hat matrix  $H$ .

*Proof.* From equation (28) we know how the estimated regression coefficients change, when observation  $i$  is deleted from the model:

$$\hat{\beta}^{(i)} - \hat{\beta} = -(X^\top X)^{-1} x_i \frac{\hat{\varepsilon}_i}{1 - h_{ii}}.$$

Thus we have

$$\begin{aligned}\hat{y}_i^{(i)} - \hat{y}_i &= (X\hat{\beta}^{(i)} - X\hat{\beta})_i \\ &= -(X(X^\top X)^{-1} x_i \frac{\hat{\varepsilon}_i}{1 - h_{ii}})_i \\ &= -x_i^\top (X^\top X)^{-1} x_i \frac{\hat{\varepsilon}_i}{1 - h_{ii}} \\ &= -\frac{h_{ii}}{1 - h_{ii}} \hat{\varepsilon}_i.\end{aligned}$$

From this we get

$$\begin{aligned}y_i - \hat{y}_i^{(i)} &= y_i - \hat{y}_i + \hat{y}_i - \hat{y}_i^{(i)} \\ &= \hat{\varepsilon}_i + \frac{h_{ii}}{1 - h_{ii}} \hat{\varepsilon}_i \\ &= \frac{1}{1 - h_{ii}} \hat{\varepsilon}_i.\end{aligned}$$

Substituting this expression into the definition of PRESS completes the proof.  $\square$

## 10.5 Akaike's Information Criterion

Akaike's Information Criterion (AIC) is defined as

$$\text{AIC} = 2q - 2 \log(\hat{L}),$$

where  $q$  is the number of parameters in the model, and  $\hat{L}$  is the maximum of the likelihood function when these  $q$  parameters are chosen optimally. For a model with  $p$  predictors and an intercept, we have  $q = p + 1$ . Good models have small AIC.

Since we assume  $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$ , i.i.d. and we have  $\varepsilon_i = y_i - x_i^\top \beta$ , the likelihood function for our model is

$$\begin{aligned}L(\beta, \sigma^2; X, y) &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_i - (X\beta)_i)^2}{2\sigma^2}\right) \\ &= \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\sum_{i=1}^n \frac{(y_i - (X\beta)_i)^2}{2\sigma^2}\right).\end{aligned}$$

Taking logarithms we get

$$\begin{aligned}\log L(\beta, \sigma^2; X, y) &= -\frac{n}{2} \log(2\pi\sigma^2) - \sum_{i=1}^n \frac{(y_i - (X\beta)_i)^2}{2\sigma^2} \\ &= -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} r(\beta),\end{aligned}$$

where  $r(\beta)$  is the residual sum of squares, as introduced in section 2. To compute the AIC we need to maximise this expression. The values of  $\beta$  and  $\sigma^2$  where the maximum is taken are called the **maximum likelihood estimate (MLE)** for  $\beta$  and  $\sigma^2$ . From lemma 2.1 we know that for fixed  $\sigma^2$ ,  $L$  takes its maximum when  $\beta$  equals the least

squares estimate  $\hat{\beta}$ . Taking derivatives we can then find the optimal value of  $\sigma^2$ . The result is

$$\hat{\sigma}_{\text{MLE}}^2 = \frac{1}{n} r(\hat{\beta}) = \frac{1}{n} \sum_{i=1}^n (y_i - (X\hat{\beta})_i)^2 = \frac{n-p-1}{n} \hat{\sigma}^2.$$

Thus we get

$$\begin{aligned} \text{AIC} &= 2q + n \log(2\pi\hat{\sigma}_{\text{MLE}}^2) + \frac{1}{\hat{\sigma}_{\text{MLE}}^2} r(\hat{\beta}) \\ &= 2q + n \log(2\pi r(\hat{\beta})/n) + n \\ &= 2q + n \log(\|\hat{\varepsilon}\|^2) + n + n \log(2\pi/n). \end{aligned}$$

When these measures indicate poor model fit, data transformations discussed in section 11 may help to better satisfy the modelling assumptions.

### Summary

- The  $R^2$  value is a numerical measure of the goodness of fit of a model. Large values indicate good fit.
- If models with different numbers of variables are compared,  $R_{\text{adj}}^2$  should be used instead of  $R^2$ .
- Minimising the error variance  $\hat{\sigma}^2$  is equivalent to maximising  $R_{\text{adj}}^2$ .
- Other measures for model quality include PRESS and AIC. Good models have small PRESS and small AIC.

## Interlude: Understanding the `lm()` Output

We have seen that the `lm()` function returns an object which contains a lot of information about the fitted model. We can inspect this information by using the `summary()` function. The aim of this section is to help you understand how the output of `summary()` relates to the mathematical expressions we have considered in the previous sections.

We will use the `stackloss` dataset as an example:

```
m <- lm(stack.loss ~ ., data = stackloss)
summary(m)
```

Call:

```
lm(formula = stack.loss ~ ., data = stackloss)
```

Residuals:

Min	1Q	Median	3Q	Max	A
-7.2377	-1.7117	-0.4551	2.3614	5.6978	

Coefficients:	B	C	D	E
	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-39.9197	11.8960	-3.356	0.00375 **
Air.Flow	0.7156	0.1349	5.307	5.8e-05 ***
Water.Temp	1.2953	0.3680	3.520	0.00263 **
Acid.Conc.	-0.1521	0.1563	-0.973	0.34405

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

F	G
Residual standard error: 3.243	on 17 degrees of freedom
Multiple R-squared: 0.9136,	Adjusted R-squared: 0.8983 H
F-statistic: 59.9 on 3 and 17 DF,	p-value: 3.016e-09 I

Here I have marked different parts of the output using red shaded boxes and using the letters A to I. We discuss each of the marked sections in turn:

- The first section, part **A**, contains summary statistics for the fitted residuals  $\hat{\varepsilon}_1, \dots, \hat{\varepsilon}_n$ . The values shown are the minimum, first quartile, median, third quartile, and maximum of the residuals. This is the same information we can get using the command `summary(resid(m))`. The mean is omitted from A, since it always equals zero.
- Column **B** shows the estimated coefficient vector  $\hat{\beta}$ . This is computed using the formula from lemma 2.1.
- Column **C** shows the standard error of the estimated coefficients. The  $i$ th entry is the (estimated) standard deviation of  $\hat{\beta}_i$ , computed as  $\sqrt{\hat{\sigma}^2 C_{ii}}$ , where  $C = (X^\top X)^{-1}$ . This corresponds to the variance shown in equation (16), where the true variance is  $\sigma^2$  replaced with the estimate  $\hat{\sigma}^2$ . These quantities are used to compute the t-test statistic in equation (24).
- Column **D** shows the t-test statistic for the coefficients. The values are computed using equation (24).
- Column **E** replicates the information from column **D** in different form, showing  $p$ -values instead of the test statistics.

- The field **F** shows the estimated standard deviation  $\hat{\sigma}$ . This is computed as the square root of  $\hat{\sigma}^2$  from equation (21).
- Field **G** shows the value  $n - p - 1$ . This is the number of degrees of freedom in lemma 5.2. The value is needed when performing hypothesis tests and computing confidence intervals for individual coefficients.
- Field **H** shows the  $R^2$  value and adjusted  $R^2$  value. These are computed using definitions 10.1 and 10.2.
- Field **I** shows the  $F$ -test statistic for testing the hypothesis  $H_i: \beta_1 = \dots = \beta_p = 0$  (omitting the coefficient  $\beta_0$  for the intercept). This value can be used to test the hypothesis that the inputs have no effect on the output. The  $F$ -test statistic is computed using equation (25), the degrees of freedom shown are  $k = p$  and  $n - p - 1$  from lemma 6.1.

## 11 Improving the Model Fit

The diagnostic plots introduced in section 9 can often reveal if the data do not fit the modelling assumptions. In cases where the assumptions are violated, sometimes a linear model can still be used if the data are transformed first.

### 11.1 Linearising the Mean

If the model mean is a non-linear function of the inputs, we can sometimes transform the variables to achieve a linear relationship. We list some examples of non-linear models which can be transformed to linear models:

Nonlinear Model	Transformation	Linear Model
$y \approx \beta_0 x^{\beta_1}$	$x' = \log(x)$ , $y' = \log(y)$	$y' \approx \log(\beta_0) + \beta_1 x'$
$y \approx \beta_0 e^{\beta_1 x}$	$y' = \log y$	$y' \approx \log \beta_0 + \beta_1 x$
$y \approx \beta_0 + \beta_1 \log x$	$x' = \log x$	$y \approx \beta_0 + \beta_1 x'$
$y \approx \frac{x}{\beta_0 x - \beta_1}$	$x' = 1/x$ , $y' = 1/y$	$y' \approx \beta_0 - \beta_1 x'$

In all such cases we also would need to check the residuals of the transformed models, to see whether linear regression can be used for the transformed model.

### 11.2 Stabilising the Variance

The assumption of constant variance is a basic requirement of regression analysis. A common reason for the violation of this assumption is for the response variable  $y$  to follow a distribution in which the variance depends on  $y$  or  $\mathbb{E}(y)$  and thus on  $x$ .

**Example 11.1.** The error in our model

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon = x^\top \beta + \varepsilon$$

is sometimes called **additive error**, since it is added to the model mean  $x^\top \beta$ . Sometimes the error is instead given in percentages of the quantity of interest. In these cases we speak of **multiplicative error**. This can, for example, be modelled as

$$Y = (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p) \exp(\varepsilon) = x^\top \beta \exp(\varepsilon).$$

For  $\varepsilon = 0$  we have  $\exp(0) = 1$  and thus  $Y = x^\top \beta$ . Similarly, for small  $\varepsilon$  we have  $Y \approx x^\top \beta$ , but the variance is now proportional to  $(x^\top \beta)^2$  instead of being constant. Also, since the exponential is nonlinear we only have  $\mathbb{E}(Y) \approx x^\top \beta$  instead of strict equality.

Some commonly-used variance stabilising transformations are:

variance	transformation
$\sigma^2 = \text{constant}$	no transformation
$\sigma^2 \propto y$	$y' = \sqrt{y}$
$\sigma^2 \propto y^2$	$y' = \log y$
$\sigma^2 \propto y^3$	$y' = \frac{1}{\sqrt[3]{y}}$
$\sigma^2 \propto y^4$	$y' = \frac{1}{y}$
$\sigma^2 \propto y(1-y)$ where $y \in [0, 1]$	$y' = \arcsin(\sqrt{y})$

These transformations can be understood via the **delta method**: if  $g$  is a smooth transformation and  $\text{Var}(Y) = c \cdot [\mathbb{E}(Y)]^p$ , then by Taylor approximation we have  $\text{Var}(g(Y)) \approx$

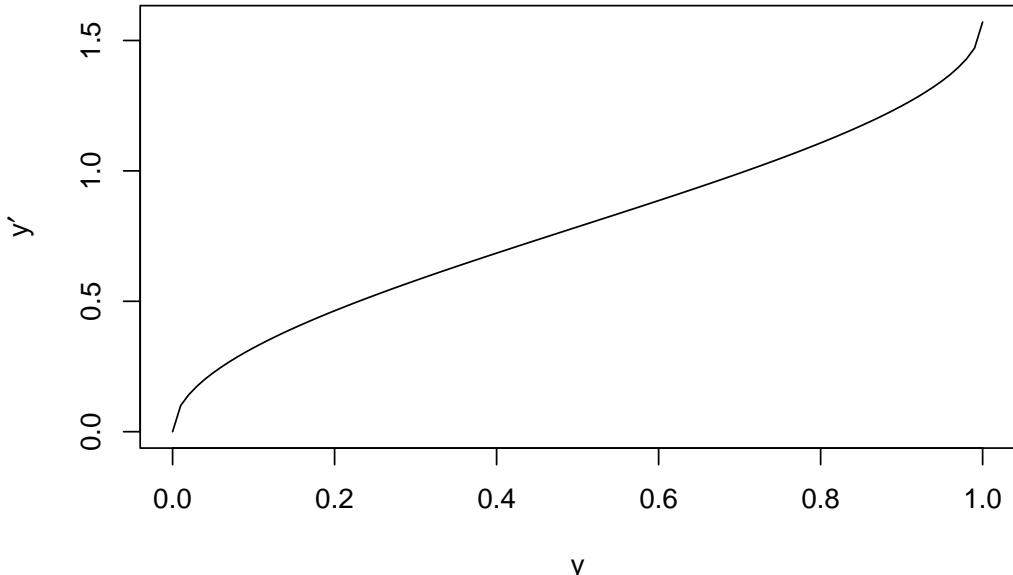
$[g'(\mathbb{E}(Y))]^2 \cdot c \cdot [\mathbb{E}(Y)]^p$ . For the variance to be constant, we need  $g'(\mu) \propto \mu^{-p/2}$ , which gives  $g(y) \propto y^{1-p/2}$ . For example, when  $p = 1$  (variance proportional to the mean), we get  $g(y) \propto \sqrt{y}$ , as shown in the table.

Of course we do not have accurate knowledge of the relationship, but it can be diagnosed from the residual plots and transformations can be selected by experimenting with different choices. Any of these transformations will also affect the mean and we need to check the model fit for the transformed data, to see whether the transformed data can still reasonably be described by a linear model.

**Example 11.2.** The last transformation in the table above corresponds to the case of binomial sampling: If  $x = p$  and  $Y \sim B(n, p)/n$  then we have  $\mathbb{E}(Y) = np/n = x$  and a linear model may be appropriate. But we also have  $\text{Var}(Y) = p(1 - p)/n \propto \mathbb{E}(Y)(1 - \mathbb{E}(Y))$ , so the assumption of constant variance is violated.

We try to apply the transformation suggested in the table. The function `arcsin` is the inverse of the sine function. In R this function is available as `asin()`. To get some intuition about this transformation, we plot the function  $y \mapsto \text{arcsin}(\sqrt{y})$ :

```
y <- seq(0, 1, l=101)
plot(y, asin(sqrt(y)), type = "l",
      ylab = expression(y * minute))
```



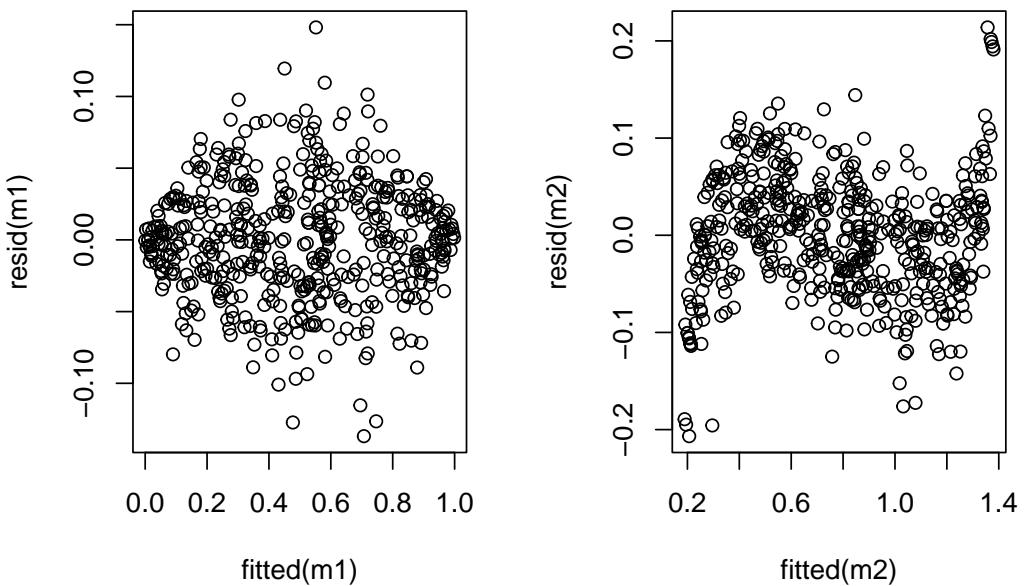
We can see that the transformation is approximately linear for most of the interval, but has a steeper slope near the edges. The effect of this is to increase the size of fluctuations for small and large  $y$ -values. We now consider residual plots for the original and transformed data, for a simulated dataset:

```
n <- 500
x <- runif(n, 0, 1)
y <- rbinom(n, 100, x) / 100

par(mfrow = c(1, 2))

m1 <- lm(y ~ x)
plot(fitted(m1), resid(m1))

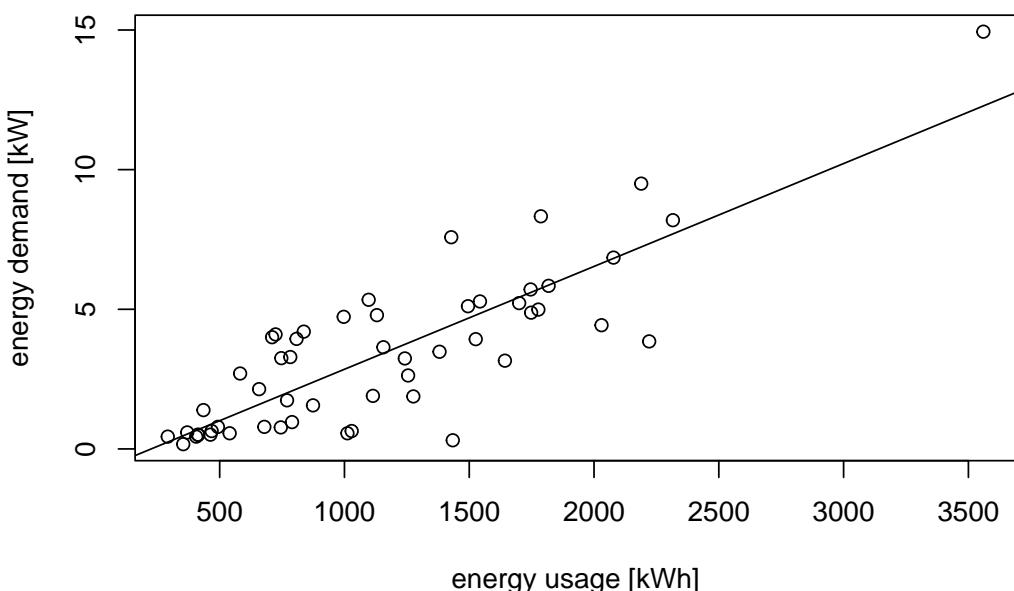
y.prime <- asin(sqrt(y))
m2 <- lm(y.prime ~ x)
plot(fitted(m2), resid(m2))
```



The plot shows that the variance has indeed improved, while linearity has suffered (an S-shaped curve is now visible). Neither model is perfect and whether the transformation is beneficial or not depends on the particular circumstances.

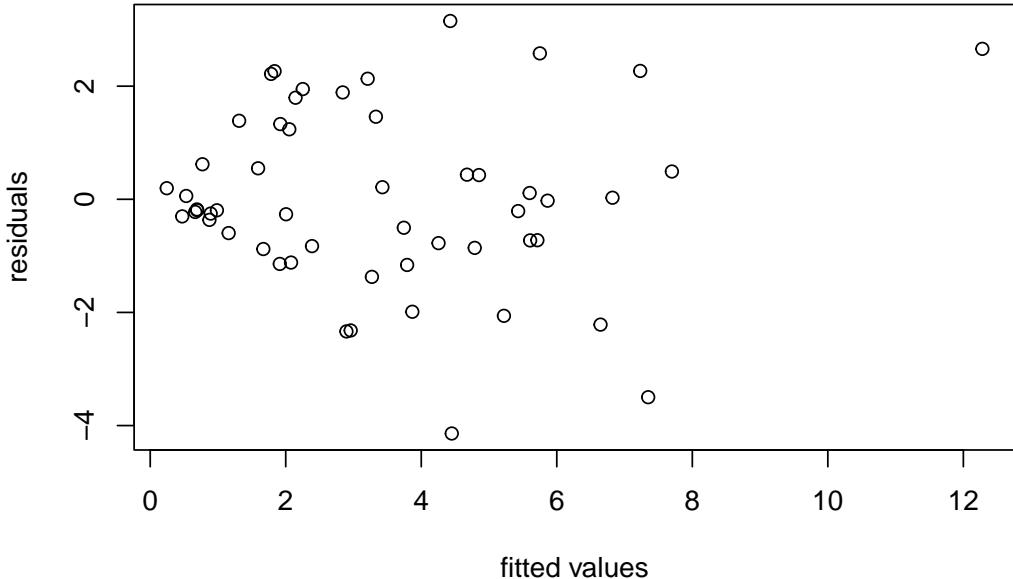
**Example 11.3.** An electric utility company is interested in developing a model relating the peak hour demand ( $y$ , measured in kW) to total energy usage during the month ( $x$ , in kWh). A scatter plot of the data is shown below:

```
# data at https://teaching.seehuhn.de/2022/MATH3714/electric.dat
d <- read.table("data/electric.dat", header=FALSE)
plot(d$V1, d$V2,
     xlab="energy usage [kWh]", ylab="energy demand [kW]")
m1 <- lm(V2 ~ ., data = d)
abline(m1)
```



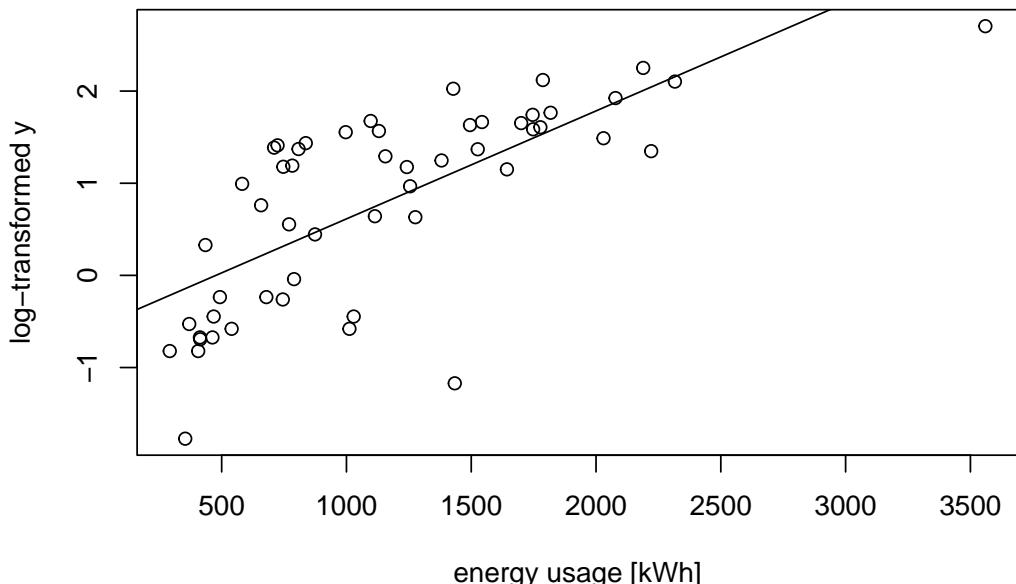
A linear relationship looks plausible, but we can see that the spread of points around the regression line widens as energy usage increases. this is more clearly visible in a residual plot:

```
plot(fitted(m1), resid(m1),
      xlab = "fitted values", ylab = "residuals")
```

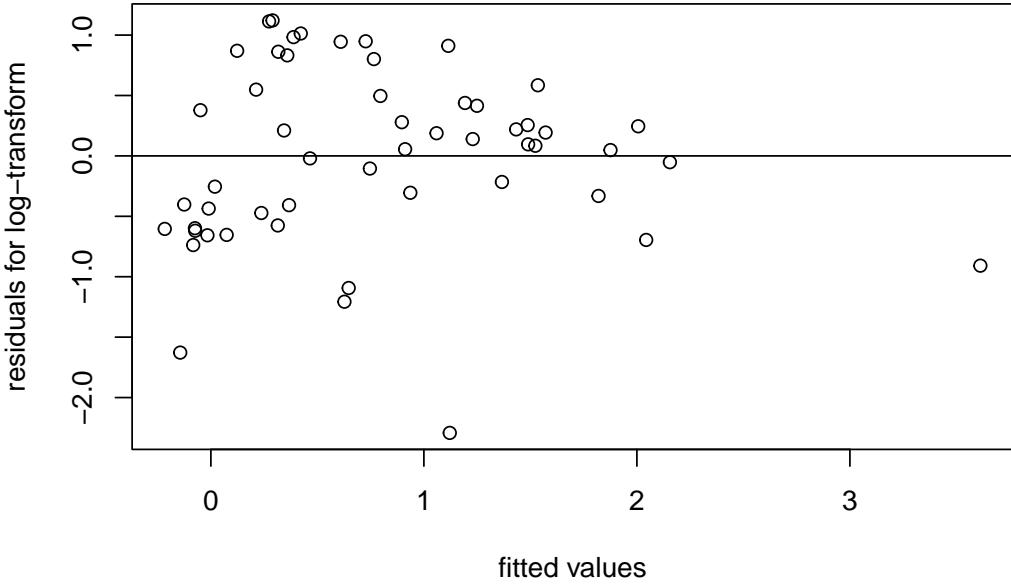


We try a transformation of the data to stabilise the variance. From the “wedge” shape on the left hand side of the plot, it is clear that the variance  $\sigma^2$  increases as  $y$  increases. Thus we can try transformations like  $y' = \log(y)$  or  $y' = \sqrt{y}$ . Taking the logarithm for illustration, we get

```
m2 <- lm(log(V2) ~ ., data = d)
plot(d$V1, log(d$V2),
      xlab="energy usage [kWh]", ylab="log-transformed y")
abline(m2)
```



```
plot(fitted(m2), resid(m2),
      xlab = "fitted values", ylab = "residuals for log-transform")
abline(h = 0)
```



The spread of residuals now looks somewhat more reasonable.

### 11.3 The Power Transform

A family of transformations for the response variable  $y$  is given by the **power transform**. These transformations only apply to strictly positive data, *i.e.*  $y > 0$ , and are defined by

$$y^{(\lambda)} = \begin{cases} \frac{y^\lambda - 1}{\lambda g^{\lambda-1}} & \text{if } \lambda \neq 0 \\ g \log y & \text{if } \lambda = 0 \end{cases}$$

where  $g = (\prod_{i=1}^n y_i)^{1/n}$  is the geometric mean.

The geometric mean is a constant (it does not depend on  $i$ ) and is not needed for the power transform, but it is usually included to make values for different  $\lambda$  more comparable. For  $\lambda = 1$  the transform is  $y' = y - 1$ . This is a simple shift which has no effect on the fitted model, it just decreases the intercept by 1 and leaves the residuals unchanged. Thus, this case is that same as applying no transformation.

Using Taylor approximation on the numerator in the definition of  $y^{(\lambda)}$  we get

$$y^\lambda = \exp(\log(y^\lambda)) = \exp(\lambda \log(y)) \approx 1 + \lambda \log(y) + O((\lambda \log(y))^2),$$

where the  $O(\dots)$  stands for terms which are negligible as  $\lambda$  converges to 0. Thus the formula given for  $\lambda \neq 0$  converges to the case for  $\lambda = 0$  as  $\lambda$  converges to 0. This makes the transformation continuous as a function of  $\lambda$ .

A heuristic rule to find a range of  $\lambda$  for which the power transform is appropriate is based on how the the residual sum of squares changes with  $\lambda$ : Let

$$r(\lambda) = \sum_{i=1}^n (y_i^{(\lambda)} - \hat{y}_i^{(\lambda)})^2,$$

where  $\hat{y}_i^{(\lambda)}$  denotes the fitted value for the model using the transformed data  $y_i^{(\lambda)}$ . It is easy to plot this function numerically. We want to choose  $\lambda$  close to where the function has its minimum. The heuristic rule is to consider all values of  $\lambda$  with

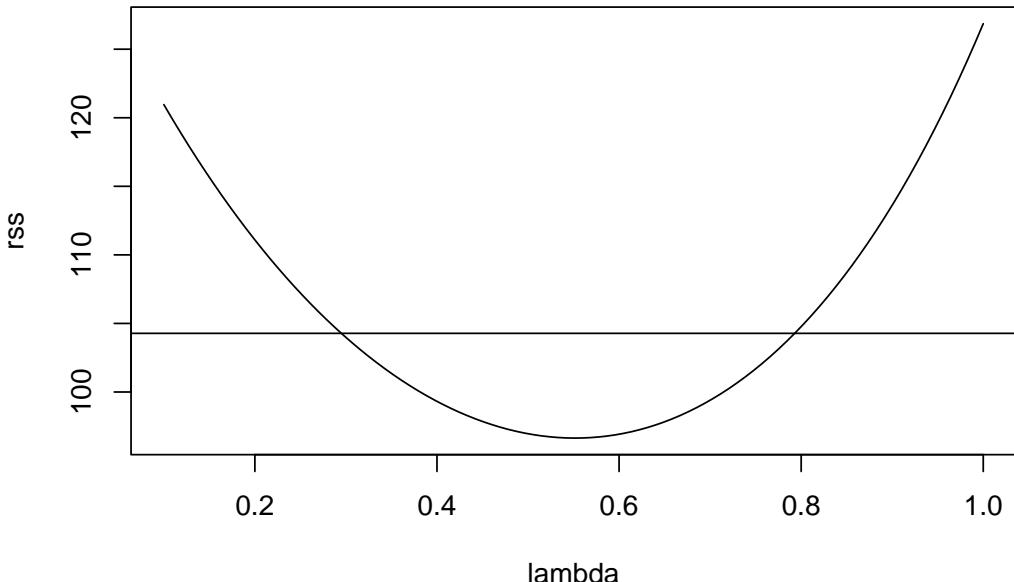
$$r(\lambda) \leq r(\lambda_{\min}) \left( 1 + \frac{t_{n-p-1}(\alpha/2)^2}{n-p-1} \right), \quad (31)$$

where  $\lambda_{\min}$  is the value of  $\lambda$  where the residual sum of squares has its minimum and  $t_{n-p-1}(\alpha/2)$  is the  $(1 - \alpha/2)$ -quantile of the  $t(n - p - 1)$ -distribution. One can show that this is an approximate  $(1 - \alpha)$  confidence interval for  $\lambda$ . If we want to interpret the model, it is usually better to select a “simple”  $\lambda$ , e.g.  $\lambda = 0.5$  rather than using the “optimal” value  $\lambda_{\min}$ .

**Example 11.4.** Continuing from example 11.3 above, we can try a power transform for the data. We start by plotting  $r(\lambda)$  as a function of  $\lambda$ , together with the cutoff suggested by equation (31):

```
x <- d$V1
y <- d$V2
gm <- exp(mean(log(y))) # more stable way to compute geometric mean
lambda <- seq(0.1, 1, length.out = 101)
rss <- numeric(length(lambda))
for (i in seq_along(lambda)) {
  li <- lambda[i]
  y.prime <- (y^li - 1) / (li * gm^(li-1))
  mi <- lm(y.prime ~ x)
  rss[i] <- sum(resid(mi)^2)
}
plot(lambda, rss, type="l")

n <- nrow(d) # 53
p <- 1
cutoff <- min(rss) * (1 + qt(0.975, n - p - 1)^2 / (n - p - 1))
abline(h = cutoff)
```



This suggests the range of reasonable  $\lambda$  values to be

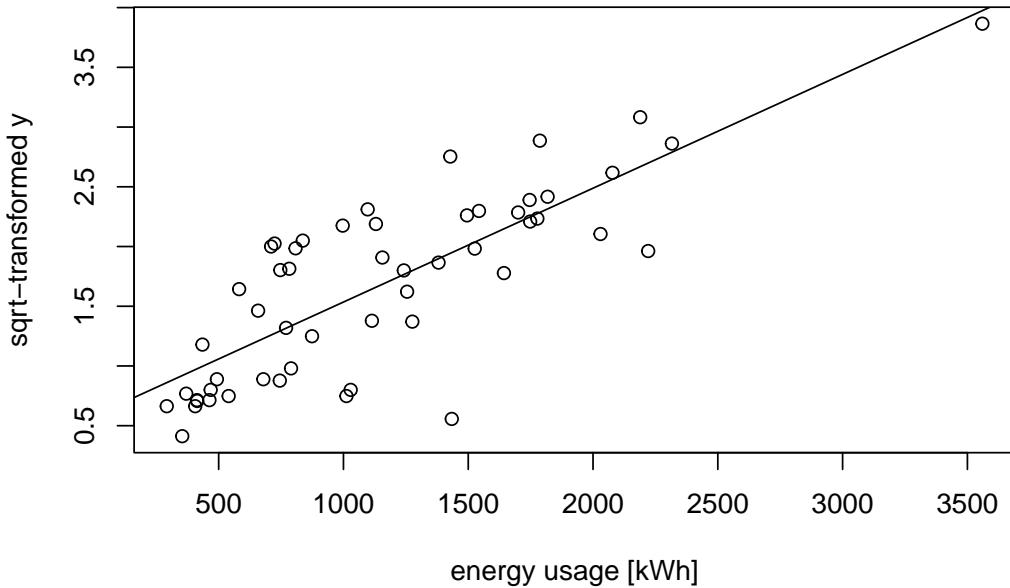
```
range(lambda[which(rss <= cutoff)])
# [1] 0.298 0.784
```

The value  $\lambda = 1$  (no transformation) is not contained in the interval, suggesting that a transformation may be helpful. Choosing a “simple” value inside the interval and close to the minimum, we try  $\lambda = 0.5$ . This leads to the following transformation:

$$y' = 2\sqrt{g}(\sqrt{y} - 1).$$

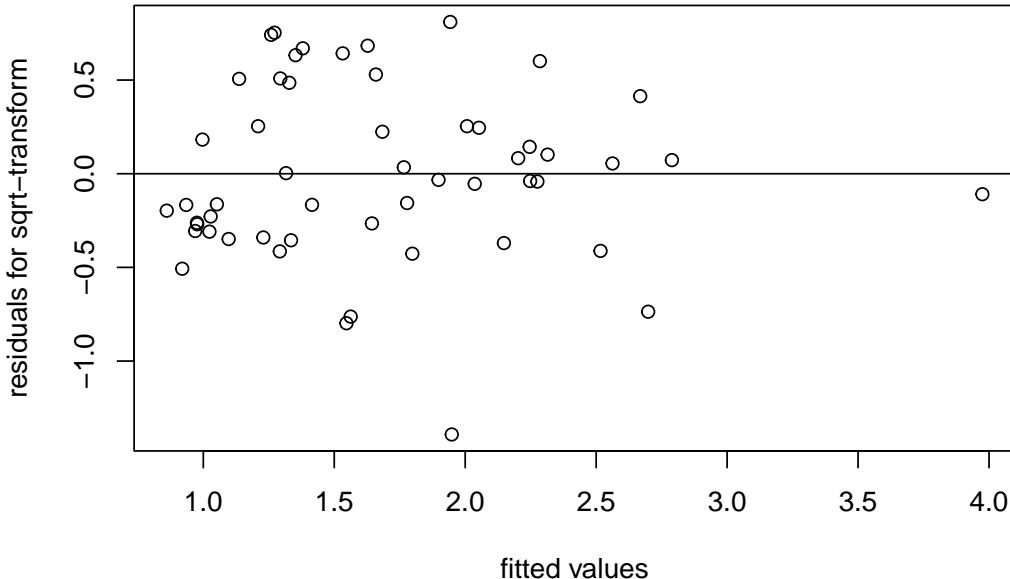
Up to the shift and scaling, this just takes the square root of the data.

```
y.prime <- sqrt(y)
plot(x, y.prime,
      xlab="energy usage [kWh]", ylab="sqrt-transformed y")
m3 <- lm(y.prime ~ x)
abline(m3)
```



To see whether the variance of the residuals has improved, we consider a residual plot:

```
plot(fitted(m3), resid(m3),
      xlab = "fitted values", ylab = "residuals for sqrt-transform")
abline(h = 0)
```



We see that the spread of the residuals has indeed improved, when compared to fitting the original data.

When applying transformations, we create new candidate variables—for example, we might have both  $x$  and  $\log x$  available as potential predictors. This leads naturally to the question of which variables (original or transformed) should be included in the final

model. We will study this question in the next section.

### Summary

- Transformations can be used to linearise the mean or to stabilise the variance of the errors.
- The power transform provides a systematic family of transformations for positive response data, with a data-driven method for selecting the transformation parameter  $\lambda$ .

## Problem Sheet 3

You should attempt all these questions and write up your solutions in advance of the workshop in week 6 where the answers will be discussed.

9. Consider the following dataset. Our aim is to predict  $y$  from the variables  $x_1$ ,  $x_2$  and  $x_3$ .

$i$	$x_{1,i}$	$x_{2,i}$	$x_{3,i}$	$y_i$
1	-2.17	-2.08	-2.16	4.47
2	-1.35	-0.50	-0.74	5.60
3	-1.22	-1.00	-1.78	4.16
4	-1.04	-0.32	-0.40	5.52
5	-0.87	-0.39	-0.67	5.27
6	-0.41	0.07	-0.66	4.70
7	0.07	0.74	0.37	5.50
8	0.25	0.35	0.02	4.84
9	0.87	1.28	0.52	4.92
10	1.53	2.30	1.35	5.35
11	2.46	2.55	1.77	4.86
12	5.00	5.04	4.05	5.09

These data are also available in machine-readable form at

- <https://teaching.seehuhn.de/2022/MATH3714/P03Q09.csv>

Using these data:

- Fit a linear model of the form  $y_i = \beta_0 + x_{1,i}\beta_1 + x_{2,i}\beta_2 + x_{3,i}\beta_3 + \varepsilon_i$ .

Solution:

To fit the required model we can use the following R commands:

```
url <- "https://teaching.seehuhn.de/2022/MATH3714/P03Q09.csv"
x <- read.csv(url)
m <- lm(y ~ x1 + x2 + x3, data=x)
```

The fitted model has the following coefficients:

```
summary(m)

#
# Call:
# lm(formula = y ~ x1 + x2 + x3, data = x)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -0.104928 -0.032723 -0.001836  0.024802  0.142993
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 4.97725   0.06026 82.598 5.15e-13 ***
# x1          -1.11954   0.07427 -15.074 3.71e-07 ***
# x2           0.28176   0.12023  2.344   0.0472 *
# x3           1.06621   0.09492 11.232 3.54e-06 ***
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Residual standard error: 0.07109 on 8 degrees of freedom
# Multiple R-squared:  0.9817, Adjusted R-squared:  0.9748
# F-statistic: 142.8 on 3 and 8 DF, p-value: 2.76e-07
```

- b. Determine a 95% confidence interval for the coefficient  $\beta_2$ .

Solution: From lectures we know that a confidence interval for a single coefficient  $\beta_j$  is given by

$$[U, V] = \left[ \hat{\beta}_j - t_{n-p-1}(\alpha/2) \sqrt{\hat{\sigma}^2 C_{jj}}, \hat{\beta}_j + t_{n-p-1}(\alpha/2) \sqrt{\hat{\sigma}^2 C_{jj}} \right],$$

where  $t_{n-p-1}$  is the  $(1 - \alpha/2)$ -quantile of the  $t$ -distribution,  $C_{jj} = (X^\top X)_{jj}^{-1}$ , and  $X$  is the design matrix.

We can read off the required values for computing the confidence interval from the output of `summary(m)`: the centre of the confidence interval can be found in the column `Estimate`, the standard error  $\sqrt{\hat{\sigma}^2 C_{jj}}$  is given in column `Std. Error`, and  $n - p - 1 = 12 - 3 - 1 = 8$ . Using these values, we can find a 95%-confidence interval for  $\beta_2$  as follows:

```
c(0.28176 - qt(0.975, 8) * 0.12023, 0.28176 + qt(0.975, 8) * 0.12023)
```

```
# [1] 0.004509123 0.559010877
```

Thus, the confidence interval is  $[0.0045, 0.5590]$ .

- c. Perform a hypothesis test, at the 95%-level, for the hypothesis  $H_0: \beta_2 = 0$  with alternative  $H_1: \beta_2 \neq 0$ .

Solution: The test statistic is

$$T = \frac{|\hat{\beta}_2|}{\sqrt{\hat{\sigma}^2 C_{jj}}} = \frac{0.28176}{0.12023} = 2.344.$$

(This value is also shown in the column `t value` of the R summary output.) The critical value is

$$t = t_{n-p-1}(\alpha/2) = 2.306.$$

Since  $T > t$ , we can reject the hypothesis  $\beta_2 = 0$  at the 95%-level.

- 10.** Let  $x_1, \dots, x_n, y_1, \dots, y_n \in \mathbb{R}$  be given. Assume that it is known that the  $y$ -values satisfy  $y \approx 1 - x + cx^2 - dx^3$ , where  $c$  and  $d$  are unknown constants.

- a. Explain how linear regression can be used to estimate the parameters  $c$  and  $d$  from the given data.

Solution: We can rewrite the equation for  $y$  as

$$y + x - 1 = cx^2 - dx^3,$$

where  $c$  and  $d$  are the unknown quantities, and  $x$  and  $y$  are given. Thus we can estimate  $c$  and  $d$  by fitting a linear model with two inputs,  $x_i^2$  and  $x_i^3$  and one output  $y_i + x_i - 1$ . The model does not include an intercept.

- b. What is the design matrix in this situation?

Solution: Since there is no intercept, the design matrix is

$$X = \begin{pmatrix} x_1^2 & x_1^3 \\ x_2^2 & x_2^3 \\ \vdots & \vdots \\ x_n^2 & x_n^3 \end{pmatrix} \in \mathbb{R}^{n \times 2}.$$

- c. Why can *linear* regression be used, despite the presence of the *non-linear* terms  $x^2$  and  $x^3$ ?

Solution: A linear model is appropriate, because the response depends on the unknown coefficients  $c$  and  $d$  in a linear way:  $c$  and  $d$  are only multiplied by known constants, and there are no non-linear functions of  $c$  and  $d$  in the model.

- 11.** In this question we consider four different datasets, given by inputs  $x_i$  and responses  $y_i$  for  $i \in \{1, 2, 3, 4\}$ .

- a. Based on the following plots, discuss model fit of each model. Describe all relevant features of the plots. Describe any problems with the model fit you find.

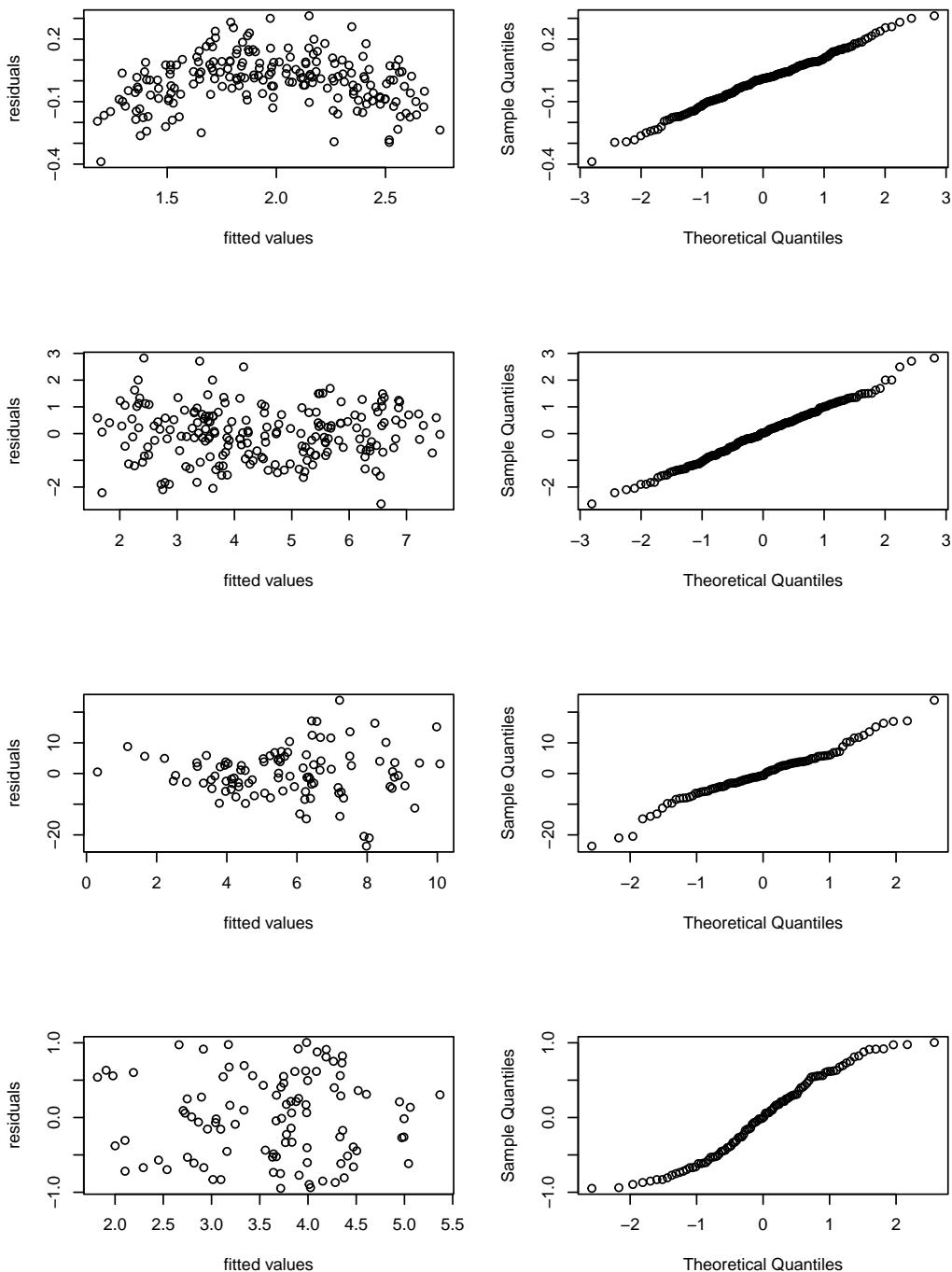
```
par(mfrow=c(4,2))

m1 <- lm(y1 ~ x1)
plot(fitted(m1), resid(m1), xlab="fitted values", ylab="residuals")
qqnorm(resid(m1), main=NULL)

m2 <- lm(y2 ~ x2)
plot(fitted(m2), resid(m2), xlab="fitted values", ylab="residuals")
qqnorm(resid(m2), main=NULL)

m3 <- lm(y3 ~ x3)
plot(fitted(m3), resid(m3), xlab="fitted values", ylab="residuals")
qqnorm(resid(m3), main=NULL)

m4 <- lm(y4 ~ x4)
plot(fitted(m4), resid(m4), xlab="fitted values", ylab="residuals")
qqnorm(resid(m4), main=NULL)
```



Solution:

We first note that the given R commands generate the plots along rows, so the first row of plots corresponds to model  $m_1$ , the second row to model  $m_2$ , and so on. The plots shown are residual plots in the left column, and Q-Q-plots in the right column.

- **$m_1$ :** Samples in the residual plot on the left seem to follow an upside down parabola indicating a non-linear relationship between  $x$  and  $y$ . Samples in the QQ-plot on the right seem to (approximately?) follow a straight line, so residuals seem to be (approximately?) normally distributed. No outliers are visible.
- **$m_2$ :** Samples in the residual plot form a band centred at zero. Possibly very negative residuals are less frequent for fitted values  $\hat{y}_i < 4$ ? No outliers are apparent.

The samples in the QQ-plot seem to clearly fall on a straight line. Overall, model fit seems very good.

- **m3:** The samples in the residual plot are centred around  $\hat{\varepsilon} = 0$ , but the width of the spread increases as the fitted values increase, leading to a triangular shape. This indicates that the variance of the residuals is not constant but increases with  $y$ . Possibly, a model with multiplicative noise would be appropriate for these data. The QQ-plot shows an approximately straight line, but fit is not as good as for model m2.
- **m4:** The samples in the residual plot form a horizontal band centred at  $\hat{\varepsilon} = 0$ , no outliers are visible. The QQ-plot shows clearly that the residuals are not normally distributed: the samples form an “S-shaped” line, indicating that the errors have lighter tails than we would expect for a normal distribution.

b. Which of the four models has the best fit?

Solution: The data in m1 seems to have a non-linear relationship between  $x$  and  $y$ , the data in m3 seems to be better modelled using multiplicative noise, and the residuals in m4 seem not to be normally distributed. Thus, the model with the best fit is m2, because it is the only model which does not show any obvious problems.

- 12.** Using singular value decomposition, we can write a design matrix  $X$  as  $X = UDV^\top$ , where  $D \in \mathbb{R}^{(p+1) \times (p+1)}$  is a diagonal matrix and  $U \in \mathbb{R}^{n \times (p+1)}$  and  $V \in \mathbb{R}^{(p+1) \times (p+1)}$  are matrices with orthonormal columns. Denote the diagonal elements of  $D$  by  $\sigma_0(X), \dots, \sigma_p(X) \geq 0$ , and the columns of  $V$  by  $v_0, \dots, v_p$ . Show that  $\|Xv_k\| = \sigma_k(X)$ . (We used this fact in example 15.4.)

Solution: Using the singular value decomposition of  $X$ , we find

$$\|Xv_k\| = \|UDV^\top v_k\|.$$

For every vector  $x$  we have  $\|Ux\|^2 = x^\top U^\top Ux = x^\top x = \|x\|^2$ . Thus, multiplying a vector  $x$  by  $U$  does not change its length. Using this rule we find

$$\|Xv_k\| = \|DV^\top v_k\|.$$

Since the columns of  $V$  are orthonormal, we have  $V^\top v_k = e_k$ , where  $e_k = (0, \dots, 1, \dots, 0)$  is the  $k$ th standard basis vector. Thus we get

$$\|Xv_k\| = \|De_k\| = \|\sigma_k(X)e_k\| = \sigma_k(X)\|e_k\| = \sigma_k(X)$$

as required. This completes the proof.

## 12 Model Selection

### 12.1 Candidate Models

Here we assume that we are given data with input variables  $x_1, \dots, x_p$ . The standard model which we have discussed so far adds an intercept to these inputs, so that there are  $q = p + 1$  model parameters in total. We can modify this model in various ways:

- When we discussed hypothesis tests, we allowed for the possibility that some inputs do not influence the output. A reasonable approach would be to fit a model with these inputs omitted. Since each input may either be included in or excluded from the model, independent of the others, and similarly the intercept may be included or not, there are  $2^{p+1}$  possible models to consider.
- In section 11 we have seen that sometimes it is useful to transform input variables before using them in the model. This can either happen individually, *e.g.*  $x'_2 = \log x_2$ , or collectively, *e.g.*  $x^* = x_1 x_2$ . The number of models we can obtain by adding transformed versions of the inputs is unlimited.

If we want to compare these candidate models in a systematic way, we need to use efficient methods for comparison, since often a large number of models needs to be considered.

### 12.2 Misspecified Models

The model is said to be **misspecified**, if the data we are using comes from a different model than the one we use to estimate the coefficients.

#### 12.2.1 Missing Variables

Assume that the data comes from the model

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon,$$

where  $p$  denotes the number of predictors (not including the intercept), but we are only using the first  $q$  predictors  $x_1, \dots, x_q$ , where  $q < p$ , to estimate the coefficients. Then the least squares estimate of  $\beta = (\beta_0, \beta_1, \dots, \beta_q)$  is given by

$$\hat{\beta} = (X^\top X)^{-1} X^\top y$$

where  $X \in \mathbb{R}^{n \times (q+1)}$  has columns  $[1, x_1, \dots, x_q]$ , and our estimate for the error variance  $\sigma^2$  is

$$\hat{\sigma}^2 = \frac{1}{n - q - 1} y^\top (I - H)y,$$

where  $H = X(X^\top X)^{-1} X^\top$  is the hat matrix computed using only the first  $q$  predictors.

If we write  $\tilde{X} \in \mathbb{R}^{n \times (p-q)}$  for the matrix with columns  $x_{q+1}, \dots, x_p$  and  $\tilde{\beta} = (\beta_{q+1}, \dots, \beta_p) \in \mathbb{R}^{p-q}$ , then the full model can be written as

$$Y = X\beta + \tilde{X}\tilde{\beta} + \varepsilon$$

and we get

$$\begin{aligned} \hat{\beta} &= (X^\top X)^{-1} X^\top Y \\ &= (X^\top X)^{-1} X^\top (X\beta + \tilde{X}\tilde{\beta} + \varepsilon) \\ &= (X^\top X)^{-1} X^\top X\beta + (X^\top X)^{-1} X^\top \tilde{X}\tilde{\beta} + (X^\top X)^{-1} X^\top \varepsilon \\ &= \beta + (X^\top X)^{-1} X^\top \tilde{X}\tilde{\beta} + (X^\top X)^{-1} X^\top \varepsilon. \end{aligned}$$

Thus, we have

$$\mathbb{E}(\hat{\beta}) = \beta + (X^\top X)^{-1} X^\top \tilde{X} \tilde{\beta}$$

and

$$\text{bias}(\hat{\beta}) = (X^\top X)^{-1} X^\top \tilde{X} \tilde{\beta}.$$

This shows that now the estimate is biased in general. There are two special cases when omitting variables does not introduce a bias: The first is when all of the omitted coefficients equal zero, *i.e.* when we have  $\tilde{\beta} = 0$ . The second case is when the omitted inputs are orthogonal to the included inputs, since then we have  $X^\top \tilde{X} = 0$ .

Using the formula for  $\hat{\beta}$  we find

$$\begin{aligned}\text{Cov}(\hat{\beta}) &= \text{Cov}\left(\beta + (X^\top X)^{-1} X^\top \tilde{X} \tilde{\beta} + (X^\top X)^{-1} X^\top \varepsilon\right) \\ &= \text{Cov}\left((X^\top X)^{-1} X^\top \varepsilon\right) \\ &= \sigma^2 (X^\top X)^{-1} X^\top I X (X^\top X)^{-1} \\ &= \sigma^2 (X^\top X)^{-1}.\end{aligned}$$

Thus, the variance of  $\hat{\beta}$  is not affected by the omitted variables. Similar to our derivation in section 4.4 one can show that

$$\mathbb{E}(\hat{\sigma}^2) = \sigma^2 + \frac{\tilde{\beta}^\top \tilde{X}^\top (I - H) \tilde{X} \tilde{\beta}}{n - q - 1}.$$

Thus, the estimate of the error variance is in general also biased.

### 12.2.2 Unnecessary Variables

If the data comes from a model with fewer inputs than the ones we are using, the model is not “misspecified” in the strict sense. It is just the case that some of the true  $\beta_j$  exactly equal zero. In this case, our previous results show that the least squares estimate is unbiased.

Including additional variables into a model still can cause problems: One can show that each unnecessary variable added increases the variance of the estimates  $\hat{\beta}_j$ . Instead of giving a proof of this fact, we illustrate the effect using a numerical example.

**Example 12.1.** Here we consider the `stackloss` dataset with an added column of noise. We have seen that

$$\text{Var}(\hat{\beta}_j) = \sigma^2 (X^\top X)_{jj}^{-1}.$$

While we don't know the true value of  $\sigma^2$ , we can determine the relative change in variance when adding a column, since this process does not change  $\sigma^2$  and thus  $\sigma^2$  will cancel when we determine the relative change in variance.

We first compute the diagonal elements of  $(X^\top X)^{-1}$  for the original dataset:

```
X1 <- model.matrix(stack.loss ~ ., data = stackloss)
d1 <- diag(solve(t(X1) %*% X1))
d1

# (Intercept)      Air.Flow    Water.Temp   Acid.Conc.
# 13.452726695  0.001728874  0.012875424  0.002322167
```

Now we add a column of noise and re-compute the values:

```
set.seed(20211115)
n <- nrow(X1)
X2 <- cbind(X1, rnorm(n))
d2 <- diag(solve(t(X2) %*% X2))
d2
```

```
# (Intercept) Air.Flow Water.Temp Acid.Conc.
# 14.397515774 0.001730570 0.015195467 0.002796487 0.064828744
```

Finally, we determine the change in variance in percent:

```
round(100 * (d2[-5] - d1) / d1, 3)

# (Intercept) Air.Flow Water.Temp Acid.Conc.
# 7.023 0.098 18.019 20.426
```

We see that the variances of the  $\hat{\beta}_j$  increased by up to 20% when we added the unnecessary input.

The example illustrates that it is important to keep the model as small as possible.

### 12.3 Testing Nested Models

In the preceding section, we discussed the bias-variance trade-off when choosing between a full model and a reduced model. A natural question arises: how can we formally test whether the additional predictors in the full model are needed? In section 6, we developed the  $F$ -test for testing linear combinations of coefficients. Here we show that for nested models, this test simplifies to a formula involving only the residual sums of squares.

We use the same setup as in the preceding section: the reduced model uses only the first  $q$  predictors, with design matrix  $X \in \mathbb{R}^{n \times (q+1)}$  (including intercept), while the full model uses all  $p$  predictors, with additional predictors in  $\tilde{X} \in \mathbb{R}^{n \times (p-q)}$ . We wish to test

$$H_0: \tilde{\beta} = 0 \quad \text{vs.} \quad H_1: \tilde{\beta} \neq 0.$$

Let  $X_{\text{full}} = [X \ \tilde{X}] \in \mathbb{R}^{n \times (p+1)}$  be the design matrix for the full model. We define the hat matrices

$$H_{\text{reduced}} = X(X^\top X)^{-1}X^\top \quad \text{and} \quad H_{\text{full}} = X_{\text{full}}(X_{\text{full}}^\top X_{\text{full}})^{-1}X_{\text{full}}^\top,$$

and the residual sums of squares as

$$\text{RSS}_{\text{reduced}} := \|y - H_{\text{reduced}}y\|^2 \quad \text{and} \quad \text{RSS}_{\text{full}} := \|y - H_{\text{full}}y\|^2.$$

**Theorem 12.1.** *Under the model  $Y = X\beta + \tilde{X}\tilde{\beta} + \varepsilon$  with  $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$ , to test  $H_0: \tilde{\beta} = 0$ , the  $F$ -statistic is given by*

$$F = \frac{(\text{RSS}_{\text{reduced}} - \text{RSS}_{\text{full}})/(p-q)}{\text{RSS}_{\text{full}}/(n-p-1)}. \quad (32)$$

Under  $H_0$ , we have  $F \sim F_{p-q, n-p-1}$ .

*Proof.* In section 6, we have seen that the  $F$ -statistic for testing  $k$  linear combinations of coefficients is given by

$$F = \frac{\|K\hat{\beta} - K\beta\|_{K(X^\top X)^{-1}K^\top}^2}{k\hat{\sigma}^2},$$

where  $K$  is a matrix that selects the coefficients of interest. For testing  $H_0: \tilde{\beta} = 0$ , we have  $k = p - q$ . It can be shown (though we omit the details) that for this choice of  $K$ , we have

$$\|K\hat{\beta} - K\beta\|_{K(X^\top X)^{-1}K^\top}^2 = \text{RSS}_{\text{reduced}} - \text{RSS}_{\text{full}}.$$

Furthermore, under the full model, we have

$$\hat{\sigma}^2 = \frac{\text{RSS}_{\text{full}}}{n - p - 1}.$$

Substituting these expressions into the  $F$ -statistic, we obtain

$$F = \frac{(\text{RSS}_{\text{reduced}} - \text{RSS}_{\text{full}})/(p - q)}{\text{RSS}_{\text{full}}/(n - p - 1)}.$$

By lemma 6.1, this follows an  $F_{p-q, n-p-1}$  distribution under  $H_0$ .  $\square$

This formula is particularly useful in practice: we can test whether predictors should be included simply by comparing residual sums of squares, without computing the Mahalanobis norm from section 6.

## 12.4 Choosing Between Models

### 12.4.1 Criteria for Model Selection

When comparing different models, we need a criterion to decide which is “best”. Several options exist:

- $R^2$  (coefficient of determination): Measures the proportion of variance explained by the model. However,  $R^2$  always increases when variables are added, even if they are irrelevant. This makes it unsuitable for model selection.
- **Adjusted  $R^2$**  (written  $R_{\text{adj}}^2$ ): Adjusts  $R^2$  to penalize model complexity. This is the criterion we will use throughout this section and section 13.
- **AIC** (Akaike Information Criterion) and **BIC** (Bayesian Information Criterion): Alternative criteria that also penalize model complexity, discussed in section 10.

In the following subsections, we describe algorithms that use these criteria to select models efficiently.

### 12.4.2 Exhaustive Search

When  $p$  is small (typically  $p < 20$ ), we can fit all  $2^p$  possible models and choose the one with the best criterion value (e.g., highest  $R_{\text{adj}}^2$ ). This guarantees finding the optimal model but becomes computationally infeasible for larger  $p$  (since  $2^{20} > 1$  million). See section 13 for efficient algorithms.

### 12.4.3 Stepwise Forward Selection

Forward selection starts with the intercept-only model  $y = \beta_0 + \varepsilon$ , then iteratively adds variables. At each step, for each variable not yet in the model, we compute the  $t$ -statistic for testing whether that variable’s coefficient is zero (lemma 5.4). We add the variable (if any) with the largest  $|t|$ -value, provided this is above a chosen threshold (commonly  $|t| > 2$ , corresponding to approximate 5% significance). The process continues until no remaining variable is above the threshold.

### 12.4.4 Stepwise Backward Selection

Backward selection starts with the full model containing all  $p$  predictors, then iteratively removes variables. At each step, we compute the  $t$ -statistic  $T_j$  for testing  $H_0: \beta_j = 0$  for each variable currently in the model (lemma 5.4). We remove the variable with the smallest  $|T_j|$ , provided this is below a chosen threshold (commonly  $|t| < 2$ ). The process continues until all remaining variables have  $|t|$ -values above the threshold.

### 12.4.5 Bidirectional Selection

Bidirectional (or hybrid) methods combine forward and backward selection. At each step, we consider both adding the most significant variable not in the model and removing the least significant variable currently in the model. Typically, different significance thresholds are used for entry and removal to avoid cycling.

*Remark.* While computationally efficient, stepwise procedures have important limitations: the resulting test statistics and confidence intervals are biased (since variable selection and testing use the same data), the methods are prone to overfitting, and small changes in the data can lead to very different selected models. These procedures should be used primarily for exploratory analysis, and any final model should ideally be validated on independent data.

#### Summary

- Misspecified models affect estimates: missing variables introduce bias  $\text{bias}(\hat{\beta}) = (X^\top X)^{-1} X^\top \tilde{X} \tilde{\beta}$ , while unnecessary variables increase variance.
- The bias-variance tradeoff: smaller models may have lower MSE despite bias if variance reduction is sufficient.
- For nested models, the F-test simplifies to comparing residual sums of squares:  $F = (\text{RSS}_{\text{reduced}} - \text{RSS}_{\text{full}})/(p - q) \div \text{RSS}_{\text{full}}/(n - p - 1)$ .
- Model selection requires choosing a criterion such as  $R_{\text{adj}}^2$ , AIC, or BIC to compare models.
- Stepwise methods (forward, backward, hybrid) provide computationally efficient heuristics for large  $p$ , but do not guarantee finding the optimal model.
- Exhaustive search can find the optimal model when  $p$  is small to moderate.

## 13 Exhaustive Model Search

### 13.1 Exhaustive Search

The stepwise methods from the previous section provide efficient heuristics, but they may not find the model with truly maximal  $R_{\text{adj}}^2$ . When  $p$  is small to moderate, exhaustive search allows us to evaluate all possible models systematically. Here we present an efficient algorithm that can often find the optimal model without having to fit all  $2^p$  models. We consider the least squares estimate throughout.

We can characterise each possible model by the set  $J \subseteq \{1, \dots, p\}$  of variables included in the model. The model includes variable  $x_j$ , if and only if  $j \in J$ . Here we assume that the intercept is always included, so that  $J = \emptyset$  corresponds to the model  $Y = \beta_0 + \varepsilon$ .

The method described in this section is based on the following three observations:

- In order to *maximise*  $R_{\text{adj}}^2$ , we can equivalently also find the  $J$  which *minimises*

$$\hat{\sigma}^2(J) := \frac{1}{n - |J| - 1} \sum_{i=1}^n (y_i - \hat{y}_i)^2,$$

where  $|J|$  is the number of variables in  $J$  and the  $\hat{y}_i$  are the fitted values for the model with inputs  $j \in J$ . We have seen in 10.3 that these criteria are equivalent.

- For  $J \subseteq \{1, \dots, p\}$ , define

$$r(J) := \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where  $\hat{y}_i$  are the fitted values for the model corresponding to  $J$ . This gives the residual sum of squares for each model. Then we have

$$\begin{aligned} \min_J \hat{\sigma}^2(J) &= \min_J \frac{1}{n - |J| - 1} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \\ &= \min_{q \in \{0, 1, \dots, p\}} \min_{J, |J|=q} \frac{1}{n - q - 1} r(J) \\ &= \min_{q \in \{0, 1, \dots, p\}} \frac{1}{n - q - 1} \min_{J, |J|=q} r(J). \end{aligned}$$

This means that we can first minimise the residual sum of squares for each fixed number  $q$  of inputs, and then find the  $q$  which gives the best  $\hat{\sigma}^2$  in a second step.

- Adding a variable never increases the residual sum of squares. Thus we have  $r(J) \leq r(K)$  whenever  $J \supseteq K$ . We can use this result to exclude certain models without having to fit them.

### 13.2 Search Algorithm

To find the model with optimal adjusted R-squared value, we perform the following steps. The algorithm is based on the ideas explained in the previous section.

- Let  $\varphi_j$  denote the residual sum of squares for the model containing all variables except  $x_j$ :

$$\varphi_j := r(\{1, \dots, p\} \setminus \{j\}).$$

Suppose that the  $x_j$  are ordered so that

$$\varphi_1 \geq \varphi_2 \geq \dots \geq \varphi_p.$$

Any model  $J$  with  $j \notin J$  has  $r(J) \geq \varphi_j$ .

B. Compute  $\min_{J, |J|=0} r(J) = r(\emptyset)$ . This is the residual sum of squares of the model which consists only of the intercept.

C. For each  $q := 1, \dots, p - 2$ :

1. Let

$$r := r(\{1, \dots, q\}).$$

This is the only model with  $q$  inputs where the first excluded variable has index  $k = q + 1$ . If  $r \leq \varphi_{k-1} = \varphi_q$ , we know from step A that  $J = \{1, \dots, q\}$  is the best model with  $q$  inputs, since any other model will exclude one of the  $x_j$  with  $j \leq q$ . In this case we have found

$$\min_{J, |J|=q} r(J) = r.$$

and we continue step C by trying the next value of  $q$ . If  $r > \varphi_{k-1}$ , no decision can be taken at this point and we continue with step 2.

2. For  $j \in \{q + 1, \dots, p\}$  let

$$r_j := r(\{1, \dots, q - 1\} \cup \{j\}).$$

These are all models with  $q$  inputs where the first excluded variable has index  $k = q$ . If  $\min(r, r_{q+1}, \dots, r_p) \leq \varphi_{k-1} = \varphi_{q-1}$ , then we know from step A that the  $J$  corresponding to the minimum is the best model with  $q$  inputs. In this case we continue step C by trying the next value of  $q$ . Otherwise we proceed to step 3.

3. Similarly to the previous step, we consider all models with  $q$  variables where the first excluded variable has index  $k = q - 1$ . If the best RSS amongst these and the previously considered models is less than or equal to  $\varphi_{k-1}$  we are done and consider the next  $q$ . Otherwise we decrease  $k$  until we reach  $k = 1$ . At this point we have considered all models with  $q$  variables and have found  $\min_{J, |J|=q} r(J)$ .

D. Compute  $\min_{J, |J|=p-1} r(J) = \min_{j \in \{1, \dots, p\}} \varphi_j$ .

E. Compute  $\min_{J, |J|=p} r(J) = r(\{1, \dots, p\})$ .

F. Find the  $q \in \{0, \dots, p\}$  for which  $\min_{J, |J|=q} r(J)/(n - q - 1)$  is smallest. Output the model which has minimal RSS for this  $q$ .

This algorithm finds the model with the maximal  $R^2_{\text{adj}}$ . Often, large savings are achieved by the early exits in step C. Only in the worst case, when all of the comparisons with  $\varphi_j$  in step C fail, this algorithm needs to fit all  $2^p$  models.

**Example 13.1.** To demonstrate the steps of the algorithm, we implement the method “by hand”. We use the QSAR dataset, which we have already seen in section 7:

```
# data from https://archive.ics.uci.edu/ml/datasets/QSAR+aqueous+toxicity
qsar <- read.csv("data/qsar_aqueous_toxicity.csv",
                 sep = ";", header = FALSE)
fields <- c(
  "TPSA",
  "SAacc",
  "H050",
  "ML0GP",
  "RDCHI",
  "GATS1p",
  "nN",
  "C040",
```

```

    "LC50"
)
names(qsar) <- fields

```

To make it easy to add/remove columns automatically, we first construct the design matrix, remove columns as needed, and then use the resulting matrix in the call to `lm()` (instead of specifying the terms to include by name).

```

X <- model.matrix(LC50 ~ ., data = qsar)
X <- X[, -1] # remove the intercept, since lm() will re-add it later
n <- nrow(X)
p <- ncol(X)

y <- qsar$LC50

m <- lm(y ~ X) # full model
summary(m)

#
# Call:
# lm(formula = y ~ X)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.4934 -0.7579 -0.1120  0.5829  4.9778
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 2.698887  0.244554 11.036 < 2e-16 ***
# XTPSA        0.027201  0.002661 10.220 < 2e-16 ***
# XSAacc      -0.015081  0.002091 -7.211 1.90e-12 ***
# XH050        0.040619  0.059787  0.679 0.497186
# XMLOGP       0.446108  0.063296  7.048 5.60e-12 ***
# XRDCHI       0.513928  0.135565  3.791 0.000167 ***
# XGATS1p      -0.571313  0.153882 -3.713 0.000227 ***
# XnN          -0.224751  0.048301 -4.653 4.12e-06 ***
# XC040        0.003194  0.077972  0.041 0.967340
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.203 on 537 degrees of freedom
# Multiple R-squared:  0.4861, Adjusted R-squared:  0.4785
# F-statistic: 63.5 on 8 and 537 DF, p-value: < 2.2e-16

```

Comparing the output to what we have seen in section 7 shows that the new method of calling `lm()` gives the same results as before. Now we follow the steps of the algorithm.

A. The values  $\varphi_1, \dots, \varphi_p$  can be computed as follows:

```

phi <- numeric(p) # pre-allocate an empty vector
for (j in 1:p) {
  idx <- (1:p)[-j] # all variables except x[j]
  m <- lm(y ~ X[,idx])
  phi[j] <- sum(resid(m)^2)
}

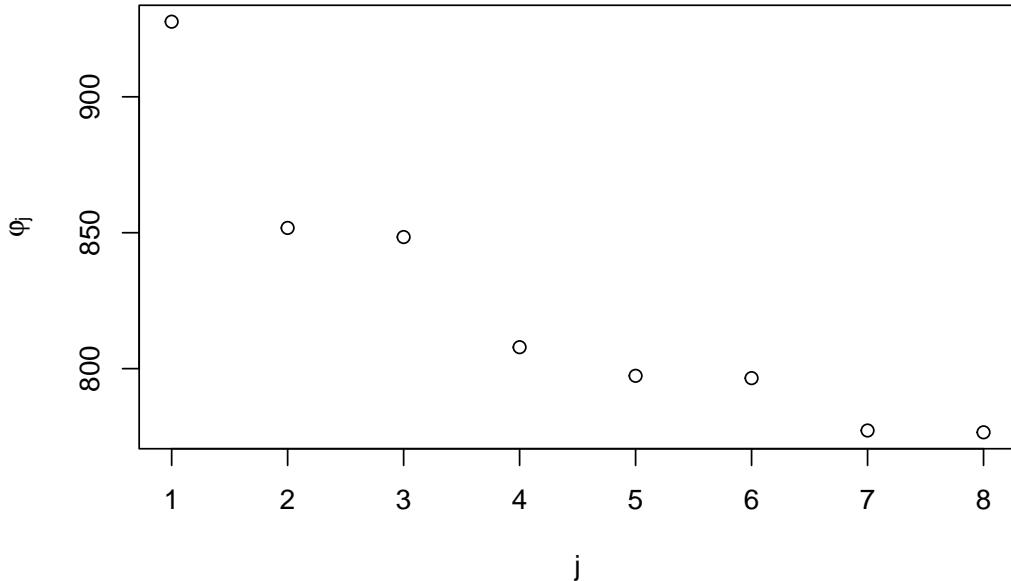
# change the order of columns in X, so that the phi_j are decreasing

```

```

jj <- order(phi, decreasing = TRUE)
X <- X[, jj]
phi <- phi[jj]
plot(phi, xlab = "j", ylab = expression(varphi[j]))

```



The plot shows the residual sum of squares for the model with input  $x_j$  omitted, for  $j$  ranging from 1 to 8.

B. Next, we compute the residual sum of squares of the model which consists only of the intercept. This is the case  $q = 0$ .

```

all.q <- 0:p
best.rss <- numeric(p + 1) # For storing the best RSS for q = 0, ..., p,
best.model <- vector("list", p + 1) # and the corresponding models.

m <- lm(y ~ 1)
best.rss[0 + 1] <- sum(resid(m)^2)
best.model[[0 + 1]] <- integer(0) # a vector of length 0 (no columns)

count <- 1 # number of models fitted so far

```

C. Now we consider  $q \in \{1, \dots, p-2\}$ . The algorithm groups these cases by the position  $k$  of the first column omitted in the model, starting with  $k = q+1$  and then decreasing  $k$  in each step. We use the function `combn` to get all possible choices of  $q-k+1$  columns out of  $\{k+1, \dots, p\}$ .

```

for (q in 1:(p-2)) {
  best.rss[q + 1] <- Inf

  # Consider all sets of q columns, ...
  for (k in (q+1):1) {
    # ... where the first omitted column is k.

    # We have to include 1, ..., k-1, and ...
    a <- seq_len(k-1)

    # ... for the remaining q - (k-1) inputs, we try all
    # possible combinations.
  }
}

```

```

bb <- combn((k+1):p, q - k + 1)
for (l in seq_len(ncol(bb))) {
  b <- bb[, l]
  included <- c(a, b)

  m <- lm(y ~ X[, included])
  count <- count + 1
  rss <- sum(resid(m)^2)

  if (rss < best.rss[q + 1]) {
    best.rss[q + 1] <- rss
    best.model[[q + 1]] <- included
  }
}

if (k > 1 && best.rss[q+1] <= phi[k-1]) {
  # If we reach this point, we know that we found the best
  # arrangement and we can exit the loop over k early.
  # This is what makes the algorithm efficient.
  break
}
}
}

```

**D.** We already fitted all models with  $p - 1$  inputs, when we computed  $\phi$ . Since we sorted the models, the best of these models is last in the list. This covers the case  $q = p - 1$ .

```

best.rss[(p - 1) + 1] <- min(phi)
omitted <- jj[length(jj)]
best.model[[p - 1 + 1]] <- (1:p)[-omitted]
count <- count + length(phi)

```

**E.** Finally, for  $q = p$  we fit the full model:

```

m <- lm(y ~ X)
best.rss[p + 1] <- sum(resid(m)^2)
best.model[[p + 1]] <- 1:p
count <- count + 1

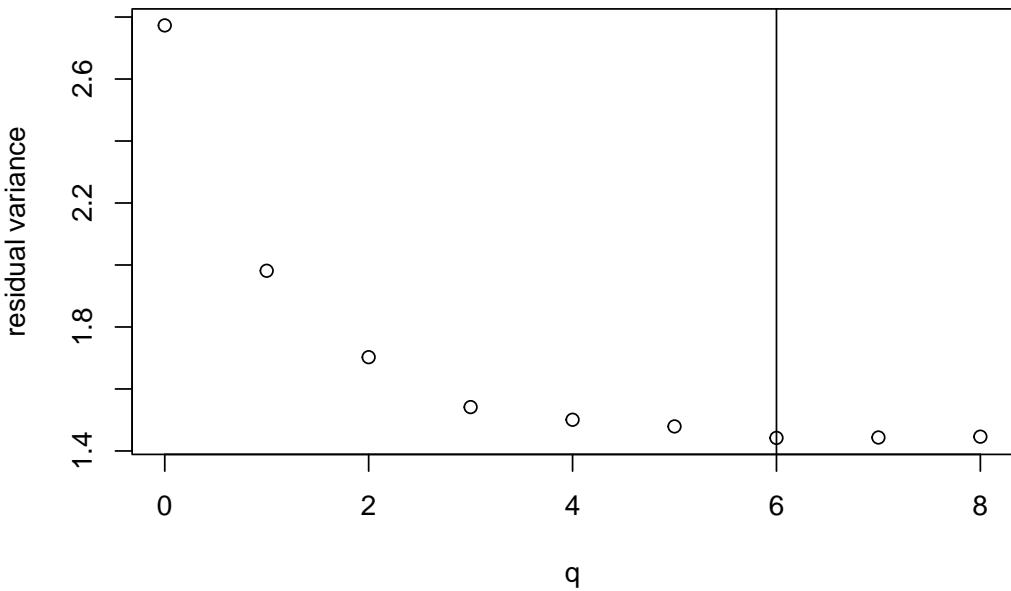
```

**F.** Now we can find the model with the best  $R_{\text{adj}}^2$ :

```

plot(all.q, best.rss / (n - all.q - 1),
     xlab = "q", ylab = "residual variance")
best.q <- all.q[which.min(best.rss / (n - all.q - 1))]
abline(v = best.q)

```



We see that the model with  $q = 6$  variables has the lowest  $\hat{\sigma}^2$  and thus the highest  $R_{\text{adj}}^2$ . The values for  $q = 7$  and  $q = 8$  are very close to optimal. The best model uses the following variables:

```
colnames(X)[best.model[[6 + 1]]]
# [1] "TPSA"    "SAacc"   "MLOGP"   "nN"       "RDCHI"   "GATS1p"
```

We can fit the optimal model from the original data:

```
m.best <- lm(LC50 ~ TPSA + SAacc + MLOGP + nN + RDCHI + GATS1p,
               data = qsar)
summary(m.best)

#
# Call:
# lm(formula = LC50 ~ TPSA + SAacc + MLOGP + nN + RDCHI + GATS1p,
#      data = qsar)
#
# Residuals:
#      Min        1Q        Median         3Q        Max 
# -4.4986 -0.7668 -0.1165  0.5529  4.9758 
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)    
# (Intercept) 2.758246  0.228483 12.072 < 2e-16 ***
# TPSA        0.026858  0.002608 10.300 < 2e-16 ***
# SAacc      -0.014267  0.001660 -8.596 < 2e-16 ***
# MLOGP       0.434578  0.060611  7.170 2.49e-12 ***
# nN          -0.218445  0.047101 -4.638 4.43e-06 ***
# RDCHI        0.514758  0.133430  3.858 0.000128 *** 
# GATS1p     -0.602971  0.146920 -4.104 4.69e-05 *** 
# ---        
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.201 on 539 degrees of freedom
# Multiple R-squared:  0.4857, Adjusted R-squared:  0.4799 
# F-statistic: 84.82 on 6 and 539 DF,  p-value: < 2.2e-16
```

This shows that  $R_{\text{adj}}^2$  has indeed marginally improved, from 0.4785 to 0.4799

To conclude, we check that the complicated algorithm indeed saved some work:

```
total <- 2^p
cat(count,
    " models fitted (", round(100 * count / total, 1), "%)\n",
    sep = "")

# 36 models fitted (14.1%)
```

This shows that we only needed to fit 88 of the 256 models under consideration.

**Example 13.2.** We can perform the analysis from the previous example automatically, using the function `regsubsets()` from the `leaps` package:

```
library(leaps)
m <- regsubsets(LC50 ~ ., data = qsar,
                  method = "exhaustive")
summary(m)

# Subset selection object
# Call: regsubsets.formula(LC50 ~ ., data = qsar, method = "exhaustive")
# 8 Variables (and intercept)
#       Forced in Forced out
# TPSA      FALSE      FALSE
# SAacc     FALSE      FALSE
# H050      FALSE      FALSE
# MLOGP     FALSE      FALSE
# RDCHI     FALSE      FALSE
# GATS1p    FALSE      FALSE
# nN        FALSE      FALSE
# C040      FALSE      FALSE
# 1 subsets of each size up to 8
# Selection Algorithm: exhaustive
#          TPSA SAacc H050 MLOGP RDCHI GATS1p nN  C040
# 1 ( 1 )   "   "   "   "   "*"   "   "   "   "   "   "
# 2 ( 1 )   "*"   "   "   "   "*"   "   "   "   "   "   "
# 3 ( 1 )   "*"   "*"   "   "   "*"   "   "   "   "   "   "
# 4 ( 1 )   "*"   "*"   "   "   "*"   "   "   "   "   "   "
# 5 ( 1 )   "*"   "*"   "   "   "*"   "   "   "*"   "   "
# 6 ( 1 )   "*"   "*"   "   "   "*"   "*"   "   "*"   "   "
# 7 ( 1 )   "*"   "*"   "*"   "*"   "*"   "*"   "*"   "   "
# 8 ( 1 )   "*"   "*"   "*"   "*"   "*"   "*"   "*"   "*"   "
```

This shows the best model of each size. The only step left is to decide which  $q$  to use. This choice depends on the cost-complexity tradeoff. Here we consider  $R_{\text{adj}}^2$  again:

```
round(summary(m)$adjr2, 4)

# [1] 0.2855 0.3860 0.4441 0.4588 0.4666 0.4799 0.4795 0.4785
```

This gives the  $R_{\text{adj}}^2$  for the optimal model of each size again. At the end of the list we recognise the values 0.4799 and 0.4785 from our previous analysis.

*Remark.* Like stepwise methods, exhaustive search is affected by using the same data for both model selection and inference: test statistics and confidence intervals from the selected model are biased and overly optimistic. Validation on independent data is advisable.

This concludes our discussion of model selection techniques. In the next section we turn

to a new topic: how to include categorical variables (called factors) in regression models.

### Summary

- Exhaustive search finds the model with truly maximal  $R_{\text{adj}}^2$ , unlike stepwise heuristics which may miss the optimal combination.
- An efficient algorithm can find the optimal model without fitting all  $2^p$  models, by using algebraic properties of the residual sum of squares.
- The `regsubsets()` function from the `leaps` package implements this algorithm in R.
- For very large  $p$ , even exhaustive search becomes infeasible, and stepwise methods remain the practical choice.

## 14 Factors

In this section we will learn how to fit linear models when some or all of the inputs are categorical. Such inputs are sometimes called “factors”. These can be binary (*e.g.* sex recorded as male/female) or ordered (*e.g.* quality recorded as poor/medium/good) or unordered (*e.g.* marital status recorded as single/married/divorced/widowed).

### 14.1 Indicator Variables

Our aim here is to include categorical input variables within the usual regression model

$$y = X\beta + \varepsilon.$$

Assume that  $x_j \in \{a_1, \dots, a_k\}$  is a factor which has  $k$  possible values. The possible values of the factor,  $a_1, \dots, a_k$  are also called the **levels** of the factor. The easiest way to include a factor in a regression model is via **indicator variables**. For this we represent  $x_j$  using  $k - 1$  columns in the design matrix, say  $\tilde{x}_1, \dots, \tilde{x}_{k-1}$ , where

$$\tilde{x}_{\ell i} = \begin{cases} 1 & \text{if } x_{ji} = a_\ell \text{ and} \\ 0 & \text{otherwise,} \end{cases}$$

for all  $\ell \in \{1, \dots, k-1\}$  and  $i \in \{1, \dots, n\}$ . Using this convention,  $x_{ji} = a_k$  is represented by setting  $\tilde{x}_{1,i} = \dots = \tilde{x}_{k-1,i} = 0$ . The value  $a_k$  which is not represented as a separate column is called the **reference level**. The regression coefficients corresponding to the columns  $\tilde{x}_1, \dots, \tilde{x}_{k-1}$  can be interpreted as the effect of level  $a_\ell$ , relative to the effect of level  $a_k$ . Since the indicator is constant 1 for all samples corresponding to a given factor, regression coefficients representing factors lead to changes of the intercept, rather than of slopes. This interpretation assumes the model includes an intercept term; without an intercept, factor coefficients would represent absolute levels rather than relative shifts.

We are using only  $k - 1$  columns to represent a factor with  $k$  levels. The reason is that using all  $k$  columns would create a logical redundancy: if an observation doesn't belong to any of the first  $k - 1$  levels, we already know it must belong to level  $a_k$ . Mathematically, if we would use  $k$  columns, defined as above, we would get

$$\sum_{\ell=1}^k \tilde{x}_{\ell i} = 1,$$

and in a model with an intercept, this redundancy makes the matrix  $X^\top X$  non-invertible (see section 15 for the general theory).

**Example 14.1.** Consider a dataset consisting of a numerical input variable and a binary factor for gender (`female`, `male`). Assume we are given data (1, male), (2, female), (3, female). Then we can encode this data using the following design matrix:

intercept	$x_1$	$1_{\{\text{female}\}}(x_2)$
1	1	0
1	2	1
1	3	1

In R there is a dedicated type `factor` for categorical variables. If factors appear in the input of linear regression problem, the function `lm()` will automatically create the indicator variables for us.

**Example 14.2.** Here we simulated data which could describe the effect of some medical treatment. In the simulated data we have two groups, one which has been “treated” and a control group. There is a “value” which decreases with age, and is lower for the group which has been treated (the intercept is 10 instead of 12).

```
age1 <- runif(25, 18, 40)
group1 <- data.frame(
  value=10 - 0.2 * age1 + rnorm(25, sd=0.5),
  age=age1,
  treated="yes")
age2 <- runif(25, 18, 80)
group2 <- data.frame(
  value=12 - 0.2 * age2 + rnorm(25, sd=0.5),
  age=age2,
  treated="no")
data <- rbind(group1, group2)

data$treated <- factor(data$treated, levels = c("no", "yes"))
```

The last line of the code tells R explicitly that the `treated` column represents a factor with levels “no” and “yes”. Internally, this column will now be represented by numbers 1 (for “no”) and 2 (for “yes”), but this numeric representation is mostly hidden from the user. Now we fit a regression model:

```
m <- lm(value ~ ., data = data)
summary(m)

#
# Call:
# lm(formula = value ~ ., data = data)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -1.76041 -0.22188  0.04535  0.23802  1.29250
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 11.525306  0.282369  40.82 < 2e-16 ***
# age         -0.189367  0.005557  -34.08 < 2e-16 ***
# treatedyes -1.845246  0.180890  -10.20 1.68e-13 ***
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 0.5452 on 47 degrees of freedom
# Multiple R-squared:  0.9635, Adjusted R-squared:  0.962
# F-statistic: 620.5 on 2 and 47 DF,  p-value: < 2.2e-16
```

We see that R used “no” as the reference level, here. The regression coefficient `treatedyes` gives the relative change of the “yes”, compared to “no”. The true value is the difference of the means:  $10 - 12 = -2$ , and the estimated value  $-1.89$  is reasonably close to this. The fitted values for this model are

$$\hat{y} = \begin{cases} \beta_0 + \beta_1 x_1 & \text{if not treated, and} \\ (\beta_0 + \beta_2) + \beta_1 x_1 & \text{if treated.} \end{cases}$$

To get a better idea of the model fit, we plot the data together with separate regression lines for “yes” (red) and “no” (black):

```

par(mfrow = c(1, 2))
plot(value ~ age, data = data,
     col = ifelse(treated == "yes", "red", "black"))

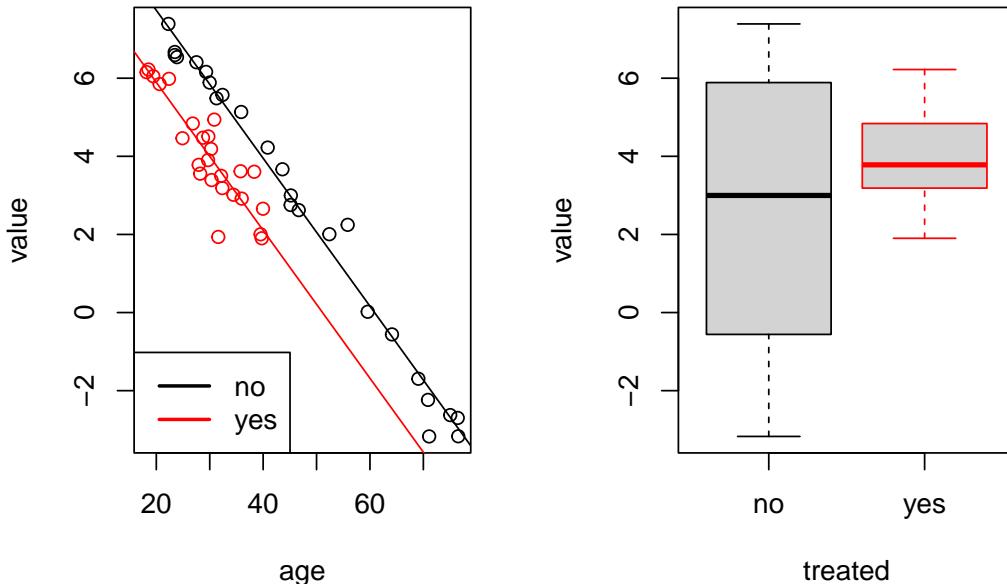
# regression line for the reference level `treatment == "no"`
abline(a = coef(m)[1], b = coef(m)[2])

# regression line for the level `treatment = "yes"`;
# here we need to add the coefficient for `treatedyes`
# to the intercept
abline(a = coef(m)[1] + coef(m)[3], b = coef(m)[2], col="red")

legend("bottomleft", c("no", "yes"),
       col = c("black", "red"), lwd = 2)

# also show a boxplot for comparison
boxplot(value ~ treated, data = data,
        border = c("black", "red"))

```



We can see that the two regression lines, corresponding to the two levels are parallel. They have the same slope but different intercepts.

The last command shows a boxplot of `value` for comparison. The boxplot does not allow to conclude that the treatment had an effect, whereas the linear model, which accounts for age, shows the effect of the treatment as a difference in intercepts. The \*\*\* in the `treatedyes` row of the `summary(m)` output shows that the difference in intercepts is statistically significant.

## 14.2 Interactions

In some situations, the strength of the dependency of the response  $y$  to an input  $x_1$  might depend on another input, say  $x_2$ . The simplest such situation would be, if the coefficient  $\beta_1$ , corresponding to  $x_1$  is itself proportional to  $x_2$ , say  $\beta_1 = \gamma x_2$ . In this case we have  $y = \dots + \beta_1 x_1 = \dots + \gamma x_1 x_2$ . Traditionally, inputs added to a model which are the product of two or more of the original inputs are called **interactions**. As a general rule, an interaction is only included if the “main effects” are also included in the model, so in any variable selection procedure, we would not drop  $x_1$  or  $x_2$  if  $x_1 x_2$  is still in

the model. An exception to this is when one can directly interpret the interaction term without the main effect.

In R, interactions (*i.e.* products of inputs) are represented by the symbol : and \* can be used to include two variables together with their product. Note also, that if a variable is known to be a factor, and it is included as an interaction term, then R will make sure to only remove the interaction term in a backward variable selection procedure whilst the main effects are also included.

**Example 14.3.** Consider the following toy dataset:

```
x1 <- c(2,2,2)
x2 <- 1:3
```

In `lm()` and related functions we can write `x1:x2` as a shorthand for `I(x1*x2)`. The column `x1:x2` in the R output corresponds to the mathematical expression  $x_1x_2$ .

```
model.matrix(~ x1 + x1:x2)

# (Intercept) x1 x1:x2
# 1           1   2     2
# 2           1   2     4
# 3           1   2     6
# attr(,"assign")
# [1] 0 1 2
```

We can write `x1*x2` as a shorthand for the model with the three terms `x1 + x2 + x1:x2`:

```
model.matrix(~ x1*x2)

# (Intercept) x1 x2 x1:x2
# 1           1   2   1     2
# 2           1   2   2     4
# 3           1   2   3     6
# attr(,"assign")
# [1] 0 1 2 3
```

Interactions also work for factors, with products of the corresponding indicator variables added to the model. While factors alone create different intercepts for different groups, factor interactions allow different slopes for different groups.

**Example 14.4.** The classical example of an interaction is to consider how the yield  $y$  of a crop is related to temperature  $x_1$  and rainfall  $x_2$ . All these variables are continuous, but we might categorize rainfall as “wet” and “dry”. Then a simplistic view could be that, for high rainfall, the yield will be positively correlated with temperature, whereas for low rainfall the correlation may be slightly negative, because in hot weather, plants need more water, and if it is very hot and dry, the plants may even die.

We generate a toy dataset in R to represent such a situation:

```
T <- runif(25, 15, 35)
wet <- data.frame(
  yield=40 + 7*T + rnorm(25, sd = 10),
  temperature=T,
  rainfall="high")
T <- runif(25, 15, 35)
dry <- data.frame(
  yield=120 - 2*T + rnorm(25, sd = 10),
  temperature=T,
  rainfall="low")
```

```

crops <- rbind(wet, dry)
crops$rainfall <- factor(crops$rainfall, levels = c("low", "high"))

```

Now we fit a model, including temperature, rainfall and an interaction term:

```

m <- lm(yield ~ temperature*rainfall, data = crops)
summary(m)

#
# Call:
# lm(formula = yield ~ temperature * rainfall, data = crops)
#
# Residuals:
#       Min        1Q    Median        3Q       Max
# -22.8996   -6.3555    0.0346    5.9355   25.0553
#
# Coefficients:
#                               Estimate Std. Error t value Pr(>|t|)
# (Intercept)                 114.2722    9.0929 12.567 < 2e-16 ***
# temperature                  -1.8873    0.3617 -5.219 4.21e-06 ***
# rainfallhigh                -71.5892   13.0342 -5.492 1.66e-06 ***
# temperature:rainfallhigh     8.7043    0.5299 16.428 < 2e-16 ***
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 10.42 on 46 degrees of freedom
# Multiple R-squared:  0.9814, Adjusted R-squared:  0.9802
# F-statistic: 810.2 on 3 and 46 DF,  p-value: < 2.2e-16

```

The fitted values for this model are

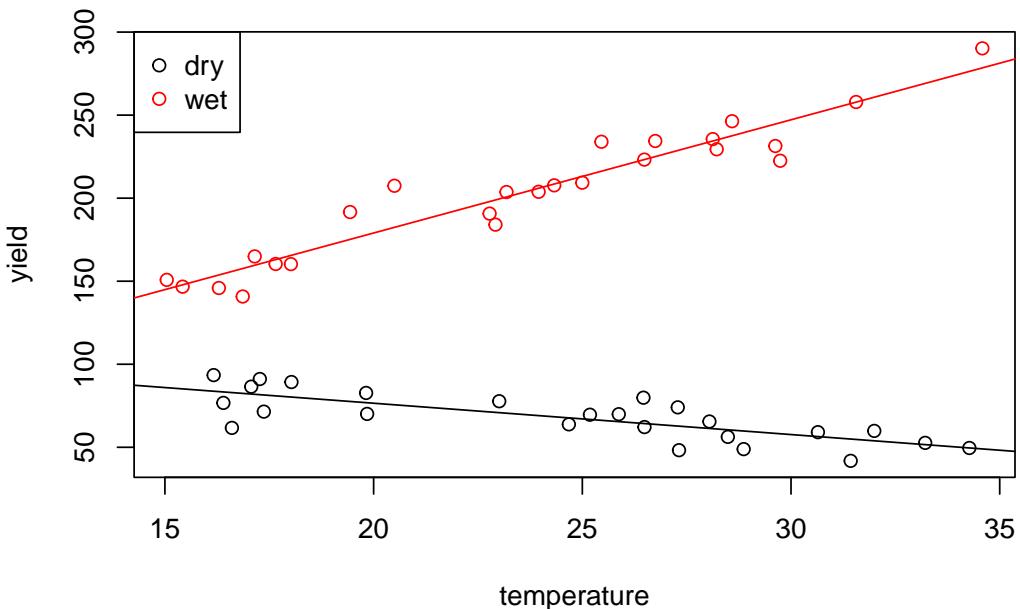
$$\hat{y} = \begin{cases} \beta_0 + \beta_1 x_1 & \text{for low rainfall, and} \\ (\beta_0 + \beta_2) + (\beta_1 + \beta_3)x_1 & \text{for high rainfall.} \end{cases}$$

Finally, we can generate a plot of the data together with the two regression lines.

```

plot(yield ~ temperature, data=crops,
      col = ifelse(rainfall == "low", "black", "red"))
abline(a = coef(m)[1], b = coef(m)[2])
abline(a = coef(m)[1] + coef(m)[3], b = coef(m)[2] + coef(m)[4],
       col="red")
legend("topleft", c("dry", "wet"),
       col = c("black", "red"), pch = 1)

```



As expected, the two lines have different intercepts and different slopes.

### 14.3 Example

**Example 14.5.** Researchers in Food Science studied how big people's mouths tend to be. It transpires that mouth volume is related to more easily measured quantities like height and weight. Here we have data which gives the mouth volume (in cubic centimetres), age, sex (female = 0, male = 1), height (in metres) and weight (in kilos) for 61 volunteers. The first few samples are as shown:

```
# data from https://teaching.seehuhn.de/2022/MATH3714/mouth-volume.txt
dd <- read.table("data/mouth-volume.txt", header = TRUE)
head(dd)

#   Mouth_Volume Age Sex Height  Weight
# 1      56.659  29   1  1.730  70.455
# 2      47.938  24   0  1.632  60.000
# 3      60.995  45   0  1.727 102.273
# 4      68.917  23   0  1.641  78.636
# 5      60.956  27   0  1.600  57.273
# 6      76.204  23   1  1.746  66.818
```

Normally it is important to check that categorical variables are correctly recognised as factors, when importing data into R. As an exception, the fact that `sex` is stored as an integer variable (instead of a factor) here does not matter, since the default factor coding would be identical to the coding in the present data.

Our aim is to fit a model which describes mouth volume in terms of the other variables. We start by fitting a basic model:

```
m1 <- lm(Mouth_Volume ~ ., data = dd)
summary(m1)

#
# Call:
# lm(formula = Mouth_Volume ~ ., data = dd)
#
# Residuals:
#       Min        1Q    Median        3Q       Max
# -10.0000  -1.0000  -0.0000  1.0000  10.0000
```

```

# -33.242 -10.721 -3.223  8.800 43.218
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept)  0.9882   45.2736   0.022  0.9827
# Age         0.3617    0.2607   1.387  0.1709
# Sex         5.5030    5.9385   0.927  0.3581
# Height      15.8980   29.1952   0.545  0.5882
# Weight       0.2640    0.1400   1.885  0.0646 .
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 15.04 on 56 degrees of freedom
# Multiple R-squared:  0.2588, Adjusted R-squared:  0.2059
# F-statistic: 4.888 on 4 and 56 DF, p-value: 0.001882

```

Since no coefficient is significantly different from zero (at 5%-level), and since the  $R^2$  value is not close to ~1, model fit seems poor. To improve model fit, we try to include all pairwise interaction terms:

```

m2 <- lm(Mouth_Volume ~ .^2, data = dd)
summary(m2)

#
# Call:
# lm(formula = Mouth_Volume ~ .^2, data = dd)
#
# Residuals:
#     Min      1Q  Median      3Q     Max
# -35.528 -8.168 -1.995  6.704 44.136
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 2.875e+02 2.337e+02  1.230  0.225
# Age        -8.370e+00 6.352e+00 -1.318  0.194
# Sex        -9.318e+01 1.325e+02 -0.703  0.485
# Height      -1.540e+02 1.505e+02 -1.023  0.311
# Weight       5.889e-01 2.713e+00  0.217  0.829
# Age:Sex     -9.023e-01 1.035e+00 -0.872  0.388
# Age:Height    5.374e+00 4.062e+00  1.323  0.192
# Age:Weight   -1.754e-03 2.027e-02 -0.087  0.931
# Sex:Height    5.989e+01 7.536e+01  0.795  0.431
# Sex:Weight    3.110e-01 4.177e-01  0.744  0.460
# Height:Weight -2.680e-01 1.755e+00 -0.153  0.879
#
# Residual standard error: 15.22 on 50 degrees of freedom
# Multiple R-squared:  0.3219, Adjusted R-squared:  0.1863
# F-statistic: 2.374 on 10 and 50 DF, p-value: 0.0218

```

None of the interaction terms look useful when used in combination. We try to select a subset of variables to get a better fit. We use the `regsubsets()` function from section 13 to find the optimal model:

```

library(leaps)
r3 <- regsubsets(Mouth_Volume ~ .^2, data = dd, nvmax = 10)
s <- summary(r3)
s

```

```

# Subset selection object
# Call: regsubsets.formula(Mouth_Volume ~ .^2, data = dd, nvmax = 10)
# 10 Variables (and intercept)
#          Forced in Forced out
# Age           FALSE      FALSE
# Sex           FALSE      FALSE
# Height        FALSE      FALSE
# Weight         FALSE      FALSE
# Age:Sex       FALSE      FALSE
# Age:Height    FALSE      FALSE
# Age:Weight    FALSE      FALSE
# Sex:Height    FALSE      FALSE
# Sex:Weight    FALSE      FALSE
# Height:Weight FALSE      FALSE
# 1 subsets of each size up to 10
# Selection Algorithm: exhaustive
#          Age Sex Height Weight Age:Sex Age:Height Age:Weight Sex:Height
# 1 ( 1 ) " " " " " " " " " "
# 2 ( 1 ) " " " " " " " " " "
# 3 ( 1 ) " " "*" " " " " " " "
# 4 ( 1 ) " " "*" " " " " " " "
# 5 ( 1 ) "*" " " "*" " " " " " "
# 6 ( 1 ) "*" " " "*" " " " " "
# 7 ( 1 ) "*" "*" "*" " " " " " "
# 8 ( 1 ) "*" "*" "*" " " " " "
# 9 ( 1 ) "*" "*" "*" " " " " "
# 10 ( 1 ) "*" "*" "*" " " " " "
#          Sex:Weight Height:Weight
# 1 ( 1 ) " "      "*"
# 2 ( 1 ) "*"      " "
# 3 ( 1 ) " "      " "
# 4 ( 1 ) "*"      " "
# 5 ( 1 ) "*"      " "
# 6 ( 1 ) "*"      " "
# 7 ( 1 ) "*"      " "
# 8 ( 1 ) "*"      " "
# 9 ( 1 ) "*"      "*"
# 10 ( 1 ) "*"     "*"

```

The table shows the optimal model for every number of variables, for  $p$  ranging from 1 to 10. To choose the number of variables we can use the adjusted  $R^2$ -value:

```
s$which[which.max(s$adjr2),]
```

	(Intercept)	Age	Sex	Height	Weight
#	TRUE	TRUE	FALSE	TRUE	FALSE
#	Age:Sex	Age:Height	Age:Weight	Sex:Height	Sex:Weight
#	TRUE	TRUE	FALSE	FALSE	TRUE
#	Height:Weight				
#	FALSE				

The optimal model consists of the five variables listed. For further examination, we fit the corresponding model using `lm()`:

```
m3 <- lm(Mouth_Volume
           ~ Age + Height + Age:Sex + Age:Height + Sex:Weight,
           data = dd)
```

```

summary(m3)

#
# Call:
# lm(formula = Mouth_Volume ~ Age + Height + Age:Sex + Age:Height +
#      Sex:Weight, data = dd)
#
# Residuals:
#    Min      1Q  Median      3Q     Max
# -36.590 -9.577 -1.545  7.728 42.779
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 265.6236   122.3362   2.171   0.0342 *
# Age         -8.4905    4.0559  -2.093   0.0409 *
# Height      -134.0835   72.8589  -1.840   0.0711 .
# Age:Sex      -0.8633    0.4944  -1.746   0.0864 .
# Age:Height    5.3644    2.4047   2.231   0.0298 *
# Sex:Weight    0.4059    0.1659   2.446   0.0177 *
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 14.65 on 55 degrees of freedom
# Multiple R-squared:  0.3096, Adjusted R-squared:  0.2468
# F-statistic: 4.932 on 5 and 55 DF,  p-value: 0.0008437

```

This looks much better: now most variables are significantly different from zero and the adjusted  $R^2$  value has (slightly) improved. Nevertheless, the structure of the model seems hard to explain and the model seems difficult to interpret. For comparison, we consider the second-best model, with  $p = 2$ :

```

m4 <- lm(Mouth_Volume ~ Age:Weight + Sex:Weight, data = dd)
summary(m4)

#
# Call:
# lm(formula = Mouth_Volume ~ Age:Weight + Sex:Weight, data = dd)
#
# Residuals:
#    Min      1Q  Median      3Q     Max
# -34.161 -10.206 -3.738  9.087 43.747
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept) 43.678187   4.788206   9.122 8.35e-13 ***
# Age:Weight  0.005554   0.002372   2.342   0.0226 *
# Weight:Sex  0.127360   0.048640   2.618   0.0113 *
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 14.72 on 58 degrees of freedom
# Multiple R-squared:  0.2651, Adjusted R-squared:  0.2398
# F-statistic: 10.46 on 2 and 58 DF,  p-value: 0.000132

```

The adjusted  $R^2$ -value of this model is only slightly reduced, and all regression coefficients are significantly different from zero.

$$\text{mouth volume} = 43.68 + \begin{cases} 0.0056 \text{ age} \times \text{weight} & \text{for females} \\ (0.0056 \text{ age} + 0.1274) \text{ weight} & \text{for males.} \end{cases}$$

This model is still not trivial to interpret, but it does show that mouth volume increases with weight and age, and that the dependency on weight is stronger for males.

### Summary

- Indicator variables can be used to represent categorical inputs in linear regression models.
- The levels of a factor correspond to different intercepts for the regression line.
- If interaction terms are used, the levels also affect the slope.

## 15 Multicollinearity

**Definition 15.1.** In linear regression, **Multicollinearity** denotes the situation when the columns of the design matrix  $X$  are (approximately) linearly dependent.

The columns of  $X$  are linearly dependent, if and only if there is a  $v \in \mathbb{R}^{p+1}$  such that  $v \neq 0$  and  $Xv = 0$ . The columns are approximately linearly dependent, if there is a vector  $v \neq 0$  such that  $\|Xv\| \ll \|v\|$ .

### 15.1 Consequences of Multicollinearity

In the derivation of the least squares estimator  $\hat{\beta} = (X^\top X)^{-1} X^\top y$  we had to assume that the matrix  $X^\top X$  is invertible. If the columns of  $X$  are linearly dependent,  $X^\top X$  is no longer invertible and the least squares estimate is no longer uniquely defined.

**Example 15.1.** Recall from section 14 that when encoding a factor with  $k$  levels using indicator variables, we use only  $k - 1$  columns rather than all  $k$  columns. If we were to use  $k$  indicator variables  $\tilde{x}_1, \dots, \tilde{x}_k$  (one for each level), then for any observation exactly one indicator equals 1 and the rest equal 0, so

$$\sum_{\ell=1}^k \tilde{x}_{\ell i} = 1.$$

In a model with intercept, this creates exact multicollinearity: the  $k$  indicator columns sum to the intercept column, making  $X^\top X$  singular. This is why we use only  $k - 1$  columns to encode a factor with  $k$  levels.

**Example 15.2.** As another illustration of exact multicollinearity, consider the following data:

$y$	$x_1$	$x_2$
2	1	1
4	2	2
6	3	3

In this case, an exact match with no residuals can be achieved as  $y = x_1 + x_2$ , *i.e.* for  $\beta_1 = \beta_2 = 1$ . But this solution is not unique: we could just as well write  $y = 2x_1$  or  $y = 2x_2$ . Any choice of  $\beta_1$  and  $\beta_2$  with  $\beta_1 + \beta_2 = 2$  will lead to zero residuals.

The problem in the example above occurs, since the two input columns in the data are identical. The same problem, in a less obvious way, would occur in datasets with more inputs when one column of  $X$  can be written as a linear combination of other columns. This is a problem of the given input data, not of the responses or of the statistical model.

In the case where there is only approximate linear dependency between the columns of  $X$ , the inverse  $(X^\top X)^{-1}$  exists and an estimate  $\hat{\beta}$  can be computed, but there will be huge uncertainties in some of the estimated coefficients. We illustrate this effect using a numerical example.

**Example 15.3.** Here we simulate data which has similar characteristics to the toy example above: we have two very similar inputs, the sum of which nearly equals the output. We fit a model without the intercept, so that there are only two coefficients to estimate and plotting these is no problem.

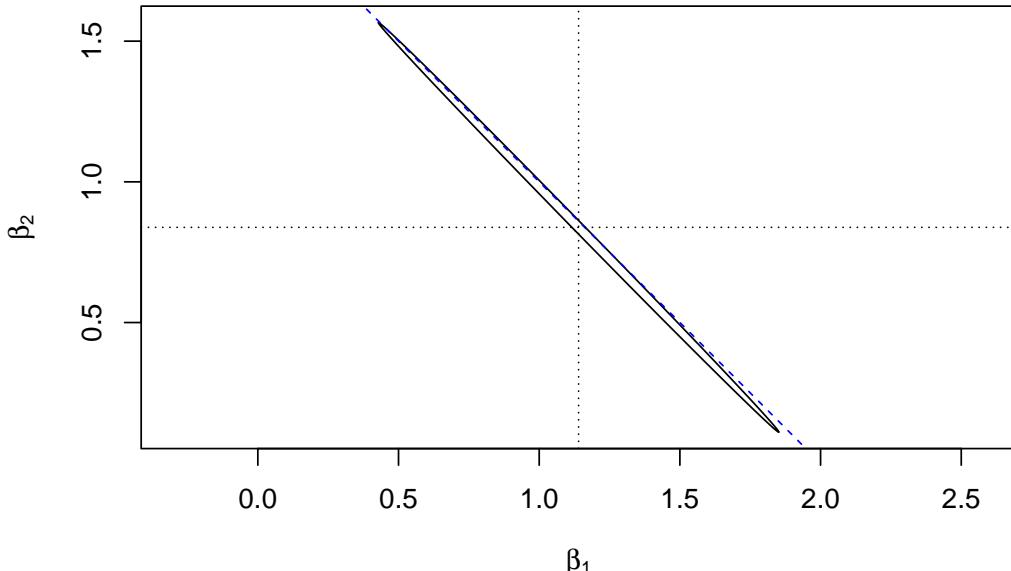
```
set.seed(20211101)
n <- 10
y <- 2 * (1:n)
x1 <- rnorm(n, 1:n, 0.15)
```

```
x2 <- rnorm(n, 1:n, 0.15)
m <- lm(y ~ 0 + x1 + x2)
```

Similar to the approach in section 6, we can plot a confidence ellipse. (Don't worry about the details of the commands used to plot the ellipse.)

```
sigma.hat <- summary(m)$sigma
X <- model.matrix(m)
svd <- La.svd(t(X) %*% X)
alpha <- 0.05
f.crit <- qf(1 - alpha, ncol(X), nrow(X) - ncol(X))
phi <- seq(0, 2*pi, length.out = 201)
circ <- rbind(cos(phi), sin(phi)) * sqrt(f.crit * ncol(X) * sigma.hat^2)
ellipse <- svd$u %*% (circ / sqrt(svd$d)) + coef(m)

plot(ellipse[1,], ellipse[2,], type = "l", asp = 1,
      xlab = expression(beta[1]),
      ylab = expression(beta[2]))
abline(2, -1, lty = "dashed", col = "blue")
abline(v = coef(m)[1], lty = "dotted")
abline(h = coef(m)[2], lty = "dotted")
```



We can see that, as in the toy example above, the confidence region places  $(\beta_1, \beta_2)$  close to the line where  $\beta_1 + \beta_2 = 2$  (the diagonal dashed line), but there is considerable uncertainty about where on this line the coefficients are located. The effect gets more pronounced when the amount of noise in the definition of  $\mathbf{x}_1$  and  $\mathbf{x}_2$  is reduced.

There are two, slightly different effects of multicollinearity:

1. In the case of exact multicollinearity,  $X^\top X$  is not invertible. If the columns of  $X$  are approximately linearly dependent, then  $(X^\top X)^{-1}$  does exist, but small changes of  $X$  lead to large changes of  $(X^\top X)^{-1}$  and numerical computation of the inverse is strongly affected by rounding errors.
2. If the columns of  $X$  are approximately linearly dependent, the computed value of the estimator  $\hat{\beta}$  is strongly affected by small changes to the system: the noise in the model strongly affects  $\hat{\beta}$  (as demonstrated in example 15.3, above), leaving out a single observation may lead to large changes in  $\hat{\beta}$  and computation of  $\hat{\beta}$  is sensitive to rounding errors.

While multicollinearity can make the regression coefficients ambiguous, the outputs  $y$  are not affected. Predictions made using a model where multicollinearity is present are still reliable.

## 15.2 Detecting Multicollinearity

While collinearity of two columns of  $X$  is easy to spot, for example in a pair scatter plot of the inputs, multicollinearity which involves more than two columns can be harder to notice. The condition number of  $X$  is a quantitative measure of how close  $X$  is to multicollinearity.

**Definition 15.2.** The **condition number** of  $X$  is defined to be

$$\kappa(X) = \frac{\sigma_{\max}(X)}{\sigma_{\min}(X)},$$

where  $\sigma_{\max}(X) = \sqrt{\lambda_{\max}(X^T X)}$  is the largest singular value of  $X$ , equal to the square root of the largest eigenvalue of  $X^T X$ , and similarly  $\sigma_{\min}(X) = \sqrt{\lambda_{\min}(X^T X)}$  is the smallest singular value of  $X$ , equal to the square root of the smallest eigenvalue of  $X^T X$ .

As a rule of thumb, if  $\kappa(X) < 10$  there are no significant problems with multicollinearity, and if  $\kappa(X) > 30$  the regression problem suffers severe problems with multicollinearity. In the case where the columns of  $X$  are exactly linearly dependent, we have  $\sigma_{\min}(X) = 0$  and  $\kappa(X) = \infty$ .

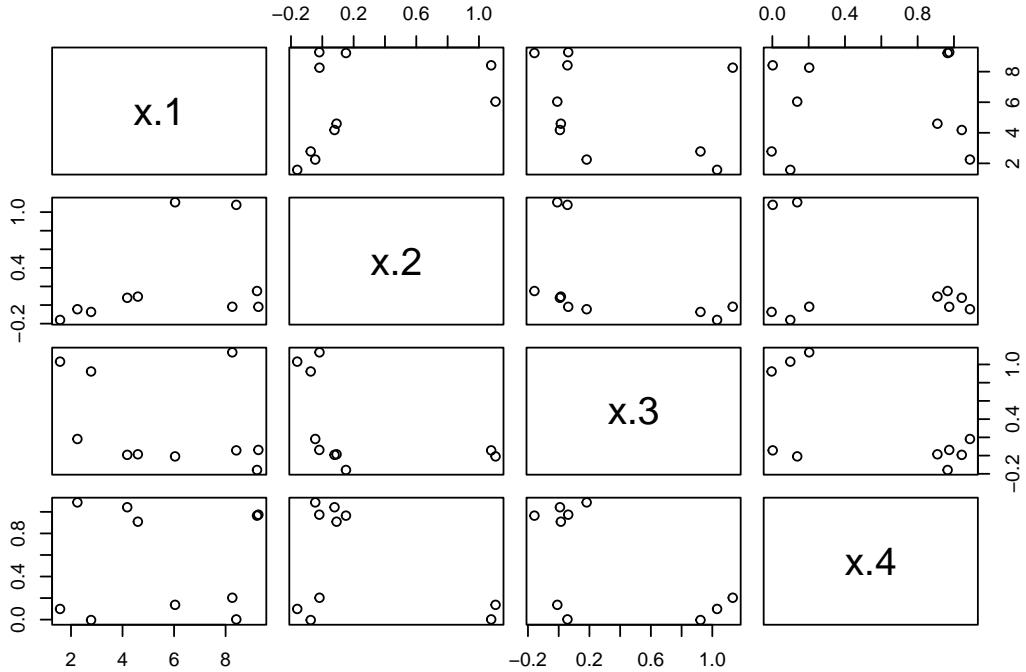
In R, the condition number can be computed using the function `kappa()`. The function can either be called as `kappa(X, exact = TRUE)`, where `X` is the design matrix, or as `kappa(m, exact = TRUE)` where `m` is the object returned by `lm()`. If the optional argument `exact = TRUE` is omitted, only an approximate result is returned (using a faster algorithm).

**Example 15.4.** Consider the following toy dataset:

```
data
#      y    x.1    x.2    x.3    x.4
# 1  7.37 4.182  0.078  0.008  1.043
# 2  9.86 6.039  1.106 -0.009  0.137
# 3 13.44 9.220  0.151 -0.158  0.965
# 4 12.95 8.260 -0.018  1.133  0.203
# 5 13.05 8.415  1.078  0.057  0.002
# 6 13.17 9.272 -0.019  0.062  0.974
# 7  5.28 1.575 -0.160  1.031  0.099
# 8  8.18 4.595  0.091  0.014  0.909
# 9  5.13 2.779 -0.074  0.923 -0.004
# 10 6.80 2.248 -0.045  0.182  1.088
```

To inspect these data, we use a pair scatter plot of the input variables, leaving out the responses in column 1:

```
pairs(data[,-1])
```



While there are visible patterns, there are no clear signs of a linear dependency between any two columns. To see whether there are problems with multicollinearity, we fit a linear model and determine the condition number.

```
m <- lm(y ~ ., data = data)
kappa(m, exact = TRUE)

# [1] 97.38214
```

Since the condition number is larger than 30, we can say that the data shows severe multicollinearity.

(The rest of the example is not examinable.)

To find out which variables are involved, we can use singular value decomposition. This allows us to write  $X$  as  $X = UDV^\top$ , where  $D \in \mathbb{R}^{(p+1) \times (p+1)}$  is a diagonal matrix and  $U \in \mathbb{R}^{n \times (p+1)}$  and  $V \in \mathbb{R}^{(p+1) \times (p+1)}$  are matrices with orthonormal columns.

```
X <- model.matrix(m)
s <- svd(X, nu = 0)
s

# $d
# [1] 20.3002516 2.0294781 1.8122508 1.2526330 0.2084597
#
# $v
# [,1]      [,2]      [,3]      [,4]      [,5]
# [1,] -0.14024576 -0.5552821 -0.04218055 -0.62161197  0.5327403485
# [2,] -0.98554152  0.1088264  0.04131956  0.12311216  0.0009051211
# [3,] -0.04170949  0.4036310  0.21603327 -0.75981456 -0.4597323397
# [4,] -0.03395454 -0.6495911  0.55665792  0.11926737 -0.5027780067
# [5,] -0.07839927 -0.3081105 -0.79998442 -0.08306065 -0.5020431792
```

We used the optional argument `nu = 0` to tell R that we won't need the matrix  $U$ . The diagonal elements  $\sigma_0(X), \dots, \sigma_p(X) \geq 0$ , stored in `s$d`, are the singular values of  $X$  in decreasing order. We can find the condition number using these values:

```
s$d[1] / s$d[length(s$d)]
```

```
# [1] 97.38214
```

This agrees with the value for  $\kappa(X)$  we found above.

Finally, the columns  $v_1, \dots, v_{p+1}$  of  $s\$v$  are called the (right) singular vectors of  $X$ . We can use these vectors to identify which variables are involved in multicollinearity: It is easy to show that  $\|Xv_k\| = \sigma_k(X)$ , so every “small”  $\sigma_k(X)$  corresponds to a vector  $v_k$  which describes an approximate linear dependency between the columns of  $X$ . Looking at  $\sigma_4(X)$  (the 5th element of  $s\$d$ ) we get

```
round(s$v[,5], 3)
```

```
# [1] 0.533 0.001 -0.460 -0.503 -0.502
```

Rounding the numbers some more and remembering that the first value corresponds to the intercept, we get that

$$-0.5 \cdot 1 + 0.5 \cdot x_2 + 0.5 \cdot x_3 + 0.5 \cdot x_4 \approx 0$$

or, equivalently

$$x_2 + x_3 + x_4 \approx 1.$$

Looking back over the original numbers we see that this relation indeed holds.

### 15.3 Mitigations

There are various ways problems resulting from multicollinearity can be addressed:

- Sometimes columns are linearly dependent, because a redundant input is present. Removing one of the input variables in a group of linearly dependent inputs can solve this problem.
- The inputs can be transformed by choosing new variables as functions of the original inputs. For example, in example 15.3 one could try the input variables  $\tilde{x}_1 = (x_1 + x_2)/2$  and  $\tilde{x}_2 = (x_1 - x_2)/2$ . The confidence ellipse shown above indicates that it should be possible to get good estimates for the coefficient corresponding to  $\tilde{x}_1$ .
- If  $n$  is small, the problem may be resolved by getting more data. In particular, for  $n < p + 1$ , we *always* have strict multicollinearity, so in this case we definitely need more data.
- Alternative estimation approaches may be used. The basic idea is to sacrifice the requirement that  $\beta$  is unbiased, in exchange for a large variance reduction. In the next section we will discuss “ridge regression” as an example of this approach.

### Summary

- Multicollinearity occurs when columns of  $X$  are (approximately) linearly dependent, causing large variances and numerical instability in coefficient estimates.
- Predictions remain reliable despite coefficient ambiguity.
- The condition number  $\kappa(X)$  detects multicollinearity:  $\kappa(X) < 10$  indicates no problems,  $\kappa(X) > 30$  indicates severe problems.
- Mitigations include removing redundant variables, transforming inputs, or using alternative estimation methods such as ridge regression.

## Problem Sheet 4

You should attempt all these questions and write up your solutions in advance of the workshop in week 8 where the answers will be discussed.

13. Consider the dataset `pressure`, built into R, which describes the vapour pressure  $P$  of mercury as a function of temperature  $T$ .

- For given  $T_0$ , explain how a model of the form  $P = \beta_0 + T\beta_1 + \max(0, T - T_0)\beta_2 + \varepsilon$  can be fitted to the data.

Solution:

We can fit a model with an intercept and two inputs,  $T$  and  $\max(0, T - T_0)$ . In R we can use the following commands to fit such a model:

```
T0 <- the.given.value # substitute the value of T0 here
m <- lm(pressure ~ temperature + I(pmax(0, temperature-T0)),
         data = pressure)
```

- Why might a model of this form make sense for the given data?

Solution: Such a model may make sense, because the slope of the samples increases faster than linear as the temperature  $T$  increases. The term  $\max(0, T - T_0)$  is zero for small  $T$ , but adds an additional slope once  $T$  exceeds the cutoff temperature  $T_0$ .

- What is a good value of  $T_0$  for this dataset?

Solution:  $T_0$  should be placed at the end of the “flat” part of the plot, where the pressure starts increasing more quickly. A quick experiment shows that the best  $R^2$  value is achieved for  $T_0 \approx 273$ :

```
T0 <- 273
m <- lm(pressure ~ temperature + I(pmax(0, temperature - T0)),
          data=pressure)
summary(m)

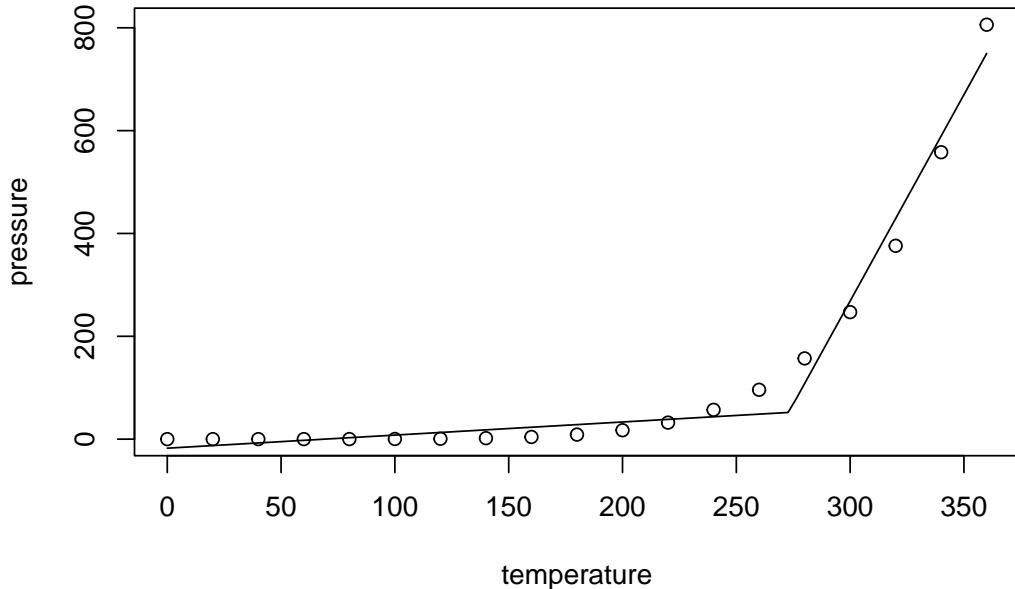
#
# Call:
# lm(formula = pressure ~ temperature + I(pmax(0, temperature -
#     T0)), data = pressure)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -53.125 -17.553  -6.308  13.017  55.839
#
# Coefficients:
#                               Estimate Std. Error t value Pr(>|t|)
# (Intercept)                 -17.62933  14.63735 -1.204  0.2459
# temperature                  0.25472   0.08774   2.903  0.0104 *
# I(pmax(0, temperature - T0))    7.77118   0.38024  20.437 6.85e-13 ***
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 29.86 on 16 degrees of freedom
# Multiple R-squared:  0.9843, Adjusted R-squared:  0.9823
# F-statistic: 501.3 on 2 and 16 DF,  p-value: 3.705e-15
```

To get a better understanding of how the extra term  $\max(0, T - T_0)$  improves model fit, we plot the data together with the fitted model:

```

plot(pressure)
T.plot <- seq(0, 360, l=100)
p.plot <- predict(m, data.frame(temperature=T.plot))
lines(T.plot, p.plot)

```



As expected, for  $T > 273 = T_0$ , the slope of the fitted line increases, leading to greatly improved model fit. (An alternative, and probably superior approach would be to transform the data and try to fit a straight line to the transformed data instead.)

**14.** Where possible, rewrite the following regression models in linear form.

a.  $y = \beta_0 \beta_1^x$

Solution: We can take logarithms:

$$\log(y) = \log(\beta_0) + x \log(\beta_1) =: \beta'_0 + x \beta'_1.$$

Notice that writing  $\log(y) = \beta'_0 + x \beta'_1 + \varepsilon$  implies  $y = \beta_0 \beta_1^x \exp(\varepsilon)$ .

b.  $y = \beta_0 + \beta_1 \sin(x_1) + \beta_2 \exp(x_2)$

Solution: We can simply set  $x'_1 = \sin(x_1)$  and  $x'_2 = \exp(x_2)$ . This transformation does not affect the error term.

c.  $y = \frac{x}{\beta_0 + \beta_1 x}$

Solution: We can write

$$\frac{1}{y} = \frac{\beta_0 + \beta_1 x}{x} = \beta_0 \frac{1}{x} + \beta_1.$$

Thus we can use  $x' = 1/x$ ,  $y' = 1/y$ ,  $\beta'_0 = \beta_1$  and  $\beta'_1 = \beta_0$ . This transformation affects the noise, too, so some care is needed.

**15.** Consider the dataset from

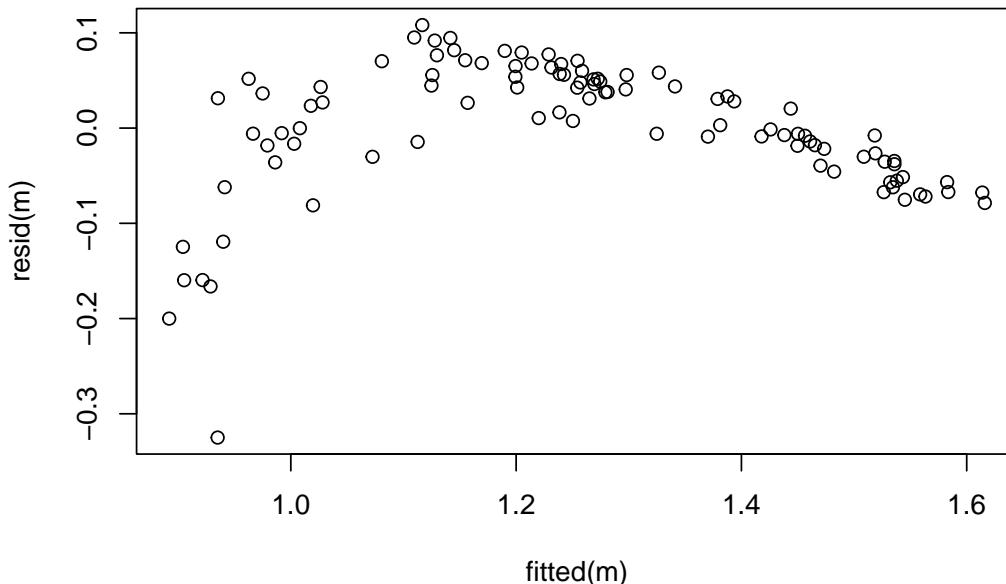
- <https://teaching.seehuhn.de/2022/MATH3714/P04Q14.csv>

The dataset contains samples  $(x_{i,1}, x_{i,2}, y_i)$ . We want to find a model for  $y$  as a function of  $x_1$  and  $x_2$ .

- a. Fit a linear model to the data and produce a residual plot. Based on the plot, discuss how well the model fits the data.

Solution: We can fit the model as follows:

```
# data from https://teaching.seehuhn.de/2022/MATH3714/P04Q14.csv
d <- read.csv("data/P04Q14.csv")
m <- lm(y ~ x1 + x2, data = d)
plot(fitted(m), resid(m))
```



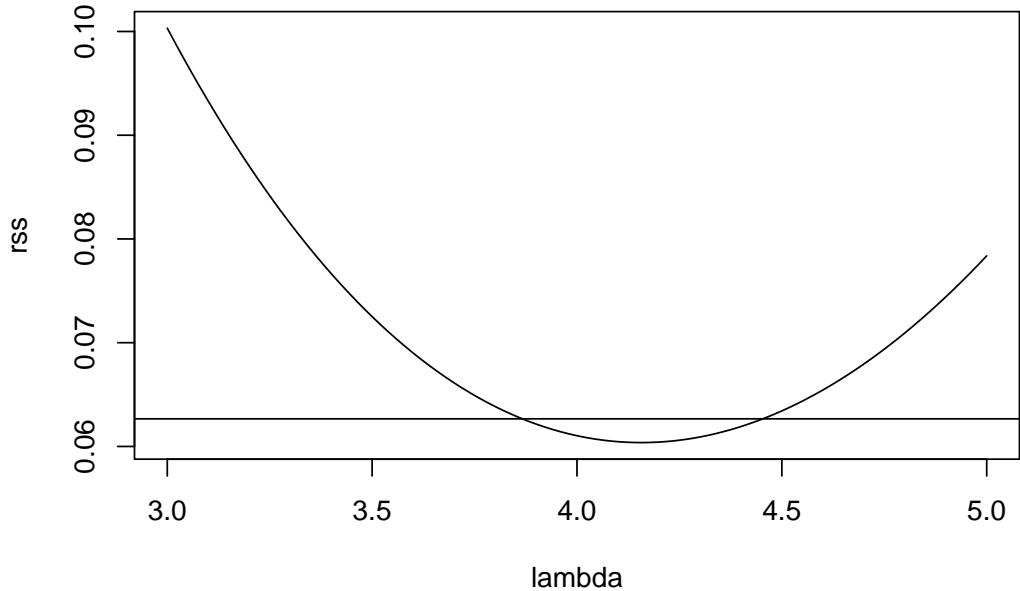
The mean of the residuals does not form a straight line, so the dependency of  $y$  on the  $x_i$  seems to be nonlinear. Also, the variance of the residuals decreases as  $\hat{y}$  increases. Model fit is not good and a transformation of the data may be useful.

- b. Apply a Power Transform to the model, as described in section 11.3 of the notes. Explain your choice of  $\lambda$ .

Solution: To choose the exponent  $\lambda$ , we plot the residual sum of squares as a function of  $\lambda$ .

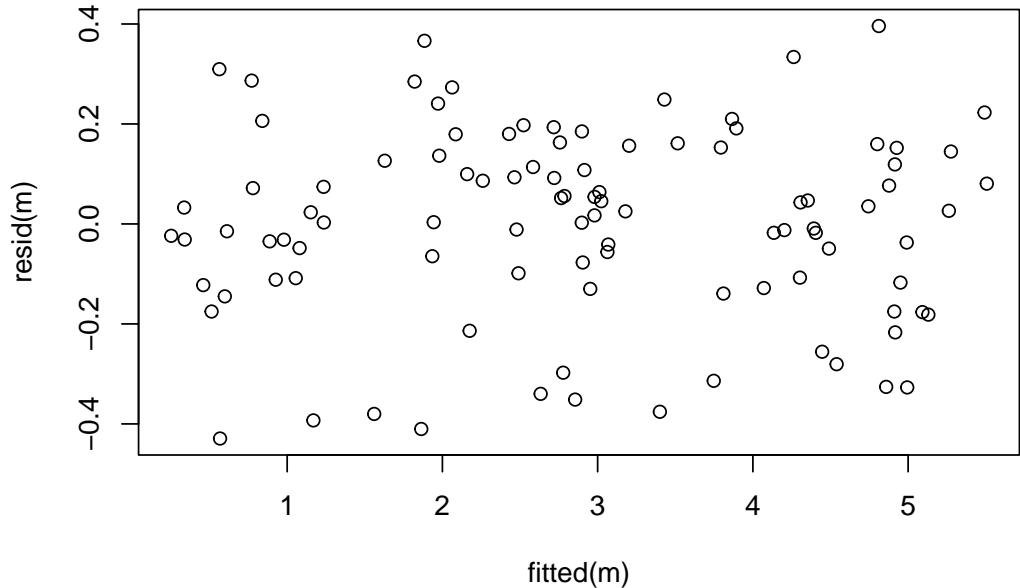
```
gm <- exp(mean(log(d$y)))
lambda <- seq(3, 5, length.out = 101)
rss <- numeric(length(lambda))
for (i in seq_along(lambda)) {
  li <- lambda[i]
  y.prime <- (d$y^li - 1) / (li * gm^(li-1))
  mi <- lm(y.prime ~ x1 + x2, data = d)
  rss[i] <- sum(resid(mi)^2)
}
plot(lambda, rss, type="l")

n <- nrow(d)
p <- 2
cutoff <- min(rss) * (1 + qt(0.971, n-p-1)^2 / (n-p-1))
abline(h = cutoff)
```



The horizontal line in this plot indicates the cutoff suggested by the rule of thumb in (31). Of the values of  $\lambda$  where `rss` is below the cutoff,  $\lambda = 4$  seems the most “simple”, so we try this value here.

```
y.prime <- d$y ^ 4
m <- lm(y.prime ~ x1 + x2, data = d)
plot(fitted(m), resid(m))
```



Now the residual plot looks perfect!

**16.** The Prediction Error Sum of Squares (PRESS) is defined as

$$\text{PRESS} = \sum_{i=1}^n (y_i - \hat{y}_i^{(i)})^2.$$

Using lemma 10.2, or otherwise, determine the PRESS value for the `stackloss` dataset built into R (using `stack.loss` as the response variable).

Solution:

We can use the formula

$$\text{PRESS} = \sum_{i=1}^n \left( \frac{\hat{\varepsilon}_i}{1 - h_{ii}} \right)^2$$

from the lemma. Implementation in R is straightforward.

```
m <- lm(stack.loss ~ ., data = stackloss)
X <- model.matrix(m)
H <- X %*% solve(t(X) %*% X, t(X))
hii <- diag(H)
sum((resid(m)/(1 - hii))^2)

# [1] 291.8689
```

## 16 Ridge Regression

In cases where  $X$  shows approximate multicollinearity, the parameter estimates  $\hat{\beta}$  have coefficients with large variance. In case of exact multicollinearity,  $\hat{\beta}$  is no longer uniquely defined, and the minimum of the residual sum of squares is attained on an unbounded subspace of the parameter space. In both cases, a more stable estimate can be obtained by changing the estimation procedure to include an additional penalty term which discourages “large” values of  $\hat{\beta}$ . This is the idea of ridge regression. In this section we will see that the resulting estimates are biased, but sometimes have smaller mean squared error than the least squares estimator.

### 16.1 Definition of the Estimator

**Definition 16.1.** In multiple linear regression, the **ridge regression** estimate for the parameter vector  $\beta$  is given by

$$\hat{\beta}^{(\lambda)} = \arg \min_{\beta} \left( \sum_{i=1}^n (y_i - (X\beta)_i)^2 + \lambda \|\beta\|^2 \right). \quad (33)$$

The parameter  $\lambda \geq 0$  is called the **regularisation parameter**.

Here we write  $\arg \min_{\beta} (\dots)$  to denote the value of  $\beta$  which minimises the expression on the right-hand side, and  $\|\beta\|$  denotes the Euclidean norm of the vector  $\beta$ , i.e.

$$\|\beta\|^2 = \sum_{j=0}^p \beta_j^2.$$

The term being minimised is

$$r^{(\lambda)}(\beta) = \sum_{i=1}^n (y_i - (X\beta)_i)^2 + \lambda \|\beta\|^2,$$

consisting of the residual sum of squares plus a penalty term. The regularisation parameter  $\lambda$  controls the relative weight of these two terms. For large  $\lambda$ , the main objective is to minimise the norm  $\|\beta\|$  and one can show that  $\lim_{\lambda \rightarrow \infty} \hat{\beta}^{(\lambda)} = 0$ . For  $\lambda \downarrow 0$  only the residual sum of squares is left and if  $X^\top X$  is invertible we get  $\hat{\beta}^{(0)} = \hat{\beta}$ , i.e. here the ridge regression estimate coincides with the least squares estimate.

As in lemma 2.1 we can find an explicit formula for the ridge regression estimate. For this we write  $r^{(\lambda)}$  as

$$r^{(\lambda)}(\beta) = (y - X\beta)^\top (y - X\beta) + \lambda \beta^\top \beta$$

and then take derivatives to find the minimum. The result is given by

$$\hat{\beta}^{(\lambda)} = (X^\top X + \lambda I)^{-1} X^\top y.$$

**Example 16.1.** To illustrate the method, we compute the ridge regression estimate for a badly conditioned toy dataset.

```
# fix the true parameters for our simulated data:
beta <- c(0, .5, .5)
sigma <- 0.01

set.seed(20211112)
x1 <- c(1.01, 2.00, 2.99, 4.02, 5.01, 5.99)
x2 <- c(0.98, 1.99, 3.00, 4.00, 4.99, 6.00)
# beta[1] in R corresponds to \beta_0, beta[2] = \beta_1, beta[3] = \beta_2
```

```

y <- beta[1] + beta[2] * x1 + beta[3] * x2 + rnorm(6, 0, sigma)

lambda <- 0.01
X <- model.matrix(y ~ x1 + x2)
beta.ridge <- solve(t(X) %*% X + lambda * diag(ncol(X)), t(X) %*% y)
beta.ridge[,1] # get first column instead of n x 1 matrix, for tidiness

# (Intercept)          x1          x2
# -0.01620501  0.52739367  0.47343531

```

For comparison, we also compute the least squares estimate:

```

m <- lm(y ~ x1 + x2)
coef(m)

# (Intercept)          x1          x2
# -0.02935851  1.03064453 -0.02749857

```

We see that despite the small value of  $\lambda$  there is a considerable difference between the estimated values  $\hat{\beta}$  and  $\hat{\beta}^{(\lambda)}$  in this example. Experimenting with different values of the seed also shows that the variance of  $\hat{\beta}^{(\lambda)}$  is much smaller than the variance of  $\hat{\beta}$ . Below we will see a theoretical explanation for this fact.

For  $\lambda > 0$  and  $v \neq 0$  we have  $\|v\| > 0$  and thus

$$\begin{aligned}
\|(X^\top X + \lambda I)v\|^2 &= v^\top (X^\top X + \lambda I)^\top (X^\top X + \lambda I)v \\
&= v^\top X^\top X X^\top X v + 2\lambda v^\top X^\top X v + \lambda^2 v^\top v \\
&= \|X X^\top X v\|^2 + 2\lambda \|X v\|^2 + \lambda^2 \|v\|^2 \\
&\geq \lambda^2 \|v\|^2 \\
&> 0.
\end{aligned}$$

This shows, by theorem A.1, that the matrix  $X^\top X + \lambda I$  is invertible for every  $\lambda > 0$ . Thus the ridge regression estimate for  $\lambda > 0$  is always uniquely defined, even in cases where the least squares estimate is *not* uniquely defined.

There are variants of the method where the penalty term  $\|\beta\|^2$  is replaced with a different penalty term. One example of this is Lasso (least absolute shrinkage and selection operator) regression, which uses  $\|\beta\|_1 = \sum_{j=0}^p |\beta_j|$  as the penalty term.

Outside statistics, ridge regression is known as **Tikhonov regularisation**.

## 16.2 Properties of the Estimate

Using the statistical model

$$Y = X\beta + \varepsilon$$

as before, we have

$$\begin{aligned}
\hat{\beta}^{(\lambda)} &= (X^\top X + \lambda I)^{-1} X^\top Y \\
&= (X^\top X + \lambda I)^{-1} X^\top (X\beta + \varepsilon) \\
&= (X^\top X + \lambda I)^{-1} (X^\top X + \lambda I)\beta \\
&\quad - (X^\top X + \lambda I)^{-1} \lambda I\beta \\
&\quad + (X^\top X + \lambda I)^{-1} X^\top \varepsilon
\end{aligned}$$

and simplifying the first term on the right-hand side we get

$$\hat{\beta}^{(\lambda)} = \beta - \lambda (X^\top X + \lambda I)^{-1} \beta + (X^\top X + \lambda I)^{-1} X^\top \varepsilon. \quad (34)$$

### 16.2.1 Bias

Using the formula for  $\hat{\beta}^{(\lambda)}$  we get

$$\mathbb{E}(\hat{\beta}^{(\lambda)}) = \beta - \lambda(X^\top X + \lambda I)^{-1}\beta + 0$$

and thus

$$\text{bias}(\hat{\beta}^{(\lambda)}) = -\lambda(X^\top X + \lambda I)^{-1}\beta.$$

Since this term in general is non-zero, we see that  $\hat{\beta}^{(\lambda)}$  is a biased estimate. The amount of bias depends on the unknown, true coefficient vector  $\beta$ .

### 16.2.2 Variance

The covariance matrix of the vector  $\hat{\beta}^{(\lambda)}$  is given by

$$\begin{aligned} \text{Cov}(\hat{\beta}^{(\lambda)}) &= \text{Cov}\left(\beta - \lambda(X^\top X + \lambda I)^{-1}\beta + (X^\top X + \lambda I)^{-1}X^\top \varepsilon\right) \\ &= \text{Cov}\left((X^\top X + \lambda I)^{-1}X^\top \varepsilon\right) \\ &= (X^\top X + \lambda I)^{-1}X^\top \text{Cov}(\varepsilon)X(X^\top X + \lambda I)^{-1} \\ &= \sigma^2(X^\top X + \lambda I)^{-1}X^\top X(X^\top X + \lambda I)^{-1} \\ &= \sigma^2(X^\top X + \lambda I)^{-1} - \lambda\sigma^2(X^\top X + \lambda I)^{-2}. \end{aligned}$$

While this is an explicit formula, the resulting covariance matrix depends on the unknown error variance  $\sigma^2$ .

If  $X^\top X$  is invertible, this covariance will converge to the covariance of the least squares estimator as  $\lambda \downarrow 0$ . From this we can find the variance of individual components as  $\text{Var}(\hat{\beta}_j^{(\lambda)}) = \text{Cov}(\hat{\beta}^{(\lambda)})_{jj}$ .

### 16.2.3 Mean Squared Error

The Mean Squared Error (MSE) of an estimator  $\hat{\beta}_j$  for  $\beta_j$  is given by

$$\text{MSE}(\hat{\beta}_j) = \mathbb{E}\left(\left(\hat{\beta}_j - \beta_j\right)^2\right).$$

It is an easy exercise to show that this can equivalently be written as

$$\text{MSE}(\hat{\beta}_j) = \text{Var}(\hat{\beta}_j) + \text{bias}(\hat{\beta}_j)^2.$$

Using the formulas for the variance and bias from above, we can find a formula for  $\text{MSE}(\hat{\beta}_j^{(\lambda)})$ , but the result is hard to interpret. Instead of considering these analytical expressions, we illustrate the MSE using a numerical example.

**Example 16.2.** Continuing from example 16.1 above, we can determine the MSE for every value of  $\lambda$ . Here we use the fact that this is simulated data where we know the true values of  $\beta$  and  $\sigma^2$ .

We start with the bias:

```
lambda <- 0.1
Q <- t(X) %*% X + lambda * diag(ncol(X))
y <- X %*% beta
lambda * solve(Q, t(X) %*% y)

# [1]
# (Intercept) 0.0009178679
# x1          0.0497789499
# x2          0.0499545553
```

For the covariance matrix we get the following:

```
C1 <- solve(Q) # Compute the inverse Q^{-1} ...
C2 <- C1 %*% C1 # ... and also Q^{-2}, to get
sigma^2 * (C1 - lambda*C2) # the covariance matrix.
```

```
#             (Intercept)          x1          x2
# (Intercept) 7.291379e-05 -7.580602e-06 -9.226941e-06
# x1         -7.580602e-06  3.831264e-06 -1.540098e-06
# x2         -9.226941e-06 -1.540098e-06  4.221464e-06
```

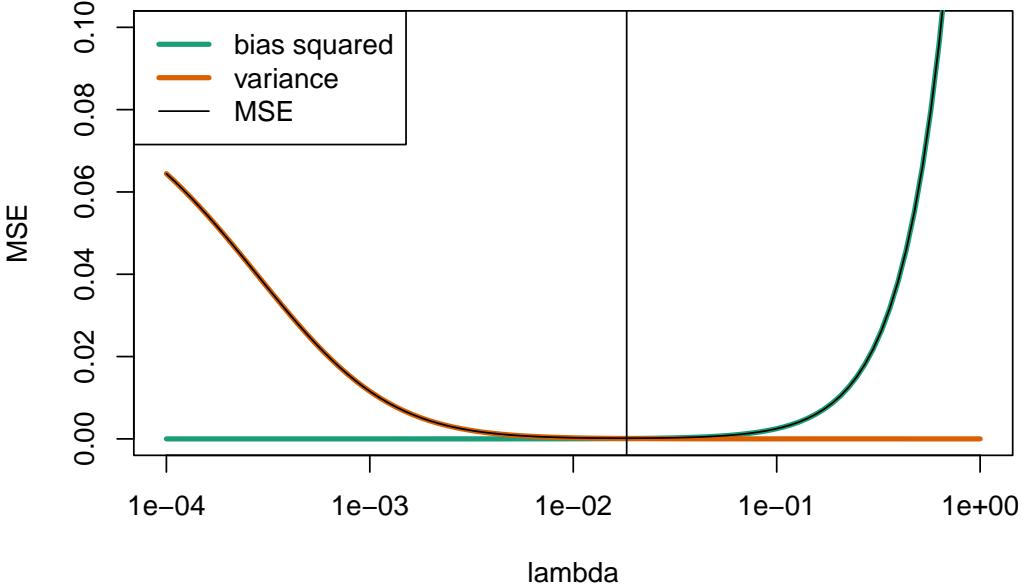
Now we repeat these calculations in a loop, to plot the MSE as a function of  $\lambda$ :

```
lambda <- 10^seq(-4, 0, length.out = 100) # range of lambda to try
j.plus.1 <- 1 + 1 # we plot the error of \beta_1

variance <- numeric(length(lambda))
bias <- numeric(length(lambda))
for (i in seq_along(lambda)) {
  lambda.i <- lambda[i]
  Q <- t(X) %*% X + lambda.i * diag(ncol(X))
  C1 <- solve(Q)
  bias[i] <- (lambda.i * solve(Q, t(X) %*% X %*% beta))[j.plus.1]
  C2 <- C1 %*% C1
  C <- C1 - lambda.i*C2
  variance[i] <- sigma^2 * C[j.plus.1, j.plus.1]
}
MSE <- variance + bias^2

plot(lambda, MSE, type = "l", log = "x", ylim = c(0, 0.1))
lines(lambda, bias^2, col="#1b9e77", lwd = 3)
lines(lambda, variance, col="#d95f02", lwd = 3)
lines(lambda, MSE) # make sure MSE is not obscured by bias/variance
abline(v = lambda[which.min(MSE)]) # mark the minimum

legend("topleft",
       c("bias squared", "variance", "MSE"),
       col = c("#1b9e77", "#d95f02", "black"),
       lwd = c(3, 3, 1))
```



The vertical line at  $\lambda = 0.0183$  marks the optimal value of  $\lambda$ . We can see that for small  $\lambda$  the MSE is dominated by the variance, whereas for large  $\lambda$  the main contribution is from the bias.

### 16.3 Standardisation

Ridge regression can be applied directly to the original data, but there are two reasons why this is often undesirable. First, the penalty term  $\|\beta\|^2$  treats all coefficients equally, which only makes sense if they have similar magnitudes. Second, the results would depend on the arbitrary choice of units for each predictor. Both issues are resolved by standardising the predictors before fitting the model: this ensures the penalty applies equally to all coefficients and makes the method independent of measurement units. The results can then be transformed back to obtain  $\hat{y}$  on the original scale.

We standardise every column of the input separately: For the input variable  $x_j$ , where  $j \in \{1, \dots, p\}$ , we get

$$w_{ij} := \frac{x_{ij} - \bar{x}_j}{s_{x_j}},$$

for all  $i \in \{1, \dots, n\}$ , where  $\bar{x}_j = \frac{1}{n} \sum_{i=1}^n x_{ij}$  and

$$s_{x_j}^2 = \frac{1}{n-1} \sum_{i=1}^n (x_{ij} - \bar{x}_j)^2$$

is the sample variance. We similarly standardise the outputs:

$$z_i := \frac{y_i - \bar{y}}{s_y},$$

where  $\bar{y}$  and  $s_y$  are the mean and standard deviation of the  $y_i$ . If we denote the regression coefficients for the transformed data by  $\gamma$ , then the residual sum of squares for the transformed data is

$$r_{\text{tfm}}(\gamma) = \sum_{i=1}^n (z_i - \gamma_0 - \gamma_1 w_{i1} - \dots - \gamma_p w_{ip})^2.$$

The transformed inputs satisfy

$$\sum_{i=1}^n w_{ij} = 0$$

for all  $j \in \{1, \dots, p\}$  and a similar relation holds for the output. Using these relations we find

$$\begin{aligned}
r_{\text{tfm}}(\gamma) &= \sum_{i=1}^n \left( (z_i - \gamma_1 w_{i1} - \dots - \gamma_p w_{ip})^2 \right. \\
&\quad \left. - 2\gamma_0(z_i - \gamma_1 w_{i1} - \dots - \gamma_p w_{ip}) + \gamma_0^2 \right) \\
&= \sum_{i=1}^n (z_i - \gamma_1 w_{i1} - \dots - \gamma_p w_{ip})^2 \\
&\quad - 2\gamma_0 \sum_{i=1}^n (z_i - \gamma_1 w_{i1} - \dots - \gamma_p w_{ip}) + n\gamma_0^2 \\
&= \sum_{i=1}^n (z_i - \gamma_1 w_{i1} - \dots - \gamma_p w_{ip})^2 \\
&\quad - 2\gamma_0 \left( \sum_{i=1}^n z_i - \gamma_1 \sum_{i=1}^n w_{i1} - \dots - \gamma_p \sum_{i=1}^n w_{ip} \right) + n\gamma_0^2 \\
&= \sum_{i=1}^n (z_i - \gamma_1 w_{i1} - \dots - \gamma_p w_{ip})^2 + n\gamma_0^2.
\end{aligned}$$

Thus, the coefficient for the intercept can be minimised separately and the optimal value is always  $\gamma_0 = 0$ . For this reason we do not include the intercept in our model for the standardised data. The design matrix is thus

$$W = \begin{pmatrix} w_{1,1} & \dots & w_{1,p} \\ w_{2,1} & \dots & w_{2,p} \\ \vdots & \ddots & \vdots \\ w_{n,1} & \dots & w_{n,p} \end{pmatrix} \in \mathbb{R}^{n \times p},$$

and the reduced coefficient vector is  $\gamma \in \mathbb{R}^p$ . The least squares estimator for the transformed data is then given by

$$\hat{\gamma} = (W^\top W)^{-1} W^\top z$$

and the ridge regression estimate is given by

$$\tilde{\gamma}^{(\lambda)} = (W^\top W + \lambda I)^{-1} W^\top z.$$

To transform back regression estimates obtained for the transformed data, we need to revert the standardisation: we have

$$x_{ij} = s_{x_j} w_{ij} + \bar{x}_j$$

and

$$y_i = s_y z_i + \bar{y}.$$

To obtain fitted values for an input  $(\tilde{x}_1, \dots, \tilde{x}_p)$  we have to first transform these inputs:  $\tilde{w}_j = (\tilde{x}_j - \bar{x}_j)/s_{x_j}$ . Note that the mean and standard deviation come from the data used to fit the model, and are not computed from the  $\tilde{x}_i$ . We then find the model mean for the transformed data:

$$\begin{aligned}
\hat{z} &= \sum_{j=1}^p \hat{\gamma}_j \tilde{w}_j \\
&= \sum_{j=1}^p \hat{\gamma}_j \frac{\tilde{x}_j - \bar{x}_j}{s_{x_j}} \\
&= - \sum_{k=1}^p \frac{1}{s_{x_k}} \hat{\gamma}_k \bar{x}_k + \sum_{j=1}^p \frac{1}{s_{x_j}} \hat{\gamma}_j \tilde{x}_j.
\end{aligned}$$

Finally, transforming back the response we get

$$\begin{aligned}\hat{y} &= (\bar{y} - \sum_{k=1}^p \frac{s_y}{s_{x_k}} \hat{\gamma}_k \bar{x}_k) + \sum_{j=1}^p \frac{s_y}{s_{x_j}} \hat{\gamma}_j \tilde{x}_j \\ &= \hat{\beta}_0 + \sum_{j=1}^p \hat{\beta}_j \tilde{x}_j,\end{aligned}$$

where

$$\hat{\beta}_j = \frac{s_y}{s_{x_j}} \hat{\gamma}_j$$

for all  $j \in \{1, \dots, p\}$  and

$$\hat{\beta}_0 = \bar{y} - \sum_{k=1}^p \frac{s_y}{s_{x_k}} \hat{\gamma}_k \bar{x}_k = \bar{y} - \sum_{k=1}^p \hat{\beta}_k \bar{x}_k.$$

This transformation can be used both for least squares regression and ridge regression estimates.

This section concludes our discussion about using linear regression in practice. In the remaining part of these notes we will discuss how to perform linear regression in the presence of outliers.

### Summary

- Ridge regression is an alternative estimator for the regression coefficients.
- The method is useful when multicollinearity is present.
- Ridge regression is biased, but can achieve lower mean squared error than least squares by reducing variance.
- It is advantageous to standardise the data before performing ridge regression.

**Part III**

**Robust Regression**

## 17 Robust Regression

The overall aim of this part of the module is to find regression estimators which work well in the presence of outliers.

### 17.1 Outliers

As before, we consider the model

$$y_i = x_i^\top \beta + \varepsilon_i,$$

and we try to estimate  $\beta$  from given data  $(x_i, y_i)$  for  $i \in \{1, \dots, n\}$ .

An **outlier** is a sample  $(x_i, y_i)$  that differs significantly from the majority of observations. The deviation can be either in the  $x$ -direction, or the  $y$ -direction, or both. Outliers can either occur by chance, or can be caused by errors in the recording or processing of the data. In this subsection we will discuss different ways to detect outliers.

#### 17.1.1 Leverage

**Definition 17.1.** The **leverage** of the input  $x_i$  is given by

$$h_{ii} = x_i^\top (X^\top X)^{-1} x_i,$$

where  $X$  is the design matrix.

Since  $x_i$  is the  $i$ th row of  $X$ , the leverage  $h_{ii}$  equals the  $i$ th diagonal element of the hat matrix  $H = X(X^\top X)^{-1} X^\top$ .

**Lemma 17.1.** *The derivative of the fitted value  $\hat{y}_i$  with respect to the response  $y_i$  is given by*

$$\frac{\partial}{\partial y_i} \hat{y}_i = h_{ii}$$

for all  $i \in \{1, \dots, n\}$ .

*Proof.* We have

$$\hat{y}_i = (Hy)_i = \sum_{j=1}^n h_{ij} y_j.$$

Taking derivatives with respect to  $y_i$  completes the proof.  $\square$

The leverage of  $x_i$  describes the *potential* for  $y_i$  to affect the fitted line or hyperplane. If  $h_{ii}$  is large, changing of  $y_i$  has a large effect on the fitted values. This is in contrast to the influence of a sample, which describes *actual* effect on the regression line: in the section about Cook's Distance, we considered a sample to be "influential", if the regression estimates with and without the sample in question were very different.

Since we have  $\sum_{i=1}^n h_{ii} = \text{tr}(H) = p + 1$  (see equation (20)), the average value of the leverage over all samples is  $(p + 1)/n$ . Using a more careful argument, one can show that  $h_i \in [1/n, 1]$  for every  $i \in \{1, \dots, n\}$ .

**Example 17.1.** We use simulated data to illustrate the effect of outliers and the difference between leverage and influence.

```
set.seed(20211130)

n <- 12
x <- seq(0, 5, length.out = n+1)[-((n/2)+1)]
y <- 1 + 0.4 * x + rnorm(n, sd = 0.3)
m <- lm(y ~ x)
```

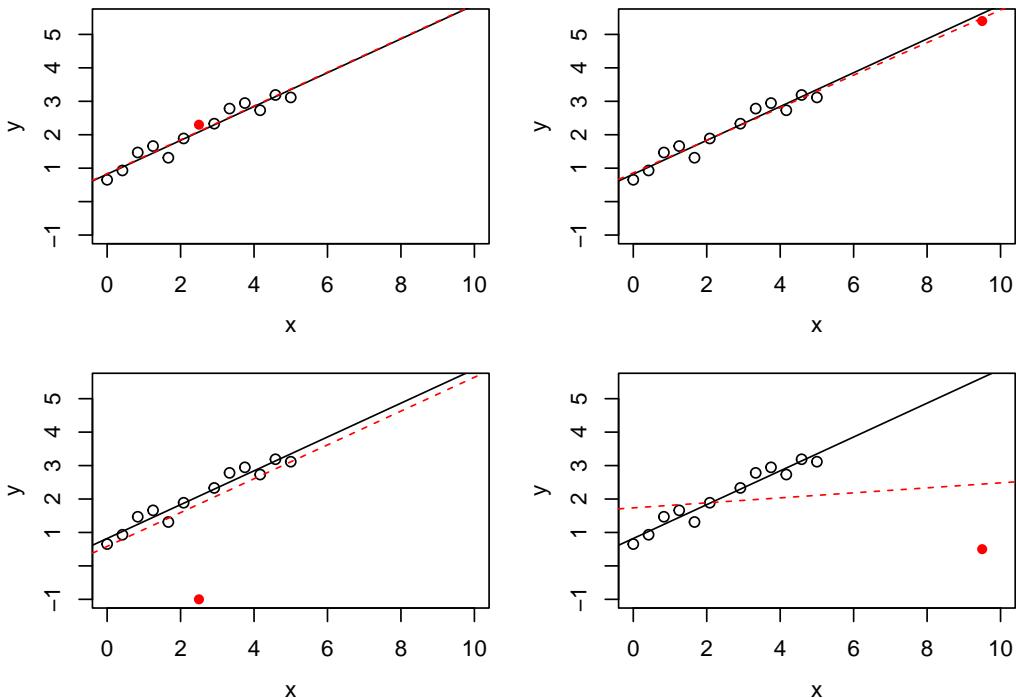
```

# we try four different extra samples, one after another:
x.extra <- c(2.5, 9.5, 2.5, 9.5)
y.extra <- c(2.3, 5.4, -1, 0.5)

par(mfrow = c(2, 2), # We want a 2x2 grid of plots,
    mai = c(0.7, 0.7, 0.1, 0.1), # using smaller margins, and
    mgp = c(2.5, 1, 0)) # we move the labels closer to the axes.
for (i in 1:4) {
  plot(x, y, xlim = c(0, 10), ylim = c(-1, 5.5))
  abline(m)

  m2 <- lm(c(y, y.extra[i]) ~ c(x, x.extra[i]))
  abline(m2, col="red", lty="dashed")
  points(x.extra[i], y.extra[i], col = "red", pch = 16)
}

```



The black circles in all four panels are the same, and the black, solid line is the regression line fitted to these points. The filled, red circle is different between the panels and the red, dashed line is the regression line fitted after this point has been added to the data. In the top-left panel there is no outlier. In the top-right panel, the red circle is an  $x$ -space outlier. The point has high leverage (since the red lines in the top-right and bottom-right panels are very different from each other), but low influence (since the red line is close to the black line). The bottom-left panel shows a  $y$ -space outlier. The red circle has low leverage (since the red line is similar to the top-left panel) and low influence (since the red line is close to the black line), but a large residual. Finally, the bottom-right panel shows an  $x$ -space outlier with high leverage and high influence.

### 17.1.2 Studentised Residuals

Sometimes,  $y$ -space outliers can be detected by having particularly large residuals. From equation (18) we know that

$$\hat{\varepsilon} \sim \mathcal{N}(0, \sigma^2(I - H)).$$

Considering the diagonal elements of the covariance matrix, we find  $\text{Var}(\hat{\varepsilon}_i) = \sigma^2(1-h_{ii})$ , where  $h_{ii}$  is the  $i$ th diagonal element of the hat matrix  $H$ . This motivates the following definition.

**Definition 17.2.** The **studentised residuals** are given by

$$r_i := \frac{\hat{\varepsilon}_i}{\sqrt{\hat{\sigma}^2(1-h_{ii})}}.$$

**Lemma 17.2.** We have  $r_i \sim t(n-p-1)$ .

*Proof.* We have

$$\begin{aligned} r_i &= \frac{\hat{\varepsilon}_i}{\sqrt{\hat{\sigma}^2(1-h_{ii})}} \\ &= \frac{\hat{\varepsilon}_i / \sqrt{\sigma^2(1-h_{ii})}}{\sqrt{\frac{(n-p-1)\hat{\sigma}^2}{\sigma^2}} / (n-p-1)}. \end{aligned}$$

The numerator is standard normally distributed. From equation (22) we know that  $(n-p-1)\hat{\sigma}^2/\sigma^2 \sim \chi^2(n-p-1)$ . Thus we find  $r_i \sim t(n-p-1)$ , by the definition of the  $t$ -distribution.  $\square$

Samples where the studentised residuals are large, compared to quantiles of the  $t(n-p-1)$ -distribution, might be  $y$ -space outliers.

With the help of lemma 8.4 we can express Cook's distance as a function of studentised residuals and leverage. We get

$$\begin{aligned} D_i &= \frac{\hat{\varepsilon}_i^2}{(p+1)\hat{\sigma}^2} \cdot \frac{h_{ii}}{(1-h_{ii})^2} \\ &= r_i^2 \frac{h_{ii}}{(p+1)(1-h_{ii})}. \end{aligned}$$

If we denote samples with  $D_i \geq 1$  as influential, we can express the condition for influential samples as

$$r_i^2 \geq (p+1) \frac{1-h_{ii}}{h_{ii}}.$$

**Example 17.2.** Continuing from the previous example, we can plot studentised residuals against leverage. As in section 8.1, we can use the function `influence()` to easily obtain the diagonal elements of the hat matrix.

```
par(mfrow = c(2, 2), # We want a 2x2 grid of plots,
    mai = c(0.7, 0.7, 0.1, 0.1), # using smaller margins, and
    mgp = c(2.5, 1, 0)) # we move the labels closer to the axes.
for (i in 1:4) {
  xx <- c(x, x.extra[i])
  yy <- c(y, y.extra[i])
  n <- length(xx)
  p <- 1

  m <- lm(yy ~ xx)

  # get the leverage
  hii <- influence(m)$hat

  # get the studentised residuals
```

```

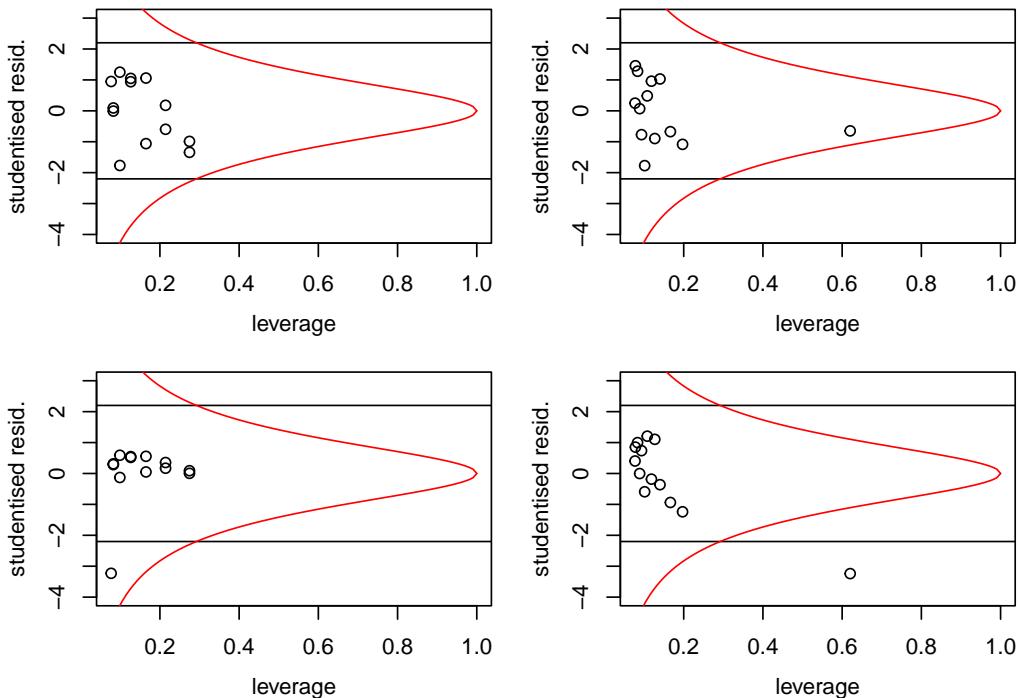
sigma.hat <- summary(m)$sigma
ri <- resid(m) / sigma.hat / sqrt(1 - hii)

plot(hii, ri, xlim=c(1/n, 1), ylim=c(-4,3),
      xlab = "leverage", ylab = "studentised resid.")

# plot a 95% interval for the residuals
abline(h = +qt(0.975, n - p -1))
abline(h = -qt(0.975, n - p -1))

# also plot the line where D_i = 1
h <- seq(1/n, 1, length.out = 100)
r.infl <- sqrt((p+1) * (1-h) / h)
lines(h, r.infl, col="red")
lines(h, -r.infl, col="red")
}

```



If the model is correct, 95% of the samples should lie in the band formed by the two horizontal lines. In the bottom-left panel we can recognise a  $y$ -space outlier by the fact that it is outside the band. In the two right-hand panels we can recognise the  $x$ -space outlier by the fact that it has much larger leverage than the other samples. Finally, samples which are to the right of the curved, red line correspond the “influential” observations.

## 17.2 Breakdown Points

In the example we have seen that changing a single observation can have a large effect on the regression line found by least squares regression. Using the formula

$$\hat{\beta} = (X^\top X)^{-1} X^\top y,$$

it is easy to see that it is enough to change a single sample, letting  $y_i \rightarrow \infty$ , to get  $\|\hat{\beta}\| \rightarrow \infty$ .

**Definition 17.3.** The **finite sample breakdown point** of an estimator  $\hat{\theta}$  is the smallest fraction of samples such that  $\|\hat{\theta}\| \rightarrow \infty$  can be achieved by only changing this fraction of samples. Mathematically, this can be expressed as follows: Let  $z = ((x_1, y_1), \dots, (x_n, y_n))$  and consider all  $z'$  such that the set  $\{i \mid z_i \neq z'_i\}$  has at most  $m$  elements. Then the finite sample breakdown point is given by

$$\varepsilon_n(\hat{\theta}) := \frac{1}{n} \min \{m \mid \sup_{z'} \|\hat{\theta}(z')\| = \infty\}.$$

The (asymptotic) **breakdown point** of  $\hat{\theta}$  is given by

$$\varepsilon(\hat{\theta}) := \lim_{n \rightarrow \infty} \varepsilon_n(\hat{\theta}).$$

Clearly we have  $\varepsilon_n(\hat{\theta}) \in [0, 1]$  for all  $n$  and thus  $\varepsilon(\hat{\theta}) \in [0, 1]$ . Robust estimators have  $\varepsilon(\hat{\theta}) > 0$ . Using the argument above, we see that  $\varepsilon_n(\hat{\beta}) = 1/n \rightarrow 0$  as  $n \rightarrow \infty$ . Thus, the least squares estimate is not robust.

**Example 17.3.** For illustration we show a very simple version of a robust estimator for the regression line in simple linear regression. The estimate is called a **resistant line** or **Tukey line**. Assume we are given data  $(x_i, y_i)$  for  $i \in \{1, \dots, n\}$ . We start by sorting the  $x_i$  in increasing order:  $x_{(1)} \leq \dots \leq x_{(n)}$ . Then we define  $x_L$ ,  $x_M$  and  $x_R$  as the median of the lower, middle and upper third of the  $x_{(i)}$ , and  $y_L$ ,  $y_M$  and  $y_R$  as the median of the corresponding  $y$  values, respectively. Finally, set

$$\hat{\beta}_1 = \frac{y_R - y_L}{x_R - x_L}$$

as an estimate of the slope, and

$$\hat{\beta}_0 = \frac{y_L + y_M + y_R}{3} - \hat{\beta}_1 \frac{x_L + x_M + x_R}{3}$$

for the intercept.

We can easily implement this method in R. To demonstrate this, we use simulated data with artificial outliers:

```
set.seed(20211129)
n <- 24
x <- runif(n, 0, 10)
y <- -1 + x + rnorm(n)

outlier <- 1:5
y[outlier] <- y[outlier] + 15
```

We start by sorting the data in order of increasing  $x$ -values:

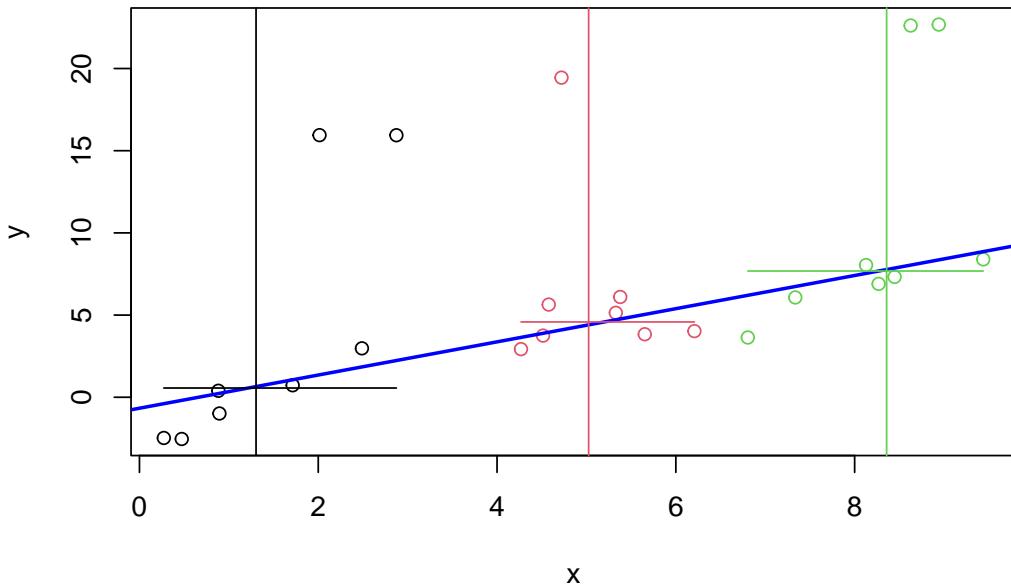
```
idx <- order(x)
x <- x[idx]
y <- y[idx]
```

Now we can compute the resistant line:

```
xL <- median(x[1:8])
xM <- median(x[9:16])
xR <- median(x[17:24])
yL <- median(y[1:8])
yM <- median(y[9:16])
yR <- median(y[17:24])
beta1 <- (yR - yL) / (xR - xL)
beta0 <- (yL + yM + yR) / 3 - beta1 * (xL + xM + xR) / 3
```

Finally, we plot the result.

```
plot(x, y, col = rep(1:3, each=8))
abline(beta0, beta1, col = "blue", lwd = 2)
abline(v = xL, col = 1)
abline(v = xM, col = 2)
abline(v = xR, col = 3)
segments(c(x[1], x[9], x[17]), c(yL, yM, yR), c(x[8], x[16], x[24]),
         col = 1:3)
```



The horizontal and vertical line segments in the plot give the medians used in the computation. The blue, sloped line is the resistant line. One can see that the line closely follows the bulk of the samples and that it is not affected by the five outliers.

A variant of this method is implemented by the R function `line()`.

### Summary

- Leverage can be used to detect  $x$ -space outliers.
- Studentised residuals can be used to detect  $y$ -space outliers.
- The breakdown point of an estimator is a measure for how robust the method is to outliers.

## 18 M-Estimators

In this section we introduce a class of estimators which can be robust to  $y$ -space outliers.

### 18.1 Definition

**Definition 18.1.** An **M-estimator** for the regression coefficients  $\beta$  is a method which computes the estimator  $\hat{\beta}$  as

$$\hat{\beta} = \arg \min_{\beta} r(\varepsilon) = \arg \min_{\beta} r(y - X\beta),$$

where  $r$  is given by

$$r(\varepsilon) = \sum_{i=1}^n \rho(\varepsilon_i)$$

and  $\rho: \mathbb{R} \rightarrow \mathbb{R}$  is a symmetric, continuous function with a unique minimum at 0. The function  $\rho$  is called the **objective function** of the M-estimator.

This is a generalisation of the least squares estimator, where the least squares estimator corresponds to the case  $\rho(\varepsilon) = \varepsilon^2$ .

For most functions  $\rho$  there is no closed-form expression for the estimate  $\hat{\beta}$ , but numerical minimisation can be used to find numerical values for  $\hat{\beta}$ . In R, the function `optim()` can be used for this purpose.

**Example 18.1.** The M-estimator with  $\rho(u) = |u|$  is called the **least absolute values** (LAV) estimator. Since  $\rho$  grows slower than  $u^2$  as  $|u| \rightarrow \infty$ , this estimator is more resistant to  $y$ -space outliers than least squares regression is. On the other hand, for  $x$ -space outliers which are sufficiently far away from the bulk of the data, the LAV line will pass exactly through the corresponding point  $(x_i, y_i)$ , so the LAV estimator is more susceptible to  $x$ -space outliers than least squares regression is, and the breakdown point is still  $1/n$ .

```
set.seed(202111202)

n <- 12
x <- seq(0, 5, length.out = n+1)[-((n/2)+1)]
y <- 1 + 0.4 * x + rnorm(n, sd = 0.3)
m <- lm(y ~ x)

# we try four different extra samples, one after another:
x.extra <- seq(2.5, 20, length.out = 4)
y.extra <- c(-1, -1, -1, -1)

lav <- function(par, x, y) {
  beta0 <- par[1]
  beta1 <- par[2]
  sum(abs(y - beta0 - beta1*x))
}

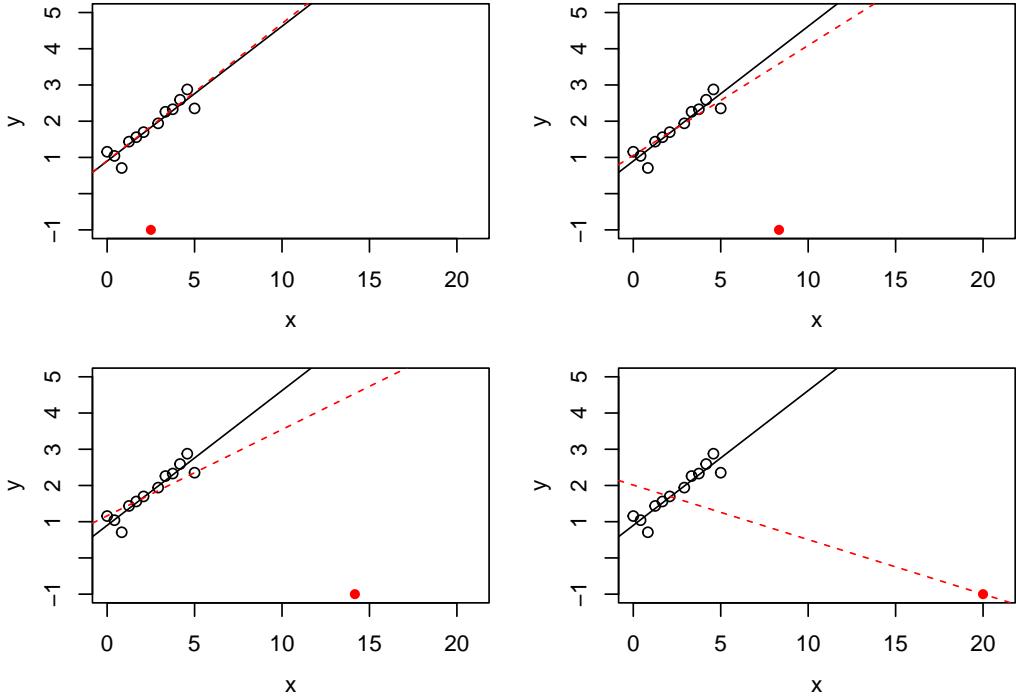
par(mfrow = c(2, 2), # We want a 2x2 grid of plots,
    mai = c(0.7, 0.7, 0.1, 0.1), # using smaller margins, and
    mgp = c(2.5, 1, 0)) # we move the labels closer to the axes.
for (i in 1:4) {
  plot(x, y, xlim = c(0, 21), ylim = c(-1, 5))
  abline(m)

  o <- optim(c(0, 0), lav, NULL, c(x, x.extra[i]), c(y, y.extra[i]))
```

```

abline(o$par[1], o$par[2], col="red", lty="dashed")
points(x.extra[i], y.extra[i], col = "red", pch = 16)
}

```



Define  $s(\beta) = r(y - X\beta)$ . Then we have

$$\hat{\beta} = \arg \min_{\beta} s(\beta). \quad (35)$$

Some care is needed since the function  $s$  may have more than one local minimum, and even the global minimum may not be uniquely defined.

**Lemma 18.1.** *Assume that  $\rho$  is convex. Then  $s$  is convex.*

*Proof.* Here we use the property that a function  $f: \mathbb{R}^{p+1} \rightarrow \mathbb{R}$  is convex, if and only if

$$f(\lambda\beta^{(1)} + (1 - \lambda)\beta^{(2)}) \leq \lambda f(\beta^{(1)}) + (1 - \lambda)f(\beta^{(2)})$$

for all  $\beta^{(1)}, \beta^{(2)} \in \mathbb{R}^{p+1}$  and all  $\lambda \in [0, 1]$ . Since  $\rho$  is convex, we find

$$\begin{aligned}
& s(\lambda\beta^{(1)} + (1 - \lambda)\beta^{(2)}) \\
&= r(y - X(\lambda\beta^{(1)} + (1 - \lambda)\beta^{(2)})) \\
&= r(\lambda(y - X\beta^{(1)}) + (1 - \lambda)(y - X\beta^{(2)})) \\
&= \sum_{i=1}^n \rho\left(\lambda(y - X\beta^{(1)})_i + (1 - \lambda)(y - X\beta^{(2)})_i\right) \\
&\leq \sum_{i=1}^n \left(\lambda\rho(y - X\beta^{(1)})_i + (1 - \lambda)\rho(y - X\beta^{(2)})_i\right) \\
&= \lambda r(y - X\beta^{(1)}) + (1 - \lambda)r(y - X\beta^{(2)}) \\
&= \lambda s(\beta^{(1)}) + (1 - \lambda)s(\beta^{(2)}).
\end{aligned}$$

Thus  $s$  is convex and the proof is complete.  $\square$

This shows that the problem of finding  $\hat{\beta}$  is better behaved when  $\rho$  is convex. For example, in this case, every local minimum of  $s$  is also a global minimum and the set of all minima is a convex set.

M-estimates in general are not scale-invariant, *i.e.* if  $y$  is measured in different units, the regression line changes. A scale-invariant, robust estimator is given by

$$\hat{\beta} = \arg \min_{\beta} r\left(\frac{\varepsilon}{\hat{\sigma}}\right) = \arg \min_{\beta} r\left(\frac{y - X\beta}{\hat{\sigma}}\right),$$

where  $\hat{\sigma}$  is a robust estimator of the residual standard deviation, for example the **median absolute deviation** (MAD) given by

$$\hat{\sigma} = \text{median}|\hat{\varepsilon}_i - \text{median}(\hat{\varepsilon}_i)|.$$

## 18.2 Iterative Methods

If  $\rho$  is differentiable, say  $\rho' = \psi$ , then gradient-based methods can be used to find the minimum in equation (35). The basis of this approach is the following lemma.

**Lemma 18.2.** *If  $\rho' = \psi$ , then the M-estimate satisfies*

$$\sum_{i=1}^n \psi((y - X\hat{\beta})_i) \begin{pmatrix} 1 \\ x_{i1} \\ \vdots \\ x_{ip} \end{pmatrix} = 0 \in \mathbb{R}^{p+1}. \quad (36)$$

*Proof.* Since  $\hat{\beta}$  minimises the function  $r$ , we have

$$\begin{aligned} 0 &= \frac{\partial}{\partial \beta_j} r(y - X\beta) \Big|_{\beta=\hat{\beta}} \\ &= \frac{\partial}{\partial \beta_j} \sum_{i=1}^n \rho((y - X\beta)_i) \Big|_{\beta=\hat{\beta}} \\ &= \sum_{i=1}^n \psi((y - X\beta)_i) \frac{\partial}{\partial \beta_j} (y - X\beta)_i \Big|_{\beta=\hat{\beta}} \\ &= \sum_{i=1}^n \psi((y - X\beta)_i) (-x_{ij}) \Big|_{\beta=\hat{\beta}} \\ &= - \sum_{i=1}^n \psi((y - X\hat{\beta})_i) x_{ij}. \end{aligned}$$

where we use the convention  $x_{i0} = 1$ . This completes the proof.  $\square$

With the result of the lemma, we have turned the problem of finding  $\hat{\beta}$  into the problem of finding the roots of a non-linear function. To solve this problem, we can for example use one of the generic root finding algorithms, for example Newton's method.

In the context of M-estimates, a more specialised method is often used in the literature. For this method we define weights

$$w_i := \frac{\psi((y - X\hat{\beta})_i)}{(y - X\hat{\beta})_i} \quad (37)$$

and write  $W$  for the diagonal matrix which has  $w_1, \dots, w_n$  on the diagonal. Using this notation, we can rewrite condition (36) as

$$X^\top W(y - X\hat{\beta}) = 0$$

and solving for  $\hat{\beta}$  gives

$$\hat{\beta} = (X^\top W X)^{-1} X^\top W y. \quad (38)$$

This equation looks very similar to our formula for the least squares estimate, the only change being the presence of the matrix  $W$ . One can check that the value  $\hat{\beta}$  computed in this way also represents the solution of the weighted least-squares problem

$$\hat{\beta} = \arg \min_{\beta} \sum_{i=1}^n w_i (y_i - \beta_0 - \beta_1 x_{i1} - \cdots - \beta_p x_{ip})^2.$$

While equation (38) looks like the solution of a linear problem at first glance, the weight matrix  $W$  depends on  $\hat{\beta}$  and this equation still represents a non-linear equation for  $\hat{\beta}$ .

The **iteratively re-weighted least squares** method is an iterative method for solving equation (38). Starting from an initial guess  $\hat{\beta}^{(0)}$  for  $\hat{\beta}$ , e.g. the least squares estimate or the zero vector, the method repeats the following steps for  $k = 0, 1, 2, \dots$ :

1. Using equation (37), compute the weight matrix  $W^{(k)}$  corresponding to  $\hat{\beta}^{(k)}$ .
2. Compute  $\hat{\beta}^{(k+1)} = (X^\top W^{(k)} X)^{-1} X^\top W^{(k)} y$ .

The algorithm finishes either after a fixed number of steps, or when the values of  $\hat{\beta}^{(k)}$  don't change much between steps any more, or when the “residual”  $X^\top W(y - X\hat{\beta})$  is “small enough”.

### 18.3 Objective Functions

In this section we will discuss different choices of the objective function  $\rho$ , together with the derivative  $\psi$  and the weight function  $w(\varepsilon) = \psi(\varepsilon)/\varepsilon$ .

#### 18.3.1 Least Squares Method

Here we can write

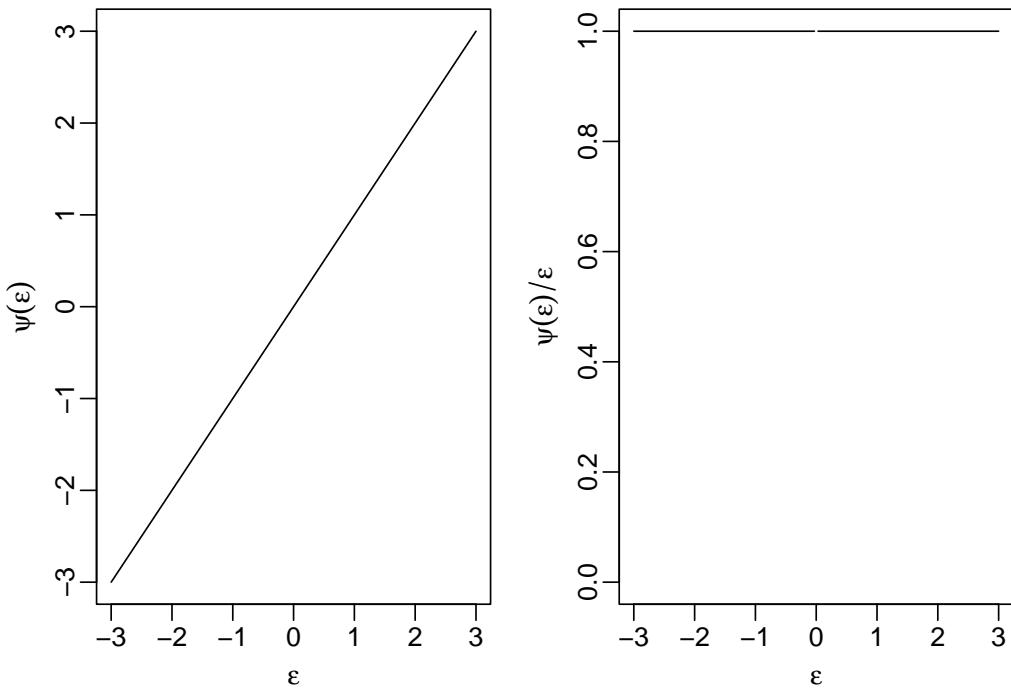
$$\rho(\varepsilon) = \varepsilon^2/2.$$

The factor 1/2, which we omitted before, does not change the estimate. We include the factor here to give  $\psi$  a simpler form and to make comparison to the following examples easier. The derivative of  $\rho$  is given by

$$\psi(\varepsilon) = \varepsilon$$

The following R code can be used to plot  $\psi$  and the weight function  $w$ :

```
eps <- seq(-3, 3, length.out = 201)
psi <- function(eps) eps
par(mfrow = c(1, 2),
mai = c(0.7, 0.7, 0.1, 0.1),
mgp = c(1.7, 0.5, 0))
plot(eps, psi(eps), type="l",
xlab = expression(epsilon), ylab = expression(psi(epsilon)))
plot(eps, psi(eps) / eps, type="l", ylim = c(0, 1),
xlab = expression(epsilon),
ylab = expression(psi(epsilon)/epsilon))
```



The right-hand plot shows that weight of observations does not depend on their magnitude. This property is what makes the least squares estimate susceptible to outliers.

### 18.3.2 Least Absolute Values

Here we have

$$\rho(\varepsilon) = |\varepsilon|.$$

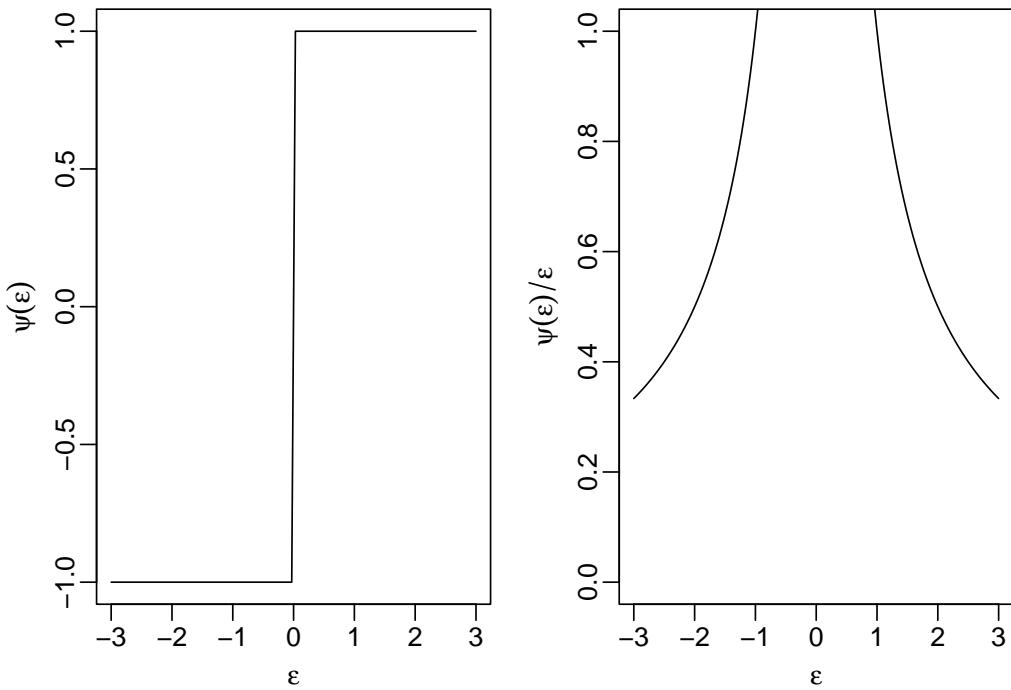
The derivative of this function is

$$\begin{aligned}\psi(\varepsilon) &= \begin{cases} -1 & \text{if } \varepsilon < 0, \\ +1 & \text{if } \varepsilon > 0 \end{cases} \\ &= \text{sign}(\varepsilon)\end{aligned}$$

and the weight function is

$$w(\varepsilon) = \frac{\text{sign}(\varepsilon)}{|\varepsilon|} = \frac{1}{|\varepsilon|}.$$

```
t <- 1
psi <- function(eps) sign(eps)
par(mfrow = c(1, 2),
mai = c(0.7, 0.7, 0.1, 0.1),
mgp = c(1.7, 0.5, 0))
plot(eps, psi(eps), type="l",
xlab = expression(epsilon), ylab = expression(psi(epsilon)))
plot(eps, psi(eps) / eps, type="l", ylim = c(0, 1),
xlab = expression(epsilon),
ylab = expression(psi(epsilon)/epsilon))
```



### 18.3.3 Huber's $t$ -function

This method uses the following objective function:

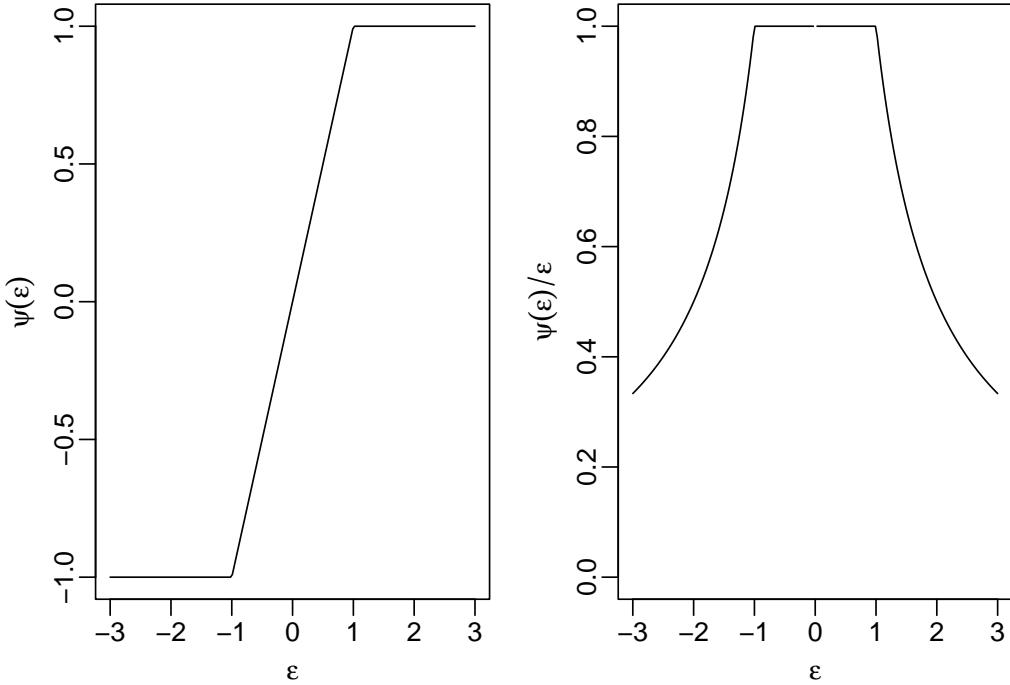
$$\rho(\varepsilon) = \begin{cases} \frac{1}{2}\varepsilon^2 & \text{if } |\varepsilon| \leq t \\ t|\varepsilon| - \frac{1}{2}t^2 & \text{if } |\varepsilon| > t \end{cases}$$

The parameter  $t > 0$  can be used to tune the method. The influence function  $\psi$  is given by

$$\psi(\varepsilon) = \begin{cases} \varepsilon & \text{if } |\varepsilon| \leq t \\ t \text{ sign}(\varepsilon) & \text{if } |\varepsilon| > t. \end{cases}$$

A plot of  $\psi$  and  $\psi(\varepsilon)/\varepsilon$  shows that for this method the weight of observations where the residuals satisfy  $|\varepsilon_i| \leq t$  is the same as for least squares, but larger residuals get lower weights, leading to a more robust estimator.

```
t <- 1
psi <- function(eps) ifelse(abs(eps) <= t, eps, t * sign(eps))
par(mfrow = c(1, 2),
mai = c(0.7, 0.7, 0.1, 0.1),
mgp = c(1.7, 0.5, 0))
plot(eps, psi(eps), type="l",
xlab = expression(epsilon), ylab = expression(psi(epsilon)))
plot(eps, psi(eps) / eps, type="l", ylim = c(0, 1),
xlab = expression(epsilon),
ylab = expression(psi(epsilon)/epsilon))
```



#### 18.3.4 Hampel's Method

Here we have tuning parameters  $0 < a < b < c$ , and the objective function is

$$\rho(\varepsilon) = \begin{cases} \frac{1}{2}\varepsilon^2 & \text{if } |\varepsilon| \leq a \\ a|\varepsilon| - \frac{1}{2}a^2 & \text{if } a \leq |\varepsilon| < b \\ a\frac{(|\varepsilon|-c)^2}{2(b-c)} + \frac{1}{2}a(b+c-a) & \text{if } b \leq |\varepsilon| \leq c \\ \frac{a(b+c-a)}{2} & \text{otherwise,} \end{cases}$$

with derivative

$$\psi(\varepsilon) = \begin{cases} \varepsilon & \text{if } |\varepsilon| \leq a, \\ a \text{sign}(\varepsilon) & \text{if } a < |\varepsilon| \leq b, \\ a \frac{\varepsilon - c \text{sign}(\varepsilon)}{b - c} & \text{if } b < |\varepsilon| \leq c, \\ 0 & \text{if } c < |\varepsilon|. \end{cases}$$

We observe an important property: for residuals with  $|\varepsilon| > c$ , the  $\psi$ -function equals zero. This property deserves a name:

**Definition 18.2.** A  $\psi$ -function is called **redescending** if  $\psi(u) \rightarrow 0$  as  $|u| \rightarrow \infty$ .

Hampel's method uses a redescending  $\psi$ -function. Observations with  $|\varepsilon_i| > c$  receive zero weight and have no influence on the regression estimate whatsoever. This provides additional robustness compared to non-redescending methods such as Huber's, where large residuals are down-weighted but still retain some influence.

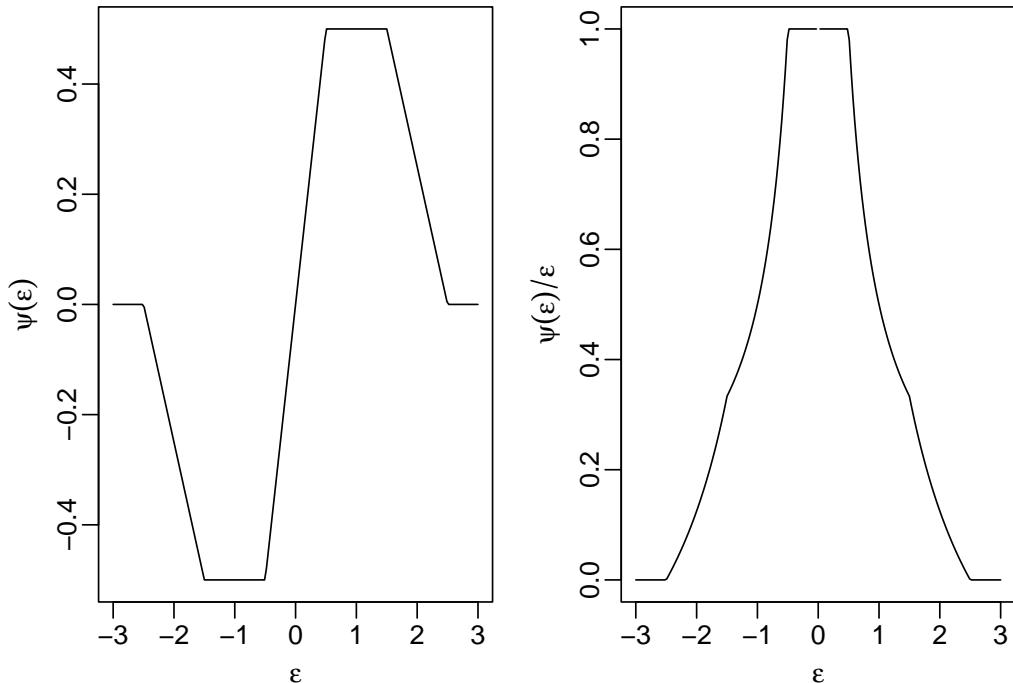
Since these formulas are tedious to understand, we consider plots of  $\psi$  and  $\psi(\varepsilon)/\varepsilon$  again:

```
a <- 0.5
b <- 1.5
c <- 2.5
psi <- function(eps) {
  ifelse(abs(eps) <= a, eps,
        ifelse(abs(eps) <= b, a * sign(eps),
              ifelse(abs(eps) <= c,
                    a * (eps - c*sign(eps)) / (b - c),
```

```

        0)))
}
par(mfrow = c(1, 2),
    mai = c(0.7, 0.7, 0.1, 0.1),
    mgp = c(1.7, 0.5, 0))
plot(eps, psi(eps), type="l",
      xlab = expression(epsilon), ylab = expression(psi(epsilon)))
plot(eps, psi(eps) / eps, type="l", ylim = c(0, 1),
      xlab = expression(epsilon),
      ylab = expression(psi(epsilon)/epsilon))

```



We see that small residuals, with  $|\varepsilon_i| \leq a$  get the same weight as for least squares regression, and the weight for larger residuals is gradually reduced. Residuals with  $|\varepsilon_i| > c$  have weight 0 and do not affect the location of the regression line at all.

We see that  $\psi$  is not increasing and therefore  $\rho$  is not convex. A consequence of this fact is that the function  $s$  may have several local minima and care must be used when choosing the starting point of iterative minimisation methods. Non-convexity is a common feature of redescending M-estimators.

### 18.3.5 Tukey's Bisquare Method

Here we have only one tuning parameter,  $a > 0$ , and the objective function is

$$\rho(\varepsilon) = \begin{cases} \frac{a^2}{6} \left(1 - (1 - (\varepsilon/a)^2)^3\right) & \text{if } |\varepsilon| \leq a \\ \frac{a^2}{6} & \text{if } |\varepsilon| > a \end{cases}$$

with derivative

$$\psi(\varepsilon) = \begin{cases} \varepsilon (1 - (\varepsilon/a)^2)^2 & \text{if } |\varepsilon| \leq a \\ 0 & \text{if } |\varepsilon| > a. \end{cases}$$

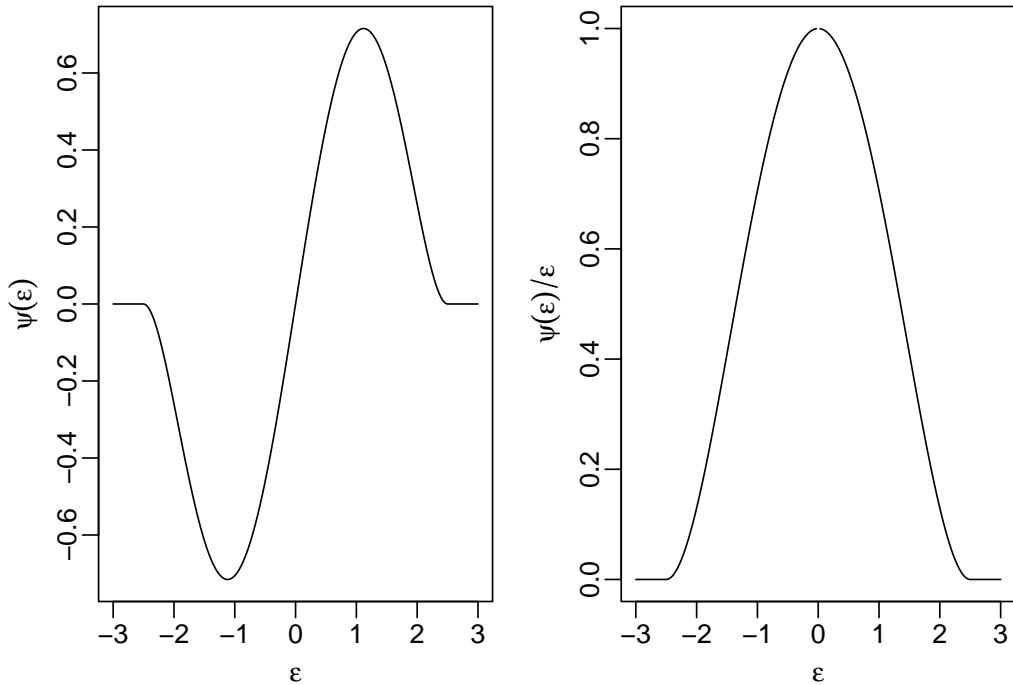
Like Hampel's method, Tukey's bisquare is also a redescending  $\psi$ -function, since  $\psi(\varepsilon) = 0$  for all  $|\varepsilon| > a$ .

The plots show that this is a simplified variant of Hampel's estimator:

```

a <- 2.5
eps <- seq(-3, 3, length.out = 201)
psi <- function(eps) {
  ifelse(abs(eps) <= a,
    eps * (1 - (eps / a)^2)^2,
    0)
}
par(mfrow = c(1, 2),
  mai = c(0.7, 0.7, 0.1, 0.1),
  mgp = c(1.7, 0.5, 0))
plot(eps, psi(eps), type="l",
  xlab = expression(epsilon), ylab = expression(psi(epsilon)))
plot(eps, psi(eps) / eps, type="l", ylim = c(0, 1),
  xlab = expression(epsilon),
  ylab = expression(psi(epsilon)/epsilon))

```



Again,  $\rho$  is not convex and care is needed when computing the estimate  $\hat{\beta}$ .

## 18.4 Breakdown Points of M-Estimators

In section 17 we introduced the breakdown point as a measure of robustness. We now consider how the choice of  $\psi$ -function affects the breakdown point of M-estimators.

For M-estimators with non-redescending  $\psi$ -functions (such as least squares, LAV, or Huber's method), the  $\psi$ -function grows without bound as  $|\varepsilon| \rightarrow \infty$ . This means that observations with arbitrarily large residuals still contribute to the objective function. Consequently, a single outlier with sufficiently large  $y$ -value can make  $\|\hat{\beta}\| \rightarrow \infty$ . Thus, these methods have breakdown point  $\varepsilon_n(\hat{\beta}) = 1/n$ .

Redescending M-estimators (such as Hampel's or Tukey's bisquare) assign zero weight to observations with large residuals. This provides additional robustness compared to non-redescending methods. However, the breakdown point is still  $1/n$  for M-estimators in general, because a single  $x$ -space outlier with high leverage can still cause breakdown. Methods with higher breakdown points are discussed in section 19.

## Summary

- We introduced the M-estimator as a robust method for estimating regression coefficients.
- We discussed the iteratively re-weighted least squares method for computing M-estimates.
- We discussed different choices for the objective function of an M-estimator.
- We defined redescending  $\psi$ -functions and showed that M-estimators have breakdown point  $1/n$ .

## 19 Efficiency of Robust Estimators

In theoretical statistics, **efficiency** is a measure of quality of an estimator. A more efficient estimator achieves smaller estimation error for a given number of samples. Here we give an informal introduction to the topic of efficiency and discuss the efficiency of different methods for linear regression.

### 19.1 Efficiency

In the section about the Mean Squared Error we have seen that

$$\text{MSE}(\hat{\theta}) = \text{Var}(\hat{\theta}) + \text{bias}(\hat{\theta})^2$$

can be used as a measure for the estimation error of an estimator  $\hat{\theta}$ , and if the estimator is unbiased, this expression simplifies to

$$\text{MSE}(\hat{\theta}) = \text{Var}(\hat{\theta}).$$

Thus, “good” estimators will have small variance. Instead of considering the full definition from theoretical statistics (which requires the concept of Fisher information), here we simply consider

$$\text{efficiency}(\hat{\theta}) = \frac{1}{\text{Var}(\hat{\theta})}$$

as a measure for the efficiency of an estimator. We will use this measure of efficiency to compare different estimators.

**Example 19.1.** Both the sample mean and the sample median can be used as estimators for the population mean. Here we show that the median has lower efficiency than the mean.

Suppose  $X_1, \dots, X_n$  are i.i.d. with CDF  $F(x)$ , i.e.  $P(X_i \leq x) = F(x)$ . As before, let  $X_{(1)} \leq \dots \leq X_{(n)}$  be the samples arranged in order of increasing value. Then the distribution of  $X_{(k)}$  has CDF

$$P(X_{(k)} \leq x) = \sum_{i=k}^n \binom{n}{i} F(x)^i (1 - F(x))^{n-i},$$

since  $X_{(k)} \leq x$  requires at least  $k$  out of  $n$  samples to be less than or equal to  $x$ . If we differentiate this (using product rule and chain rule) we get the density of  $X_{(k)}$ :

$$\begin{aligned} f_{(k)}(x) &= \frac{d}{dx} P(X_{(k)} \leq x) \\ &= \dots \\ &= f(x) \frac{n!}{(n-k)!(k-1)!} F(x)^{k-1} (1 - F(x))^{n-k}. \end{aligned}$$

For simplicity we assume that  $n$  is odd, say  $n = 2m + 1$ . In this case the median is  $X_{\text{median}} = X_{(m+1)}$ . Thus, the density of the median is

$$\begin{aligned} f_{\text{median}}(x) &= f_{(m+1)}(x) \\ &= f(x) \frac{n!}{(n-m-1)!m!} F(x)^m (1 - F(x))^{n-m-1} \\ &= f(x) \frac{n!}{m!m!} F(x)^m (1 - F(x))^m. \end{aligned}$$

This density can be used to understand the behaviour of the median.

Now assume that  $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$ , i.e. the density is

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

and the CDF is

$$F(x) = \Phi\left(\frac{x-\mu}{\sigma}\right),$$

where  $\Phi$  is the CDF of the standard normal distribution. In this case we know that

$$\text{Var}(\bar{X}) = \frac{\sigma^2}{n}.$$

For comparison, we can use the density of  $X_{\text{median}}$  to show (in a series of complicated steps) that

$$\text{Var}(X_{\text{median}}) \sim \frac{\pi}{2} \frac{\sigma^2}{n},$$

as  $n \rightarrow \infty$ . Thus, for large  $n$ , the relative efficiency of the median compared to the mean is

$$\begin{aligned} \frac{\text{efficiency}(X_{\text{median}})}{\text{efficiency}(\bar{X})} &= \frac{\text{Var}(\bar{X})}{\text{Var}(X_{\text{median}})} = \frac{\frac{\sigma^2}{n}}{\frac{\pi}{2} \frac{\sigma^2}{n}} \\ &= \frac{2}{\pi} = 0.637. \end{aligned}$$

Thus, the sample median is a less efficient estimator for the mean than the sample mean is.

The situation in the example carries over to linear regression: more robust estimators tend to be less efficient, and there is a trade-off between robustness and efficiency. Without proof, here we list some examples of this principle:

- One can show that usually the variance of the least squares estimator decreases proportionally to  $1/n$ , and thus the efficiency of the least squares estimator increases proportionally to  $n$ .
- The value  $t$  in Huber's method can be used to control the balance between robustness and efficiency. As  $t \rightarrow \infty$ , the method converges to least squares regression and becomes less robust, but at the same time efficiency increases. Huber suggests the value  $t = 1.345\sigma$  and showed that for this choice the method is 95% efficient for large  $n$ , compared to least squares regression.
- Similarly, the parameter  $a$  in Tukey's Bisquare Method controls the trade-off between robustness and efficiency, with smaller  $a$  leading to a more robust method. In the literature it is suggested that  $a = 4.685\sigma$  leads to 95% efficiency for large  $n$ , compared to least squares regression.
- The efficiency of the least absolute values estimator can be shown to be 64%.

## 19.2 Robust estimators

As shown in section 18, M-estimators (both redescending and non-redescending) have breakdown point  $1/n$  because a single  $x$ -space outlier with high leverage can cause breakdown. We now consider two estimators which have a higher breakdown point, but lower efficiency.

### 19.2.1 Least Median of Squares

Rather than minimise the sum of the residual sum of squares (or a weighted version of it), this estimator minimises the median of squared residuals. The estimate is given by

$$\hat{\beta}^{(\text{LMS})} := \arg \min_{\beta} \text{median}_{i \in \{1, \dots, n\}} (y_i - x_i^T \beta)^2,$$

where  $x_1, \dots, x_n$  are the rows of the design matrix  $X$ . This is very robust with respect to outliers, both in  $x$ -direction and  $y$ -directions: Since the median is used instead of the sum, up to half of the squared residuals can increase to infinity while the estimate stays bounded. Thus the asymptotic breakdown point of the method is  $1/2$ .

The least median of squares method has poor asymptotic efficiency  $n^{2/3}$ . In the limit, the relative efficiency compared to ordinary least squares is

$$\frac{\text{efficiency}(\hat{\beta}^{(\text{LMS})})}{\text{efficiency}(\hat{\beta}^{(\text{LSQ})})} \propto \frac{n^{2/3}}{n} \rightarrow 0$$

as  $n \rightarrow \infty$ .

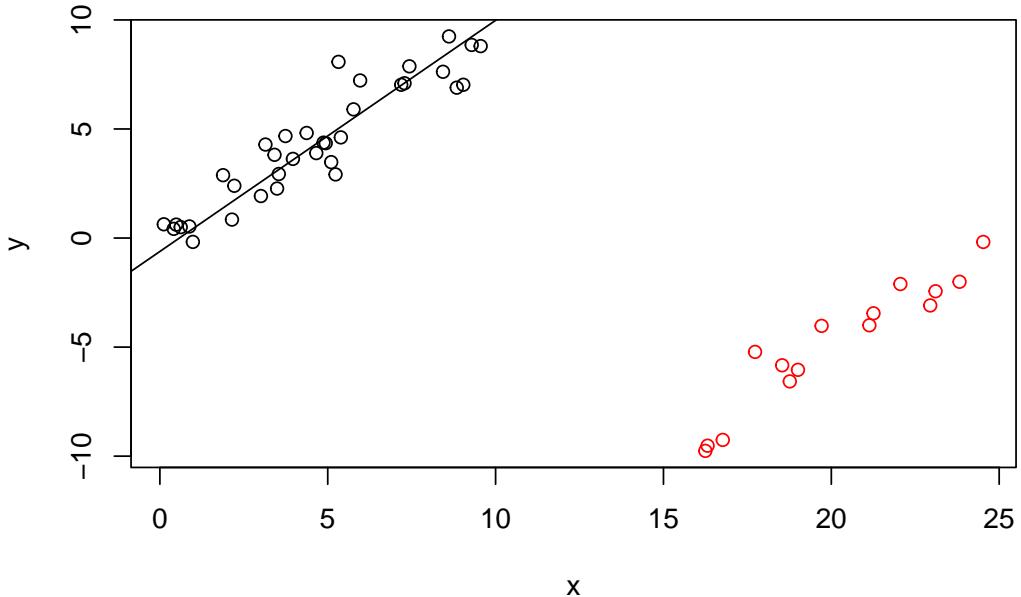
**Example 19.2.** The following code computes an LMS regression estimate. We introduce artificial outliers by shifting 30% of the data to the bottom right. These artificial outliers are represented by the red circles in the plot.

```
library("MASS") # for lqs()

set.seed(20211207)
n <- 50
x <- runif(n, 0, 10)
y <- x + rnorm(n)

# add 30% outliers
n.ol <- floor(0.3*n)
idx <- sample.int(n, n.ol)
x[idx] <- x[idx] + 15
y[idx] <- y[idx] - 10

m <- lqs(y~x, method="lms")
plot(x, y, col = ifelse(1:n %in% idx, "red", "black"))
abline(m)
```



### 19.2.2 Least Trimmed Squares

This takes as its objective function the sum of  $h$  smallest squared residuals and was proposed as a remedy to the low asymptotic efficiency of LMS. The least trimmed

squares estimator  $\hat{\beta}^{(\text{LTS})}$  is defined as

$$\hat{\beta}^{(\text{LTS})} := \arg \min_{\beta} \sum_{i=1}^k r_{[i]}^2(\beta),$$

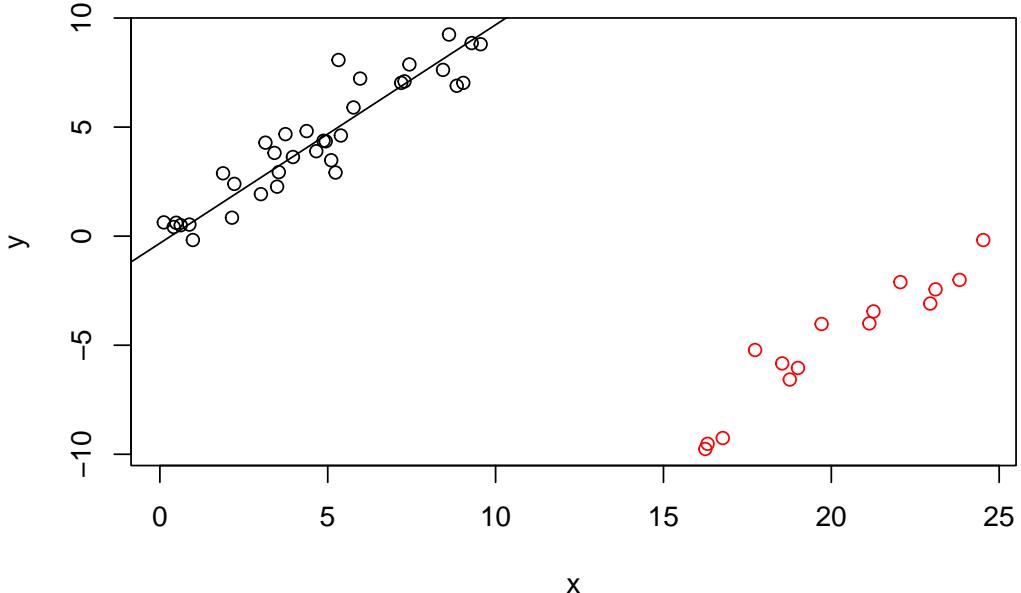
where  $r_{[i]}^2(\beta)$  represents the  $i$ th smallest value amongst  $r_i(\beta)^2 = (y_i - x_i^T \beta)^2$ .

The value  $k$  controls the trade-off between robustness and efficiency and the value must satisfy  $n/2 < k \leq n$ . For a given  $k$  the method can tolerate  $n - k$  outliers. The boundary case  $k = n$  corresponds to the ordinary least squares method. The breakdown point of the method is  $(n - k + 1)/n$ .

Computing the LTS estimate is a non-trivial problem, which involves fitting the least-squares estimate to a carefully chosen subset of the samples.

**Example 19.3.** The following code computes an LTS regression estimate. The data is the same as in the previous example.

```
m <- lqs(y~x, method = "lts", quantile = floor(n/2)+1)
plot(x, y, col = ifelse(1:n %in% idx, "red", "black"))
abline(m)
```



One can show that LTS has an efficiency of approximately 0.08 compared to ordinary least squares regression.

### Summary

- In this section we have informally discussed the efficiency of different estimators.
- We have introduced the Least Median of Squares estimator.
- We have introduced the Least Trimmed Squares estimator.

## Interlude: Robust Regression in R

This section explains how to use the robust regression methods discussed in sections 17, 18 and 19 in R.

### M-Estimators

The `rlm()` function from the `MASS` package implements the iteratively reweighted least squares algorithm from section 18. The function takes a formula interface similar to `lm()`, and the `psi` argument specifies which  $\psi$ -function to use:

```
library(MASS)

rlm1 <- rlm(y ~ x, psi = psi.huber)      # Huber's method
rlm2 <- rlm(y ~ x, psi = psi.bisquare)    # Tukey's bisquare
rlm3 <- rlm(y ~ x, psi = psi.hampel)      # Hampel's method
```

The available `psi` functions correspond to the objective functions discussed in section 18:

- `psi.huber` implements Huber's  $t$ -function from section 18.3.3.
- `psi.bisquare` implements Tukey's bisquare method.
- `psi.hampel` implements Hampel's method.

Information can be extracted from the fitted model object:

- `coef(rlm1)` returns the estimated regression coefficients  $\hat{\beta}$ .
- `rlm1$resid` returns the residuals.
- `rlm1$w` returns the weights assigned to each observation.

The fitted line can be plotted using `abline(rlm1)`.

### LAV Estimation

The `rq()` function from the `quantreg` package computes the least absolute values (LAV) estimator from section 18.1:

```
library(quantreg)

rq1 <- rq(y ~ x)
```

The `rq()` function uses specialized algorithms (interior point methods) which are more efficient and have better convergence properties than the general-purpose `optim()` approach shown in section 18.1. For pedagogical purposes, section 18.1 shows the `optim()` implementation to illustrate what the LAV estimator actually minimises, but for practical work the `rq()` function should be used.

Coefficients can be extracted using `coef(rq1)` and residuals using `resid(rq1)`. The fitted line can be plotted using `abline(rq1)`.

### High Breakdown Point Methods

The `lqs()` function from the `MASS` package implements both the least median of squares (LMS) and least trimmed squares (LTS) estimators from section 19:

```
library(MASS)

lms1 <- lqs(y ~ x, method = "lms")
lts1 <- lqs(y ~ x, method = "lts")
```

For the LTS estimator, the `quantile` argument can be used to specify the value of  $h$  (the number of observations to use in the objective function):

```
lts1 <- lqs(y ~ x, method = "lts", quantile = floor(n/2) + 1)
```

As discussed in section 19.2.2, the value of  $h$  controls the trade-off between robustness and efficiency. Smaller values of  $h$  give higher breakdown points but lower efficiency.

Coefficients can be extracted using `coef(lms1)` or `coef(lts1)`, and the fitted lines can be plotted using `abline(lms1)` or `abline(lts1)`.

## Summary

The following table summarises the R functions for robust regression:

Method	Function	Package	Section
LAV	<code>rq(y ~ x)</code>	<code>quantreg</code>	18.1
Huber	<code>rlm(y ~ x, psi = psi.huber)</code>	<code>MASS</code>	18.3.3
Bisquare	<code>rlm(y ~ x, psi = psi.bisquare)</code>	<code>MASS</code>	18.3.5
Hampel	<code>rlm(y ~ x, psi = psi.hampel)</code>	<code>MASS</code>	18.3.4
LMS	<code>lqs(y ~ x, method = "lms")</code>	<code>MASS</code>	19.2.1
LTS	<code>lqs(y ~ x, method = "lts")</code>	<code>MASS</code>	19.2.2

All of these functions return model objects that work with `coef()`, `resid()`, and `abline()`.

## Problem Sheet 5

You should attempt all these questions and write up your solutions in advance of the workshop in week 11 where the answers will be discussed.

**17.** Consider the dataset at

- <https://teaching.seehuhn.de/2022/MATH3714/P05Q17.csv>

which contains samples from variables  $x_1, x_2, y \in \mathbb{R}$  and  $x_3 \in \{\text{R, G, B}\}$ .

- a. Load the data into R.
- b. Fit a simple linear model to describe  $y$  as a function of  $x_1, x_2$  and  $x_3$ , taking into account that  $x_3$  is a categorical variable. Show that the behaviour of the residuals depends on the levels of  $x_3$ .
- c. Find an improved model, which includes some of the interaction terms between  $x_3$  and the other variables. For each level of  $x_3$ , write the mathematical equation for the fitted model mean of your chosen model.

**18.** Consider the dataset at

- <https://teaching.seehuhn.de/2022/MATH3714/P05Q18.csv>

Identify the  $x$ -space outlier in this dataset.

**19.** The sample median is a robust estimator of the mean. Determine the breakdown point.

**20.** Determine the breakdown point for the resistant line from example 17.3.

## 20 Examples

In this section we compare the robust regression methods from sections 17, 18 and 19 by applying them to synthetic data. We will see how methods with different breakdown points behave in the presence of outliers, how the weights assigned by different M-estimators differ in practice, and how robust methods produce cleaner residual patterns than least squares regression.

### 20.1 Comparing Robust Methods

**Example 20.1.** We compare several robust estimators on a synthetic dataset with outliers. This example illustrates how methods with high breakdown points resist contamination, whilst methods with low breakdown points can be severely affected.

We start by generating data from a linear relationship with three outliers:

```
set.seed(20251006)

n <- 30
x <- runif(n, 0, 10)
y <- 2 + 0.5*x + rnorm(n, sd = 0.5)

# Add three contaminants:
outliers <- c(5, 15, 25)
x[outliers] <- c(9, 8.5, 9.5)
y[outliers] <- c(-2, -1.5, -2.5)
```

Now we fit several different regression methods to this data:

```
library(MASS)      # for rlm() and lqs()
library(quantreg) # for rq()

# Loading required package: SparseM
lm1   <- lm(y ~ x)                      # LSQ
rq1   <- rq(y ~ x)                      # LAV
rlm1  <- rlm(y ~ x, psi = psi.huber)    # Huber
rlm2  <- rlm(y ~ x, psi = psi.bisquare) # Bisquare
rlm3  <- rlm(y ~ x, psi = psi.hampel)   # Hampel
lms1  <- lqs(y ~ x, method = "lms")     # LMS
lts1  <- lqs(y ~ x, method = "lts")      # LTS
```

The left plot in figure 2 shows the fitted lines from all seven methods. As expected, only those methods with high breakdown point (LMS and LTS) have resisted the gross outliers. The least squares, LAV and M-estimator lines all pass between the bulk of the data and the outliers, demonstrating their susceptibility to contamination.

The right plot shows how the LTS estimator behaves for different values of the quantile parameter  $h$  (called `quantile` in R). For smaller values of  $h$ , the method uses only the observations with smallest residuals and has higher breakdown point. As  $h$  increases towards  $n = 30$ , the method gradually converges to the least squares estimate.

We see that for small  $h$  the LTS line passes through the bulk of the data and ignores the outliers, whilst for larger  $h$  it is increasingly influenced by the outliers until it converges to the least squares line.

### 20.2 Residual Analysis

**Example 20.2.** Continuing with the same dataset, we now examine the residual patterns from different methods. When outliers influence the fitted line, the residuals from

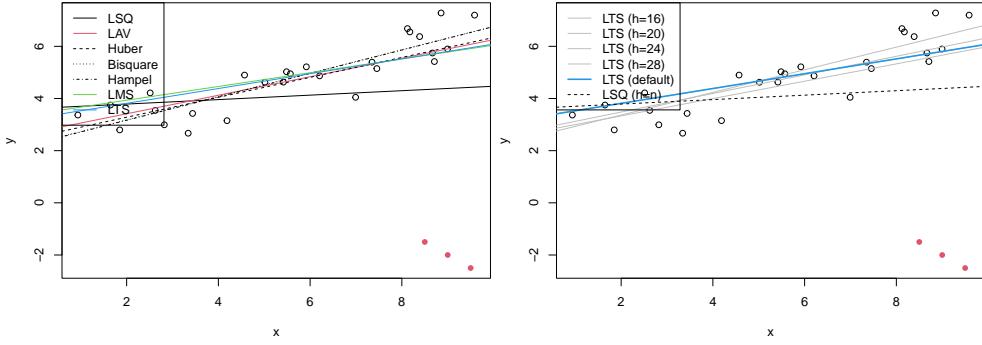


Figure 2: On the left we compare several methods. As expected, only those with high breakdown point have resisted the gross outliers. On the right plot, we compare different values of the quantile parameter  $h$  for the LTS estimator.

the remaining observations often exhibit systematic patterns.

Figure 3 shows the residuals from three methods, excluding the three known outliers. The least squares residuals (left plot) show a clear curved pattern: residuals are positive for small and large  $x$ -values, and negative for intermediate values. This pattern indicates that the outliers have pulled the regression line away from the bulk of the data.

The LAV and Huber methods (centre and right plots) show much less pronounced patterns. The residuals are more evenly scattered around zero, indicating that these methods have been less influenced by the outliers. This demonstrates one advantage of robust methods: they not only provide better parameter estimates in the presence of outliers, but also produce more reliable residual plots for model diagnostics.

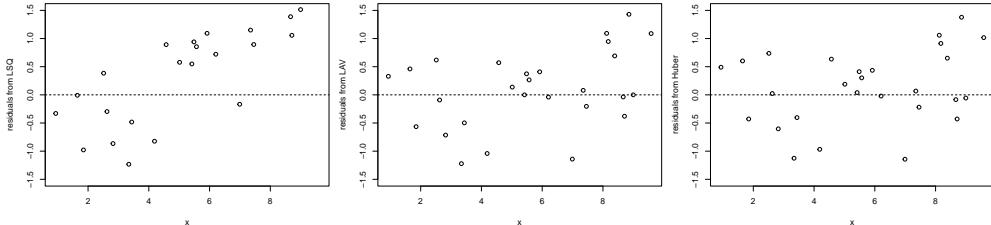


Figure 3: Residuals from non-outlier observations for three methods (left: LSQ; centre: LAV; right: Huber). The least squares residuals show a clear pattern due to the influence of the outliers.

### 20.3 Weight Comparisons

**Example 20.3.** We now examine the weights assigned by different M-estimators. Recall from section 18 that M-estimators assign weights to observations based on the magnitude of their residuals, with larger residuals receiving smaller weights.

Figure 4 shows the weights assigned by three different M-estimators: Huber, Bisquare and Hampel. The left plot shows the weights for all 30 observations. We can clearly see that observations 5, 15 and 25 (the outliers) receive very low weights from all three methods, confirming that these are correctly identified as outliers.

The centre and right plots compare the weights pairwise between methods. Most observations lie on or near the diagonal line, indicating that different methods assign similar weights to these observations. However, for the outliers (points far from the diagonal), the methods differ:

- The Bisquare and Hampel methods assign more extreme weights than the Huber method, with some observations receiving weights very close to zero.
- The Huber method assigns intermediate weights even to the outliers, which reflects the fact that the Huber  $\psi$ -function does not completely down-weight large residuals.

These differences reflect the different shapes of the weight functions  $w(\varepsilon) = \psi(\varepsilon)/\varepsilon$  discussed in section 18. The Bisquare and Hampel methods use redescending  $\psi$ -functions, assigning zero weight to sufficiently large residuals. The Huber method uses a non-redescending  $\psi$ -function, so all observations retain some influence.

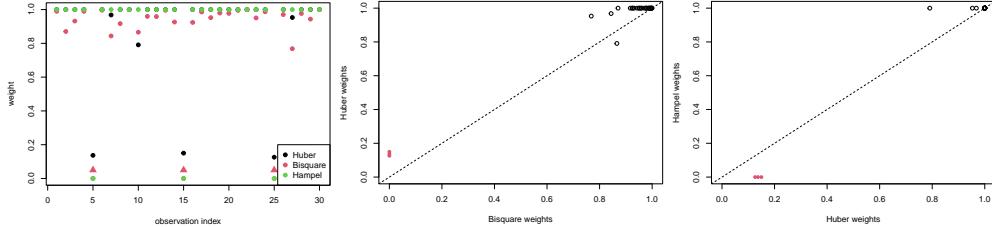


Figure 4: Comparisons of weights assigned by different M-estimators. The left plot shows weights for all observations. The centre and right plots compare weights pairwise between methods, with outliers shown as red points.

### Summary

- We have compared several robust regression methods on synthetic data with outliers.
- Methods with high breakdown points (LMS, LTS) resist outliers, whilst methods with low breakdown points (least squares, LAV, M-estimators) can be severely affected.
- Robust methods produce cleaner residual patterns than least squares when outliers are present, making diagnostics more reliable.
- M-estimators assign weights to observations based on residual magnitude, with different methods (Huber, Bisquare, Hampel) assigning weights differently.
- Redescending M-estimators (Bisquare, Hampel) assign zero weight to sufficiently large residuals, whilst the Huber method retains some influence for all observations.
- The choice of robust method involves a trade-off between breakdown point and efficiency, as discussed in sections 17–19.

## A Linear Algebra Reminders

### A.1 Vectors

We write  $v \in \mathbb{R}^d$  if  $v = (v_1, \dots, v_d)$  for numbers  $v_1, \dots, v_d \in \mathbb{R}$ . We say that  $v$  is a  $d$ -dimensional vector, and  $\mathbb{R}^d$  is the  $d$ -dimensional Euclidean space. Vectors are often graphically represented as “column vectors”:

$$v = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_d \end{pmatrix}.$$

If  $u, v \in \mathbb{R}^d$  are two vectors, the **inner product** of  $u$  and  $v$  is given by

$$u^\top v = \sum_{i=1}^d u_i v_i. \quad (39)$$

Note that the two vectors must have the same length for the inner product to exist.

Using this notation, the **Euclidean length** of a vector  $v$  can be written as

$$\|v\| = \sqrt{\sum_{i=1}^d v_i^2} = \sqrt{v^\top v}.$$

Vectors  $v_1, \dots, v_n$  are said to be **orthogonal**, if  $v_i^\top v_j = 0$  for all  $i \neq j$ . The vectors are said to be **orthonormal**, if they are orthogonal and satisfy  $\|v_i\| = 1$  for all  $i$ .

### A.2 Matrices

We write  $A \in \mathbb{R}^{m \times n}$  if

$$A = \begin{pmatrix} a_{1,1} & \dots & a_{1,n} \\ a_{2,1} & \dots & a_{2,n} \\ \vdots & \ddots & \vdots \\ a_{m,1} & \dots & a_{m,n} \end{pmatrix},$$

where  $a_{i,j}$ , sometimes also written as  $a_{ij}$  are numbers for  $i \in \{1, \dots, m\}$  and  $j \in \{1, \dots, n\}$ .

#### A.2.1 Transpose

If  $A \in \mathbb{R}^{m \times n}$ , then the **transpose** of  $A$  is the matrix  $A^\top \in \mathbb{R}^{n \times m}$ , with  $(A^\top)_{ij} = a_{ji}$  for all  $i \in \{1, \dots, n\}$  and  $j \in \{1, \dots, m\}$ . Graphically, this can be written as

$$A^\top = \begin{pmatrix} a_{1,1} & a_{2,1} & \dots & a_{m,1} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1,n} & a_{2,n} & \dots & a_{m,n} \end{pmatrix},$$

**Definition A.1.** A matrix  $A$  is called **symmetric**, if  $A^\top = A$ .

#### A.2.2 Matrix-vector Product

If  $A \in \mathbb{R}^{m \times n}$  and  $v \in \mathbb{R}^n$ , then  $Av \in \mathbb{R}^m$  is the vector with

$$(Av)_i = \sum_{j=1}^n a_{ij} v_j$$

for all  $i \in \{1, \dots, m\}$ .

If we consider  $v$  to be a  $(n \times 1)$ -matrix instead of a vector,  $Av$  can also be interpreted as a matrix-matrix product between an  $m \times n$  and an  $n \times 1$  matrix. Using this convention,  $v^\top$  is then interpreted as an  $1 \times n$  matrix and if  $u \in \mathbb{R}^m$  we have  $u^\top A \in \mathbb{R}^{1 \times n} \cong \mathbb{R}^n$  with

$$(u^\top A)_j = \sum_{i=1}^m u_i a_{ij}$$

for all  $j \in \{1, \dots, n\}$ . Going one step further, this notation also motivates the expression  $u^\top v$  in equation (39).

### A.2.3 Matrix-matrix Product

If  $A \in \mathbb{R}^{\ell \times m}$  and  $B \in \mathbb{R}^{m \times n}$ , then  $AB \in \mathbb{R}^{\ell \times n}$  is the matrix with

$$(AB)_{ik} = \sum_{j=1}^m a_{ij} b_{jk}$$

for all  $i \in \{1, \dots, \ell\}$  and  $k \in \{1, \dots, n\}$ . This is called the **matrix product** of  $A$  and  $B$ . Note that  $A$  and  $B$  must have compatible shapes for the product to exist.

Properties:

- The matrix product is associative: if  $A$ ,  $B$  and  $C$  are matrices with shapes such that  $AB$  and  $BC$  exist, then we have  $A(BC) = (AB)C$ . It does not matter in which order we perform the matrix products here.
- The matrix product is transitive: if  $A$ ,  $B$  and  $C$  have the correct shapes, we have  $A(B + C) = AB + AC$ .
- The matrix product is *not* commutative: if  $AB$  exists, in general  $A$  and  $B$  don't have the correct shapes for  $BA$  to also exist, and even if  $BA$  exists, in general we have  $AB \neq BA$ .
- Taking the transpose swaps the order in a matrix product: we have

$$(AB)^\top = B^\top A^\top \quad (40)$$

### A.2.4 Rank

**Definition A.2.** The **rank** of a matrix  $A \in \mathbb{R}^{m \times n}$  is the dimension of the image space of  $A$ :

$$\text{rank}(A) = \dim\{Av \mid v \in \mathbb{R}^n\}.$$

The rank can also be characterised as the largest number of linearly independent columns of  $A$ , or the largest number of linearly independent rows of  $A$ . Thus, for  $A \in \mathbb{R}^{m \times n}$  we always have  $\text{rank}(A) \leq \min(m, n)$ . The matrix  $A$  is said to have “full rank” if  $\text{rank}(A) = \min(m, n)$ .

### A.2.5 Trace

**Definition A.3.** The **trace** of a matrix  $A \in \mathbb{R}^{n \times n}$  is given by

$$\text{tr}(A) = \sum_{i=1}^n a_{ii}.$$

Properties:

- $\text{tr}(A + B) = \text{tr}(A) + \text{tr}(B)$
- $\text{tr}(A^\top) = \text{tr}(A)$
- $\text{tr}(ABC) = \text{tr}(BCA) = \text{tr}(CAB)$ . The individual matrices  $A, B, C$  don't need to be square for this relation to hold, but the relation only holds for cyclic permutations as shown. In general  $\text{tr}(ABC) \neq \text{tr}(ACB)$ .

### A.2.6 Matrix Inverse

If  $A$  is a square matrix and if there is a matrix  $B$  such that  $AB = I$ , then  $A$  is called **invertible** and the matrix  $B$  is called the **inverse** of  $A$ , denoted by  $A^{-1} := B$ . Some important properties of the inverse:

- The inverse, if it exists, is unique.
- Left-inverse and right-inverse for matrices are the same:  $A^{-1}A = I$  holds if and only if  $AA^{-1} = I$ .
- If  $A$  is symmetric and invertible, then  $A^{-1}$  is also symmetric. This is true because  $A(A^{-1})^\top = (A^{-1}A)^\top = I^\top = I$  and thus  $(A^{-1})^\top$  is an inverse of  $A$ . Since the inverse is unique,  $(A^{-1})^\top = A^{-1}$ .

**Theorem A.1.** Let  $A \in \mathbb{R}^{n \times n}$ . Then the following statements are equivalent:

- $A$  is invertible
- $A$  has full rank, i.e.  $\text{rank}(A) = n$ .
- The equation  $Ax = 0$  has  $x = 0$  as its only solution.
- The equation  $Ax = b$  has exactly one solution  $x$  for every  $b \in \mathbb{R}^n$ .

### A.2.7 Orthogonal Matrices

**Definition A.4.** A matrix  $U$  is called **orthogonal**, if  $U^\top U = I = UU^\top$ .

Some important properties of orthogonal matrices:

- If  $U$  is orthogonal, the inverse and the transpose are the same:  $U^\top = U^{-1}$ .
- We have  $\|Ux\|^2 = x^\top U^\top Ux = x^\top x = \|x\|^2$ . Thus, multiplying a vector  $x$  by an orthogonal matrix  $U$  does not change its length.

### A.2.8 Positive Definite Matrices

**Definition A.5.** A symmetric matrix  $A \in \mathbb{R}^{n \times n}$  is called **positive definite**, if

$$x^\top Ax > 0$$

for all  $x \in \mathbb{R}^n$  with  $x \neq 0$ . The matrix is called **positive semi-definite**, if

$$x^\top Ax \geq 0$$

for all  $x \in \mathbb{R}^n$ .

### A.2.9 Idempotent Matrices

**Definition A.6.** The matrix  $A$  is **idempotent**, if  $A^2 = A$ .

## A.3 Eigenvalues

**Definition A.7.** Let  $A \in \mathbb{R}^{n \times n}$  be a square matrix and  $\lambda \in \mathbb{R}$ . The number  $\lambda$  is called an **eigenvalue** of  $A$ , if there exists a vector  $v \neq 0$  such that  $Ax = \lambda x$ . Any such vector  $x$  is called an **eigenvector** of  $A$  with eigenvalue  $\lambda$ .

While there are very many results about eigenvectors and eigenvalues in Linear Algebra, here we will only use a small number of these results. We summarise what we need for this module:

- If  $A$  is idempotent and  $x$  is an eigenvector with eigenvalue  $\lambda$ , then we have  $\lambda x = Ax = A^2x = \lambda Ax = \lambda^2 x$ . Thus we have  $\lambda^2 = \lambda$ . This shows that the only eigenvalues possible for idempotent matrices are 0 and 1.

**Theorem A.2.** *Let  $A \in \mathbb{R}^{n \times n}$  be symmetric. Then there is an orthogonal matrix  $U$  such that  $D := UAU^\top$  is diagonal. The diagonal elements of  $D$  are the eigenvalues of  $A$  and the rows of  $U$  are corresponding eigenvectors.*

## B Probability Reminders

### B.1 Independence

**Definition B.1.** Two random variables  $X$  and  $Y$  are (statistically) **independent**, if  $P(X \in A, Y \in B) = P(X \in A)P(Y \in B)$  for all sets  $A$  and  $B$ .

We list some properties of independent random variables:

- If  $X$  and  $Y$  are independent, and if  $f$  and  $g$  are functions, then  $f(X)$  and  $g(Y)$  are also independent.

### B.2 Expectation

The **expectation** or **mean** of a random variable  $X$  is denoted  $E(X)$ . Some properties of expectations are:

- Linearity: For all constants  $a$  and  $b$ , and random variables  $X$  and  $Y$  we have

$$\mathbb{E}(aX + bY) = a\mathbb{E}(X) + b\mathbb{E}(Y).$$

- For every constant  $c$  we have

$$\mathbb{E}(c) = c.$$

- For independent random variables  $X$  and  $Y$  we have

$$\mathbb{E}(XY) = \mathbb{E}(X)\mathbb{E}(Y).$$

### B.3 Variance

The variance of a random variable  $X$ , denoted  $\text{Var}(X)$ , measures its spread around the mean. Important properties include:

- For constants  $a$  and  $b$ , and a random variable  $X$  we have

$$\text{Var}(aX + b) = a^2 \text{Var}(X).$$

- For every constant  $c$  we have

$$\text{Var}(c) = 0$$

- For independent random variables  $X$  and  $Y$  we have

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y).$$

- The variance can be computed as

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}(X))^2) = \mathbb{E}(X^2) - (\mathbb{E}(X))^2.$$

### B.4 Covariance

The covariance between two random variables  $X$  and  $Y$ , denoted  $\text{Cov}(X, Y)$ , measures their linear relationship. Key properties are:

1. Symmetry:

$$\text{Cov}(X, Y) = \text{Cov}(Y, X)$$

2. For constants  $a, b, c$  and  $d$ , and random variables  $X$  and  $Y$  we have

$$\text{Cov}(aX + b, cY + d) = ac \text{Cov}(X, Y).$$

3. For independent random variables  $X$  and  $Y$  we have

$$\text{Cov}(X, Y) = 0.$$

4. The covariance can be computed as

$$\text{Cov}(X, Y) = \mathbb{E}((X - \mathbb{E}(X))(Y - \mathbb{E}(Y))) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y).$$

5. We have  $\text{Var}(X) = \text{Cov}(X, X)$ .

## B.5 Well-Known Distributions

### B.5.1 The Chi-Squared Distribution

**Definition B.2.** Let  $X_1, \dots, X_\nu \sim \mathcal{N}(0, 1)$  be i.i.d. Then the distribution of  $\sum_{i=1}^\nu X_i^2$  is called the  $\chi^2$ -distribution with  $\nu$  degrees of freedom. The distribution is denoted by  $\chi^2(\nu)$ .

Some important properties of the  $\chi^2$ -distribution are:

- $\chi^2$ -distributed random variables are always positive.
- If  $Y \sim \chi^2(\nu)$ , then  $\mathbb{E}(Y) = \nu$  and  $\text{Var}(Y) = 2\nu$ .
- The R command `pchisq(lx, nu)` gives the value  $\Phi_\nu(x)$  of the CDF of the  $\chi^2(\nu)$ -distribution.
- The R command `qchisq(alpha, nu)` can be used to obtain the  $\alpha$ -quantile of the  $\chi^2(\nu)$ -distribution.
- More properties can be found on Wikipedia.

### B.5.2 The t-distribution

**Definition B.3.** Let  $Z \sim \mathcal{N}(0, 1)$  and  $Y \sim \chi^2(\nu)$  be independent. Then the distribution of

$$T = \frac{Z}{\sqrt{Y/\nu}} \tag{41}$$

is called the  $t$ -distribution with  $\nu$  degrees of freedom. This distribution is denoted by  $t(\nu)$ .

Some important properties of the  $t$ -distribution are:

- The  $t$ -distribution is symmetric: if  $T \sim t(\nu)$ , then  $-T \sim t(\nu)$
- If  $T \sim t(\nu)$ , then  $\mathbb{E}(T) = 0$ .
- The R command `pt(lx, nu)` gives the value  $\Phi_\nu(x)$  of the CDF of the  $t(\nu)$ -distribution.
- The R command `qt(alpha, nu)` can be used to obtain the  $\alpha$ -quantile of the  $t(\nu)$ -distribution.
- More properties can be found on Wikipedia.