

Prob 1

1-1. $\max_{x_j} b_{ij}^*(x_i, x_j)$ & $b_{ii}^*(x_i)$ for max-product algorithm

$$\begin{aligned} \max_{x_j} b_{ij}^*(x_i, x_j) &= \max_{x_j} \psi_{ij}(x_i, x_j) \cdot \phi_i(x_i) \phi_j(x_j) \cdot \prod_{k \in N(i) \setminus j} m_{k \rightarrow i}(x_i) \cdot \prod_{k \in N(j) \setminus i} m_{k \rightarrow j}(x_j) \\ &= \phi_i(x_i) \cdot \prod_{k \in N(i) \setminus j} m_{k \rightarrow i}(x_i) \cdot \underbrace{\max_{x_j} \psi_{ij}(x_i, x_j) \cdot \phi_j(x_j) \cdot \prod_{k \in N(j) \setminus i} m_{k \rightarrow j}(x_j)}_{\text{This term is } m_{j \rightarrow i} \text{ by definition of message in max product.}} \end{aligned}$$

This term is $m_{j \rightarrow i}$ by definition of message in max product.

$$= \phi_i(x_i) \cdot \prod_{k \in N(i) \setminus j} m_{k \rightarrow i}(x_i) = \phi_i(x_i) \cdot \prod_{k \in N(i)} m_{k \rightarrow i}(x_i) = b_{ii}^*(x_i).$$

\therefore proved.

1-2. $\sum_{x_j} b_{ij}^*(x_i, x_j)$ & $b_{ii}^*(x_i)$ for sum-product.

$$\begin{aligned} \sum_{x_j} b_{ij}^*(x_i, x_j) &= \sum_{x_j} \psi_{ij}(x_i, x_j) \cdot \phi_i(x_i) \cdot \phi_j(x_j) \cdot \prod_{k \in N(i) \setminus j} m_{k \rightarrow i}(x_i) \cdot \prod_{k \in N(j) \setminus i} m_{k \rightarrow j}(x_j) \\ &= \phi_i(x_i) \cdot \prod_{k \in N(i) \setminus j} m_{k \rightarrow i}(x_i) \cdot \underbrace{\sum_{x_j} \psi_{ij}(x_i, x_j) \cdot \phi_j(x_j) \cdot \prod_{k \in N(j) \setminus i} m_{k \rightarrow j}(x_j)}_{\text{Like above This term is } m_{j \rightarrow i} \text{ in sum-product algorithm for same reason.}} \end{aligned}$$

Like above This term is $m_{j \rightarrow i}$ in sum-product algorithm for same reason.

$$= \phi_i(x_i) \cdot \prod_{k \in N(i) \setminus j} m_{k \rightarrow i}(x_i) \cdot m_{j \rightarrow i} = \phi_i(x_i) \cdot \prod_{k \in N(i)} m_{k \rightarrow i}(x_i) = b_{ii}^*(x_i).$$

\therefore proved.

Prob 1-3.

MAX-product convex belief propagation algorithm update equations of the sum-product algorithm at temperature T , as the T approaches zero by standard form of zero limit equation. Formally, if a set of messages form a fixed point of sum-product at temperature T . As $T \rightarrow 0$, then these same messages raised to the $1/T$ power, will form a fixed-point of the max-product algorithm. Under some assumption, $\phi(x)$ is non-negative, belief free energy is strictly convex, and will give global minima.

\therefore Zero temperature limit of convexified sum-product algorithms are guaranteed to solve MAP LP relaxation as $T \rightarrow 0$, free energy objective tends to the LP objective

\therefore belief can be reformulated to converge to a set of beliefs there are max-product calibrated and these are fixed points of the convex max-product BP algorithm. Thus, we can hope to use max-product BP to find limiting belief (using zero-limit property)

Prob 3.

$$p(x) = \frac{1}{Z} \prod_{\bar{i} \in V} \exp(h_{\bar{i}} x_{\bar{i}}) \cdot \prod_{(\bar{i}, \bar{j}) \in E} \exp(J_{\bar{i}\bar{j}} x_{\bar{i}} x_{\bar{j}})$$

Here, $h_{\bar{i}} = 0$ and $J_{\bar{i}\bar{j}} = J$ for every edges \therefore we can reformulate as.

$$p(x) = \frac{1}{Z} \prod_{(\bar{i}, \bar{j}) \in E} e^{J x_{\bar{i}} x_{\bar{j}}}$$

$$\log p(x) = \sum_{(\bar{i}, \bar{j}) \in E} J \cdot x_{\bar{i}} \cdot x_{\bar{j}} - \log Z.$$

Since we are given samples from unknown Ising model over

- ① $(-1, -1, 1) \dots$
- ② $(1, -1, 1) \dots$
- ③ $(1, 1, 1) \dots$
- ④ $(-1, 1, 1) \dots$
- ⑤ $(1, -1, -1) \dots$

we have to consider

① 15 different combination of $x_{\bar{i}}, x_{\bar{j}}$

~~② 5 different Z~~ ② 5 Z,

number ① ~ ⑤ are model numbers.

$$\begin{aligned} \therefore \log p(x) &= J \cdot (-1) \cdot (-1) + J(-1)(1) + J(-1) \cdot (1) - \log Z^{①} \\ &+ J(1)(-1) + J(1)(-1) + J(1) \cdot (-1) - \log Z^{②} \\ &+ J(1)(1) + J(1)(1) + J(1)(1) - \log Z^{③} \\ &+ J(-1)(-1) + J(-1)(-1) + J(-1)(-1) - \log Z^{④} \\ &+ J(1)(-1) + J(1)(-1) + J(-1)(-1) - \log Z^{⑤} \\ &= 9J - 6J - \cancel{7J} - \cancel{5J} = 3J - \cancel{\log(Z + \dots + Z)} \\ &\quad - 5 \log Z. \end{aligned}$$

$$\begin{aligned} \log Z &= \log \left(\sum_{\bar{i}, \bar{j}} \prod_{(\bar{i}, \bar{j}) \in E} e^{J x_{\bar{i}} x_{\bar{j}}} \right) \\ &= \log 3 (2 \cdot e^{3J} + 3 \cdot e^{-J}) = \log (6 \cdot e^{3J} + 9 \cdot e^{-J}) \end{aligned}$$

$$\therefore \log p(x) = 3J - 5 \cdot \log (6 \cdot e^{3J} + 9 \cdot e^{-J})$$

$$\frac{d}{dJ} \log p(x) = 3 - 5 \cdot \frac{1}{6 \cdot e^{3J} + 9 \cdot e^{-J}} (18 \cdot e^{3J} - 9 \cdot e^{-J}) = 0.$$

$$\Rightarrow 3 = \frac{5}{6 \cdot e^{3J} + 9 \cdot e^{-J}} (18 \cdot e^{3J} - 9 \cdot e^{-J})$$

$$\Rightarrow 1 = \frac{5}{6 \cdot e^{3J} + 9 \cdot e^{-J}} (6 \cdot e^{3J} - 3 \cdot e^{-J})$$

$$\Rightarrow 1 = \frac{5}{2 \cdot e^{3J} + 3 \cdot e^{-J}} (2 \cdot e^{3J} - e^{-J})$$

$$2 \cdot e^{3J} + 3 \cdot e^{-J} = 10 e^{3J} - 5 e^{-J}$$

$$\Rightarrow 8 e^{3J} = 8 e^{-J}$$

$$\Rightarrow e^{4J} = 1$$

$$\Rightarrow 4J \log e = \log 1$$

$$\Rightarrow 4J = 0.$$

$$\therefore J = 0 //$$