

# Exercise Sheet 8

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## Gauss-Markov Models

### 1. Kalman Filters

For the Kalman prediction we get:

$$\begin{aligned} p(x_t|Y_{0:t-1}) &= \int p(x_t|x_{t-1}) p(x_{t-1}|Y_{0:t-1}) dx_{t-1} \\ &= \int \mathcal{N}(x_t; Ax_{t-1}, Q) \cdot \left( \int \mathcal{N}(x_{t-1}; Ax_{t-2}, Q) \cdot p(x_{t-2}|Y_{0:t-2}) \right) \end{aligned}$$

Through this recursive property going back to state  $x_0$  with  $p(x_0) = \mathcal{N}(x_0; m_0^-, P_0^-)$  one can see that:  $p(x_t|Y_{0:t-1}) = \mathcal{N}(x_t; Am_{t-1}, AP_{t-1}A^\top + Q)$ .

For the Kalman estimation we get:

$$\begin{aligned} p(x_t|Y_{0:t}) &= \frac{p(y_t|x_t) p(x_t|Y_{0:t-1})}{p(y_t)} \\ &= \frac{\mathcal{N}(y_t; Hx_t, R) \int p(x_t|x_{t-1}) p(x_{t-1}|Y_{0:t-1}) dx_{t-1}}{\sum_{j=1}^n \mathcal{N}(y_t; Hx_t, R) \mathcal{N}(x_t; m_t^-, P_t^-)} \\ &= \frac{\mathcal{N}(y_t; Hx_t, R) \mathcal{N}(x_t; m_t^-, P_t^-)}{\sum_{j=1}^n \mathcal{N}(y_t; Hx_t, R) \mathcal{N}(x_t; m_t^-, P_t^-)} \\ &= \mathcal{N}\left(x_t; m_t^- + P_t^- H^\top (HP_t^- H^\top + R)^{-1} (y_t - Hm_t^-), (I - P_t^- H^\top (HP_t^- H^\top + R)^{-1} H) P_t^-\right) \end{aligned}$$

Which is essentially  $\mathcal{N}(x_t; m_t^- + K_t (y_t - Hm_t^-), (I - KH)P_t^-)$  for  $K_t := P_t^- H^\top (HP_t^- H^\top + R)^{-1}$ .

For the Rauch-Tung-Striebel smoothed estimation we get:

$$\begin{aligned} p(x_t|Y) &= p(x_t|Y_{0:t}) \int p(x_{t+1}|x_t) \frac{p(x_{t+1}|Y)}{p(x_{t+1}|Y_{0:t})} dx_{t+1} \\ &= \mathcal{N}(x_t; m_t, P_t) \int \mathcal{N}(x_{t+1}; Ax_t, Q) \frac{p(x_{t+1}|Y)}{\mathcal{N}(x_{t+1}; m_{t+1}, P_{t+1})} dx_{t+1} \end{aligned}$$

## 2. Stochastic Differential Equations

$$\begin{aligned} m(t) &= e^{F(t-t_0)} x_0 \\ k(t_a, t_b) &= \int_{t_0}^{\min(t_a, t_b)} e^{F(t_a-\tau)} LL^\top e^{F^\top(t_b-\tau)} d\tau = \left[ -\frac{LL^\top e^{F^\top(t_b-\tau)+F(t_a-\tau)}}{F + F^\top} \right]_{t_0}^{\min(t_a, t_b)} \end{aligned}$$

(a)

Starting off with  $F = 0$  and  $L = \theta$  and substituting in the equations from above gives:

$$\begin{aligned} m(t) &= e^{0(t-t_0)} x_0 \\ &= x_0 \\ k(t_a, t_b) &= \int_{t_0}^{\min(t_a, t_b)} e^{F(t_a-\tau)} LL^\top e^{F^\top(t_b-\tau)} d\tau \\ &= \int_{t_0}^{\min(t_a, t_b)} e^{0(t_a-\tau)} \theta\theta^\top e^{0^\top(t_b-\tau)} d\tau \\ &= \int_{t_0}^{\min(t_a, t_b)} \theta\theta^\top d\tau \\ &= \int_{t_0}^{\min(t_a, t_b)} \theta\theta^\top d\tau \\ &= \left[ \theta\theta^\top \tau \right]_{t_0}^{\min(t_a, t_b)} \\ &= \theta\theta^\top \cdot \min(t_a, t_b) - \theta\theta^\top t_0 \\ &= \theta^2(\min(t_a, t_b) - t_0) \end{aligned}$$

(b)

Starting off with  $F = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$  and  $L = \begin{bmatrix} 0 \\ \theta \end{bmatrix}$  and substituting in the equations from above gives:

$$\begin{aligned} m(t) &= e^{F(t-t_0)} x_0 \\ &= e^{Ft-Ft_0} x_0 \end{aligned}$$

Computing  $Ft - Ft_0$  gives the matrix  $A = \begin{bmatrix} 0 & t - t_0 \\ 0 & 0 \end{bmatrix}$ , also rewriting  $e^x := \sum_{n=0}^{\infty} \frac{x^n}{n!}$  gives:

$$\begin{aligned} m(t) &= e^A x_0 \\ &= x_0 \sum_{n=0}^{\infty} \frac{A^n}{n!} \\ &= x_0 \sum_{n=0}^{\infty} \frac{\begin{bmatrix} 0 & t - t_0 \\ 0 & 0 \end{bmatrix}^n}{n!} \end{aligned}$$

Now looking at the matrix A shows, that it is nilpotent for all  $n \geq 2$  this yields the following:

$$\begin{aligned} m(t) &= x_0 \left( \frac{\begin{bmatrix} 0 & t - t_0 \\ 0 & 0 \end{bmatrix}^1}{1!} + \frac{\begin{bmatrix} 0 & t - t_0 \\ 0 & 0 \end{bmatrix}^0}{0!} \right) \\ &= x_0 \left( \begin{bmatrix} 0 & t - t_0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right) \\ &= \begin{bmatrix} 1 & t - t_0 \\ 0 & 1 \end{bmatrix} x_0 \end{aligned}$$

Using the general solution for the integral of the kernel and rewriting  $e^x := \sum_{n=0}^{\infty} \frac{x^n}{n!}$  again gives the following:

$$\begin{aligned} k(t_a, t_b) &= \left[ - \frac{LL^\top e^{F^\top(t_b - \tau) + F(t_a - \tau)}}{F + F^\top} \right]_{t_0}^{\min(t_a, t_b)} \\ &= \left[ - \frac{[0 \ \theta^2] \sum_{n=0}^{\infty} \frac{(F^\top(t_b - \tau) + F(t_a - \tau))^n}{n!}}{F + F^\top} \right]_{t_0}^{\min(t_a, t_b)} \end{aligned}$$

Because  $F$  is nilpotent for all  $n \geq 2$  this yields the following:

$$\begin{aligned}
k(t_a, t_b) &= \left[ - \frac{\begin{bmatrix} 0 \\ \theta^2 \end{bmatrix} \cdot \left( \frac{(F^\top(t_b - \tau) + F(t_a - \tau))^1}{1!} + \frac{(F^\top(t_b - \tau) + F(t_a - \tau))^0}{0!} \right)}{F + F^\top} \right]_{t_0}^{\min(t_a, t_b)} \\
&= \left[ - \frac{\begin{bmatrix} 0 \\ \theta^2 \end{bmatrix} \cdot \left( F^\top(t_b - \tau) + F(t_a - \tau) + I \right)}{F + F^\top} \right]_{t_0}^{\min(t_a, t_b)} \\
&= \left[ - \frac{\begin{bmatrix} 0 \\ \theta^2 \end{bmatrix} \cdot \left( \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} (t_b - \tau) + \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} (t_a - \tau) + I \right)}{\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}} \right]_{t_0}^{\min(t_a, t_b)} \\
&= \left[ - \frac{\begin{bmatrix} 0 \\ \theta^2 \end{bmatrix} \cdot \begin{bmatrix} 1 & t_a - \tau \\ t_b - \tau & 1 \end{bmatrix}}{\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}} \right]_{t_0}^{\min(t_a, t_b)} \\
&= \left[ - \frac{\begin{bmatrix} \theta^2(t_a - \tau) \\ \theta^2 \end{bmatrix}}{\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}} \right]_{t_0}^{\min(t_a, t_b)} \\
&= \left[ \begin{bmatrix} \theta^2(t_a - \tau) \\ \theta^2 \end{bmatrix} \cdot \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}^{-1} \right]_{t_0}^{\min(t_a, t_b)} \\
&= \left[ \begin{bmatrix} \theta^2(t_a - \tau) \\ \theta^2 \end{bmatrix} \cdot \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix} \right]_{t_0}^{\min(t_a, t_b)} \\
&= \left[ \begin{bmatrix} -\theta^2 \\ -\theta^2(t_a - \tau) \end{bmatrix} \right]_{t_0}^{\min(t_a, t_b)} \\
&= \begin{bmatrix} -\theta^2 \\ -\theta^2(t_a - \min(t_a, t_b)) \end{bmatrix} - \begin{bmatrix} -\theta^2 \\ -\theta^2(t_a - t_0) \end{bmatrix} \\
&= \begin{bmatrix} 0 \\ \theta^2 \min(t_a, t_b) - \theta^2 t_0 \end{bmatrix} \\
&= \begin{bmatrix} 0 \\ \theta^2(\min(t_a, t_b) - t_0) \end{bmatrix}
\end{aligned}$$

(c)

Starting off with  $F = -\xi$  and  $L = \theta$  and substituting in the equations from above gives:

$$m(t) = e^{-\xi(t-t_0)}x_0$$

Using the general solution for the integral of the kernel gives the following:

$$\begin{aligned} k(t_a, t_b) &= \left[ -\frac{\theta\theta^\top e^{(-\xi)^\top(t_b-\tau)+(-\xi)(t_a-\tau)}}{(-\xi) + (-\xi)^\top} \right]_{t_0}^{\min(t_a, t_b)} \\ &= \left[ -\frac{\theta^2 e^{-\xi(t_a+t_b-2\tau)}}{-2\xi} \right]_{t_0}^{\min(t_a, t_b)} \\ &= \left( -\frac{\theta^2 e^{-\xi(t_a+t_b-2\min(t_a, t_b))}}{-2\xi} \right) - \left( -\frac{\theta^2 e^{-\xi(t_a+t_b-2t_0)}}{-2\xi} \right) \\ &= \frac{-(\theta^2 e^{-\xi(t_a+t_b-2\min(t_a, t_b))}) + \theta^2 e^{-\xi(t_a+t_b-2t_0)}}{-2\xi} \\ &= \frac{\theta^2 e^{-\xi(t_a+t_b)}(e^{2\xi\min(t_a, t_b)} + e^{2\xi t_0})}{-2\xi} \end{aligned}$$

(d)

Starting off with  $F = \begin{bmatrix} 0 & 1 \\ -\xi^2 & -2\xi \end{bmatrix}$  and  $L = \begin{bmatrix} 0 \\ \theta \end{bmatrix}$  and using the hint we first compute the eigenvalues  $\lambda$  from  $F$ :

$$\begin{aligned} \det(\lambda I - F) &= \det\left(\begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} - \begin{bmatrix} 0 & 1 \\ -\xi^2 & -2\xi \end{bmatrix}\right) \\ &= \det\left(\begin{bmatrix} \lambda & -1 \\ \xi^2 & \lambda + 2\xi \end{bmatrix}\right) \\ &= \lambda(\lambda + 2\xi) + \xi^2 \\ &= \lambda^2 + 2\xi\lambda + \xi^2 \end{aligned}$$

Solving the characteristic polynomial gives the eigenvalues  $\lambda$ :

$$\begin{aligned} \lambda_{1,2} &= \frac{-2\xi \pm \sqrt{(2\xi)^2 - 4 \cdot 1 \cdot \xi^2}}{2} \\ \lambda_1 &= -\xi \\ \lambda_2 &= -\xi \end{aligned}$$

The eigenvectors are acquired by solving  $Fx = \lambda x$  like:

$$\begin{aligned} \begin{bmatrix} 0 & 1 \\ -\xi^2 & -2\xi \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} &= \lambda \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\ \begin{bmatrix} 0 & 1 \\ -\xi^2 & -2\xi \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} &= \begin{bmatrix} -\xi x_1 \\ -\xi x_2 \end{bmatrix} \\ \text{I} \quad 0 \cdot x_1 + 1 \cdot x_2 &= -\xi x_1 \\ \text{II} \quad -\xi^2 x_1 - 2\xi x_2 &= -\xi x_2 \end{aligned}$$

This yields the eigenvector for  $\lambda = -\xi$  with  $x_\lambda = \lambda \begin{bmatrix} 1 \\ -1 \end{bmatrix}$ . If we try to compute the mean we get:

$$\begin{aligned} m(t) &= e^{F(t-t_0)} x_0 \\ &= e^{Ft-Ft_0} x_0 \end{aligned}$$

Computing  $Ft - Ft_0$  gives the matrix  $A = \begin{bmatrix} 0 & t-t_0 \\ \xi^2(t_0-t) & 2\xi(t_0-t) \end{bmatrix}$ , also rewriting  $e^x := \sum_{n=0}^{\infty} \frac{x^n}{n!}$  gives:

$$\begin{aligned} m(t) &= e^A x_0 \\ &= x_0 \sum_{n=0}^{\infty} \frac{A^n}{n!} \\ &= x_0 \sum_{n=0}^{\infty} \frac{\begin{bmatrix} 0 & t-t_0 \\ \xi^2(t_0-t) & 2\xi(t_0-t) \end{bmatrix}^n}{n!} \end{aligned}$$

Unfortunately the matrix  $F$  isn't nilpotent nor diagonalizable, so we need to use jordan normal form.  $F$  can therefore be written as  $F = VJV^{-1}$ , where  $J$  is the jordan normal form with  $J = D + N$ , with the diagonal matrix of eigenvalues  $D$  and a nilpotent matrix  $N$ . This leads to  $J = \begin{bmatrix} -\xi & 1 \\ 0 & -\xi \end{bmatrix}$  for our example. We can now rewrite  $e^F = e^{VJV^{-1}} = Ve^JV^{-1} = V(e^De^N)V^{-1}$  which shows that all  $n \geq 2$  for the sum notation of  $e^F$  cancel. This leads to:

$$\begin{aligned} m(t) &= x_0 \left( \frac{(Ft - Ft_0)^1}{1!} + \frac{(Ft - Ft_0)^0}{0!} \right) \\ &= x_0 \left( \begin{bmatrix} 0 & t-t_0 \\ \xi^2(t_0-t) & 2\xi(t_0-t) \end{bmatrix} + I \right) \\ &= \begin{bmatrix} 1 & t-t_0 \\ \xi^2(t_0-t) & 2\xi(t_0-t) + 1 \end{bmatrix} x_0 \end{aligned}$$