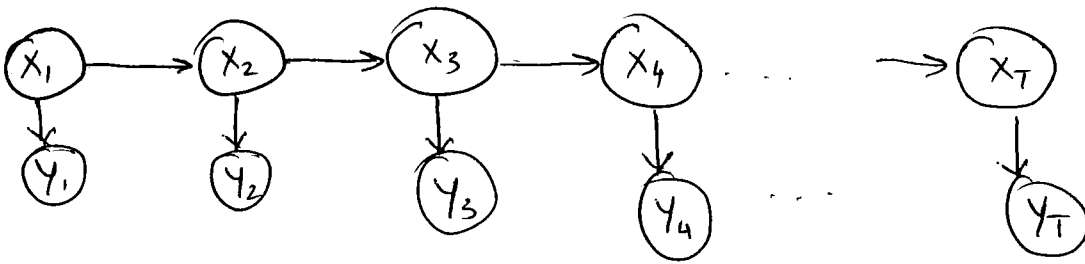


# Kalman Filtering

Vinayak Rao



$x_1 \sim \mathcal{N}(m_0, \Sigma_0)$  Gaussian prior distribution on  $\boxed{x_i \in \mathbb{R}^D}$

$x_i = Ax_{i-1} + \epsilon_i$ ,  $\epsilon_i \sim \mathcal{N}(0, \Sigma_\epsilon)$  Linear Gaussian dynamics.

$y_i = Bx_i + \xi_i$ ,  $\xi_i \sim \mathcal{N}(0, \Sigma_z)$  Linear Gaussian observations  $y_i \in \mathbb{R}^d$

$P(x_1, \dots, x_T, y_1, \dots, y_T) \rightarrow$  A big Gaussian.  ~~$\mathbb{R}^d$~~   $(T(D+d))$ -dimensional

$P(x_1, \dots, x_T | y_1, \dots, y_T) \rightarrow$  Gaussian conditional

①  $P(x_i | y_1, \dots, y_T) \rightarrow$  Gaussian marginal.

Can't calculate directly because of large matrices involved. Is  $O(T^3)$ .

Calculating  
Equation ① is the smoothing problem.

$$P(x_i | y_1 \dots y_T) = \frac{P(x_i, y_1 \dots y_T)}{P(y_1 \dots y_T)} \leftarrow \text{A constant that doesn't depend on } x_i, \text{ discard it.}$$

$$\propto P(x_i, y_1 \dots y_T)$$

$$= P(x_i, y_1 \dots y_i) P(y_{i+1} \dots y_T | x_i, y_1 \dots y_i)$$

$$= P(x_i, y_1 \dots y_i) P(y_{i+1} \dots y_T | x_i) \quad (\text{Markov property})$$

$$= \alpha_i(x_i) \beta_i(x_i) \leftarrow \text{Backward message, information from the future.}$$

Forward message: Information from the past & present

$$\text{Note: } \alpha_i(x_i) = P(x_i | y_1 \dots y_i) \propto P(x_i | y_1 \dots y_i).$$

Calculating this is the filtering problem.

$$\alpha_i(x_i) = P(x_i, y_1 \dots y_i) = \int P(x_i, x_{i-1}, y_1 \dots y_i) dx_{i-1}$$

$$= \int P(x_{i-1}, y_1 \dots y_{i-1}) P(x_i | x_{i-1}, y_1 \dots y_{i-1}) P(y_i | x_i, x_{i-1}, y_1 \dots y_{i-1}) dx_{i-1}$$

$$= \int \alpha_{i-1}(x_{i-1}) P(x_i | x_{i-1}) P(y_i | x_i) dx_{i-1} \quad (\text{Markov}).$$

↑  
New filtering estimate

↑  
Previous filtering estimate

↑  
Prediction

↑  
Update with new data

We thus have a recursion relating  $\alpha_i$  to  $\alpha_{i-1}$ . Given  $\alpha_{i-1}$  we need to solve the above integral over  $x_{i-1}$  (and NOT  $\{x_1 \dots x_{i-1}\}$ )

Convince yourself that the integral is solvable (even if you might not know the exact solution). In particular, convince yourself that the integrand is of the form  $Z_{i-1} \exp(-\frac{1}{2}(x_{i-1} - \mu_{i-1})^T \Sigma_{i-1}^{-1} (x_{i-1} - \mu_{i-1}))$ , for some parameters  $Z_{i-1}, \mu_{i-1}, \Sigma_{i-1}$ . This <sup>does</sup> not depend on  $T$ .

Now, we can successively calculate  $\alpha_1, \alpha_2 \dots \alpha_T$ . Overall, this is  $O(T)$

We have solved the filtering problem, now on to the smoothing problem.  
How do we calculate  $\beta_i(x_i)$ ?

$$\begin{aligned}\beta_i(x_i) &= P(y_{i+1} \dots y_T | x_i) = \int P(y_{i+1}, \dots, y_T, x_{i+1} | x_i) dx_{i+1} \\ &= \int P(x_{i+1} | x_i) P(y_{i+1} | x_{i+1}, x_i) P(y_{i+1}, \dots, y_T | x_i, x_{i+1}, y_{i+1}) dx_{i+1} \\ &= \int P(x_{i+1} | x_i) P(y_{i+1} | x_{i+1}) \beta_{i+1}(x_{i+1}) dx_{i+1}. \quad \textcircled{1}\end{aligned}$$

We now have a backward recursion for  $\beta_i$  from  $\beta_{i+1}$ .

$$\begin{aligned}\text{Also } \beta_{T-1}(x_{T-1}) &= P(y_T | x_{T-1}) = \int P(y_T, x_T | x_{T-1}) dx_T \\ &= \int P(x_T | x_{T-1}) P(y_T | x_T) dx_T. \quad \textcircled{2}\end{aligned}$$

Again, convince yourself that eqs ① & ② are solvable.

We can thus successively calculate  $\beta_{T-1}, \beta_{T-2} \dots \beta_1$ .

This is the backward message passing stage.

Now,  $P(x_i | y_1 \dots y_T) \propto \alpha_i(x_i) \beta_i(x_i)$ .

We have both terms, and can also calculate the normalization term.

Extra:- Can you calculate  $P(x_i, x_{i+1} | y_1 \dots y_T)$  as a function of the  $\alpha$ 's,  $\beta$ 's and the system parameters?