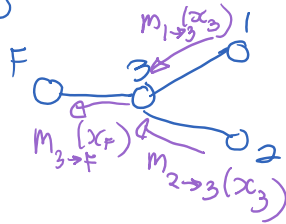


today: Sum-product
Max-product
junction tree

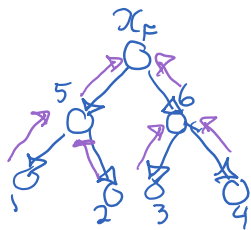
inference on trees

graph Eliminate on a tree
→ good order is to eliminate leaves first

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



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



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

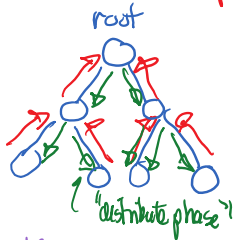
child parent
new factors containing i in the active list

sum-product alg. (for trees)

alg. to get all node/edge marginals cheaply by storing (caching)

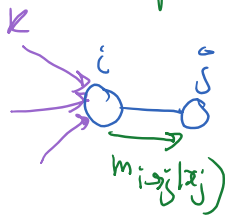
re-using messages (dynamic programming)

"collect phase"



goal: $\{i,j\} \in E$, 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



"distribute phase"

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

at end (node marginal)

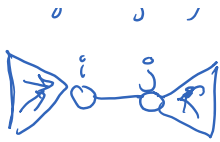
$$p(x_i) \propto \prod_{j \in N(i)} m_{j \rightarrow i}(x_i) \psi_i(x_i)$$

normalize: $Z = \sum_{x_i} (\dots)$

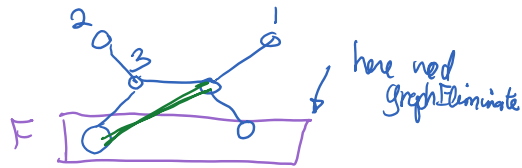
(edge marginal)



$$p(x_i, x_j) = \frac{1}{Z} \psi_i(x_i) \psi_j(x_j) \psi_{ij}(x_i, x_j) \prod_{k \in N(i) \setminus \{j\}} m_{k \rightarrow i}(x_i) \cdot \dots$$



$$p(x_i, x_j) = \frac{1}{Z} \psi_i(x_i) \psi_j(x_j) \psi_{ij}(x_i, x_j) \prod_{k \in N(i)} \psi_{k \rightarrow i}(x_i) \cdot \prod_{k' \in N(j)} \psi_{k' \rightarrow j}(x_j)$$



Sum-product schedules

a) done, collect/distribute schedule

b) (flooding) parallel schedule:

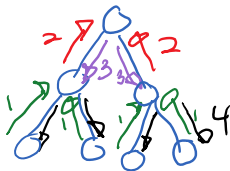
1) initialize all $M_{i \rightarrow j}(x_j)$ messages to uniform dist $\forall \{i, j\}$ s.t. $\{i, j\} \in E$

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

as if the neighbor messages were correctly computed

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

all messages are correctly computed (for a tree) (and are fixed pt.)



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

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

* this gives exact answer on trees (fixed pt. → yields correct marginals)

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

* on (not too loopy) graphs → approximate solution

Getting conditionals:

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

indicates values we are conditioning on
 $\bar{x}_E = \bar{x}_E$

keep this fixed during marginalization for each $j \in E$

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

Kronecker delta fn.
 $\delta(a, b) \triangleq \begin{cases} 1 & \text{if } a=b \\ 0 & \text{aw.} \end{cases}$

$$\delta(a,b) \stackrel{\text{Kronecker delta}}{\equiv} \begin{cases} 1 & \text{if } a=b \\ 0 & \text{otherwise} \end{cases}$$

Computing $M_{j \rightarrow i}(x_i)$:

$$\sum_{x_j} \tilde{\Psi}_j(x_j) \text{stuff}(x_i, x_j) = \Psi_j(\bar{x}_j) \text{stuff}(x_i, \bar{x}_j)$$

at the end, result of sum-product

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

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

16ho2

Max-product alg:

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

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

↳ don't need additive inverses

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

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

[max-sum alg.]

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

↳ "max-product"

$$\max_{x_i \in \mathcal{X}_i} \prod_j f_j(x_j) = \prod_i \max_{x_i} f_i(x_i)$$

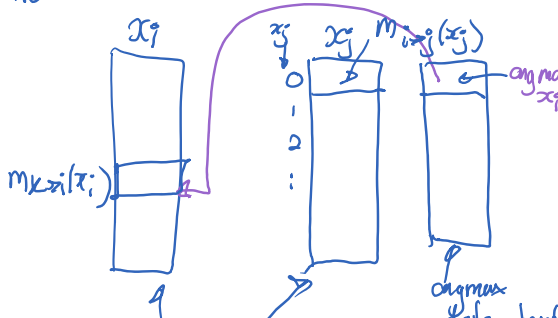
$$M_{i \rightarrow j}(x_j) = \max_{x_i} \left[\Psi_i(x_i) \Psi_{ij}(x_i, x_j) \prod_{k \in N(i) \setminus \{j\}} M_{k \rightarrow i}(x_i) \right]$$

for getting argmax

store argument of this max as a fcn. of x_j

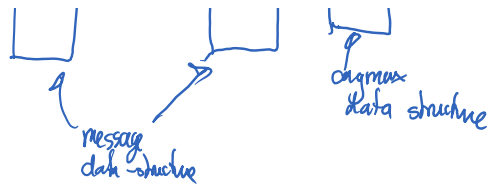


$$\max_{x_1, \dots, x_5} \frac{1}{Z} \prod_c \Psi_c(x_c) = \frac{1}{Z} \max_{x_5} \left[M_{4 \rightarrow 5}(x_5) \cdot \Psi_5(x_5) \right]$$



argmax x_j for this value of x_j
argmax $f(x_i, x_j)$
argmax x_i

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

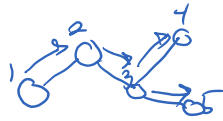


- run max-product alg. (only forward messages)
- back-track the original pointers to get full original

aka Viterbi algorithm

property of tree LGM

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



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

$$p(x) = p(x_5|x_3) \frac{p(x_3)}{p(x_3)} p(x_4|x_3) \frac{p(x_3)}{p(x_3)} p(x_3|x_2) \frac{p(x_2)}{p(x_2)} p(x_2|x_1) p(x_1)$$

⊗ Similar to DBM, for any set of factors $\{f_{ij}(x_i, x_j)\}, \{f_i(x_i)\}$ $f_{ij} \geq 0$ $f_i \geq 0$

S.t. "local consistency property"

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

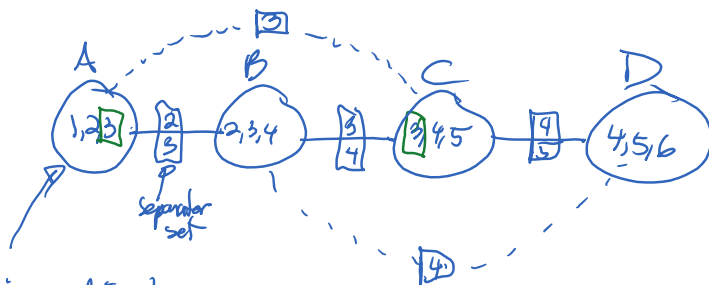
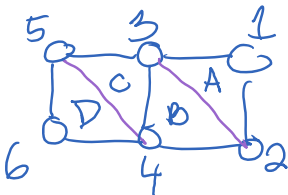
then it defines a joint $p(x) = \prod_i f_i(x_i) \prod_{\{i,j\} \in E} \frac{f_{ij}(x_i, x_j)}{f_i(x_i) f_j(x_j)}$

(we could show that we get correct marginals)

ie $p(x_i) = f_i(x_i)$ etc

junction tree algorithm : generalization of sum-product to a clique tree

(with J.T. property)



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

↳ if $j \in C_1 \cap C_2$, then

to build a J.T.
on a Δ -graph:

• use maximum weight spanning tree
alg. on clique graph (with size of separator set as weight on edges) \Rightarrow running intersection property

$j \in C_k \forall C_k$ along path from C_1 to C_2

\exists a J.T. \Leftrightarrow triangulated graph / decomposable graph \Leftrightarrow running graph elimination

⊛ when have a J.T., one can show

$$p(x_V) = \frac{\prod_C p(x_C)}{\prod_S p(x_S)}$$

separator sets in the J.T.

J.T. alg.: reconstruct the above formulation

by starting with $p(x_V) = \frac{\prod_C \psi_C(x_C)}{\prod_S \psi_S(x_S)}$ where $\psi_S(x_S) = 1$ at initialization

do message passing on J.T. to update at the end
 $\psi_C^{new}, \psi_S^{new} \rightarrow p(x_C), p(x_S)$