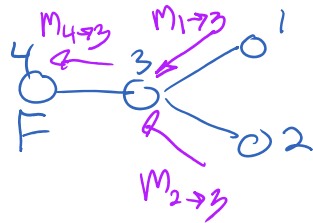


today: sum-product
max-product

Inference on trees

graph eliminate on a tree

good order: eliminate leaves first

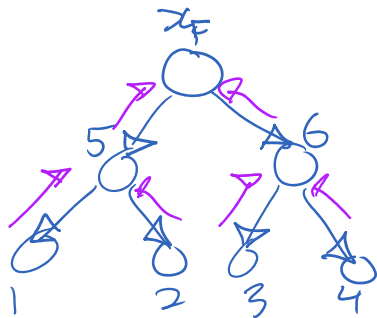


$$p(x) = \frac{1}{Z} \prod_i \psi_i(x_i) \prod_{(i,j) \in E} \psi_{ij}(x_i, x_j)$$

$$p(x_4) = \frac{\psi_4(x_4)}{Z} \sum_{x_3} \psi_3(x_3) \psi(x_4, x_3) \left(\sum_{x_2} \psi(x_2) \psi(x_3, x_2) \right) \left(\sum_{x_1} \psi(x_1) \psi(x_4, x_1) \right)$$

$M_{2 \to 3}(x_3)$ $M_{1 \to 3}(x_3)$
 $M_{3 \to 4}(x_4)$

order: make a directed tree by using x_F as a root
singleton



start from leaves; go up towards root

$$M_{i \rightarrow j}(x_j) = \sum_{x_i} \psi_i(x_i) \psi_{ij}(x_i, x_j) \prod_{k \in \text{children}(i)} M_{k \rightarrow i}(x_i)$$

child parent

1 2 3 4

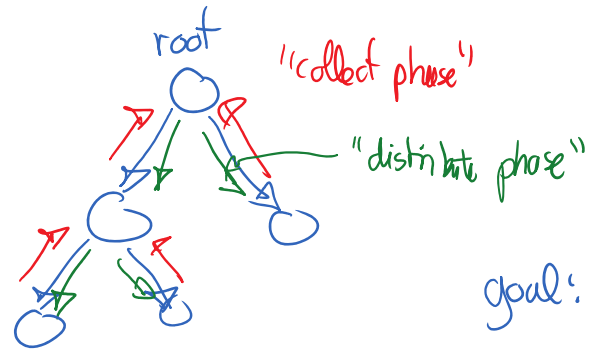
child parent

x_i

$K \in \text{children}(i)$
 new factors containing i
 on active list

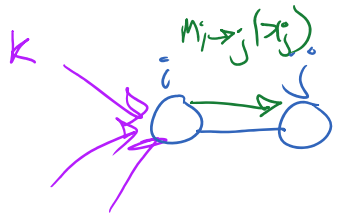
Sum-product alg. (for trees)

get all marginals cheaply by storing (caching) & re-using messages (dynamic programming)



goal: $\forall \{i,j\} \in E$, compute $m_{i \rightarrow j}(x_j)$
 $m_{j \rightarrow i}(x_i)$

rule: i can only send message to neighbor j
 when it has received all messages from other neighbors

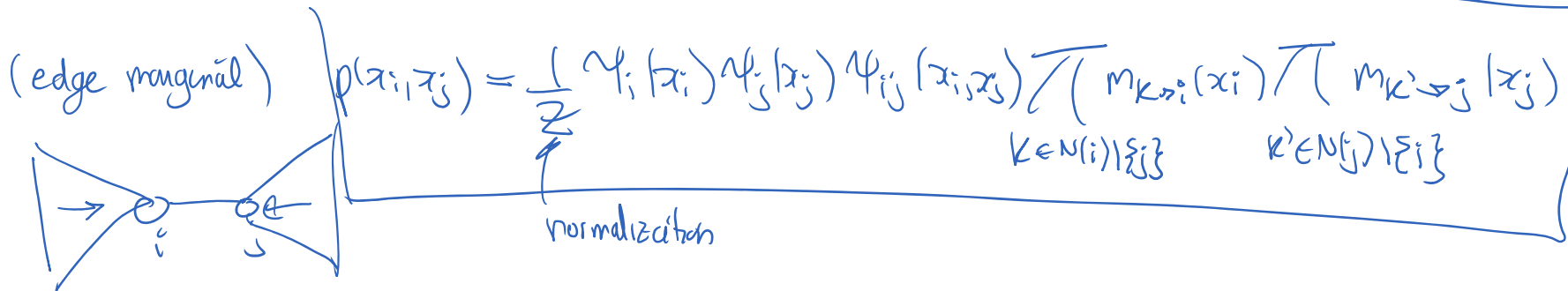


$$m_{i \rightarrow j}(x_j) = \sum_{x_i} \psi_i(x_i) \psi_{ij}(x_i, x_j) \prod_{\substack{K \in N(i) \\ K \neq j}} m_{K \rightarrow i}(x_i)$$

child parent
neighbors

at end: $p(x_i) \propto \prod_{j \in N(i)} m_{j \rightarrow i}(x_i) \psi_i(x_i)$
 (node marginal)

normalization $\sum_{x_i} (\quad)$



sum-product schedules

a) above, distribute/collect schedule

b) (flooding) parallel schedule:

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

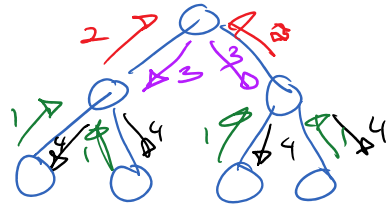
2) at every step (in parallel) compute $m_{i \rightarrow j}^{\text{new}}(x_j)$

as if the neighbor messages were already correctly computed

→ can prove that after "diameter of the tree" # of steps, all messages are correctly computed for a tree (and are fixed points)



for a tree (and the fixed points)



Loopy Belief Propagation (loopy BP) : approximate inference

$$m_{i \rightarrow j}^{(new)}(x_j) = \left(m_{i \rightarrow j}^{(old)}(x_j) \left(\sum_{x_i} \psi_i(x_i) \psi_{ij}(x_i, x_j) \prod_{k \in N(i) \setminus \{j\}} m_{k \rightarrow i}(x_i) \right)^{\alpha} \right)^{1-\alpha}$$

$\alpha \in [0, 1]$ "damping"

- this gives exact answers on tree (fixed pt. yields correct marginals)
- on (not too loopy) graphs \rightarrow approximate solution

getting conditionals:

$$p(x_i | \bar{x}_E) \propto p(x_i, \bar{x}_E)$$

indicate values we are conditioning on

keep this fixed during marginalization for each $i \in E$:

(formal trick) : redefine $\psi_j(x_j) \triangleq \psi_j(x_j) \cdot \delta(x_j, \bar{x}_j)$

ρ
 Kroneck-delta
 def. $\delta(a,b) = \begin{cases} 1 & \text{if } a=b \\ 0 & \text{o.w.} \end{cases}$

computing $M_{j \rightarrow i}(x_i); \quad \sum_{x_j} \tilde{\Psi}_j(x_j) \cdot \text{stuff}(x_j, x_i)$
 $= \Psi_j(\bar{x}_j) \text{stuff}(\bar{x}_j, x_i)$

at the end, result of sum-product

will give $p(x_i, \bar{x}_E) = \frac{1}{Z} \Psi_i(x_i) \prod_{K \in N(i)} M_{K \rightarrow i}(x_i)$

(4h3)

$p(x_i | \bar{x}_E)$ ρ renormalize over x_i

Max-product algorithm:

for sum-product, main property used was distributivity of \oplus over \odot

$(\mathbb{R}, \oplus, \odot)$ is a semi-ring

\hookrightarrow don't need additive inverse

can do "sum-product" on other semi-rings

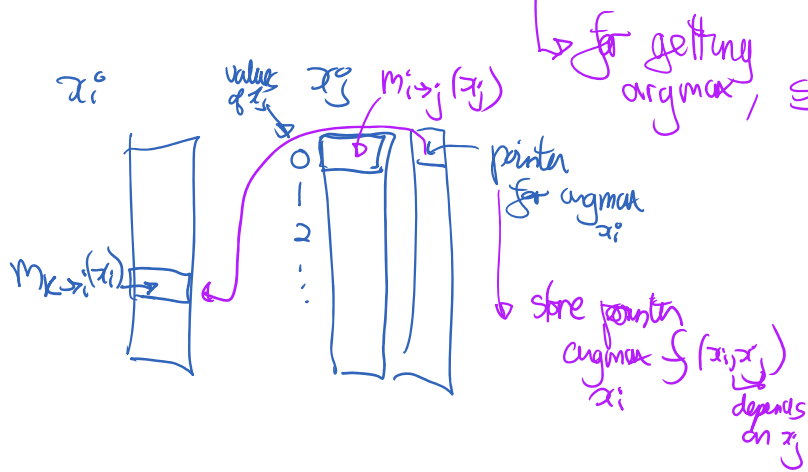
$$(\mathbb{R}, \max, \oplus) \quad \max(a \oplus b, a \oplus c) = a \oplus \max(b, c)$$

$$(\mathbb{R}_+, \max, \odot) \quad \max(a \odot b, a \odot c) = a \odot \max(b, c)$$

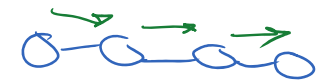
↳ "max-product"

$$\max_{x_{1:n}} \prod_i f_i(x_i) = \prod_i \max_{x_i} f_i(x_i)$$

$$M_{i \rightarrow j}(x_j) = \max_{x_i} [\psi_i(x_i) \psi_{ij}(x_i, x_j) \prod_{k \in N(i) \setminus \{j\}} M_{k \rightarrow i}(x_i)]$$



↳ for getting argmax, store argument of this max as fct. of x_j



to get argmax $p(x_{1:n})$ "decoding"

- run max-product alg (only forward messages)
- backtrack the argmax pointers to get full argmax

aka. viterbi algorithm

property: $p \in \mathcal{J}(\text{tree})$
with non-zero marginals

$$\Rightarrow \left| p(x) = \prod_{i \in V} p(x_i) \prod_{\{i,j\} \in E} \frac{p(x_i, x_j)}{p(x_i)p(x_j)} \right|$$

~~graphical~~ $p(x) = \prod_{i \in V} p(x_i)$
with non-zero marginals

$$\rightarrow p(x) = \prod_{i \in V} p(x_i) \prod_{\{i,j\} \in E} \frac{p(x_i, x_j)}{p(x_i)p(x_j)}$$

(proof: simple exercise)

* similar to DGM; for any set of factors $\{f_{ij}(x_i, x_j)\}_{i,j \in E}$, $\{f_i(x_i)\}_{i \in V}$ $f_{ij} \geq 0$
 $f_i \geq 0$
s.t. "local consistency property"

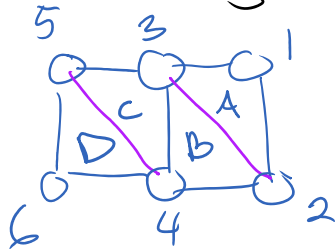
$$\begin{cases} \sum_{x_j} f_{ij}(x_i, x_j) = f_i(x_i) \quad \forall x_i \\ \sum_{x_i} f_{ij}(x_i, x_j) = f_j(x_j) \quad \forall x_j \\ \sum_{x_i} f_i(x_i) = 1 \end{cases}$$

then if define joint
(for tree)

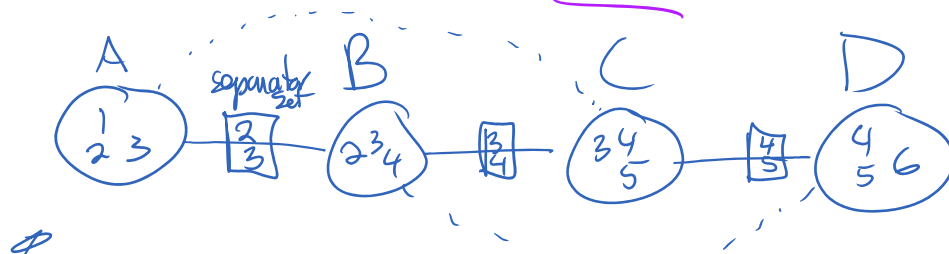
$$p(x) = \prod_i f_i(x_i) \prod_{\{i,j\} \in E} \frac{f_{ij}(x_i, x_j)}{f_i(x_i)f_j(x_j)}$$

we get correct marginals i.e. $p(x_i) = f_i(x_i)$ etc...

Junction tree alg. :



generalization of sum-product to a clique tree





above is a clique tree with the "running intersection property" "junction tree"

to build JT: • use max weighted spanning tree alg - (with size of separator sets as weight on the edges)
on clique graph from a Δ -graph

JT \Leftrightarrow triangulated graph / decomposable graph \Leftrightarrow running graph Eliminate graph

when have J.T., you can show

$$p(x_v) = \frac{\prod_C p(x_c)}{\prod_{S_i} p(x_{S_i})}$$

← separator set in any J.T.

J.T. free alg. \therefore reconstruct the above formulation

$$p(x_v) = \frac{\prod_C \psi_C(x_c)}{\prod_S \psi_S(x_s)}$$

where $\psi_S(x_s) = 1$ at beginning

do message passing to update ψ_C^{new} ψ_S^{new} \rightarrow at end $p(x_c) \dots p(x_s)$