



**Aufgabe 1** 8 Punkte

Consider a linear model  $Y = B\beta + \varepsilon$  according to Definition 1.4.1 with  $n \geq p$  and design matrix  $B \in \mathbb{R}^{n \times p}$  having columnwise full rank, i.e.  $\text{rank}(B) = p$ . Further, let  $y \in \mathbb{R}^n$  be a realization of  $Y$ . Then, the usual objective function for that linear model is  $\psi(\beta) := \|y - B\beta\|_2^2$ ,  $\beta \in \mathbb{R}^p$ .

with  $\|\cdot\|_2$  denoting the corresponding Euclidean norm, each of the uniquely determined least-squares estimate  $\hat{\beta}^{LS}$  of  $\beta$ . As another **loss function** for that linear model, consider  $\tilde{\psi}(\beta) := \|y - B\beta\|_2^2 + \lambda \|\beta\|_2^2$ ,  $\beta \in \mathbb{R}^p$ , with some  $\lambda > 0$ . Let the (also uniquely determined) solution of the corresponding minimization problem

$$\tilde{\beta}(\lambda) := \arg \min_{\beta \in \mathbb{R}^p} \tilde{\psi}(\beta)$$

known as ridge-estimator of  $\beta$ , be denoted by  $\tilde{\beta}^{ridge}$ . Here, we use the same notation for the estimator as for the corresponding estimator, i.e. the corresponding random variable.

Hint: The **regularized function**  $\tilde{\psi}$  can be represented as follows:

$$\tilde{\psi}(\beta) = \|y - B\beta\|_2^2 + \lambda \|\beta\|_2^2$$

with  $\tilde{B} := \begin{pmatrix} B \\ \sqrt{\lambda} I_p \end{pmatrix} \in \mathbb{R}^{(n+p) \times p}$  and  $\tilde{y} := \begin{pmatrix} y \\ 0_p \end{pmatrix} \in \mathbb{R}^{n+p}$ .

(a) Under the given assumptions, show that the following equation holds:

$$\tilde{\beta}^{ridge} = c(\lambda) \hat{\beta}^{LS}$$

with some factor  $c(\lambda) \in \mathbb{R}$ , which (only) depends on  $\lambda$ .

Calculate the factor  $c(\lambda)$  for  $\lambda = \frac{1}{4}$ .

Give the value of  $c(\lambda)$  with a precision of one decimal place.

4/5

(b) In this part, assume  $p = 2$  and that the variance parameter of the considered linear model is given by  $\sigma^2 = 9$ . Further, assume that the two estimators fulfill the following equation:

$$\tilde{\beta}^{ridge} = c(\lambda) \hat{\beta}^{LS}$$

with  $c(\lambda) = \frac{2}{\lambda + 2}$  for some suitably chosen  $\lambda > 0$ .

Calculate the entries of the covariance matrix  $\text{Cov}(\tilde{\beta}^{ridge}) = \begin{pmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{pmatrix}$ .

Give the value of  $c_{11}$ .

6

Give the value of  $c_{12}$ .

0

Calculate the entries of the covariance matrix  $\text{Cov}(\tilde{\beta}^{ridge}) = \begin{pmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{pmatrix}$ .

Give the value of  $c_{11}$ .

6

Give the value of  $c_{12}$ .

0

Give the value of  $c_{22}$ .

6

**Aufgabe 2** 12 Punkte

Let  $X_1, \dots, X_n$  be stochastically independent and identically distributed continuous random variables, each with density function  $f(x; \alpha, \beta) : \mathbb{R} \rightarrow [0, \infty)$  defined by

$$f(x; \alpha, \beta) = \begin{cases} \frac{1}{\beta} \exp\left\{-\frac{x-\alpha}{\beta}\right\} & , x \geq \alpha \\ 0 & , x < \alpha \end{cases}$$

with parameters  $\alpha \in \mathbb{R}$  and  $\beta > 0$ .

In the following tasks, round your derived numerical solutions to three decimal places, if necessary.

(a) For a given realization  $x = (x_1, \dots, x_n)'$  of  $X = (X_1, \dots, X_n)'$ , the corresponding **log-likelihood function**  $L(\alpha, \beta; x) : (0, \infty) \times \mathbb{R} \rightarrow (-\infty, \infty)$  is given by

$$L(\alpha, \beta; x) = \begin{cases} -n \log \frac{1}{\beta} - \frac{1}{\beta} \sum_{i=1}^n (x_i - \alpha) & , \alpha \leq \min\{x_1, \dots, x_n\} \\ -\infty & , \alpha < \min\{x_1, \dots, x_n\} \end{cases}$$

where  $x_{(1)} := \min\{x_1, \dots, x_n\}$  denotes the minimum of  $x = (x_1, \dots, x_n)'$ .

In this part, consider the profile likelihood approach for estimating the parameter  $\alpha$ . **Task 1** denotes the maximum likelihood estimate of the nuisance parameter  $\beta$  for fixed  $\alpha \in [0, \infty)$ .

Suppose that the following sample of size  $n = 4$  has been observed:

$$x_1 = 4, x_2 = 8, x_3 = 2, x_4 = 6$$

$$\begin{aligned} \frac{1}{a)} \psi(\beta) &= \|y - B\beta\|_2^2, \beta \in \mathbb{R}^p \\ \tilde{\psi}(\beta) &= \|y - B\beta\|_2^2 + \lambda \|B\beta\|_2^2, \beta \in \mathbb{R}^p, \lambda \geq 0 \\ &= \|\tilde{y} - \tilde{B}\beta\|_2^2, \beta \in \mathbb{R}^p \\ \arg \max (\psi(\beta)) &= \hat{\beta}^{LS} = (\tilde{B}'\tilde{B})^{-1} \tilde{B}'y = \hat{\beta}^{LS} \quad (*) \\ \Leftrightarrow \arg \max (\tilde{\psi}(\beta)) &= (\tilde{B}'\tilde{B})^{-1} \tilde{B}'\tilde{y} \\ \tilde{B}'\tilde{B} &= \begin{pmatrix} B' & \sqrt{\lambda} I_p \end{pmatrix} \begin{pmatrix} B \\ \sqrt{\lambda} I_p \end{pmatrix} = B'B + \lambda I_p = \begin{pmatrix} B'B & 0 \\ 0 & \lambda I_p \end{pmatrix} \\ \tilde{B}'\tilde{B}^{-1} &= \frac{1}{\lambda} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = \frac{1}{\lambda} I_p \quad (*)2 \\ \tilde{B}'\tilde{B}^{-1} \tilde{B}' &= \frac{1}{\lambda} I_p \begin{pmatrix} B' & \sqrt{\lambda} I_p \end{pmatrix} = \frac{1}{\lambda} \begin{pmatrix} B' & \sqrt{\lambda} I_p \end{pmatrix} \\ \tilde{B}'\tilde{B}^{-1} \tilde{B}'y &= \frac{1}{\lambda} \begin{pmatrix} B' & \sqrt{\lambda} I_p \end{pmatrix} \begin{pmatrix} y \\ 0_p \end{pmatrix} = \frac{1}{\lambda} B'y \\ \text{with } (*)1: \hat{\beta}^{LS} &= B'y \\ \arg \max (\tilde{\psi}(\beta)) &= \frac{1}{\lambda} \hat{\beta}^{LS} \\ \Rightarrow c(\lambda) &= \frac{1}{\lambda + 2}, \text{ for } \lambda = \frac{1}{4} \Rightarrow \frac{4}{5} = c(\lambda) \end{aligned}$$

b)

$$\begin{aligned} c(\lambda) &= \frac{1}{\lambda + 2} = \frac{2}{5}, \text{ for } \lambda = \frac{1}{4} \\ \text{Cov}(\tilde{\beta}^{ridge}) &= \sigma^2 (\tilde{B}'\tilde{B})^{-1} \quad (*)2 \\ &= 9 \cdot \frac{2}{5} I_2 = \begin{pmatrix} 6 & 0 \\ 0 & 6 \end{pmatrix} \end{aligned}$$

2)

Note:

The maximum likelihood estimator of the full likelihood function is  $\hat{\beta}$  for which the full likelihood function becomes maximum.

$$\begin{aligned} \Rightarrow \max(\beta) &= X_{(n)} = \min(X_1, \dots, X_n) \\ &= \alpha = \beta(\alpha) \end{aligned}$$

Note:

$$\begin{aligned} \hat{\alpha}^{MLE} &= MLE \text{ of } \alpha \\ &\rightarrow \max(L(\alpha, 2)) \\ &\Rightarrow L(\alpha, 2) = -4 \exp\left\{-\frac{\alpha}{2}\right\} \exp\left\{-\frac{1}{2}(5-2)\right\} \\ &= -4 \exp\left\{-\frac{\alpha}{2}\right\} \exp\left\{-\frac{3}{2}\right\} = -4 \exp\left\{-\frac{\alpha}{2}\right\} \end{aligned}$$

$$\begin{aligned} \max(L(\alpha, 2)) &\rightarrow \nabla L(\alpha, 2) \stackrel{!}{=} 0 \\ \rightarrow \frac{d}{d\alpha} -4 e^{-\frac{\alpha}{2}} &= -4 \cdot -\frac{1}{2} e^{-\frac{\alpha}{2}} = 2 e^{-\frac{\alpha}{2}} \\ &= -4 e^{-\frac{\alpha}{2}} + 12 e^{-\frac{\alpha}{2}} = 0 \end{aligned}$$

**1.4.8 Definition**

Let  $Y = B\beta + \varepsilon$  be a LM and  $y$  be a realization of  $Y$ . Then, a solution  $\hat{\beta}^* = \hat{\beta}^*(y)$  of the minimization problem

$$\psi(\beta) = \|y - B\beta\|_2^2$$

is called **least-squares-estimate**.

$\hat{\beta}^*(Y)$  is called **least-squares-estimator (LSE)** for  $\beta$ .

For  $\lambda \in \mathbb{R}^{k \times p}$ , a LSE of  $\lambda\beta$  is defined as  $\lambda\hat{\beta}^*(Y)$ .

**1.4.9 Theorem (LSE in LM)**

Given a LM with design matrix  $B \in \mathbb{R}^{n \times p}$ , a LSE  $\hat{\beta} = \hat{\beta}^{LS}$  is given by

$$\hat{\beta} = (B'B)^{-1} B'y$$

If  $B^+$  and  $(B'B)^+$  denote the Moore-Penrose inverse of  $B$  and  $(B'B)$  respectively, then  $\hat{\beta} = B^+y$  and  $\hat{\beta} = (B'B)^+ B'y$  with  $\psi(\hat{\beta}) = \min_{\beta \in \mathbb{R}^p} \psi(\beta)$ .

The set of all LSEs is given by  $\{\hat{\beta} = \hat{\beta}^{LS} + (I_p - B^+B)\alpha : \alpha \in \mathbb{R}^p\}$ .

**1.4.12 Corollary (LSE in LM)**

Given a LM with design matrix  $B$  satisfying  $\text{rank}(B) = p$ , the LSE  $\hat{\beta} = \hat{\beta}^{LS}$  is unique and given by

$$\hat{\beta} = (B'B)^{-1} B'y$$

**1.4.13 Remark**

In case the LSE is unique, we write for short  $\hat{\beta} = (B'B)^{-1} B'y$ .

**Properties of the LSE  $\hat{\beta}^+$**

**1.4.25 Theorem**

Given a LM with design matrix  $B$ , the LSE  $\hat{\beta}^+$  has the following properties:

- $E\hat{\beta}^+ = B^+B\beta$ ,  $\text{Cov}(\hat{\beta}^+) = \sigma^2(B^+B)^+$
- Under a NoLM,  $\hat{\beta}^+ \sim N_p(B^+B\beta, \sigma^2(B^+B)^+)$

If the design matrix  $B$  has  $\text{rank}(B) = p$ , then the (unique) LSE  $\hat{\beta} = \hat{\beta}^{LS}$  is given by

$$\hat{\beta} = (B'B)^{-1} B'y$$

In particular, we get under a NoLM,  $\hat{\beta} \sim N_p(\beta, \sigma^2(B'B)^{-1})$ .

## BLUEs and MLEs

**1.4.29 Definition**

In the situation of Theorem 1.4.28, the LSE  $\hat{\beta}$  is called **best linear unbiased estimator (BLUE)** of  $\beta$ . For  $c \in \mathbb{R}^p$ ,  $c'\beta$  is called BLUE of  $c'\beta$ .

**1.4.30 Remark**

Notice that the derivation of LSEs and BLUEs as well as their means and variances do not depend on the particular distributional assumption. However, their distributions depend on the distribution of the error term  $\varepsilon$ .

**1.4.31 Theorem**

Given a NoLM with a regular matrix  $B'B$  and unknown variance parameter  $\sigma^2 > 0$ ,  $\hat{\beta}$  is also the **Maximum Likelihood Estimator (MLE)** of  $\beta$ .

With  $P = I_n - B(B'B)^{-1}B'$ , the MLE of  $\sigma^2$  is given by  $\hat{\sigma}^2 = \frac{1}{n} Y'PY$ .

Note:

log likelihood will have the same result, since logarithm is a monotonic function  $\Rightarrow \max(\ln(L(\alpha))) = \max(L(\alpha))$

then:

$$\hat{\beta} \rightarrow \min_{\beta \in \mathbb{R}^p} \|y - B\beta\|_{\text{Fro}}^2 \quad (1.1)$$

$\beta$ .

$y$ ) has to satisfy the normal equations

3 and  $B'B$ , respectively, a solution is given

$$= y'(I_n - B(B'B)^+ B')y.$$

$z \in \mathbb{R}^p$  }.

et( $B'B$ )  $> 0$ , the unique LSE is given by

$$(B'B)^{-1} B'Y.$$

instead of  $\hat{\beta}^+$  for the LSE based on the Moore-Penrose

owing properties:

LSE  $\hat{\beta}^+$  is an unbiased estimator for  $\beta$ ,

equals the inverse matrix  $(B'B)^{-1}$ .

estimate of the nuisance parameter  $\beta$  for fixed  $\alpha \in [0, \infty]$ . Suppose that the following sample of size  $n=4$  has been observed:

$x_1 = 1, x_2 = 3, x_3 = 2, x_4 = 3$ .

(i) Based on the observed sample, calculate the corresponding estimate  $\hat{\beta}(\alpha)$  of  $\beta$  for  $\alpha = 0$ .

Give the value of  $\hat{\beta}(\alpha)$ .

2

(ii) Based on the observed sample, calculate the corresponding profile maximum likelihood estimate  $\hat{\alpha}_{\text{profile}}$  of  $\alpha$ .

same result, since logarithm is a monotonic function  $\rightarrow \max(\ln(L(\alpha))) = \max(L(\alpha))$

$$\rightarrow \frac{d}{d\alpha} \alpha^{-4} e^{-\frac{12}{\alpha}} = -4\alpha^{-5} e^{-\frac{12}{\alpha}} + \alpha^{-4} 12\alpha^{-2} e^{-\frac{12}{\alpha}}$$

$$= (-4\alpha^{-5} + 12\alpha^{-6}) e^{-\frac{12}{\alpha}} = 0$$

$$\rightarrow -\alpha^{-5} + 3\alpha^{-6} = 0$$

$$\alpha^{-5} (3\alpha^{-1} - 1) = 0$$

$$\rightarrow \alpha = 0 \text{ or } 3\alpha^{-1} - 1 = 0$$

$$3\alpha^{-1} = 1$$

$$\rightarrow \alpha = 3$$

(ii) Based on the observed sample, calculate the corresponding profile maximum likelihood estimate  $\hat{\alpha}_{\text{profile}}$  of  $\alpha$ .

Give the value of  $\hat{\alpha}_{\text{profile}}$ .

3

(b) In this part, let  $X$  be a continuous random variable with corresponding density function  $f(x; \alpha, \beta)$  given by (1) for some  $\alpha, \beta > 0$ . Further, let  $Y$  be a discrete random variable with values  $\{0, 1\}$  with the conditional distribution of  $Y$  under the condition  $X = x$ ,  $x \in (0, \infty)$ , being a Poisson distribution with parameter  $\alpha$ , i.e.,

$$P(Y=y | X=x) = P(y; \alpha), \quad x \in (0, \infty),$$

with  $P$  denoting the underlying probability distribution. Then, by conditioning on  $X$ , the expectation  $E(Y)$  of  $Y$  can be determined as follows:

$$E(Y) = E(E(Y|X)) = \int_0^\infty E(Y | X=x) f(x; \alpha, \beta) dx$$

Here,  $E(Y | X=x)$  denotes the expectation with respect to the distribution  $P(Y=y | X=x)$  for  $x \in (0, \infty)$ .

i)

$$f(x; \alpha, \beta) := \begin{cases} \frac{1}{\beta} \exp(-\frac{x}{\beta}), & x \geq \beta \\ 0, & x < \beta \end{cases}$$

$$E(Y) = \int_{-\infty}^{\infty} E(Y|X=x) f(x; \alpha, \beta) dx$$

$$\alpha = 5, \beta = 1$$

$$\rightarrow E(Y) = \int_1^\infty \frac{x}{5} \exp(-\frac{x}{5}) dx$$

$$= \frac{1}{5} \int_1^\infty x \cdot \exp(-\frac{x}{5}) dx$$

$$= \frac{1}{5} \left( \left[ 5x \exp(-\frac{x}{5}) - \int_1^\infty 5 \exp(-\frac{x}{5}) dx \right] \right)$$

$$= \frac{1}{5} \left( 5 \left[ 5 + \left[ -5 \exp(-\frac{x}{5}) \right]_1^\infty \right] \right)$$

$$= 39/5 = 7.8 \checkmark$$

Here,  $E(Y | X=x)$  denotes the expectation with respect to the distribution  $P(Y=y | X=x)$  for  $x \in (0, \infty)$ .

For  $\alpha = 5$  and  $\beta = 1$ , calculate the expectation  $E(Y)$ .

Give the value of  $E(Y)$ .

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Vorherige Aufgabe

Alle Antworten wurden gespeichert

R Task 1

Please provide numbers in the requested precision within each question. The use of different precision is evaluated as wrong.

Consider the following contingency table describing the attitude of Germans to genetically modified (GM) foods according to their income (low/middle/high). Let  $X$  denote the attitude for GM foods (against GM foods/for GM foods). This contingency table is a realization of a random contingency table with independent row probabilities  $\pi_{1+}$  and  $\pi_{2+}$  for  $j = 1, 2$  and  $j = 1, 2, 3$ .

|                  | High income | Middle income | Low income | Total |
|------------------|-------------|---------------|------------|-------|
| For GM foods     | 320         | 288           | 228        | 836   |
| Against GM foods | 150         | 165           | 112        | 427   |
| Total            | 470         | 453           | 340        | 1263  |

Read the contingency table above in R in a `data.frame` format appropriate for fitting log-linear models with the `glm` function.

(a) Provide the marginal probabilities  $\pi_{1+}$  and  $\pi_{2+}$ . (requested precision: 2 digits)

(a) Provide the marginal probabilities  $\pi_{1+}$  and  $\pi_{2+}$ . (requested precision: 2 digits)

$\pi_{1+}$

0.66

$\pi_{2+}$

0.34

(b) Fit the log-linear model of independence that estimates the expected cell frequencies  $\mu_{ij}$ ,  $i = 1, 2, j = 1, 2, 3$ , under the hypothesis of independence of the classification variables  $X$  and  $Y$ . Provide the corresponding Pearsonian residual for the case of responders having medium income and being against GM foods. Provide the value of the Pearson's  $\chi^2$  goodness of fit statistic. (requested precision: 2 digits)

Pearsonian residual for the case of responders having medium income and being against GM foods

1.2





Pearsonian residual for the case of responders having medium income and being against GM foods 1 Punkt

Zahl

Pearsons  $\chi^2$  statistic 1 Punkt

Zahl

(c) For the model fitted in (b), provide the value of the likelihood ratio statistic  $G^2$ . Further, provide the corresponding asymptotic p-value. Based on  $G^2$  and at significance level  $\alpha = 0.05$ , does the independence model adequately describe this dataset? (requested precision: 2 digits) 2 Punkte

value of likelihood ratio statistic  $G^2$  1 Punkt

Zahl

0.5 Punkte

1 2 3 4

asymptotic p-value 1.5 Punkte

Zahl

Based on  $G^2$  and at significance level  $\alpha = 0.05$ , does the independence model adequately describe this dataset? 0.5 Punkte

Bitte auswählen

(d) Fit the saturated log-linear model. Give the resulting estimate for  $\lambda$ . (requested precision: 2 digits) 2 Punkte

estimate for  $\lambda$  2 Punkte

Zahl

(e) Starting with the model in (d), select an appropriate nested model based on AIC using backward selection. Give the resulting value for AIC of this selected model. (requested precision: 2 digits) 1 Punkt

1 2 3 4

(e) Starting with the model in (d), select an appropriate nested model based on AIC using backward selection. Give the resulting value for AIC of this selected model. (requested precision: 2 digits) 1 Punkt

AIC 1 Punkt

Zahl

(f) For the model selected in (e), give the 95% asymptotic (Wald) confidence interval for the intercept (requested precision: 3 digits) 2 Punkte

lower bound 1 Punkt

Zahl

upper bound 1 Punkt

Zahl

1 2 3 4

R Task 2

Please provide numbers in the requested precision within each question. The use of different precision is evaluated as wrong.

The file `Houses.txt`, which can be downloaded by clicking on the button "Houses", contains data with information of 100 house sales in Gainesville, Florida. Find the details of the dataset below.

| attribute | description & properties  |
|-----------|---|
| case      | index   |
| price     | whether the selling price of the house (in thousands of dollars) is $\geq 200$ or not (1 = yes, 0 = no) |
| size      | size of the house (sq. ft.)   |
| new       | whether the house is new (1 = yes, 0 = no)  |
| taxes     | tax bill (dollars)  |
| bedrooms  | number of bedrooms  |
| baths     | number of bathrooms   |

Houses

1 2 3 4

(a) Load the data file into your workspace and transform the attribute `new` into a factor variable. Obtain the number of houses in the dataset for which the tax bills are greater than 3000 dollars and the number of bedrooms are at least equal to 2. 1 Punkt

value 1 Punkt

Zahl

(b) Fit a GLM using the canonical link from predicting the value of `price` using the variables `size`, `new`, `taxes`, `bedrooms`, `baths` as explanatory variables. Provide the resulting value for the estimated coefficient of the attribute `bedrooms`. (requested precision: 3 digits) 1 Punkt

value for estimated coefficient of attribute `bedrooms` 1 Punkt

Zahl

(c) Let  $\beta_4$  denote the coefficient of the attribute `taxes` in the model fitted in (b) above. Test at significance level  $\alpha = 0.01$  the hypotheses  $H_0: \beta_4 = 0$  versus  $H_1: \beta_4 \neq 0$ . Base your test on

1 2 3 4



(c) Let  $\beta_4$  denote the coefficient of the attribute **taxes** in the model fitted in (b) above. Test at significance level  $\alpha = 0.01$  the hypotheses  $H_0: \beta_4 = 0$  versus  $H_1: \beta_4 \neq 0$ . Base your test on the Wald's test statistic and provide the  $p$ -values and your decision. (requested precision: 3 digits) 1 Punkt

p-value 0.5 Punkte  
Zahl

decision 0.5 Punkte  
Score & explanation

(d) Based on the model fitted in (b), predict the probability of having a price  $\geq 200$  thousands dollars for a house that is new, has a size of 1000 square feet, a tax bill of 1200 dollars, 2 bedrooms and 2 baths. (requested precision: 3 digits) 3 Punkte

(d) Based on the model fitted in (b), predict the probability of having a price  $\geq 200$  thousands dollars for a house that is new, has a size of 1000 square feet, a tax bill of 1200 dollars, 2 bedrooms and 2 baths. (requested precision: 3 digits) 3 Punkte

predicted probability 3 Punkte  
Zahl

(e) For the model fitted in (b), compute 95% profile likelihood confidence interval for  $\beta_6$  (coefficient of **baths**). (requested precision: 3 digits)\* 2 Punkte

lower bound 1 Punkt  
Zahl

upper bound 1 Punkt  
Zahl

(d) Obtain the area under the curve (AUC) for the ROC curve of the model in (b). (requested precision: 2 digits) 2 Punkte

AUC 2 Punkte  
Zahl

Vorherige Aufgabe

Alle Antworten wurden gespeichert

