

Ling 5801: Lecture Notes 14

Message Passing for Probability Models

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14.1 Efficient inference by ‘message passing’

Most queries don’t need to calculate the full joint distribution (through 8,000,000 iterations):

$$\begin{aligned} P_{\theta_{Sp}}(b) &= \sum_{p,v,f_0,f_1,f_2} P_{\theta_{Sp}}(p, v, b, f_0, f_1, f_2) \\ &\stackrel{\text{def}}{=} \sum_{p,v,f_0,f_1,f_2} P_{\theta_P}(p) \cdot P_{\theta_V}(v | p) \cdot P_{\theta_B}(b | p) \cdot P_{\theta_{F_0}}(f_0 | v) \cdot P_{\theta_{F_1}}(f_1 | b) \cdot P_{\theta_{F_2}}(f_2 | b) \end{aligned}$$

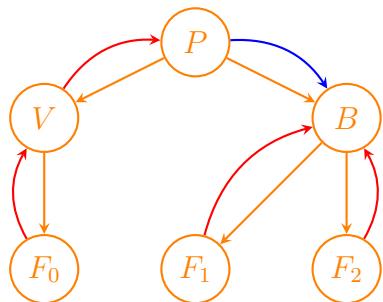
Instead, marginalize as we go, storing marginals (conditional probability tables) as ‘messages’:

$$\begin{aligned} P_{\theta_{Sp}}(b) &= \sum_{p,v,f_0,f_1,f_2} P_{\theta_{Sp}}(p, v, b, f_0, f_1, f_2) \\ &\stackrel{\text{def}}{=} \sum_p \left(P(p) \cdot \left(\sum_v P(v | p) \cdot \left(\sum_{f_0} P(f_0 | v) \right) \right) \right) \cdot P(b | p) \cdot \left(\sum_{f_1} P(f_1 | b) \right) \cdot \left(\sum_{f_2} P(f_2 | b) \right) \end{aligned}$$

(Re-arrangement of terms just comes from distributing products over sums in the full joint.)

Blue parens show *forward messages*: distributions over free modeled variables (subscripts).

Red parens show *backward messages*: likelihood fns over free conditioned-on variables (subscripts).



Now just need space of a conditional probability distribution per variable!

14.2 Example

For example, to solve the following query (where variable F_0 is actually observed):

$$\begin{aligned} \mathbb{P}_{\theta_{Sp}}(b, f_0=12) &= \sum_{p,v,f_1,f_2} \mathbb{P}_{\theta_{Sp}}(p, v, b, f_0=12, f_1, f_2) \\ &\stackrel{\text{def}}{=} \sum_p \left(\mathbb{P}(p) \cdot \left(\sum_v \mathbb{P}(v | p) \cdot \mathbb{P}(f_0=12 | v) \right) \right) \cdot \mathbb{P}(b | p) \cdot \left(\sum_{f_1} \mathbb{P}(f_1 | b) \right) \cdot \left(\sum_{f_2} \mathbb{P}(f_2 | b) \right) \end{aligned}$$

given the following models:

$$\mathbb{P}_{\theta_P}(P) = \begin{array}{|c|c|} \hline /i/ & /u/ \\ \hline .4 & .6 \\ \hline \end{array}$$

$$\mathbb{P}_{\theta_V}(V | P) = \begin{array}{|c|c|c|} \hline P & + & - \\ \hline /i/ & .8 & .2 \\ \hline /u/ & 1 & 0 \\ \hline \end{array}$$

$$\mathbb{P}_{\theta_{F_0}}(F_0 | V) = \begin{array}{|c|c|c|c|c|c|} \hline V & \dots & 11 & 12 & 13 & \dots \\ \hline + & \dots & .04 & .02 & .01 & \dots \\ \hline - & \dots & .01 & .01 & .01 & \dots \\ \hline \end{array}$$

$$\mathbb{P}_{\theta_B}(B | P) = \begin{array}{|c|c|c|} \hline P & + & - \\ \hline /i/ & 0 & 1 \\ \hline /u/ & .5 & .5 \\ \hline \end{array}$$

we would generate the following messages:

$$\text{from } F_0 \text{ to } V: \mathbb{P}(F_0=12 | V) = \begin{array}{|c|c|} \hline V & 12 \\ \hline + & .02 \\ \hline - & .01 \\ \hline \end{array}$$

$$\begin{array}{|c|c|} \hline P & F_0 = 12 \\ \hline /i/ & \mathbb{P}_{\theta_{F_0}}(12 | +) \cdot \mathbb{P}_{\theta_V}(+ | /i/) + \mathbb{P}_{\theta_{F_0}}(12 | -) \cdot \mathbb{P}_{\theta_V}(- | /i/) \\ & = .02 \cdot .8 + .01 \cdot .2 = .018 \\ \hline /u/ & \mathbb{P}_{\theta_{F_0}}(12 | +) \cdot \mathbb{P}_{\theta_V}(+ | /u/) + \mathbb{P}_{\theta_{F_0}}(12 | -) \cdot \mathbb{P}_{\theta_V}(- | /u/) \\ & = .02 \cdot 1 + .01 \cdot 0 = .020 \\ \hline \end{array}$$

$$\begin{array}{|c|c|c|} \hline & P=/i/, F_0=12 & P=/u/, F_0=12 \\ \hline \text{from } P \text{ to } B: \mathbb{P}(P, F_0=12) & \mathbb{P}_{\theta_P}(/i/) \cdot \mathbb{P}(F_0=12 | P=/i/) & \mathbb{P}_{\theta_P}(/u/) \cdot \mathbb{P}(F_0=12 | P=/u/) \\ & = .4 \cdot .018 = .0072 & = .6 \cdot .020 = .0120 \\ \hline \end{array}$$

$$\text{from } F_1 \text{ to } B: \mathbb{P}(\text{any } F_1 | B) = \begin{array}{|c|c|} \hline B & \text{any} \\ \hline + & 1 \\ \hline - & 1 \\ \hline \end{array}$$

$$\text{from } F_2 \text{ to } B: \mathbb{P}(\text{any } F_2 | B) = \begin{array}{|c|c|} \hline B & \text{any} \\ \hline + & 1 \\ \hline - & 1 \\ \hline \end{array}$$

Product of model and three messages at B:

$P(B, F_0=12) =$	
$B=+, F_0=12$	$B=-, F_0=12$
$P(P=/i/, F_0=12) \cdot P_{\theta_B}(+ /i/) \cdot 1 \cdot 1$	$P(P=/i/, F_0=12) \cdot P_{\theta_B}(- /i/) \cdot 1 \cdot 1$
$+ P(P=/u/, F_0=12) \cdot P_{\theta_B}(+ /u/) \cdot 1 \cdot 1$	$+ P(P=/u/, F_0=12) \cdot P_{\theta_B}(- /u/) \cdot 1 \cdot 1$
$= .0072 \cdot 0 \cdot 1 \cdot 1 + .0120 \cdot .5 \cdot 1 \cdot 1 = .0060$	$= .0072 \cdot 1 \cdot 1 \cdot 1 + .0120 \cdot .5 \cdot 1 \cdot 1 = .0132$

Normalized:

$$P(B | F_0=12) = \begin{array}{cc|c} & B=+ & B=- \\ \hline & \frac{.0060}{.0060+.0132} = .3125 & \frac{.0132}{.0060+.0132} = .6875 \end{array}$$

14.3 Example program

Find $P(B | F_0 = 12)$ from Model modP, CondModels modV, modB, modF0, modF1, modF2:

```

bkwdF0 = {}
for v in modF0:    # obtain likelihood of observation given V (backward message)
    bkwdF0[v] = modF0[v]['12']
bkwdV = {}
for p in modV:    # marginalize or 'sum out' V to get likelihood given P (bkwd msg)
    for v in modV[p]:
        bkwdV[p] = bkwdV.get(p, 0.0) + (modV[p][v] * bkwdF0[v])
fwrldP = {}
for p in modP:    # multiply prior over P by likelihood given P (backward message)
    fwrldP[p] = modP[p] * bkwdV[p]
...

```

Practice

Complete the above example.

14.4 Limits of message passing

Message passing degrades when network is not singly-connected.

For example, adding variable for height w. dependencies from P , to F_2 , creates a ‘diamond’:

$$\langle P \times V \times B \times H \times F_0 \times F_1 \times F_2, 2^{P \times V \times B \times H \times F_0 \times F_1 \times F_2}, \mathbb{P} \rangle$$

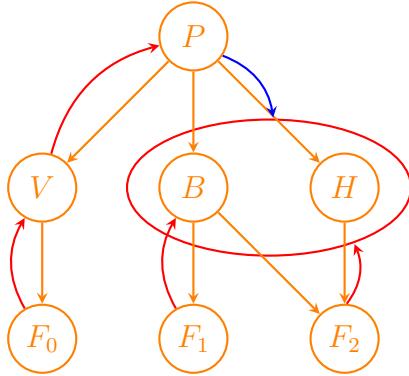
where $P = \{/i/, /u/\}, V = \{+, -\}, B = \{+, -\}, H = \{+, -\}, F_0 = \mathbb{I}_0^{99}, F_1 = \mathbb{I}_0^{99}, F_2 = \mathbb{I}_0^{99}$

$$\begin{aligned}
\mathsf{P}_{\theta_P}(P) &\stackrel{\text{def}}{=} \mathsf{P}(P) \\
\mathsf{P}_{\theta_V}(V | P) &\stackrel{\text{def}}{=} \mathsf{P}(V | P) \\
\mathsf{P}_{\theta_B}(B | P, V) &\stackrel{\text{def}}{=} \mathsf{P}(B | P) \\
\mathsf{P}_{\theta_H}(H | P, V, B) &\stackrel{\text{def}}{=} \mathsf{P}(H | P) \\
\mathsf{P}_{\theta_{F_0}}(F_0 | P, V, B, H) &\stackrel{\text{def}}{=} \mathsf{P}(F_0 | V) \\
\mathsf{P}_{\theta_{F_1}}(F_1 | P, V, B, H, F_0) &\stackrel{\text{def}}{=} \mathsf{P}(F_1 | B) \\
\mathsf{P}_{\theta_{F_2}}(F_2 | P, V, B, H, F_0, F_1) &\stackrel{\text{def}}{=} \mathsf{P}(F_2 | B, H)
\end{aligned}$$

This means some marginals will have multiple free variables (which makes them larger):

$$\begin{aligned}
\mathsf{P}_{\theta_{Sp}}(b) &= \sum_{p,v,h,f_0,f_1,f_2} \mathsf{P}_{\theta_{Sp}}(p, v, b, h, f_0, f_1, f_2) \\
&\stackrel{\text{def}}{=} \sum_p \left(\mathsf{P}(p) \cdot \left(\sum_p \mathsf{P}(v | p) \dots \right) \right) \cdot \mathsf{P}(b | p) \cdot \left(\sum_b \mathsf{P}(f_1 | b) \right) \cdot \sum_h \mathsf{P}(h | p) \cdot \left(\sum_{b,h} \mathsf{P}(f_2 | b, h) \right)
\end{aligned}$$

Graphically, messages must pass through ‘junctions’ of joint variables:



Well, they’re not full joints at least.