

TAM 598 Lecture 19 :

# State Space Models – Filtering

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Announcements:

- HW 5 covers lectures 17-20; due on Fri Apr 18

## State Space Models - Filtering

\* given a dynamical system, we observe a noisy measurement of the system's state and want to figure out the actual state

our stochastic dynamical system is described by state variables  $\underline{x}_t$  at discrete time steps  $t = 0, 1, 2, \dots, n$ .

Given a closed system (no external perturbations) then

transition probability  $\rightarrow$

$$P(\underline{x}_{n+1} \mid \underline{x}_{0:n}) = P(\underline{x}_{n+1} \mid \underline{x}_n)$$

Markov property - state at  $n+1$  depends ONLY on the state at  $n$ .

This means:

$$\left\{ \begin{array}{l} p(x_{0:1}) = \underbrace{p(x_0)}_{\text{red}} p(x_1 | x_0) \\ p(x_{0:2}) = \underbrace{p(x_{0:1})}_{\text{red}} p(x_2 | x_{0:1}) \\ = \underbrace{p(x_0)}_{\text{red}} p(x_1 | x_0) p(x_2 | x_1) \\ p(x_{0:3}) = \underbrace{p(x_{0:2})}_{\text{red}} p(x_3 | x_{0:2}) \\ = \underbrace{p(x_0)}_{\text{red}} p(x_1 | x_0) p(x_2 | x_1) p(x_3 | x_2) \end{array} \right.$$

Joint  
density  
of sequences  
over  
all states

$$P(x_{0:n}) = p(x_0) \prod_{t=0}^{n-1} p(x_{t+1} | x_t)$$

Now we introduce observations - sensors that measure something  $\tilde{y}_t$  at each time step.

Assume  $\tilde{y}_t$  only depends on the state of the system at time  $t$ ,  $\tilde{x}_t$

$$P(\tilde{y}_t \mid \tilde{x}_{0:t}) = P(\tilde{y}_t \mid \tilde{x}_t)$$

} ← emission probability

Then the joint probability density of the system state and the observations is

$$P(\tilde{x}_{0:n}, \tilde{y}_{1:n}) = P(\tilde{x}_0) \prod_{t=0}^{n-1} P(\tilde{x}_{t+1} \mid \tilde{x}_t) P(\tilde{y}_t \mid \tilde{x}_t)$$

Next we introduce controls - at every timestep, we pass a control command  $u_{\tilde{n}t}$  to the system that affects where the system state goes in the next time step.

For a Markovian system

$$P(x_{t+1} \mid x_{0:t}, u_{0:t}) = P(x_{\tilde{n}t+1} \mid x_t, u_t)$$

transition  
prob. w/  
controls

and the joint probability density is

$$P(x_{0:n}, y_{1:n} \mid u_{0:n-1}) = p(x_0) \prod_{t=0}^{n-1} p(x_{\tilde{n}t+1} \mid x_t, u_t) p(y_{\tilde{n}t} \mid x_t)$$

Filtering Problem - estimate the current state given all data

$$P(\underline{x}_n \mid \underline{y}_{1:n}, \underline{u}_{0:n})$$

Smoothing - estimating all states (including the past) given all data

$$P(\underline{x}_{0:n} \mid \underline{y}_{1:n}, \underline{u}_{0:n-1})$$

$$\begin{aligned} P(A \mid B, C) &= \\ P(A, B \mid C) &\Big/ P(B \mid C) \end{aligned}$$

$$\frac{P(\underline{x}_{0:n}, \underline{y}_{1:n} \mid \underline{u}_{0:n-1})}{P(\underline{y}_{1:n} \mid \underline{u}_{0:n-1})}$$

$$\propto P(\underline{x}_0) \prod_{t=0}^{n-1} P(\underline{x}_{t+1} \mid \underline{x}_t, \underline{u}_t) P(\underline{y}_t \mid \underline{x}_t)$$

Example: linear transitions and gaussian emission probabilities  
via equations

↳ initial conditions

$$x_{\sim 0} = \underline{m}_0 + z_{\sim 0}$$

↙  
fixed parameter

$$z_{\sim 0} \sim N(0, \underline{\underline{v}})$$

↳ transitions

$$x_{\sim t+1} = \underline{A} x_{\sim t} + \underline{B} u_{\sim t} + z_{\sim t}$$

$\underline{A} = \underline{x}_t$      $\underline{B} = \underline{u}_t$

$$z_{\sim t} \sim N(0, \underline{\underline{Q}}) \quad \text{where } \underline{\underline{Q}} \text{ is process covariance}$$

↳ emissions

$$y_t = \underline{C} x_t + \underline{w}_t$$
$$\rightarrow N(0, \underline{\underline{R}})$$

$\underline{\underline{R}}$  is our measurement covariance

Example: linear transitions and gaussian emission probabilities  
via probabilistic modeling

↳ initial conditions

$$p(x_0) = N(x_0 | \underline{\mu}_0, \underline{\Sigma}_0)$$

We assume  
 $A = I$ ,  $B = 0$ ,  $\underline{\Sigma} = I$

$$\underline{\Sigma}_0, \underline{\mu}_0$$

$Q = R = 0$   
are known.

↳ transitions

$$p(x_{t+1} | x_t, u_t) = N(x_{t+1} | \underline{A}x_t + \underline{B}u_t, \underline{Q})$$

↳ emissions

$$p(y_t | x_t) = N(y_t | \underline{C}x_t, \underline{R})$$