

# Modeling and System Identification – Microexam 2

Prof. Dr. Moritz Diehl, IMTEK, Universität Freiburg December 18, 2017, 08:15-09:45, Freiburg

Surname:

First Name:

Matriculation number:

Subject:

Programme: Bachelor  Master  Lehramt  others

Signature:

Please fill in your name above and tick exactly ONE box for the right answer of each question below.

1. Give an approximation of the covariance  $\Sigma_{\hat{\theta}}$  of a maximum likelihood (ML) estimate. The model is given as  $y_N = \Phi_N \theta + \epsilon_N$  with  $\epsilon_N \sim \mathcal{N}(0, \Sigma_\epsilon)$ ,  $Q_N = \Phi_N^\top \Phi_N$  and  $L(\theta, y_N)$  is the negative log likelihood function.  $\Sigma_{\hat{\theta}} \approx \dots$

(a) <input type="checkbox"/> $\Phi_N^\top \Sigma_{\epsilon_N} \Phi_N$	(b) <input type="checkbox"/> $(\Phi_N^\top \Sigma_{\epsilon_N}^{-1} \Phi_N)^{-1}$	(c) <input type="checkbox"/> $Q_N^{-1}$	(d) <input type="checkbox"/> $\nabla_{\theta}^2 L(\theta, y_N)$
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2. Given the probability density function  $p_X(x) = \theta e^{-\theta x}$  for  $x \geq 0$  (and 0 otherwise) with unknown  $\theta$  and positive i.i.d. measurements  $y_N = [y(1), y(2), \dots, y(N)]^T$  that are assumed to follow the above distribution, what is the minimisation problem you need to solve for a ML-estimate of  $\theta$ ? The problem is:  $\min_{\theta} \dots$ ?

(a) <input type="checkbox"/> $\ \theta e^{-\theta y(k)}\ _2^2$	(b) <input type="checkbox"/> $-N \log(\theta) + \theta \sum_{k=1}^N y(k)$
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(c) <input type="checkbox"/> $\ y(k) - \theta e^{-\theta}\ _2^2$	(d) <input type="checkbox"/> $-\log \sum_{k=1}^N \theta e^{-\theta y(k)}$
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3. For the problem in the previous question, what is a lower bound on the covariance  $\Sigma_{\hat{\theta}}$  for any unbiased estimator  $\hat{\theta}(y_N)$ , assuming that  $\theta_0$  is the true value?  $\Sigma_{\hat{\theta}} \succeq \dots$

(a) <input type="checkbox"/> $N/\theta^2$	(b) <input type="checkbox"/> $\theta_0^2/N$
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(c) <input type="checkbox"/> $(\int_{y_N} N \theta^{N-2} \exp[-\theta \sum_k y_k] dy_N)^{-1}$	(d) <input type="checkbox"/> $\int_{y_N} N \theta_0^{N-2} \exp[-\theta \sum_k y_k] dy_N$
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4. Suppose you are given the Fisher information matrix  $M = \int_{y_N} \nabla_{\theta}^2 L(\theta_0, y_N) \cdot p(y_N | \theta_0) dy_N$  of the corresponding problem, what is the relation with the covariance matrix  $\Sigma_{\hat{\theta}}$  of your estimate  $\hat{\theta}$ ?

5. Give the name of the theorem that provides us with the above result.

6. Given a set of measurements  $y_N = [y(1), y(2), \dots, y(N)]^T$  with i.i.d. Gaussian noise and the linear model  $y_N = \Phi \theta$ , where  $\Phi = [\varphi(1), \varphi(2), \dots, \varphi(N)]^T$ , which of the following minimisation problems is solved at each iteration step of the RLS algorithm to estimate the parameter  $\hat{\theta}(N+1)$  after  $N+1$  measurements?  $\hat{\theta}(N+1) = \arg \min_{\theta} \frac{1}{2} (\dots)$

(a) <input type="checkbox"/> $\ \theta - \hat{\theta}(N)\ _2^2 + \ y(N+1) - \varphi(N+1)^\top \theta\ _2^2$	(b) <input type="checkbox"/> $\ y_N - \Phi_N \cdot \theta\ _{Q_N}^2$
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(c) <input type="checkbox"/> $\ \theta - \hat{\theta}(N)\ _{Q_N}^2 + \ y(N) - \varphi(N)^\top \theta\ _2^2$	(d) <input type="checkbox"/> $\ y_{N+1} - \Phi_{N+1} \cdot \theta\ _2^2$
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7. In  $L_1$  estimation the measurement errors are assumed to follow a  $\dots$  distribution and it is generally speaking more  $\dots$  to outliers compared to  $L_2$  estimation.

(a) <input type="checkbox"/> Laplace, robust	(b) <input type="checkbox"/> Gaussian, robust	(c) <input type="checkbox"/> Gaussian, sensitive	(d) <input type="checkbox"/> Laplace, sensitive
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8. Write a general expression for an Auto Regressive model with Exogenous Inputs (ARX) with output errors:

9. The PDF of a random variable  $Y$  is given by  $p(y) = \frac{1}{2\sqrt{2\pi}} \exp(-\frac{1}{2} \frac{\|y-\theta\|_2^2}{4})$ , with unknown  $\theta \in \mathbb{R}$ . We obtained three measurements,  $y(1) = 2$ ,  $y(2) = 4$ , and  $y(3) = 6$ . What is the minimizer  $\theta^*$  of the negative log-likelihood function ?

(a) <input type="checkbox"/> 6	(b) <input type="checkbox"/> 3	(c) <input type="checkbox"/> 5	(d) <input type="checkbox"/> 4
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10. Which of the following statements is **NOT** correct. Recursive Least Squares (RLS):

(a) <input type="checkbox"/> implicitly assumes that there is only i.i.d. and Gaussian measurement noise	(b) <input type="checkbox"/> computes an estimation with a computational cost independent of the number of past measurements
(c) <input type="checkbox"/> can be used as an alternative to Maximum Likelihood Estimation	(d) <input type="checkbox"/> can use prior knowledge on the estimated parameter $\theta$

11. We want to estimate the resistance  $R$  of a new metal and we found in the only existing previous article that an estimate of  $R$  is given by  $5[\Omega]$  with standard deviation  $0.25\Omega$ . Our own measurement apparatus sets a current  $I$  as a noise-free input, and measures the output voltage  $V$  which has Gaussian errors with a standard deviation of  $0.1[V]$ . Given a set of  $N$  measurements,  $[V(1), \dots, V(N)]$  obtained from a set  $[I(1), \dots, I(N)][A]$ , what function is minimized by the Bayesian Maximum-A-Posteriori (MAP) estimator in this context? To simplify notation we assume that all variables are made unitless.

(a) <input type="checkbox"/> $\frac{(R-10)^2}{0.5} + \sum_{i=1}^N \frac{(V(i)-I(i)R)^2}{0.1}$	(b) <input type="checkbox"/> $\frac{(R-5)^2}{0.0625} + \sum_{i=1}^N 100(V(i) - I(i)R)^2$
(c) <input type="checkbox"/> $0.5(R-10)^2 + \sum_{i=1}^N 0.1(V(i) - I(i)R)^2$	(d) <input type="checkbox"/> $\frac{(R-10)^2}{0.5} + \sum_{i=1}^N \frac{(V(i)/I(i)-R)^2}{0.1}$

12. Which of the following models with input  $u(k)$  and output  $y(k)$  is **NOT** linear-in-the-parameters w.r.t.  $\theta \in \mathbb{R}^2$ ?

(a) <input type="checkbox"/> $y(k) = \theta_1 \sqrt{u(k)} + \theta_2 u(k)$	(b) <input type="checkbox"/> $y(k) = y(k-1) \cdot (\theta_1 + \theta_2 u(k))$
(c) <input type="checkbox"/> $y(k) = \theta_1 u(k)^4 + \theta_2 \exp(u(k))$	(d) <input type="checkbox"/> $y(k) = \theta_1 \exp(\theta_2 u(k))$

13. Which of the following models is time invariant?

(a) <input type="checkbox"/> $\ddot{y}(t)^2 = u(t)^t + e^{u(t)}$	(b) <input type="checkbox"/> $t \cdot \ddot{y}(t) = u(t)^3$	(c) <input type="checkbox"/> $\dot{y}(t) = 5u(t) + t$	(d) <input type="checkbox"/> $\dot{y}(t) = \sqrt{u(t)}$
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14. By which of the following formulas is the joint distribution for  $N$  independent measurements  $y_N \in \mathbb{R}^N$  given?  $p(y_N|\theta) = \dots$

(a) <input type="checkbox"/> $\sum_{i=0}^N p(y(i) \theta)$	(b) <input type="checkbox"/> $\int_{y_N} p(y \theta) dy$	(c) <input type="checkbox"/> $\sum_{i=0}^N p(y(i) \theta)^2$	(d) <input type="checkbox"/> $\prod_{i=0}^N p(y(i) \theta)$
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15. Which of the following statements about Maximum A Posteriori (MAP) estimation is not true

(a) <input type="checkbox"/> $\hat{\theta}_{\text{MAP}} = \arg \min_{\theta \in \mathbb{R}} [-\log(p(y_N \theta)) - \log(p(\theta))]$	(b) <input type="checkbox"/> MAP assumes a linear model
(c) <input type="checkbox"/> MAP is a generalization of ML	(d) <input type="checkbox"/> MAP requires a-priori knowledge on $\theta$

16. Assume a model  $h_i(\theta)$  and measurements  $y_i, i = 1, \dots, N$ . The PDF to obtain a measurement  $y_i$  for a parameter  $\theta$  is known to be proportional to  $\exp(-|y_i - h_i(\theta)|)$  and measurement noises uncorrelated. What function of  $\theta$  does the MLE minimize?

(a) <input type="checkbox"/> $\sum_{i=1}^N  y_i - h_i(\theta) $	(b) <input type="checkbox"/> $ \sum_{i=1}^N y_i - \sum_{i=1}^N h_i(\theta) $
(c) <input type="checkbox"/> $\frac{1}{2} \ h(\theta) - y\ _2^2$	(d) <input type="checkbox"/> $\sum_{i=1}^N (y_i - h_i(\theta))^2$

17. Regard the LLS estimate  $\hat{\theta}$  minimizing  $f(\theta) = \|y_N - \Phi_N \theta\|_2^2$ , where measurements are generated by  $y_N = \Phi_N \theta_0 + \epsilon_N$  with  $\theta_0$  the unknown true value, and  $\epsilon_N = (\epsilon(1), \dots, \epsilon(N))^T$  the measurement errors (i.i.d., zero mean, variance  $\sigma^2$ , but not necessarily Gaussian). What would be the covariance matrix  $\Sigma_{\hat{\theta}}$  of  $\hat{\theta}$ ?

(a) <input type="checkbox"/> $\sigma^2 (\Phi_N^T \Phi_N)^{-1}$	(b) <input type="checkbox"/> $\sigma (\Phi_N^+) (\Phi_N^+)^T$
(c) <input type="checkbox"/> not computable	(d) <input type="checkbox"/> $(\Phi_N^T \sigma^2 \Phi_N)^{-1}$