
Supplement: Belief Propagation in Conditional RBMs for Structured Prediction

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A Gradients of Log-likelihood

Similar to Eq. (5) in the main text, the gradients of log-likelihood with other weights and biases are,

$$\begin{aligned}\frac{\partial \log p(\mathbf{v}^n | \mathbf{x}^n)}{\partial W^{vx}} &= \mathbf{v}^n \mathbf{x}^{n\top} - \mathbb{E}_{p(\mathbf{v}, \mathbf{h} | \mathbf{x}^n)} [\mathbf{v} \mathbf{x}^{n\top}], \\ \frac{\partial \log p(\mathbf{v}^n | \mathbf{x}^n)}{\partial W^{hx}} &= \boldsymbol{\mu}^n \mathbf{x}^{n\top} - \mathbb{E}_{p(\mathbf{v}, \mathbf{h} | \mathbf{x}^n)} [\mathbf{h} \mathbf{x}^{n\top}], \\ \frac{\partial \log p(\mathbf{v}^n | \mathbf{x}^n)}{\partial b^v} &= \mathbf{v}^n - \mathbb{E}_{p(\mathbf{v}, \mathbf{h} | \mathbf{x}^n)} [\mathbf{v}], \\ \frac{\partial \log p(\mathbf{v}^n | \mathbf{x}^n)}{\partial b^h} &= \boldsymbol{\mu}^n - \mathbb{E}_{p(\mathbf{v}, \mathbf{h} | \mathbf{x}^n)} [\mathbf{h}],\end{aligned}$$

where $\boldsymbol{\mu}^n = \mathbb{E}_{p(\mathbf{h} | \mathbf{v}^n, \mathbf{x}^n)} [\mathbf{h}] = \sigma(W^{vh\top} \mathbf{v}^n + W^{hx} \mathbf{x}^n + \mathbf{b}^h)$. All the negative parts of these gradients are intractable to calculate, and must be approximated during learning.

B Derivation of Matrix-based BP

In this section we give additional proof details of our matrix-based BP update equations.

B.1 Proof of the update rule for M^{vh} in Eq. (13):

$$\begin{aligned}M_{ij}^{vh} &= \frac{m_{j \rightarrow i}(v_i = 1)}{m_{j \rightarrow i}(v_i = 1) + m_{j \rightarrow i}(v_i = 0)}, \\ &= \sigma \left(\log \frac{\exp(W_{ij}^{vh}) \cdot \frac{\tau_j^h}{M_{ji}^{hv}} + \frac{1 - \tau_j^h}{1 - M_{ji}^{hv}}}{\frac{\tau_j^h}{M_{ji}^{hv}} + \frac{1 - \tau_j^h}{1 - M_{ji}^{hv}}} \right), \text{ by Eq. (8)} \\ &= \sigma \left(\log \frac{\exp(W_{ij}^{vh}) \cdot (1 - M_{ji}^{hv}) \tau_j^h + M_{ji}^{hv} (1 - \tau_j^h)}{(1 - M_{ji}^{hv}) \tau_j^h + M_{ji}^{hv} (1 - \tau_j^h)} \right).\end{aligned}$$

Then, one can verify the update of M^{vh} (13) holds. The derivation is analogous for updating M^{hv} (14).

B.2 Proof of the update rule for τ^v in Eq. (16):

$$\begin{aligned}\tau_i^v &= \frac{\tau(v_i = 1)}{\tau(v_i = 1) + \tau(v_i = 0)}, \\ &= \frac{1}{1 + \frac{\exp(0 + \sum_{j=1}^{|\mathbf{h}|} \log m_{j \rightarrow i}(v_i = 0))}{\exp(b_i + \sum_{j=1}^{|\mathbf{h}|} \log m_{j \rightarrow i}(v_i = 1))}}, \text{ by Eq. (11)} \\ &= \frac{1}{1 + \exp \left\{ -b_i^1 - \sum_{j=1}^{|\mathbf{h}|} (\log M_{ij}^{vh} - \log(1 - M_{ij}^{vh})) \right\}}, \\ &= \sigma \left(b_i^1 + (\log M_{i\bullet}^{vh} - \log(\mathbf{1}^{\mathbf{h}\top} - M_{i\bullet}^{vh})) \cdot \mathbf{1}^h \right).\end{aligned}$$

Then, one can verify the update of τ^v (16) holds. The update of τ^h in Eq. (17) is derived similarly.

B.3 The (i, j) element of pairwise belief matrix:

$$\begin{aligned}\Gamma_{ij} &= \frac{\tau(v_i = 1, h_j = 1)}{\sum_{v_i, h_j} \tau(v_i, h_j)} = \\ &= \frac{\frac{\exp(w_{ij}^{vh}) \tau_i^v \tau_j^h}{M_{ij}^{vh} M_{ji}^{hv}}}{\frac{\exp(w_{ij}^{vh}) \tau_i^v \tau_j^h}{M_{ij}^{vh} M_{ji}^{hv}} + \frac{(1 - \tau_i^v) \tau_j^h}{(1 - M_{ij}^{vh}) M_{ji}^{hv}} + \frac{\tau_i^v (1 - \tau_j^h)}{M_{ij}^{vh} (1 - M_{ji}^{hv})} + \frac{(1 - \tau_i^v) (1 - \tau_j^h)}{(1 - M_{ij}^{vh}) (1 - M_{ji}^{hv})}}\end{aligned}$$

We can denote the intermediate terms

$$\begin{aligned}\Gamma^{11} &= \exp(W^{vh}) \circ (\boldsymbol{\tau}^v \cdot \boldsymbol{\tau}^{h\top}) \circ (\mathbf{1}^{vh} - M^{vh}) \circ (\mathbf{1}^{hv} - M^{hv})^\top, \\ \Gamma^{01} &= ((\mathbf{1}^v - \boldsymbol{\tau}^v) \cdot \boldsymbol{\tau}^{h\top}) \circ M^{vh} \circ (\mathbf{1}^{hv} - M^{hv})^\top, \\ \Gamma^{10} &= (\boldsymbol{\tau}^v \cdot (\mathbf{1}^h - \boldsymbol{\tau}^h)^\top) \circ (\mathbf{1}^{vh} - M^{vh}) \circ M^{hv\top}, \\ \Gamma^{00} &= ((\mathbf{1}^v - \boldsymbol{\tau}^v) \cdot (\mathbf{1}^h - \boldsymbol{\tau}^h)^\top) \circ M^{vh} \circ M^{hv\top}.\end{aligned}$$

Then, the pairwise belief matrix $\Gamma = \frac{\Gamma^{11}}{\Gamma^{11} + \Gamma^{01} + \Gamma^{10} + \Gamma^{00}}$.