

Lecture 20: State-space models - Kalman filters

Professor Ilias Bilonis

Derivation of Kalman filter - Update

Derivation of Kalman filter - Update

PREDICT:

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

Then Predict:

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

μ_n^P - for prediction, likelihood

Σ_n^P

use prediction

UPDATE:

posterior: $p(x_n | y_{1:n}, u_{0:n-1}) \propto p(y_n | x_n) p(x_n | y_{1:n-1}, u_{0:n-1})$

Bayes

Emission

$\mathcal{N}(Cx_n, R)$

$\mathcal{N}(\mu_n^P, \Sigma_n^P)$

(complete \Rightarrow the square)



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

$$\mu_n = \mu_n^P + K_n (y_n - C\mu_n^P)$$

correction term

$$\Sigma_n = \Sigma_n^P - K_n C \Sigma_n^P$$

correction term

Kalman gain :

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

way to carry this out so you don't need to invert (computationally expensive)