

$$x_t = Ax_{t-1} + \epsilon_t$$

$$y_t = Hx_t + \eta_t$$

$$t=1, 2, \dots, T$$

$$\epsilon_t \sim \mathcal{N}(0, Q)$$

$$\eta_t \sim \mathcal{N}(0, R)$$

$$x_1 \sim \mathcal{N}(\mu_0, Q_0)$$

Prediction :

$$P(x_t | y_{1:t-1})$$

Filtering :

$$P(x_t | y_{1:t})$$

Smoothing :

$$P(x_t | y_{1:T})$$

$$P(x_1) \approx \mathcal{N}(\mu_0, Q_0)$$

$$P(y_1 | x_1) = \mathcal{N}(Hx_1, R)$$

$$P(x_1 | y_1) = \frac{P(y_1 | x_1) \cdot P(x_1)}{\int P(y_1 | x_1) \cdot P(x_1)} \quad (\text{Bayes Rule})$$

$$= P(y_1)$$

At $t = 1$

$$P(x_1) = \mathcal{N}(x_1; \mu_0, Q_0)$$

$$P(y_1 | x_1) = \mathcal{N}(y_1; Hx_1, R)$$

We know, that

$$\text{If } p(x) = \mathcal{N}(x; \mu, \Sigma)$$

$$p(y|x) = \mathcal{N}(y; Hx + d, \Gamma)$$

then

$$p(x|y) = \mathcal{N}(\mu_{x|y}, \Sigma_{x|y})$$

where,

$$(\Sigma^{-1} - \Gamma^{-1} H^T \Gamma^{-1} H)^{-1}$$

Bayes
Rule
Gaussian

$$\Sigma_{x|y} = (\Sigma^{-1} + H^T \Gamma^{-1} H)$$

$$\mu_{x|y} = (\Sigma^{-1} + H^T \Gamma^{-1} H)^{-1} [H^T \Gamma^{-1} (y - d) + \Sigma^{-1} \mu]$$

Plugging this into the problem above:

$$p(x_i | y_i) = \mathcal{N}(\mu_{i|i}, P_{i|i}), \text{ where}$$

$$P_{i|i} = (Q_0^{-1} + C^T R^{-1} C)^{-1}$$

$$\mu_{i|i} = (Q_0^{-1} + C^T R^{-1} C)^{-1} [C^T R^{-1} y_i + Q_0^{-1} \mu_0]$$

By the Woodbury Matrix Identity:

$$(A + B D^{-1} C)^{-1} = A^{-1} - A^{-1} B (D + C A^{-1} B)^{-1} C A^{-1}$$

Therefore,

$$\begin{aligned} P_{i|i} &= (Q_0^{-1} + C^T R^{-1} C)^{-1} = Q_0 - \underbrace{Q_0 C^T (R + C Q_0 C^T)^{-1} C}_{=K} Q_0 \\ &= (I - K C) Q_0. \end{aligned}$$

Now,

$$\begin{aligned} &(Q_0^{-1} + C^T R^{-1} C)^{-1} C^T R^{-1} \\ &= (I - K C) Q_0 C^T R^{-1} \\ &= Q_0 C^T R^{-1} - Q_0 C^T (R + C Q_0 C^T)^{-1} C Q_0 C^T R^{-1} \\ &= Q_0 C^T \underbrace{(I - (R + C Q_0 C^T)^{-1} C Q_0 C^T)}_{(I + R^{-1} \cdot C Q_0 C^T)^{-1}} R^{-1} \end{aligned}$$

Now,

$$\begin{aligned}(I + AB)^{-1} A &= A (I + BA)^{-1} \\&= Q_0 C^T R^{-1} (I + C Q_0 C^T R^{-1})^{-1} \\&= Q_0 C^T R^{-1} (R R^{-1} + C Q_0 C^T R^{-1})^{-1} \\&= Q_0 C^T R^{-1} [(R + C Q_0 C^T) R^{-1}]^{-1} \\&= Q_0 C^T R^{-1} [R (R + C Q_0 C^T)^{-1}] \\&= Q_0 C^T (R + C Q_0 C^T)^{-1} = K_1\end{aligned}$$

Therefore,

$$P_{1|1} = (I - KC) Q_0$$

$$\mu_{1|1} = \underbrace{(Q_0^{-1} + C^T R^{-1} C)^{-1} C^T R^{-1}}_{= K} y_1 + \underbrace{(Q_0^{-1} + C^T R^{-1} C)^{-1} Q_0^{-1} \mu_0}_{(I - KC) Q_0}$$

$$\mu_{1|1} = K_1 y_1 + (I - KC) \cancel{Q_0}^{\hat{I}} Q_0 \mu_0$$

$$= \mu_0 + K_1 (y_1 - \underbrace{C \mu_0}_{\text{predicted mean of } y_1})$$

↳ predicted mean
of y_1