The Sum-product algorithm

- · special case of sum-product aly. is belief propagation.
- either can be converted to a factor graph.

Goal:
1) efficient, exact inference alg for computing marginals
2) share computations when computing several marginals

Again, was start with.

$$p(x) = \text{If } f_s(x_s)$$

$$p(x_i) = \text{If } p(x) = \text{If } f_s(x_s)$$

$$x_i x_i = \text{all } x_j \text{ except Maj} = i$$

$$F_s(x, X_s)$$
:
 f_s
 χ

Can partition the factors of the joint distr. into groups:

$$p(\underline{x}) = \prod_{s \in ne(x)} F_s(x, X_s)$$

ne(x) = wasaphouse set of factor nodes that are neighbors of x add ?

Xs set of all vars in
The subtree connected
to the var node X.
Via factor node fs.

Fs(X, Xs) puts product of all factors in the group associated with factor fs.

CAMPAD

$$\chi_{1}$$
 χ_{2} χ_{3} χ_{4} χ_{5} χ_{5} χ_{7} χ_{7}

partile (x3)

MARRIER

$$P(x) = TT(s(x))$$

= $f_1(\chi_1,\chi_2,\chi_2)$ $f_2(\chi_3,\chi_4,\chi_5)$ $f_3(\chi_3,\chi_6,\chi_7)$

$$p(\chi) = TT F_s(\chi, X_s) = Sene(\chi)$$

M

SE ne(x3) = f1, f2, f3

 $X_{s}: \quad X_{1} = \{\chi_{1}, \chi_{2}\}$ $X_{2} = \{\chi_{4}, \chi_{5}\}$ $X_{3} = \{\chi_{6}, \chi_{7}\}$

 $F_{s}(\chi, \chi_{s})$ $F(\chi, \chi_{1}) = f_{1}(\chi_{1}, \chi_{2}, \chi)$ $F(\chi, \chi_{2}) = f_{2}(\chi, \chi_{4}, \chi_{5})$ $F(\chi, \chi_{3}) = f_{3}(\chi, \chi_{6}, \chi_{1})$

- = set of factor nodes that are neighbors of x.
- = set of all vars in the subtree connected to the variable node x via factor node fs
 - = product of all the factors in the group associated with factor fs.

$$p(\underline{x}) = TT f_s(\underline{x}_s)$$

$$= f_4(\underline{x}_1, \underline{x}_8, \underline{x}_9) f_1(\underline{x}_1, \underline{x}_1, \underline{x}_2) f_2(\underline{x}_1, \underline{x}_4, \underline{x}_5) f_3(\underline{x}_1, \underline{x}_6, \underline{x}_7) f_{\underline{z}}(\underline{x}_2, \underline{x}_{10})$$

$$p(x) = TT F_s(x, X_s)$$

 $sene(x)$

SE
$$ne(x) = \{f_1, f_2, f_3\}$$
 = neighboring factor nodes
 $X_5: X_1 = \{\chi_1, \chi_2, \chi_8, \chi_9\}$ = set of all vars in the subtree connected to the variable node χ via factor node f_5 .

product of all the factors in the group associated with factor S.

$$F_{5}(x, \chi_{s}) = F_{1}(x, \chi_{i}) = f_{1}(x, \chi_{i}, \chi_{i}) f_{4}(x_{i}, \chi_{8}, \chi_{9})$$

$$F_2(\chi,\chi_2) = f_2(\chi,\chi_4,\chi_5) f_5(\chi_4,\chi_{10})$$

where: $P(x) = TT F_s(x, X_s)$ Sine(x)

and $p(x) = \sum p(x)$

= $\sum TF_s(x, X_s)$ sxx sene(x)

Or from our example:

 $\sum_{x \in \mathcal{X}} F_1(x, X_1) F_2(x, X_2) F(x, X_3)$

ANAMA

 $\sum_{X_1} \sum_{X_2} F_1(x,X_1) F_2(x,X_2) \sum_{X_3} F_3(x_3,X_3)$

 $\sum_{X_1} F_1(\chi_1, X_1) \sum_{X_2} F_2(\chi_1, X_2) \sum_{X_3} F_3(\chi_3, X_3)$

generalizing: $\prod_{\text{Sene}(x)} \left[\sum_{X_S} F_s(x, X_S) \right] \equiv \prod_{\text{Sene}(x)} \mu f_{s \to x}(x)$

Can you just "interchange Sum and products"?

 $\sum_{x} \prod_{s} f_{s}(x, x_{s})$

E Taij

anarz @3 + a 21 azz (2) + 10191032 53

TZaij = (a11+ a12) (B) x (au + azz)

> LOSSOR = a , a 21 + a , a 21

+ a, azz + a, zazz

491-L8 - Inf GM2

Interchanging sum and products:

$$p(x_i) = \sum_{x \mid x_i} p(x)$$

=
$$\sum_{\chi_i \chi_i} \prod_{s \in ne(\chi_i)} F_s(\chi_i, \chi_s)$$
 = $\prod_{\chi_i \chi_i} \sum_{s \in ne(\chi_i)} \sum_{\chi_s} F_s(\chi_i, \chi_s)$

ヹ. T a:j チザヹ a:j

$$a_{11}a_{12} + a_{21}a_{22} \neq (a_{11} + a_{22})^{\frac{2}{3}}(a_{21} + a_{22})$$

$$= (a_{11}a_{21} + a_{12}a_{21})(a_{11}a_{22} + a_{12}a_{22})$$

What's going on?

$$\Sigma$$
... Σ Σ ... Σ T $F_s(x_{\epsilon}, X_s)$
 χ_1 χ_{i-1} χ_{i+1} χ_N $S \in Ne(\chi_{\epsilon})$

Thuse can be group into χ_s $F_s(\chi_{\epsilon}, \chi_s)$ only depends

on Xs iso Z canhe pushadin.

$$= \sum_{X_1} F_1(\chi_{\mathbf{E}_1} X_1) \left[\sum_{X_2} F_2(\chi_{\mathbf{E}_1} X_2) \left[\dots \sum_{X_M} F_M(\chi_{\mathbf{E}_1} X_M) \right] \right]$$

$$p(x) = \prod_{s \in ne(x)} \left[\sum_{X_s} F_s(x_s X_s) \right] = A A$$

=
$$TT$$
 $Mfs \rightarrow \chi_{\xi}(\chi_{\xi})$ = $\frac{\text{product of all}}{\text{messages arriving at node}\chi_{\xi}}$

$$\mu f_{s \to \chi_{s}}(\chi_{s}) \equiv \sum_{X_{s}} F_{s}(\chi_{s}, \chi_{s}) \longrightarrow \chi_{s}$$

can be nowed as the messages from factor nodes for to var node x.

$$F_{s}(x,x_{s}): \qquad \qquad F_{s}(x_{s})$$

$$\chi_{M} = \chi_{M} = \chi_{M$$

$$\chi_{m} \xrightarrow{\chi_{m}} \chi_{m} \chi_{m}$$

$$\mu_{f_s \to \chi}(\chi) = \sum_{\chi_s} F_s(\chi, \chi_s)$$

$$\mu_{f_{s\rightarrow x}}(x) = \sum_{\chi_{i}} \sum_{\chi_{M}} f_{s}(\chi_{i}\chi_{i:M}) \prod_{m \in ne(f_{s}) \setminus x} \left[\sum_{\chi_{sm}} G_{m}(\chi_{m},\chi_{sm}) \right]$$

Two kinds of messages. =
$$\mu_{\chi_m} \rightarrow f_s(\chi_m)$$

() $\mu_s \rightarrow \chi(\chi) \in \mathcal{D} \ \mu_{\chi_m} \rightarrow f_s(M_{\mu_s} \chi_m)$ Note: fins of factor nodes to var nodes to factor nodes $\chi \not = \chi_m$

How do we do this for the whole graph? We have recursive definitions => need base cases. How do we hande leaf nodes?

> $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x) = 1$ leaf is a var node

be cause your Allowing Allowing that X has only f as a neighbor.

Mf $\rightarrow \xi_{x}(x) = f(x)$ leaf is a factor f

Z. $\sum_{\chi_1} f_s(\chi_1, \chi_2, ..., \chi_m) \prod_{M \in \chi_m \to f_s} (\chi_m)$ there are none none equiv to node always =1 So we just ha $fs(x) \cdot 1$

Like before we can efficiently compute all marginals by propagating msgs through whole graph, and the calculatest each marginal from the incomming msgs

 $P(x_i) = TT M_{fs \rightarrow x}(x)$ $SENE(x_i)$ # msgs = 2* #links

For a set: $p(\chi_s) = f_s(\chi_s) \prod_{i \in ne(f_s)} \mu_{\chi_i \to f_s}(\chi_i)$

What about Z? Easy to compute by computing Z for any one of p(Xi).

CAMPAL

Sun-product algorithm summany/illustration:

p(x) = \frac{1}{2} fa (x1, x2) fb (x2, x3) fc (x2, x4)

Arbitrarily say X3 is root.

Campute msqs:

that leaf nodes are= 1.

 $\mathcal{M}_{\chi_2 \to f_b}(\chi_2) = TT \mathcal{M}_{f_0 \to \chi_2}(\chi_2) = \mathcal{M}_{f_0 \to \chi_2}(\chi_2) \mathcal{M}_{f_c \to \chi_2}(\chi_2)$ lene(χ_2) f_b

$$\mathcal{M}_{f_b \to \chi_3}(\chi_3) = \sum_{\chi_2} f_b(\chi_2, \chi_3) \mu_{\chi_2 \to f_b}(\chi_2)$$

Now we can go the other way to get the complete set of msgs

GAMPA

$$\mu_{\chi_3 \to f_b} = 1$$

$$\mu_{f_b \to \chi_2(\chi_2)} = \sum_{\chi_3} f_b(\chi_2, \chi_3) \cdot 1$$

$$M f_a \rightarrow \chi_i(\chi_i) = \sum_{\chi_2} f_a(\chi_{i_1}\chi_2) \mu_{\chi_2 \rightarrow f_a}(\chi_2)$$

$$= \frac{1}{2} \mu_{fa} \rightarrow \chi_{2} (\chi_{2}) \mu_{fb} \rightarrow \chi_{1} (\chi_{2}) \mu_{fc} \rightarrow \chi_{2} (\chi_{3})$$

$$= \left[\sum_{\chi_{1}} f_{a} (\chi_{1}, \chi_{2}) \right] \left[\sum_{\chi_{3}} f_{b} (\chi_{2}, \chi_{3}) \right] \left[\sum_{\chi_{4}} f_{c} (\chi_{2}, \chi_{4}) \right]$$

=
$$\sum_{\chi_1,\chi_3,\chi_4}$$
 $f_a(\chi_1,\chi_2) f_b(\chi_2,\chi_3) f_c(\chi_2,\chi_4) = \sum_{\chi_1,\chi_2} p(\chi_2)$

(2)

Whit about observed vars?

General approach: partition was vars into hidden & visible

the Let $\hat{Y} = observed values of Y h$

Then we can write

 $P(\underline{x}) \prod_{i} I(v_{i}, \hat{v}_{i}) \qquad I(v, \hat{v}) = 1$

 $\begin{cases}
\text{Want } p(\mathbf{x} \text{hi} | \underline{V} = \widehat{\underline{V}}) = p(\text{hi}, \underline{V} = \widehat{\underline{V}}) \\
p(\underline{V} = \widehat{\underline{V}})
\end{cases}$

p(hi, V=V) 12 an unnormalize

version of p({hi|v=v)

So we can compute p(h:, V=V) by clamping all the visible vars to their values, rather

than summing over all possible values. > The sums collapse to a single term The we just normalize locally like before

CAMPA