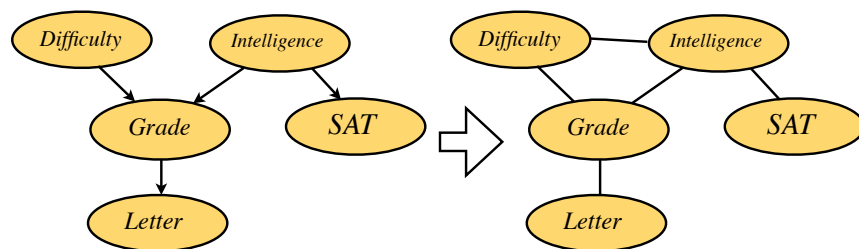


Example of converting directed to undirected



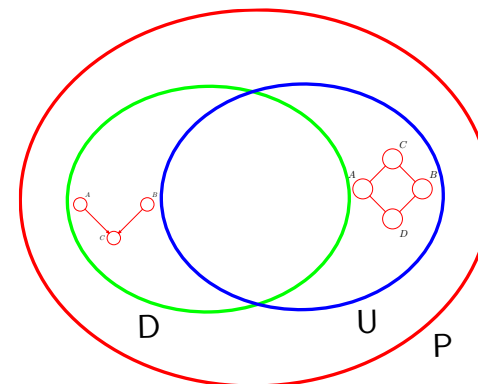
$$P(I, D, G, L, S) = P(I)P(D)P(G|I, D)P(L|G)P(S|I)$$

$$P = \psi(D, G, I)\psi(S, I)\psi(L, G)$$

$$\psi(D, G, I) = P(I)P(D)P(G|I, D) \quad \psi(S, I) = P(S|I) \quad \psi(L, G) = P(L|G)$$

$$\psi(D, G, I) = P(D)P(G|I, D) \quad \psi(S, I) = P(I)P(S|I) \quad \psi(L, G) = P(L|G)$$

Directed and undirected perfect maps



D is subset of distributions in P that are perfectly represented by directed graphs; similarly U for undirected graphs.

Inference on graphs

- Given a graph and its conditionals or potentials compute

$$p(\theta|e) \quad (\text{particular } \theta \text{ and } e, \text{ marginalizing out other variables})$$

$$p(X) \quad (\text{particular event, marginalizing out other variables})$$

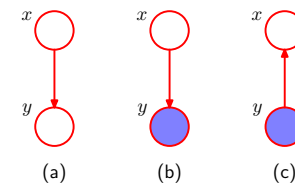
$$\text{argmax } p(\theta|e) \quad (\text{particular } \theta \text{ and } e; \text{ marginalizing other variables})$$

$$\text{argmax } p(\theta, \theta_N, e_N|e) \quad (\text{all variables, will nuisance / unobserved})$$

Inference on graphs

- Simplest example (Bayes rule)

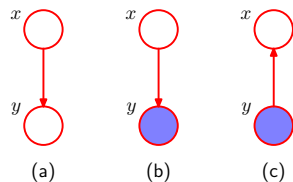
- (a) model
- (b) illustrates observed
- (c) inference **reverses** the arrow



Inference on graphs

- Simplest example (Bayes' rule)

- (a) model
- (b) illustrates observed
- (c) inference **reverses** the arrow



- Computationally

$$p(x|y) = \frac{p(y|x)p(x)}{\sum_{x'} p(y|x')p(x')}$$

Marginals on a chain

Recall 

$$p(\mathbf{x}) = p(x_1)p(x_2|x_1)p(x_3|x_2) \cdots p(x_{N-1}|x_{N-2})p(x_N|x_{N-1})$$

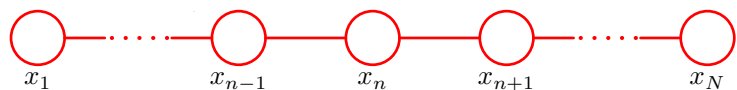
Converted to 

$$p(\mathbf{x}) = \psi_{1,2}(x_1, x_2)\psi_{2,3}(x_2, x_3) \cdots \psi_{N-2,N-1}(x_{N-2}, x_{N-1})\psi_{N-1,N}(x_{N-1}, x_N)$$

Assume N discrete variables, with K values each.

Compute the marginal of a node in the middle, $p(x_n)$

Marginals on a chain

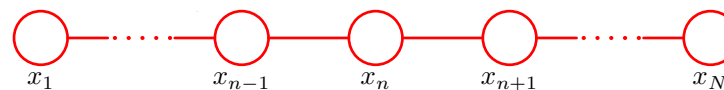


$$p(\mathbf{x}) = \psi_{1,2}(x_1, x_2)\psi_{2,3}(x_2, x_3) \cdots \psi_{N-2,N-1}(x_{N-2}, x_{N-1})\psi_{N-1,N}(x_{N-1}, x_N)$$

Direct calculation of $p(x_n)$

$$p(x_n) = ?$$

Marginals on a chain



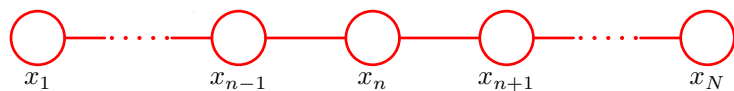
$$p(\mathbf{x}) = \psi_{1,2}(x_1, x_2)\psi_{2,3}(x_2, x_3) \cdots \psi_{N-2,N-1}(x_{N-2}, x_{N-1})\psi_{N-1,N}(x_{N-1}, x_N)$$

Direct calculation of $p(x_n)$

$$p(x_n) = \sum_{x_1} \sum_{x_2} \cdots \sum_{x_{n-1}} \sum_{x_{n+1}} \cdots \sum_{x_{N-1}} \sum_{x_N} p(\mathbf{x})$$

↑
Skip x_n

Marginals on a chain



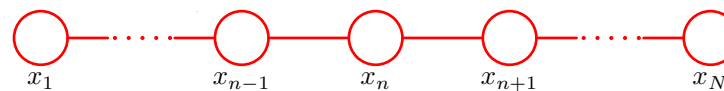
$$p(\mathbf{x}) = \psi_{1,2}(x_1, x_2) \psi_{2,3}(x_2, x_3) \dots \psi_{N-2, N-1}(x_{N-2}, x_{N-1}) \psi_{N-1, N}(x_{N-1}, x_N)$$

Direct calculation of $p(x_n)$

$$p(x_n) = \sum_{x_1} \sum_{x_2} \dots \sum_{x_{n-1}} \sum_{x_{n+1}} \dots \sum_{x_{N-1}} \sum_{x_N} p(\mathbf{x})$$

What is the computational complexity?

Marginals on a chain



$$p(\mathbf{x}) = \psi_{1,2}(x_1, x_2) \psi_{2,3}(x_2, x_3) \dots \psi_{N-2, N-1}(x_{N-2}, x_{N-1}) \psi_{N-1, N}(x_{N-1}, x_N)$$

Direct calculation of $p(x_n)$

$$p(x_n) = \sum_{x_1} \sum_{x_2} \dots \sum_{x_{n-1}} \sum_{x_{n+1}} \dots \sum_{x_{N-1}} \sum_{x_N} p(\mathbf{x})$$

Computational complexity is $O(K^N)$. **Way too slow!**