

Series 2

1. The following R-code generates an artificial dataset with predictors **x1**, **x2** and response **y**.

```
> set.seed(0)
> n<-100
> z1<-rnorm(n)
> z2<-rnorm(n)
> M=matrix(c(1,1,0.1,-0.1),2,2)
> X=t(M%*%rbind(z1,z2))
> beta<-c(0.5,-1.0)
> x1=X[,1]
> x2=X[,2]
> y=5+beta[1]*x1+beta[2]*x2 +rnorm(n)
```

- Create a plot of the observations of the two predictor variables **x1** and **x2**.
- Fit a linear model `fit1<-lm(y~x1+x2)` and print the summary using `summary(fit1)`.
- Recompute the t-value corresponding to $\hat{\beta}_1$ by hand using the estimate $\hat{\beta}_1$ and its estimated standard error $se(\hat{\beta}_1)$.
- Give the definition of a p-value. Then compute the p-value corresponding to $\hat{\beta}_1$ using the t-value from part c) and the quantile function of the t-distribution `pt()`.
Note: You need to provide the correct number of degrees of freedom.
- Report the p-value of the overall F-test and reproduce it using `anova()`.
- The overall F-test is significant. However, the p-values for **x1** and **x2** are not significant. Explain how this can be true.
- Report the residual standard error, interpret it, and recompute it based on `residuals(fit1)`.
- Report the R^2 value, interpret it, and recompute it using `residuals(fit1)`.
- Assume now that we only observed the values for **x1** and **y** whereas **x2** is a hidden predictor that we do not observe. Fit the model `fit3<-lm(y~x1)` and print the summary `summary(fit3)`. Compare the estimated coefficient corresponding to **x1** to the one in part b). Interpret the coefficient of **x1** in both models.

2. In this exercise, we will code a categorical variable by hand. The dataset **Carseats** contains the number of child car seat sales and several predictors in 400 locations. We will only use the quantitative predictor **advertising** (local advertising budget for company at each location in thousands of dollars) and the qualitative predictor **shelveLoc** (a factor with levels 'Bad', 'Good' and 'Medium' indicating the quality of the shelving location for the car seats at each site). Consider the following R code:

```
> # prepare data
> library(ISLR)
> data(Carseats) #use ?Carseats for an explanation of the dataset
> shelveLoc=Carseats$ShelveLoc
> sales=Carseats$Sales
> advertising=Carseats$Advertising
> # fit using automatic coding
> fit<-lm(sales~shelveLoc+advertising)
> summary(fit)
```

- a) Encode the factor variable `shelvelec` in the same way as done automatically by R by constructing appropriate predictors `a1` and `a2`. `a1` shall be 1 when the level of `shelvelec` is `medium` and `a2` shall be 1 if its level is `good`. The so-called *contrast coding* in this case can be seen in Table 1. Fit the model `fit_a<-lm(sales~a1+a2+advertising)`. Verify that `fit` and `fit_a` are indeed equal and give an interpretation of the coefficients corresponding to `a1` and `a2`.

R-hint:

```
> # boolean vectors for easy construction of a1, a2, b1,...
> bad<- levels(shelvelec)[1]==shelvelec
> medium<- levels(shelvelec)[3]==shelvelec
> good<- levels(shelvelec)[2]==shelvelec
> a1<-medium*1
```

Table 1: Contrast codings in a), b), c)

shelvelec	a1	a2	shelvelec	b1	b2	shelvelec	c1	c2	c3
bad	0	0	bad	1	0	bad	1	0	0
medium	1	0	medium	0	0	medium	0	1	0
good	0	1	good	0	1	good	0	0	1

- b) Construct predictor variables `b1` and `b2` according to the contrast coding in Table 1 and fit the model `fit_b<-lm(sales~b1+b2+advertising)`. Give an interpretation of the coefficients of `b1` and `b2`.
- c) Construct predictor variables `c1`, `c2` and `c3` according to Table 1. Then fit the model `fit_c<-lm(sales~c1+c2+c3+advertising)`. This causes a problem. Why?
- d) Remove the intercept by using `fit_c<-lm(-1+...)`. Interpret the coefficients corresponding to `c1`, `c2` and `c3`.
- e) Show that the fitted values are the same for `fit_a`, `fit_b` and `fit_c`.
Note: Due to rounding errors the values are not *exactly* the same. Show that they are very close.
R-hint: `max(abs(fitted(fit_a)-fitted(fit_b)))`
- f) We now want to know if distinguishing between all three categories is significantly better than distinguishing only between “bad” (level `bad`) and “not bad” (level `medium` or `good`) each time also accounting for advertising. In which of the summaries of the fits `fit_a`, `fit_b`, `fit_c` can we see this directly? Explain.
- g) Suppose we used the coding from `fit_a`. Conduct a partial F-test to check if we need to distinguish between `medium` and `good` by fitting a model `fit_d` with a new dummy variable.
3. The dataset `airline` contains the monthly number of flight passengers in the USA in the years 1949-1960 ranging from January 1949 to December 1960. Read the data with the command:
- ```
airline <- scan("http://stat.ethz.ch/Teaching/Datasets/airline.dat")
```
- a) Plot the data against time and describe what you observe.
- b) Compute the logarithm of the data and plot against time. Comment on the difference.
- c) Define a linear model of the form

$$\log(y_t) = \beta t + \sum_{j=1}^{12} \gamma_j x_{tj} + \epsilon_t$$

where the month is coded in the predictors  $x_{\cdot,1}, \dots, x_{\cdot,12}$ , i.e. for  $j \in \{1, \dots, 12\}$

$$x_{tj} = \begin{cases} 1 & \text{if } t \text{ corresponds to the } j\text{-th month in a year} \\ 0 & \text{otherwise.} \end{cases}$$

and  $t \in \{1, \dots, 144\}$  is the month index starting with 1 for January 1949. Construct appropriate predictors `t`, `x1`, ..., `x12` and fit this model in R.

**R-hint:** You should not use an intercept parameter (see 2 c)). Use `-1` in the model formula of `lm()` to exclude the intercept.

**R-hint:** `x1<-rep(c(1,rep(0,11)),12)` and `t<-1:144`.

- d) Plot the fitted values and residuals against time. Do you think that the model assumptions hold?
- e) Give an interpretation of the parameter  $\beta$  in the above model if we consider the original scale.  
**Hint:** How does a model prediction  $\hat{y}_t := \exp(\widehat{\log(y_t)})$  change if we increase  $t$  by 12?
- f) Conduct a partial F-test to check whether we can use four predictors indicating the seasons  $s_1, \dots, s_4$  ( $s_1$  for spring (month 3,4,5),  $\dots$ ,  $s_4$  for winter (month 12,1,2)) instead of twelve indicators  $x_1, \dots, x_{12}$  encoding the month.

**R-hint:** Construct appropriate predictors `s1, ..., s4` for the seasons.

**Preliminary discussion:** Friday, March 08.

**Deadline:** Friday, March 15.