

# Exercise sheet 5

Lars Kühnischel  
Nicolas Wolf

## Task 2. M-Step in a linear Gaussian state space model

Consider a linear Gaussian state space model.

$$\begin{aligned} z_t &= A z_{t-1} + C z_t + \epsilon, & \epsilon &\sim N(0, \Sigma) \\ x_t &= B z_t + \eta, & \eta &\sim N(0, \Gamma) \end{aligned}$$

In the lecture we derived the M-step to determine the transition matrix  $A$  and last week you derived the M-step for the covariance matrix  $\Sigma$ . Now, derive the M-step for the latent control variable  $C$ , the factor loading matrix  $B$  and for the observation noise covariance matrix  $\Gamma$  by maximizing the expected log-likelihood  $E[\log p(X, Z)]$ , with respect to  $C$ ,  $B$ , and  $\Gamma$  where  $X = \{x_t\}_{t=1}^T$  and  $Z = \{z_t\}_{t=1}^T$  are the sets of all latent states and observations from time 1 to  $T$ . (Hints: First spell out the ELBO for this model and then identify the parts in the ELBO that explicitly depends on the parameters and ignore the rest. Keep in mind that you want all maximization to depend only on  $E[z_t]$ ,  $E[z_t z_t^T]$ , and  $E[z_{t-1} z_{t-1}^T]$ . The matrix cookbook by Petersen and Pedersen (2012) <https://www.math.uwaterloo.ca/~hwolkowi/matrixcookbook.pdf> provides a helpful summary for matrix algebra).

2

$$\begin{aligned} E[\log p(X, Z | \theta)] &= E\left[\log\left[p(z_1)p(x_1|z_1)\prod_{t=2}^T p(z_t|z_{t-1})p(x_t|z_t)\right]\right] \\ &= E_q\left[\log p(z_1)\right] + E_q\left[\sum_{t=2}^T \log p(z_t|z_{t-1})\right] + E_q\left[\sum_{t=1}^T \log p(x_t|z_t)\right] \\ &= E_q\left[-\frac{M}{2}\log(2\pi) - \frac{1}{2}\log|\Sigma| - \frac{1}{2}(z_1 - \mu_0)^T \Sigma^{-1}(z_1 - \mu_0)\right] \\ &\quad + E\left[\sum_{t=2}^T \left(-\frac{M}{2}\log(2\pi) - \frac{1}{2}\log|\Sigma| - \frac{1}{2}(z_t - A z_{t-1} - C s_t)^T \Sigma^{-1}(z_t - A z_{t-1} - C s_t)\right)\right] \\ &\quad + E\left[-\frac{MT}{2}\log(2\pi) - \frac{T}{2}\log|\Gamma| - \frac{1}{2}\sum_{t=1}^T (x_t - B z_t)^T \Gamma^{-1}(x_t - B z_t)\right] \end{aligned}$$

a) C:

$$\begin{aligned} \leadsto E[\log p(X, Z)] &= -\frac{1}{2} E\left[\sum_{t=2}^T (z_t - A z_{t-1} - C s_t)^T \Sigma^{-1}(z_t - A z_{t-1} - C s_t)\right] + \text{const} \\ &= -\frac{1}{2} E\left[\sum_{t=2}^T \left(-z_t^T \Sigma^{-1} C s_t + z_{t-1}^T A^T \Sigma^{-1} C s_t + s_t^T C^T \Sigma^{-1} C s_t \right. \right. \\ &\quad \left. \left. - s_t^T C^T \Sigma^{-1} z_t + s_t^T C^T \Sigma^{-1} A z_{t-1}\right)\right] + \text{const} \\ &= -\frac{1}{2} \left[\sum_{t=2}^T \left(-E[z_t^T] \Sigma^{-1} C s_t + E[z_{t-1}^T] A^T \Sigma^{-1} C s_t + s_t^T C^T \Sigma^{-1} C s_t \right. \right. \\ &\quad \left. \left. - s_t^T C^T \Sigma^{-1} E[z_t] + s_t^T C^T \Sigma^{-1} A E[z_{t-1}]\right)\right] + \text{const} \end{aligned}$$

$$\bullet \partial_x (a^T x b)^{(30)} = a b^T$$

$$\bullet \partial_x (a^T x^T b)^{(31)} = b a^T$$

$$\bullet \partial_x (b^T x^T D x c)^{(32)} = D^T x b c^T + D x c b^T$$

$$\Rightarrow \bullet \partial_c (E[z_t^T] \Sigma^{-1} C s_t) = (E[z_t^T] \Sigma^{-1})^T \cdot s_t^T = \Sigma^{-1} E[z_t] s_t^T = \Sigma^{-1} E[z_t] s_t^T$$

$$\bullet \partial_c (E[z_{t-1}^T] A^T \Sigma^{-1} C s_t) = (E[z_{t-1}^T] A^T \Sigma^{-1})^T \cdot s_t^T = \Sigma^{-1} A E[z_{t-1}] \cdot s_t^T$$

$$\bullet \partial_c (s_t^T C^T \Sigma^{-1} C s_t) = \Sigma^{-1} C s_t s_t^T + \Sigma^{-1} C s_t s_t^T = 2 \Sigma^{-1} C s_t s_t^T$$

$$\bullet \partial_c (s_t^T C^T \Sigma^{-1} E[z_t]) = \Sigma^{-1} E[z_t] s_t^T$$

$$\bullet \partial_c (s_t^T C^T \Sigma^{-1} A E[z_{t-1}]) = \Sigma^{-1} A E[z_{t-1}] \cdot s_t^T$$

$$\Rightarrow 0 \stackrel{!}{=} \partial_c E[\log p(X, Z | \theta)]$$

$$\begin{aligned} &= -\frac{1}{2} \sum_{t=2}^T \left[ -\Sigma^{-1} E[z_t] s_t^T + \Sigma^{-1} A E[z_{t-1}] s_t^T + 2 \Sigma^{-1} C s_t s_t^T \right. \\ &\quad \left. - \Sigma^{-1} E[z_t] s_t^T + \Sigma^{-1} A E[z_{t-1}] s_t^T \right] \end{aligned}$$

$$\stackrel{2.2}{\Rightarrow} 0 = \sum_{t=2}^T -E[z_t] s_t^T + A E[z_{t-1}] s_t^T + C s_t s_t^T$$

$$\Rightarrow C \sum_{t=2}^T s_t s_t^T = \sum_{t=2}^T (E[z_t] - A E[z_{t-1}]) s_t^T$$

$$\Rightarrow C = \left( \sum_{t=2}^T (E[z_t] - A E[z_{t-1}]) s_t^T \right) \cdot \left( \sum_{t=2}^T s_t s_t^T \right)^{-1}$$

b)  $\beta$ :

$$\begin{aligned} \sim E[\log p(x, z | \theta)] &= -\frac{1}{2} E\left[\sum_{t=2}^T (x_t - \beta z_t)^T \Gamma^{-1} (x_t - \beta z_t)\right] + \text{const} \\ &= -\frac{1}{2} E\left[\sum_{t=2}^T -x_t^T \Gamma^{-1} \beta z_t - z_t^T \beta^T \Gamma^{-1} x_t + z_t^T \beta^T \Gamma^{-1} \beta z_t\right] + \text{const} \\ &= -\frac{1}{2} \sum_{t=2}^T \left[-x_t^T \Gamma^{-1} \beta E[z_t] - E[z_t^T] \beta^T \Gamma^{-1} x_t + \text{tr}(\beta^T \Gamma^{-1} \beta E[z_t z_t^T])\right] + \text{const} \end{aligned}$$

$$\begin{aligned} \Gamma \cdot \partial_x (a^T x b) &\stackrel{(20)}{=} a b^T \quad \cdot \partial_x (a^T x^T b) \stackrel{(21)}{=} b a^T \\ \cdot \partial_x \text{tr}(x^T B x C) &\stackrel{(19)}{=} B x C + B^T x C^T \quad \Gamma^T = \Gamma \\ \Rightarrow \cdot \partial_\beta (x_t^T \Gamma^{-1} \beta E[z_t]) &= (x_t^T \Gamma^{-1})^T E[z_t] = \Gamma^{-1} x_t E[z_t^T] \\ \cdot \partial_\beta (E[z_t^T] \beta^T \Gamma^{-1} x_t) &= \Gamma^{-1} x_t E[z_t^T] \quad \underbrace{\Gamma^{-1}} = \Gamma^{-1} \quad \underbrace{E[z_t z_t^T]} = E[z_t z_t^T] \\ \cdot \partial_\beta (\text{tr}(\beta^T \Gamma^{-1} \beta E[z_t z_t^T])) &= \Gamma^{-1} \beta E[z_t z_t^T] + \Gamma^{-T} \beta E[z_t z_t^T]^T = 2 \Gamma^{-1} \beta E[z_t z_t^T] \end{aligned}$$

$$\begin{aligned} \Rightarrow 0 &\stackrel{!}{=} \partial_\beta E[\log p(x, z | \theta)] \\ &= -\frac{1}{2} \sum_{t=2}^T \left[ \Gamma^{-1} x_t E[z_t^T] - \Gamma^{-1} x_t E[z_t^T] + 2 \Gamma^{-1} \beta E[z_t z_t^T] \right] \end{aligned}$$

$$\stackrel{\Gamma^{-1}}{\Rightarrow} \beta \sum_{t=2}^T E[z_t z_t^T] = \sum_{t=2}^T x_t E[z_t^T]$$

$$\Rightarrow \beta = \left( \sum_{t=2}^T x_t E[z_t^T] \right) \cdot \left( \sum_{t=2}^T E[z_t z_t^T] \right)^{-1}$$

c)  $\Gamma$ :

$$\begin{aligned} E[\log p(x, z | \theta)] &= -\frac{1}{2} E\left[\text{tr} \log |\Gamma| + \sum_{t=2}^T (x_t - \beta z_t)^T \Gamma^{-1} (x_t - \beta z_t)\right] \\ &= -\frac{1}{2} \log |\Gamma| - \frac{1}{2} E\left[\sum_{t=2}^T x_t^T \Gamma^{-1} x_t - x_t^T \Gamma^{-1} \beta z_t - z_t^T \beta^T \Gamma^{-1} x_t + z_t^T \beta^T \Gamma^{-1} \beta z_t\right] \\ &= -\frac{1}{2} \log |\Gamma| - \frac{1}{2} \sum_{t=2}^T \left[ x_t^T \Gamma^{-1} x_t - x_t^T \Gamma^{-1} \beta E[z_t] - E[z_t^T] \beta^T \Gamma^{-1} x_t + \text{tr}(\beta^T \Gamma^{-1} \beta E[z_t z_t^T]) \right] \end{aligned}$$

$$\begin{aligned} \Gamma \cdot \partial_x \log |x| &\stackrel{(57)}{=} x^{-T} \quad \cdot \partial_x (a^T x^{-1} b) \stackrel{(61)}{=} -x^{-T} a b^T x^{-T} \\ \cdot \partial_x (\text{tr}(A x^{-1} B)) &\stackrel{(63)}{=} - (x^{-1} B A x^{-1})^T = -x^{-T} A^T B^T x^{-T} \\ \Rightarrow \cdot \partial_\Gamma \log |\Gamma| &= \Gamma^{-T} = \Gamma^{-1} \\ \cdot \partial_\Gamma (x_t^T \Gamma^{-1} x_t) &= -\Gamma^{-T} x_t x_t^T \Gamma^{-T} = -\Gamma^{-1} x_t x_t^T \Gamma^{-1} \\ \cdot \partial_\Gamma (x_t^T \Gamma^{-1} \beta E[z_t]) &= -\Gamma^{-T} x_t (E[z_t^T] \beta^T \Gamma^{-T}) = -\Gamma^{-1} x_t E[z_t^T] \beta^T \Gamma^{-1} \\ \cdot \partial_\Gamma (E[z_t^T] \beta^T \Gamma^{-1} x_t) &= -\Gamma^{-T} (E[z_t^T] \beta^T)^T x_t^T \Gamma^{-T} = -\Gamma^{-1} \beta E[z_t] x_t^T \Gamma^{-1} \\ \cdot \partial_\Gamma (\text{tr}(\beta^T \Gamma^{-1} \beta E[z_t z_t^T])) &= -\Gamma^{-T} \beta (E[z_t z_t^T])^T \Gamma^{-T} = -\Gamma^{-1} \beta E[z_t z_t^T] \beta^T \Gamma^{-1} \end{aligned}$$

$$\begin{aligned} \Rightarrow 0 &\stackrel{!}{=} \partial_\Gamma E[\log p(x, z | \theta)] \\ &= -\frac{1}{2} \Gamma^{-1} - \frac{1}{2} \sum_{t=2}^T \left[ -\Gamma^{-1} x_t x_t^T \Gamma^{-1} + \Gamma^{-1} x_t E[z_t^T] \beta^T \Gamma^{-1} + \Gamma^{-1} \beta E[z_t] x_t^T \Gamma^{-1} - \Gamma^{-1} \beta E[z_t z_t^T] \beta^T \Gamma^{-1} \right] \end{aligned}$$

$$\stackrel{-2\Gamma^{-1} \cdot \Gamma}{\Rightarrow} 0 = \text{tr} \Gamma - \sum_{t=2}^T \left[ x_t x_t^T - (x_t E[z_t^T] \beta^T + \beta E[z_t] x_t^T) + \beta E[z_t z_t^T] \beta^T \right]$$

$$\Rightarrow \Gamma = \frac{1}{T} \sum_{t=2}^T \left[ x_t x_t^T - (x_t E[z_t^T] \beta^T + \beta E[z_t] x_t^T) + \beta E[z_t z_t^T] \beta^T \right]$$