

today: inference: graph Eliminate
sum-product alg.

graph elimination alg. (for inference in generic VGM)

- consider $p \in \mathcal{F}(G)$

$$p(x) = \frac{1}{Z} \prod_{c \in \mathcal{C}} \psi_c(x_c)$$

undirected

say want to compute $p(x_F)$ for some $F \subseteq V$ "query nodes"

main trick: use distributivity of \oplus over $\odot \rightarrow c \odot (a \oplus b) = c \odot a \oplus c \odot b$

$$\sum_{x_1, x_2} f(x_1) g(x_2) = \left(\sum_{x_1} f(x_1) \right) \left(\sum_{x_2} g(x_2) \right)$$

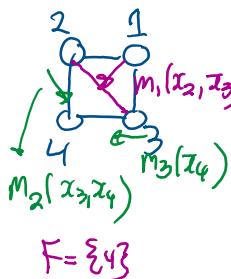
[convince yourself]

More generally

$$\sum_{x_1:n} \prod_i f_i(x_i) = \prod_{i=1}^n \left(\sum_{x_i} f_i(x_i) \right)$$

$$\mathcal{O}(k^n) \rightarrow \mathcal{O}(k \cdot n)$$

x_i takes k values



$$\begin{aligned}
 p(x_4) &= \frac{1}{Z} \sum_{x_1, x_2, x_3} \psi(x_1, x_2) \psi(x_2, x_4) \psi(x_3, x_4) \\
 &= \frac{1}{Z} \left[\sum_{x_3} \left[\sum_{x_2} \left[\sum_{x_1} \psi(x_1, x_2) \right] \right] \right] \left[\sum_{x_2} \left[\sum_{x_1} \psi(x_1, x_2) \right] \right] \left[\sum_{x_4} \psi(x_3, x_4) \right] \\
 &\quad \text{M}_1(x_2, x_3) \quad \text{"message"} \\
 &= \frac{1}{Z} M_3(x_4) \quad \text{Last message is proportional to marginal } p(x_4) \\
 \sum_{x_4} M_3(x_4) &= Z \quad \boxed{p(x_4) = \frac{M_3(x_4)}{Z}} = \frac{M_3(x_4)}{\sum_{x_4} M_3(x_4)}
 \end{aligned}$$

general alg: graph Eliminate

init: a) choose an elimination ordering s.t. F are the last nodes

b) put all $\psi_c(x_c)$ on "active list"

b) put all $\Psi_\alpha(x_\alpha)$ on "active list"

"update" c) repeat, in order of variables to eliminate

i) (say x_i is variable to eliminate)

remove all factors from active list with x_i in it ∇ take their product

$$\text{i.e. } \prod_{\substack{\alpha \in \text{act.} \\ i \in \alpha}} \Psi_\alpha(x_\alpha)$$

ii) sum over x_i to get a new factor $m_i(x_{S_i})$ (think as $\Psi_{S_i}(x_{S_i})$)

i.e. S_i are all variables in these factors except i

$$\text{get } m_i(x_{S_i}) \triangleq \sum_{x_i} \prod_{\substack{\alpha \in \text{act.} \\ i \in \alpha}} \Psi_\alpha(x_\alpha)$$

$$S_0 \triangleq (\bigcup_{\alpha \in \text{act.}}) \setminus \{x_i\} \quad \text{new clique to sum over } S_0 \cup S_i$$

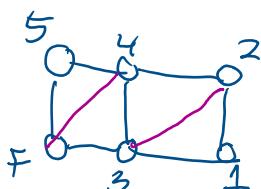
iii) put back $m_i(x_{S_i})$ in active list $(\Psi_{S_i}(x_{S_i}))$

"normalize": d) last product of factors has only $x_F \Rightarrow$ proportional $p(x_F)$

Suppose $x_i \in \{0,1\}$ memory needed? $\approx 2^{\max_i |S_i|}$ (max size of active list) $\leq 1e6$

$$\text{computational} = \underbrace{(2^{\max_i |S_i| + 1})}_\text{data, related "tree width" of a graph} n$$

⊕ "augmented graph" \rightarrow graph obtained by running graph Eliminate + keeping track of (for specific ordering) all edges added



⊕ note augmented graph obtained after graph eliminate is always

a) triangulated graph

def.: graph with no cycle of size 4 or more that cannot be broken by a "chord"



an edge between two non-neighboring nodes in a cycle

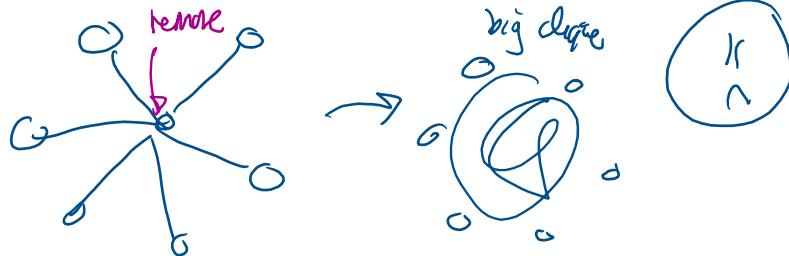




treewidth of a graph \triangleq min over all possible elimination orderings { size of biggest clique in augmented graph - 1 } \hookrightarrow connective tree width (tree) = 1

both memory & running time of graph Eliminate is dominated by
size of biggest clique
when using best ordering tree width = 1

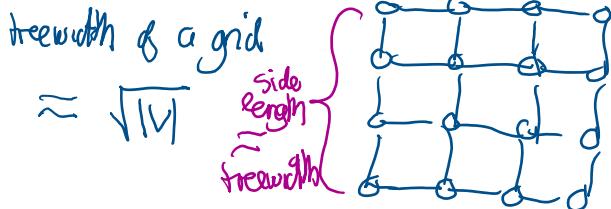
not all orderings are good



bad news:

- NP hard to compute treewidth of a general graph (or find best ordering)
- NP hard to do (exact) inference in general UGM
 \Rightarrow need approximate methods

example:



15h26 good news:

\rightarrow inference is linear time for tree (treewidth 1) ("sum-product alg.")
 $\rightarrow |V| + |E|$ (HMM, Markov chain)

\leftarrow efficient for "small treewidth" graph
 \rightarrow use junction tree alg.



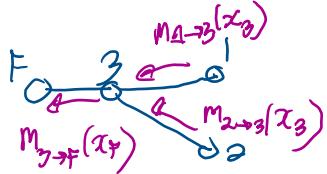
inference on trees

α reach Eliminate, on a tree

Influence on trees

graph Eliminate on a tree

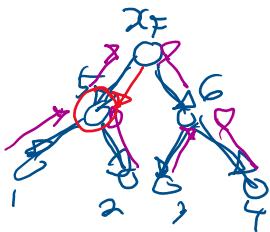
→ good order is to dominate learns first



$$p(x) = \frac{1}{Z} \prod_i \psi_i(x_i) \prod_{i < j} \psi_{ij}(x_i, x_j)$$

(Consuming F is singletons)

Order: make a directed tree by using $2F$ as a root

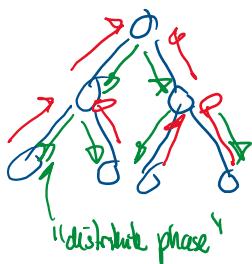


$$m_{\text{child} \rightarrow \text{parent}}(x_j) = \sum_{x_i} \psi_i(x_i) \psi_{ij}(x_i, x_j) \prod_{k \neq i} m_{K \rightarrow i}(x_k)$$

new factors containing i
in the active list

Sum-product alg. (for trees)

alg. to get all node/edge margins cheaply by storing (caching) { re-using messages }



"collect phase")

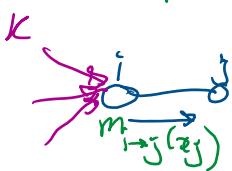
(dynamic programming)

goal: $\{i_j\}_{j \in E}$, compute $M_{i_j \rightarrow j}(x_j)$

$$m_{j \rightarrow i}(x_i^*)$$

rule: i can only send messages to neighbor j

when it has received all messages from other neighbors



$$m_{i \rightarrow j}(x_i) \triangleq \sum_{x_i} \psi_i(x_i) \psi_j(x_i, x_i) \prod_{k \in N(i)} m_{k \rightarrow i}(x_i)$$

at end

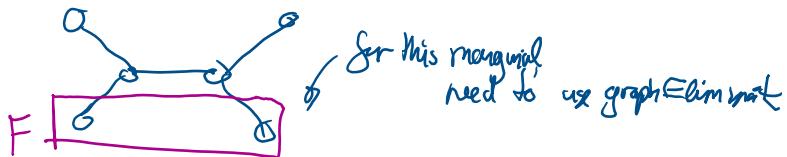
$$(\text{node marginal}) \quad p(x_i) \propto \psi_i(x_i) \prod_{j \in N(i)} m_j \rightarrow i(x_j)$$

normalize $Z = \frac{Z}{x_i} (1)$

(edge marginal)

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$$p(x_i, x_j) = \frac{1}{Z} \prod_{k \in N(i) \setminus \{j\}} m_{k \rightarrow i}(x_i) \prod_{k \in N(j) \setminus \{i\}} m_{k \rightarrow j}(x_j)$$



sum-product schedules

- a) above, collect/distribute schedule
- b) (flooding) parallel schedule

1) initialize all $m_{i \rightarrow j}(x_j)$ to uniform dist. $\forall (i, j) \text{ s.t. } \{i, j\} \in E$

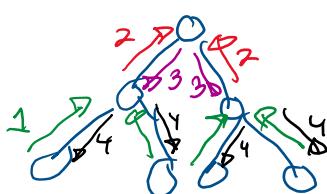
2) at every step (in parallel) compute $m_{i \rightarrow j}^{(new)}(x_j) \setminus \{i, j\}$

as if the neighbors were correctly computed

→ one can prove that after "diameter of tree" # of steps

all messages are correctly computed (for a tree)

(and are fixed to a fixed point)



Loopy belief propagation (loopy BP) ≈ approximate inference for graphs with cycles

$$m_{i \rightarrow j}^{(new)}(x_j) = \left(m_{i \rightarrow j}^{(old)}(x_j) \right)^{\frac{1}{\alpha}} \left(\prod_{k \in N(i) \setminus \{j\}} m_{k \rightarrow i}^{(old)}(x_i) \right)^{\alpha}$$

$\alpha \in [0, 1]$ "damping"
↓ step-size

④ this gives exact answer on trees

(fixed pt. → yields correct marginal)

✗ on (not too loopy) graph → "nice" approximate solution



