

Probabilistic Graphical Models

Provides us with a framework for inference on probability distribution

Graphical model: Nodes represent RVs

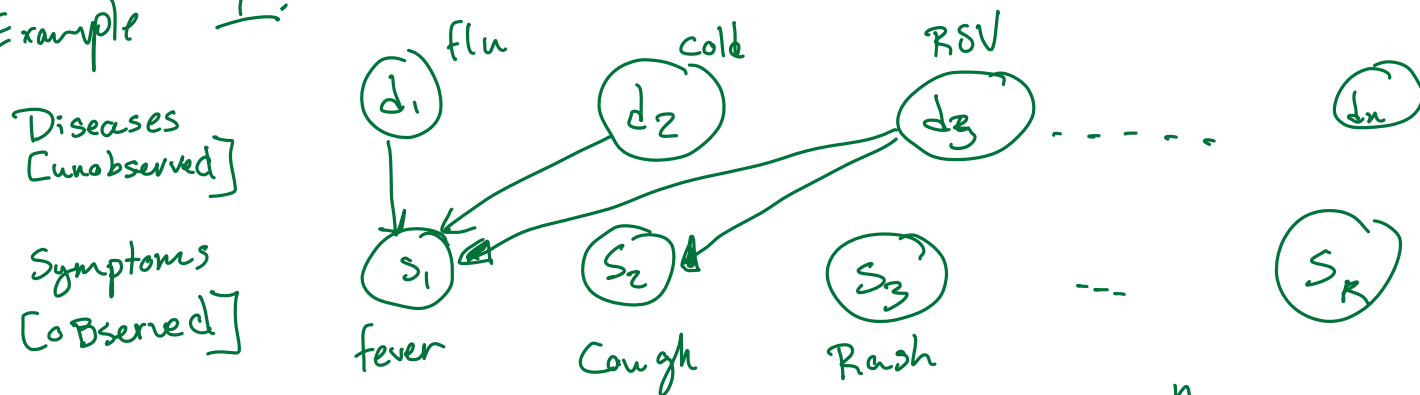
(informally) edges represent influence

Less dense graphs will correspond to probability distributions with structure that can allow for efficient inference.

Inference tasks

Draw conclusions about distribution

Example 1:

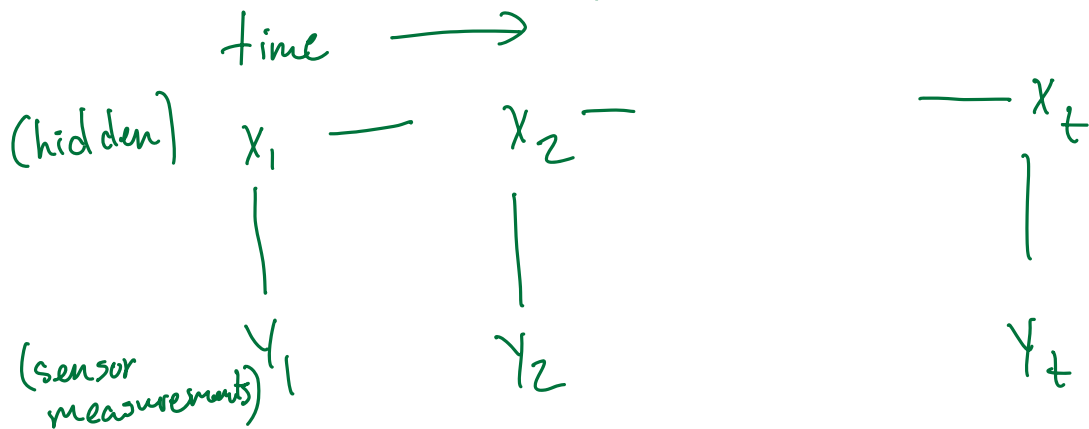
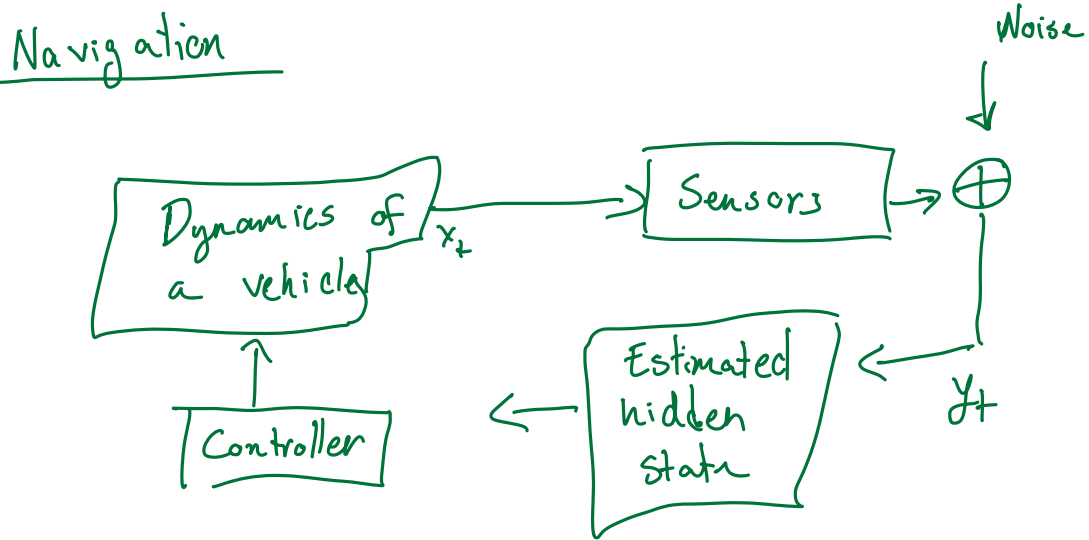


A patient can be represented as $d \in \{0,1\}^n$

Also as $f_i \in \{0,1\}^k$

Structure of this Bayesian network will allow efficient inference of, e.g. $\Pr[d_3=1 \mid s=(011000)]$

Navigation



Inference Given a transcript y_1, \dots, y_t

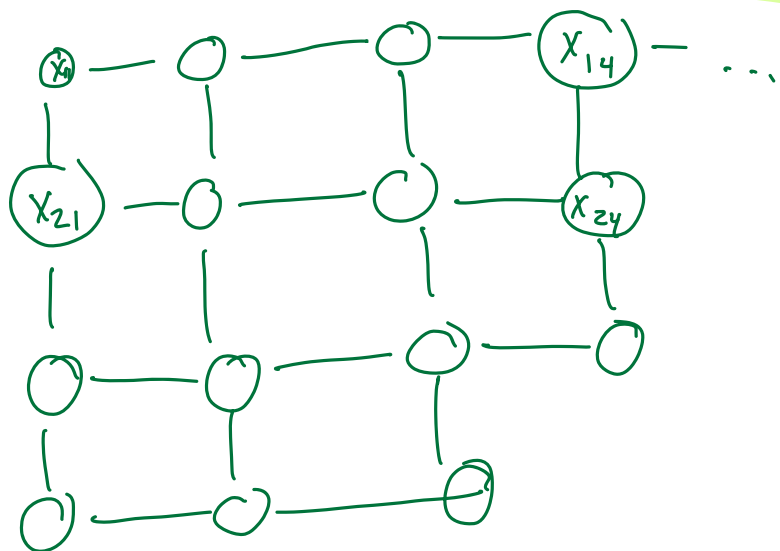
$\Pr_Y[x_t | y_1, \dots, y_t]$

Image superresolution

Markov Random field

Given a low-dimensional set of pixels, fill in the other pixels

$$\Pr[X | x_{11}, x_{14}, x_{21}, x_{24}]$$



General theme

[We know] Probability distribution over $X = [x_1, \dots, x_n]$
 $x_i \in \mathcal{X}$

We observe $Y = [y_1, \dots, y_k]$ $|X| < \infty$

[We want] Inference

Examples

Find the most probable realization

$$\operatorname{argmax}_x \Pr_Y(x)$$

- Marginals

$$\Pr_Y[x_1]$$

- Sample

$$x \sim \Pr_Y(x)$$

Hard?

$$n \gg 1$$

$$k \gg 1$$

$$\tilde{O}(|X|^{n \times k})$$

If, for example $x_i \perp x_j \mid Y \quad \forall i, j$

then $\Pr_Y(x)$, representable using $O(|X| \cdot n)$

PGMS

Graph Separation

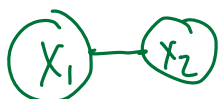
↑

Graph

→ Factorizations

→ (Conditional)

Independence



$$\Pr[x_1, x_2]$$



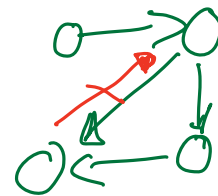
$$\Pr[x_1] \Pr[x_2]$$

$$x_1 \perp x_2$$

* Directed Graphical Models

Def: Directed, acyclic graph $G = (V, E)$

- Parent set of $i \in V$ $\pi(i) = \{j \in V \mid (j, i) \in E\}$



A directed graphical model on $G = (V, E) \Rightarrow$ a DAG is a family of distributions that factorizes as

$$Pr[x_1, \dots, x_n] \triangleq \prod_{i=1}^n f_i(x_i, x_{\pi(i)}) \quad (\exists f_i)$$

Claim

$$f_i(x_i, x_{\pi(i)}) = P[x_i \mid x_{\pi(i)}]$$