LGBIO2060: Modelling of biological systems

Session 5 : Kalman filter

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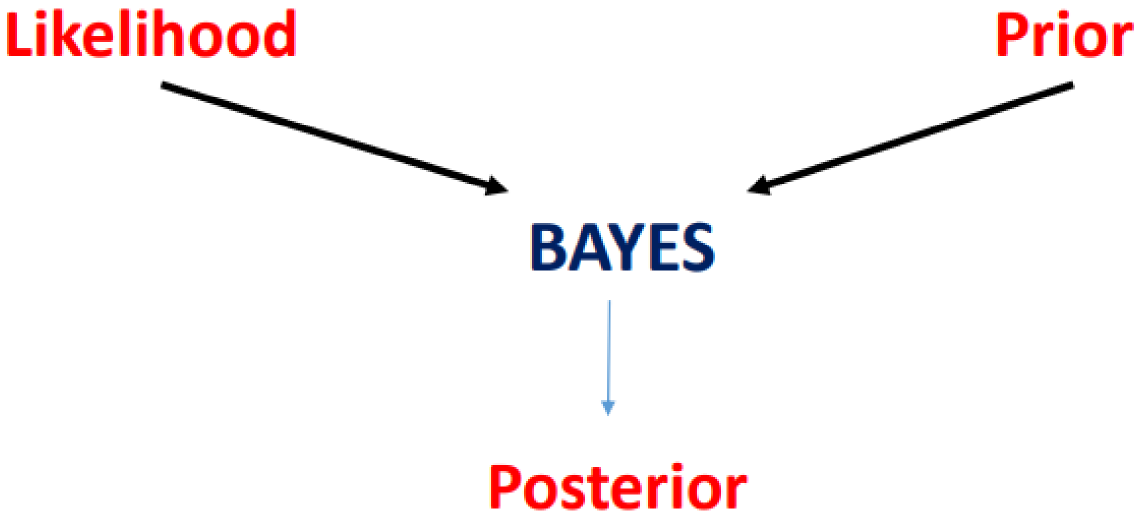
What have we seen until now ?

- Sensory inputs are noisy, delayed and uncertain

→ For a given stimulus, we end up with a distribution of probable true location of the latent state (=the likelihood)

- If we have prior knowledge of how the system works we can have some additional information (=the prior)

Bayes Theorem



Worked for a discrete stimulus and prior!
What about continously varying stimulii???

Dynamical system

A dynamical system (DS) can be described by its dynamics :

$$\dot{x}(t) = Ax(t) + noise(t)$$

$$x[t+1] = Ax[t] + noise[t]$$

!!! The state x can be a vector (for example we track x- and y- positions of the fly)

Dynamical system-Observation

Consider the discrete LDS :

$$x[t+1] = Ax[t] + noise[t]$$

Sensory inputs => We cannot know x exactly, we have to observe it

$$y[t] = Hx[t] + observation\_noise[t]$$

Kalman filter

At every time step, combines likelihood and prior with weighting factor related to the trust in these two

$$\hat{x}[t+1] = trust_{prior} x_{prior} + trust_{likelihood} x_{likelihood}$$

$$\hat{x}[t+1] = A\hat{x}[t] + K[t](y[t] - H\hat{x}[t])$$

K is the kalman gain evaluated at that time (this is the weighting factor), computed recursively

Example : plane position

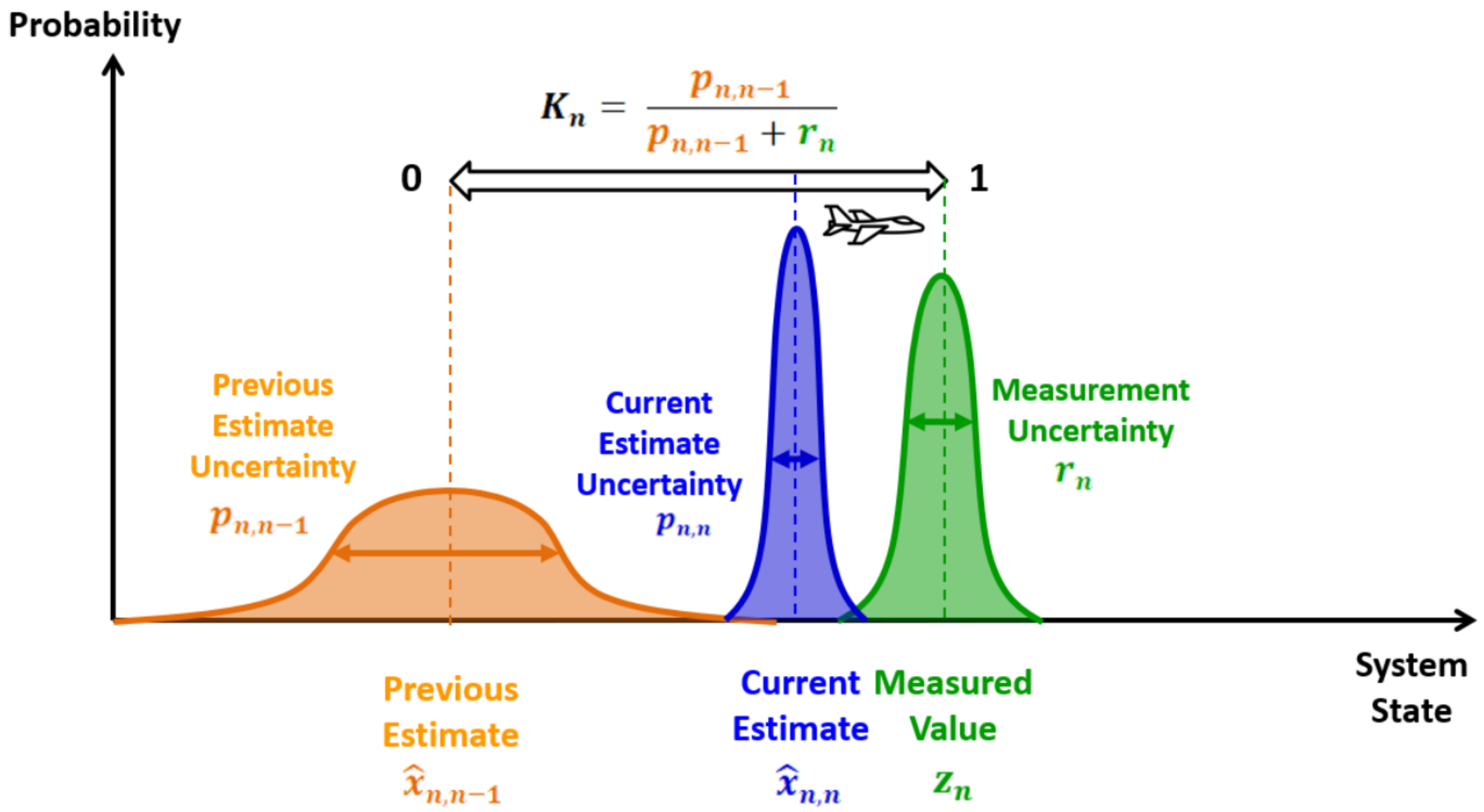


Image from : https://www.kalmanfilter.net/kalman1d.html

Exercise session

- Model 2D dynamical system
- Kalman 1D : Intuition
- Bonus : Kalman with the 2D model