

Technology

STAT. METH. IN CS – JUNCTION TREES, PREP. FOR CH 20, 19

Lecture 7

EXACT ALGORITHMS FOR GRAPHICAL MODELS

- * Many problems are NP-hard (marginalization etc.)
- * For trees they are many of them can be solved by DP
- * When the graph is "tree-like" find a representation of the "treelikness" and use it to guide DP
- * Unfortunately, finding the representation is not always easy
- * Today assuming the representation is given.
- * Independent set as exercise.

ALGORITHM -MARGINALIZATION TREE DGM

- Given Bernoulli DGM with G binary directed tree and evidence x_e, for evidence set e
- * Subproblem, subsolution



 $s(u,i) = P(X_{V(T_u) \setminus e}, x_{V(T_u) \cap e} | X_u = i)$

ALGORITHM -MARGINALIZATION TREE DGM

- \star Given Bernoulli DGM with G binary directed tree and evidence x_{e} for evidence set e
- * Visit the vertices of G from leaves to root
 - * when at leaf I

 $s(l,i) = \begin{cases} 0 \text{ if } l \in e \text{ and } x_l \neq i \\ 1 \text{ otherwise} \end{cases}$

* when at vertex u with children v and w



 $s(u,i) = \begin{cases} 0 \text{ if } u \in e \text{ and } x_u \neq i \text{ otherwise case below} \\ \left(\sum_{j \in \{0,1\}} P(X_v = j | X_u = i) s(v,j)\right) \left(\sum_{j \in \{0,1\}} P(X_w = j | X_u = i) s(w,j)\right) \end{cases}$















































JUNCTION TREE









JUNCTION TREE







CLIQUES AND SEPARATORS IN G







































































UGM * UGMs - Undirected graphical models * What is the direction between 2 pixels, 2 proteins? Coherence * Probabilistic interpretation? Difficulty Intelligence ★ p factorizes over G – can be SAT expressed as normalized product Letter over factors associated with Job cliques

| $\begin{array}{c c} \phi_1(A,B) \\ \hline a^0 & b^0 & 30 \\ a^0 & b^1 & 5 \\ a^1 & b^0 & 1 \\ a^1 & b^1 & 10 \\ \end{array} \\ \begin{array}{c} b \\ b \\ b \\ b \\ b \\ \end{array}$ | $\phi_2(B, C)$ ϕ $0 c^0 100 c^0$ $0 c^1 1 c^0$ $1 c^0 1 c^1$ $1 c^1 100 c^1$ | $\begin{array}{cccc} & \phi_{3}(C,D) & \phi_{4} \\ & d^{0} & 1 & d^{0} \\ & d^{1} & 100 & d^{0} \\ & d^{0} & 100 & d^{1} \\ & d^{1} & 1 & d^{1} \end{array}$ | $a^{0} 100$ $a^{1} 1$ $a^{0} 1$ $a^{1} 100$ |
|---|---|--|---|
| | (b) Assign | (c) nent Unnorm $\begin{pmatrix} 0^{0} & d^{1} \\ c^{1} & d^{0} \\ c^{1} & c^{1} \\ c^{1} & $ | (d) alized Normalized 0,000 0.14 100 $1.4 \cdot 10^{-5}$ 100 $1.4 \cdot 10^{-5}$ 100 $1.4 \cdot 10^{-5}$ |
| UGMS | $ \begin{array}{cccccccccccccccccccccccccccccccccccc$ | $\left[\begin{array}{c} \frac{1}{2} & 0 & d^1 \\ \frac{1}{2} & d^0 & 10 \\ \frac{1}{2} & d^1 & 10 \end{array} \right]$ | 00,000 0.014 00,000 0.014 00,000 0.014 |







$$MARGINALIZE$$

$$p(\mathbf{X}_m | \mathbf{x}_e, \theta) = \frac{p(\mathbf{X}_m, \mathbf{x}_e | \theta)}{p(\mathbf{x}_e | \theta)} = \frac{\sum_{\mathbf{x}_{V \setminus (m \cup e)}} p(\mathbf{x}_{V \setminus (m \cup e)}, \mathbf{X}_m, \mathbf{x}_e | \theta)}{\sum_{\mathbf{x}_{V \setminus e}} p(\mathbf{x}_{V \setminus (m \cup e)}, \mathbf{x}_e | \theta)}$$

$$\cdot \text{ The denominator contains a marginal likelihood}$$

$$\cdot \text{ Summing out V binary hidden variables - O(2^V)}$$

$$\cdot \text{ K values - O(K^V)}$$

EQUIVALENCE I-MAP AND FACTORIZATION

• For positive distributions p (i.e., $\forall y$, p(y)>0),

 $\mathsf{I}(\mathsf{G}) \subseteq \mathsf{I}(\mathsf{p}) \Leftrightarrow \mathsf{p} \text{ can be expressed as a normalised product over}$ factors of G (as below)

$$p(\mathbf{y}|\boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta})} \prod_{c \in \mathcal{C}} \psi_c(\mathbf{y}_c|\boldsymbol{\theta}_c)$$







