Conditional independencies in state space models

Sensor fusion & nonlinear filtering

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STATE SPACE MODELS AND CONDITIONAL INDENDENCIES

• We represent state space models in one of two forms:

$$\begin{cases} \mathbf{x}_k &= f_{k-1}(\mathbf{x}_{k-1}, \mathbf{q}_{k-1}) \\ \mathbf{y}_k &= h_k(\mathbf{x}_k, \mathbf{r}_k) \end{cases} \iff \begin{cases} \rho(\mathbf{x}_k | \mathbf{x}_{k-1}) \\ \rho(\mathbf{y}_k | \mathbf{x}_k). \end{cases}$$

• For the form on the left hand side we assume:

Both the motion noise, \mathbf{q}_{k-1} , and the measurement noise, \mathbf{r}_k , are independent of all other noise vectors.

• The corresponding assumptions for the density representation:

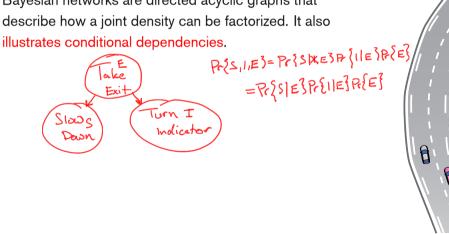
$$\rho(\mathbf{x}_k | \mathbf{x}_{0:k-1}, \mathbf{y}_{1:k-1}) = \rho(\mathbf{x}_k | \mathbf{x}_{k-1})$$

$$\rho(\mathbf{y}_k | \mathbf{x}_{0:k}, \mathbf{y}_{1:k-1}) = \rho(\mathbf{y}_k | \mathbf{x}_k)$$
(2)

 Note: Both x_k and y_k are stochastic processes and the assumption in (1) implies that x_k is a Markov process.

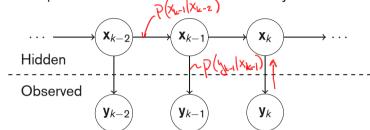
BAYESIAN NETWORKS AND CONDITIONAL INDEPENDENCIES

- A Bayesian network (also known as belief networks or Bayes net) is a probabilistic graphical model.
- Bayesian networks are directed acyclic graphs that describe how a joint density can be factorized. It also



STATE SPACE MODELS AND BAYESIAN NETWORKS

• A state space model can be described as a Bayesian network:



• The graph illustrates that:

$$p(\mathbf{x}_{0:k}, \mathbf{y}_{1:k}) = p(\mathbf{y}_{1:k} | \mathbf{x}_{0:k}) p(\mathbf{x}_{0:k})$$

$$= p(\mathbf{y}_{1} | \mathbf{x}_{0:k}) p(\mathbf{y}_{2} | \mathbf{y}_{1}, \mathbf{x}_{0:k}) \dots p(\mathbf{y}_{k} | \mathbf{y}_{1:k-1}, \mathbf{x}_{0:k})$$

$$p(\mathbf{x}_{0}) p(\mathbf{x}_{1} | \mathbf{x}_{0}) p(\mathbf{x}_{2} | \mathbf{x}_{0:1}) \dots p(\mathbf{x}_{k} | \mathbf{x}_{0:k-1})$$

$$= p(\mathbf{y}_{1} | \mathbf{x}_{1}) p(\mathbf{y}_{2} | \mathbf{x}_{2}) \dots p(\mathbf{y}_{k} | \mathbf{x}_{0:k-1})$$

$$= p(\mathbf{y}_{1} | \mathbf{x}_{1}) p(\mathbf{y}_{2} | \mathbf{x}_{2}) \dots p(\mathbf{y}_{k} | \mathbf{x}_{k-1}) p(\mathbf{x}_{2} | \mathbf{x}_{2}) \dots p(\mathbf{x}_{k} | \mathbf{x}_{k-1})$$

SELF-ASSESSMENT

Suppose the Bayesian network

describes the joint distribution over variables x_{k-1} , x_k and y_k . Check all that apply:

•
$$p(x_k, x_{k-1}, y_k) = p(x_k | x_{k-1}) p(x_{k-1}) p(y_k | x_k)$$

•
$$p(x_k, y_k) = p(y_k|x_k)p(x_k)$$

•
$$p(y_k|x_k,x_{k-1}) = p(y_k|x_k)$$