

Lecture 20: State-space models - Kalman filters

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Derivation of Kalman filter - Update

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PREDICT:

$$p(x_{n-1} | y_{1:n-1}, u_{0:n-2}) = \mathcal{N}(x_{n-1} | \mu_{n-1}, \Sigma_{n-1})$$

Then Predict:

$$p(x_n | y_{1:n-1}, u_{0:n-2}, u_{n-1}) = \mathcal{N}(x_n | \underbrace{A\mu_{n-1} + Bu_{n-1}}_{\mu_n^P}, \underbrace{A\Sigma_{n-1}A^T + Q}_{\Sigma_n^P})$$

UPDATE:

$$\underbrace{p(x_n | y_{1:n}, u_{0:n-1})}_G \propto \underbrace{p(y_n | x_n)}_{\text{Emission}} \underbrace{p(x_n | y_{1:n-1}, u_{0:n-1})}_{\mathcal{N}(\mu_n^P, \Sigma_n^P)}$$

(complete

the square



$$p(x_n | y_{1:n}, u_{0:n-1}) = \mathcal{N}(x_n | \mu_n, \Sigma_n)$$

$$\mu_n = \underbrace{\mu_n^P}_{d \times 1} + \underbrace{K_n}_{d \times d} (\underbrace{y_n - C\mu_n^P}_{1 \times d})$$

$$\Sigma_n = \Sigma_n^P - \underbrace{K_n}_{d \times d} \underbrace{C}_{1 \times d} \underbrace{\Sigma_n^P}_{d \times d}$$

Kalman gain :

$$K_n = \underbrace{\Sigma_n^P}_{d \times d} \underbrace{C^T}_{d \times 1} \underbrace{(C \Sigma_n^P C^T + R)^{-1}}_{1 \times 1}$$

$d \times 1$