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**Exam Statistical Inference (WI4455)**  
**April 17, 2019, 13.30–16.30**

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- This is an open book exam.
- Unless stated differently, always add an explanation to your answer.
- Please write on top of your exam:

*I declare that I have made this examination on my own, with no assistance and in accordance with the TU Delft policies on plagiarism, cheating and fraud.*

and add your signature below.

- You can write down your answers on your own piece of paper, but please write down your name, student number, and course number on the first page and a page number on each piece of paper. When you are done, take a photo of your work or scan your work and send me your work as one pdf-file by email [f.h.vandermeulen@tudelft.nl](mailto:f.h.vandermeulen@tudelft.nl). Please ensure that a photo of your student ID card is also in the file (on one of the photos that are combined to a pdf file).
  - In case of questions about the exam, or technical problems at an earlier stage, send me an email at [f.h.vandermeulen@tudelft.nl](mailto:f.h.vandermeulen@tudelft.nl); I'll be monitoring my inbox the entire duration of the exam.
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1. Define the probability density function

$$f(x; \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{-\alpha-1} e^{-\beta/x} \mathbf{1}_{[0, \infty)}(x),$$

where  $\alpha$  and  $\beta$  are strictly positive parameters and  $\Gamma$  is the Gamma-function.

- (a) Verify that  $f$  is of exponential family type.
  - (b) Suppose  $X_1, \dots, X_n$  are independent and identically distributed with density  $f$ . Derive a sufficient statistic for  $(\alpha, \beta)$  and argue why it is complete. *Hint: natural parameter space.*
  - (c) We now consider the Bayesian viewpoint. Suppose  $X_1, \dots, X_n$  are independent with density  $f$ , conditional on  $\beta$ . Assume  $\beta \sim \text{Exp}(2)$ . Derive an expression for the posterior density of  $\beta$ , while assuming  $\alpha$  is fixed (that is, known).
  - (d) Now suppose also  $\alpha$  is endowed with a prior distribution: assume  $\alpha \sim \text{Exp}(1)$ . Give the steps of an MCMC-algorithm to draw from the posterior of  $(\alpha, \beta)$ .
2. (a) Suppose  $X \sim N(0, \psi)$ . Derive an expression for the Fisher-information  $I(\psi)$ . Note that  $\psi > 0$  is the variance of the Normal distribution, so there is no square appearing.

- (b) Suppose  $h : (0, \infty) \rightarrow (0, \infty)$  is bijective, differentiable, with differentiable inverse. Show that if we parametrise by  $h(\psi)$  instead of  $\psi$ , then the Fisher information satisfies  $I_h(\psi) = h'(\psi)^2 I(h(\psi))$ . Here  $I_h(\psi)$  denotes the Fisher-information when  $h(\psi)$  is used as parametrisation.
3. Assume  $p$  pairs of observations  $(X_1, Y_1), \dots, (X_p, Y_p)$ , where all pairs are assumed conditionally independent upon parameters  $\theta_1, \dots, \theta_p$ . We further assume  $X_i \sim N(0, 1)$  and  $Y_i \mid X_i = x \sim N(\theta_i x, 1)$ .
- Following a Bayesian approach, assume that the parameters are random quantities themselves. Hence, write the parameters as  $\Theta_1, \dots, \Theta_p$  and assume these random variables are independent with  $N(0, \tau^2)$ -distribution. Find The Bayes estimator for  $\Theta_i$  under squared error loss.
  - Determine  $E Y_i^2$  and use this result to define a method of moments estimator for  $\tau^2$ .
  - Derive empirical Bayes estimators for  $\theta_i$  ( $i \in \{1, \dots, p\}$ ) by combining parts (a) and (b).
  - Now consider a frequentist approach and derive the maximum likelihood estimator for  $\theta_i$  ( $i \in \{1, \dots, p\}$ )
4. Suppose  $X_1, \dots, X_n$  are identically distributed and independent, conditional on the parameter  $\Theta$ . Assume we endow  $\Theta$  with a prior distribution.
- For  $c > 0$  consider the loss function

$$L_c(\theta, a) = \Psi(c(\theta - a)) \quad \text{with} \quad \Psi(x) = e^x - x - 1.$$

We consider the Bayes rule for estimating  $\theta$  using  $L_c$ . What is considered more costly, under- or over estimation of  $\theta$ ?

- Show that the Bayes rule satisfies

$$d_c(x_1, \dots, x_n) = -\frac{1}{c} \log \int e^{-c\theta} f_{\Theta \mid X_1, \dots, X_n}(\theta_1 \mid x_1, \dots, x_n) d\theta.$$

- What is the Bayes rule in the limit where we let  $c \downarrow 0$ ? Sketch the main argument, you don't have to be fully rigorous.