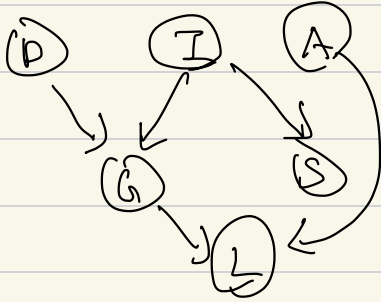


2.1.3/25 Factor graph + Sum-product algorithm.



Converting to factor graph

What is factor graph?

- Bipartite graph w/ two types of nodes
 - Variable nodes V and
 - Factor nodes F

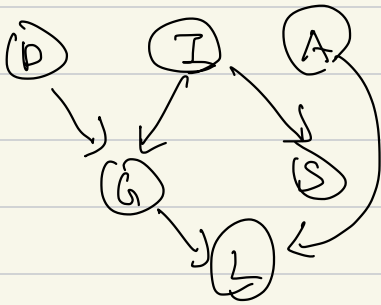
Random variables: round nodes

Factor nodes: square nodes

Given a DAG, $G = (V, E)$ convert
it to a factor graph
 $G' = (V, F, E)$

Every node in the original graph remains as a variable in G^1

For each variable $v \in V$ create a factor $f_v = P(v | \text{pa}(v)) \subseteq \text{conditional prob. distr.}$
The factor connects to v and $\text{pa}(v)$.



For variable v whose parent factor f_v connects only to v .

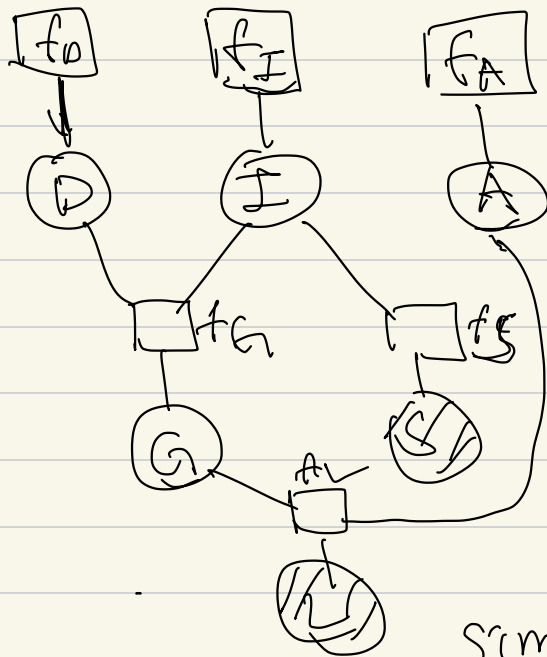
If the resulting factor graph has no cycles, we can perform exact inference

$V \rightarrow F$ message

$$m_{x \rightarrow f}(x) = \prod_{h \in n(x) \setminus \{f\}} m_{h \rightarrow x}(x)$$

$$m_{f \rightarrow x}(x) = \sum_{-x} f(x) \prod_{y \in n(f) \setminus \{x\}} m_{y \rightarrow f}(y)$$

$n(f), n(x)$: neighbors of f, x



pass

①

$$m_{f_0 \rightarrow D}(d)$$

$$= \sum_{-d} f_0(d) \prod_{y \in n(f_0) \setminus \{d\}} (y)$$

$$n(f_0) \setminus \{d\} = \emptyset$$

$$= f_0(d) = P(d)$$

similarly

$$m_{f_I \rightarrow I}(i) = f_I(i) = P(i), \quad m_{f_A \rightarrow A}(a) = f_A(a) = P(a)$$

$$\textcircled{2} \quad D \rightarrow f_G, I \rightarrow f_G, I \rightarrow f_S$$

$$m_{D \rightarrow f_G}(d) = \sum_{h \in n(d) \setminus \{f_G\}} m_{h \rightarrow d}(d)$$

$$n(d) = \{f_D, f_G\} \quad \text{so}$$

$$n(d) \setminus \{f_G\} = \{f_D\}$$

$$m_{D \rightarrow f_G}(d) = m_{f_D \rightarrow d}(d) = p(d)$$

$$m_{I \rightarrow f_G}(i) = m_{f_G \rightarrow i}(i) = p(i)$$

$$m_{I \rightarrow f_S}(i) = p(i)$$

$$\textcircled{3} \quad f_G \rightarrow G \quad n(G) \setminus \{G\} = \{D, I\}$$

$$m_{f_G \rightarrow G}(g) = \sum_{d, i} f_G(d, i, g) \cdot m_{D \rightarrow f_G}(d) \cdot m_{I \rightarrow f_G}(i)$$

$$= \sum_{d, i} P(g|d, i) p(d) p(i)$$

$$= p(g)$$

$$f_S \rightarrow S \quad n(f_S) = \{I, S\}$$

$$n(f_S) \setminus \{S\} = \{I\}$$

$$m_{f_S \rightarrow S}(S) = \sum_{-S} f(S, i) m_{I \rightarrow f_S}(i)$$

$$= \sum_i P(S|I) P(I) = P(S)$$

(4) $G \rightarrow t_L \quad n(G) = \{f_G, t_L\}$

$$n(G) \setminus \{t_L\} = \{f_G\}$$

$$m_{G \rightarrow t_L}(g) = m_{f_G \rightarrow G}(g) = P(g)$$

$$A \rightarrow t_L \quad n(A) \setminus \{t_L\} = \{t_A\}$$

$$m_{A \rightarrow t_L}(a) = m_{t_A \rightarrow A}(a) = P(a)$$

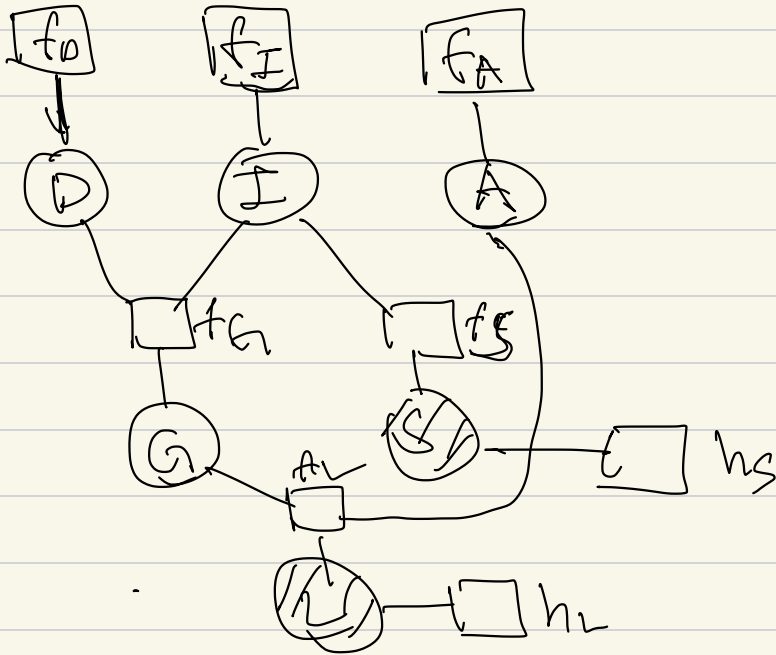
(5) $t_L \rightarrow L \quad n(t_L) = \{G, A, L\}$

$$m_{t_L \rightarrow L}(l) = \sum_{-L} f(l, g, a) m_{G \rightarrow t_L}(g) m_{A \rightarrow t_L}(a)$$

$$= \sum_{g, a} P(l|g, a) P(a) P(g)$$

$$= P(l)$$

To handle observations, we will add a univariate factor for each observed variable



These factors will be indicator functions

$$h_2(l) = \mathbb{1}[l = l^*]$$

$$h_5(s) = \mathbb{1}[s = s^*]$$

let l^*, h^*
denote
observed
values,

$$\textcircled{6} \quad L \rightarrow h_L \quad n(L) \setminus \{h_L\} = \{L\}$$

$$\begin{aligned} m_{L \rightarrow h_L}(L) &= m_{L \rightarrow L}(L) \\ &= P(L) \end{aligned}$$

$$S \rightarrow h_S$$

$$m_{S \rightarrow h_S}(S) = P(S)$$

Essentially, nodes gather messages
by taking the product

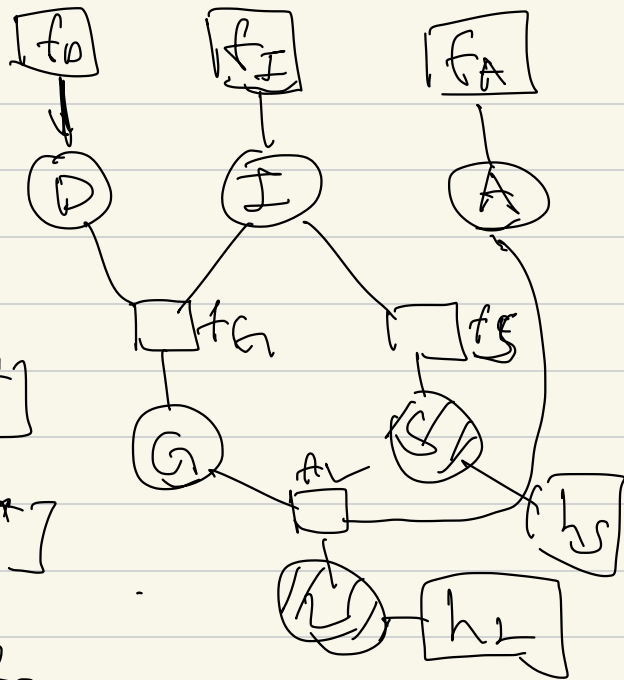
factors perform marginalization,
via summation.

Pass 2

$$\textcircled{1} m(l) \\ h_L \rightarrow L$$

$$= h_L(l) = g[l = l^*]$$

$$m_{h_S \rightarrow S}(s) = g[s = s^*]$$



$$\textcircled{2} L \rightarrow f_L, S \rightarrow f_S$$

$$m_{L \rightarrow f_L}(l) = h_L(l) = g[l = l^*]$$

$$m_{S \rightarrow f_S}(s) = h_S(s) = g[s = s^*]$$

$$\textcircled{3} f_L \rightarrow G \quad n(f_L) \setminus \{G\} = \{L, A\}$$

$$m_{f_L \rightarrow G}(g) = \sum_{-g} P_L(g, a, l) m(l) m(a)$$

$\begin{matrix} L \rightarrow f_L & A \rightarrow f_L \end{matrix}$

$$= \sum_{a, l} P(l|g, a) \underbrace{g[l = l^*]} p(a)$$

$$= P(l^*|g)$$

$$\textcircled{4} G \rightarrow f_G$$

$$m_{G \rightarrow f_G}(g) = m_{f_G \rightarrow G}(g) = p(e^*(g))$$

$$\textcircled{5} f_G \rightarrow I, f_S \rightarrow I$$

$$m_{f_G \rightarrow I}(i) = \sum_{-i} f_G(i, d, g) m_{G \rightarrow f_G}(g) m_{f_G \rightarrow G}(g)$$

$$= \sum_{d, g} p(g|d, i) p(d) p(e^*(g))$$

$p(g, d, e^*(i)) = p(e^*(i))$

$$m_{f_S \rightarrow I}(i) = \sum_S p(S|i) \mathbb{1}_{S=S^*}$$

$$= p(S^*|i)$$

compute $p(i|e^*, s^*)$

$$= p(e^*, s^* | i) / p(e^*, s^*)$$

Combine messages

$$m_{f_I \rightarrow I}(i) \times m_{f_G \rightarrow I}(i) \times m_{f_S \rightarrow I}(i)$$

$$= p(i) \cdot p(e^*|i) p(s^*|i) = \boxed{p(e^*, s^* | i)}$$

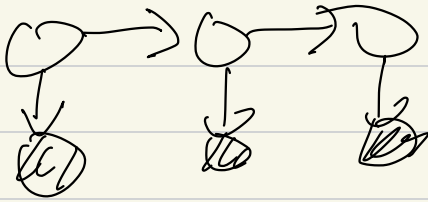
Belief propagation

first proposed by Judea Pearl
in the 80's for trees (poly trees)

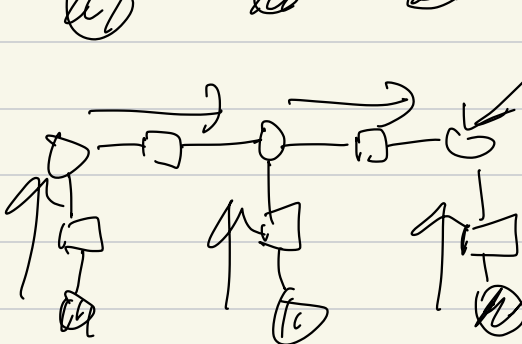
Sum-product algorithm
is exact if the right ordering is
used.

Otherwise, we get loopy belief
propagation.

HMM as message passing

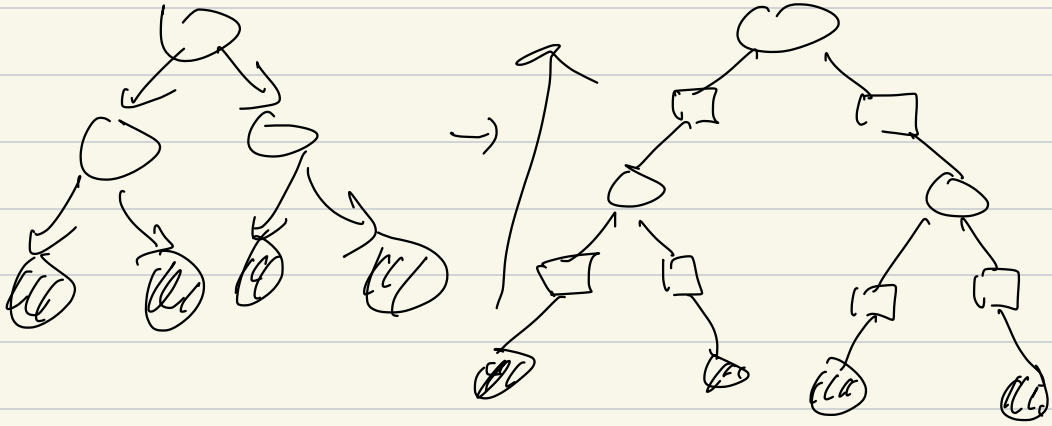


Choose a root



Messages from
Obs (leaf)
to root

Felsenstein as BP



leaf to root.