

连续权重感知机在二分类任务中的泛化误差

LYH & WYC
PMI Group Meeting
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Introduction

teacher

$$y = \text{sign} \left(\frac{1}{\sqrt{n}} \mathbf{X} \mathbf{w}^* \right)$$

$$P_{\mathbf{w}^*} \sim \mathcal{N}(0, 1)$$

student

$$P(\mathbf{w}|\mathbf{y}, \mathbf{X}) = \frac{P(\mathbf{y}|\mathbf{X}, \mathbf{w})P(\mathbf{w})}{P(\mathbf{y}, \mathbf{X})} = \frac{1}{\mathcal{Z}} P(\mathbf{y}|\mathbf{X}, \mathbf{w})P(\mathbf{w})$$

$$P(\mathbf{y}|\mathbf{X}, \mathbf{w}) = \mathbb{1} \left[y = \text{sign} \left(\frac{1}{\sqrt{n}} \mathbf{X} \mathbf{w} \right) \right]$$

generalization error

$$\varepsilon_{\text{gen}} = \mathbb{E}_{\mathbf{y}, \mathbf{X}} [\Theta(-\mathbf{y}\hat{\mathbf{y}})] = \mathbb{E}_{\mathbf{y}, \mathbf{X}} [\Theta(-\mathbf{z}\hat{\mathbf{z}})]$$

$$= \frac{1}{\pi} \arccos \left(\frac{\sigma_{\mathbf{w}^* \hat{\mathbf{w}}}}{\sqrt{\rho_{\mathbf{w}^*} \sigma_{\hat{\mathbf{w}}}}} \right)$$

$$= \frac{1}{\pi} \arccos \left(\sqrt{\frac{q}{\rho_{\mathbf{w}^*}}} \right)$$

Nishimori condition

$$\sigma_{\mathbf{w}^* \hat{\mathbf{w}}} = \lim_{n \rightarrow \infty} \mathbb{E}_{\mathbf{w}^*, \mathbf{X}} \frac{1}{n} \hat{\mathbf{w}}^\top \mathbf{w}^* = \sigma_{\hat{\mathbf{w}}} = \lim_{n \rightarrow \infty} \mathbb{E}_{\mathbf{w}^*, \mathbf{X}} \frac{1}{n} \|\hat{\mathbf{w}}\|_2^2$$

$$\rho_{\mathbf{w}^*} = \sigma_{\mathbf{w}^*} \equiv \lim_{n \rightarrow \infty} \mathbb{E}_{\mathbf{w}^*} \frac{1}{n} \|\mathbf{w}^*\|_2^2$$

$$\alpha = d/n$$

$$\mathbf{z} = \mathbf{X} \mathbf{w}^* / \sqrt{n}, \quad \hat{\mathbf{z}} = \mathbf{X} \hat{\mathbf{w}} / \sqrt{n}$$

$$\sigma = \lim_{n \rightarrow \infty} \mathbb{E}_{\mathbf{w}^*, \mathbf{X}} \frac{1}{n} \begin{bmatrix} \mathbf{w}^{*\top} \mathbf{w}^* & \mathbf{w}^{*\top} \hat{\mathbf{w}} \\ \mathbf{w}^{*\top} \hat{\mathbf{w}} & \hat{\mathbf{w}}^\top \hat{\mathbf{w}} \end{bmatrix} \equiv \begin{bmatrix} \sigma_{\mathbf{w}^*} & \sigma_{\mathbf{w}^* \hat{\mathbf{w}}} \\ \sigma_{\mathbf{w}^* \hat{\mathbf{w}}} & \sigma_{\hat{\mathbf{w}}} \end{bmatrix}$$

$$\hat{\mathbf{z}} = \sqrt{\sigma_{\hat{\mathbf{w}}}} \mathbf{x}_1$$

$$\mathbf{z} = \sqrt{\frac{\sigma_{\mathbf{w}^* \hat{\mathbf{w}}}}{\sigma_{\hat{\mathbf{w}}}}} \mathbf{x}_1 + \sqrt{\sigma_{\mathbf{w}^*}^2 - \frac{\sigma_{\mathbf{w}^* \hat{\mathbf{w}}}}{\sigma_{\hat{\mathbf{w}}}}} \mathbf{x}_2$$

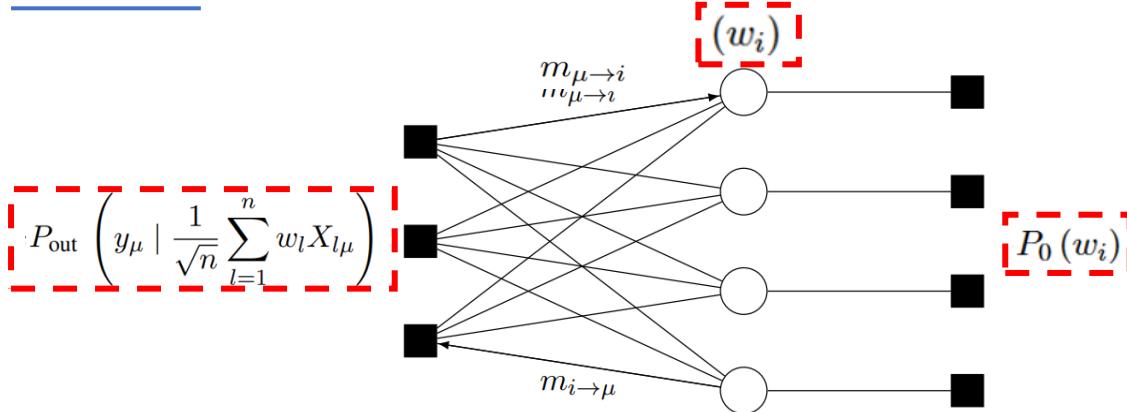
$$\varepsilon_{\text{gen}} = \mathbb{E}_{\mathbf{y}, \mathbf{X}} [\Theta(-\mathbf{z}\hat{\mathbf{z}})]$$

$$= \int D\mathbf{x}_1 \int D\mathbf{x}_2 \Theta \left(-\sqrt{\sigma_{\hat{\mathbf{w}}}} \mathbf{x}_1 \left(\sqrt{\frac{\sigma_{\mathbf{w}^* \hat{\mathbf{w}}}^2}{\sigma_{\hat{\mathbf{w}}}}} \mathbf{x}_1 + \sqrt{\sigma_{\mathbf{w}^*}^2 - \frac{\sigma_{\mathbf{w}^* \hat{\mathbf{w}}}^2}{\sigma_{\hat{\mathbf{w}}}}} \mathbf{x}_2 \right) \right)$$

$$= \int D\mathbf{x}_1 \int D\mathbf{x}_2 \Theta(-\mathbf{x}_1) \Theta \left(\sqrt{\frac{\sigma_{\mathbf{w}^* \hat{\mathbf{w}}}^2}{\sigma_{\hat{\mathbf{w}}}}} \mathbf{x}_1 + \sqrt{\sigma_{\mathbf{w}^*}^2 - \frac{\sigma_{\mathbf{w}^* \hat{\mathbf{w}}}^2}{\sigma_{\hat{\mathbf{w}}}}} \mathbf{x}_2 \right)$$

$$= \frac{1}{\pi} \arccos \left(\frac{\sigma_{\mathbf{w}^* \hat{\mathbf{w}}}}{\sqrt{\rho_{\mathbf{w}^*} \sigma_{\hat{\mathbf{w}}}}} \right)$$

AMP



BP equation

$$m_{i \rightarrow \mu}(w_i) = \frac{1}{z_{i \rightarrow \mu}} P_0(w_i) \prod_{\gamma \neq \mu} m_{\gamma \rightarrow i}(w_i)$$

$$m_{\mu \rightarrow i}(w_i) = \frac{1}{z_{\mu \rightarrow i}} \int \prod_{j \neq i} dw_j P_{\text{out}} \left(y_\mu \mid \frac{1}{\sqrt{n}} \sum_{l=1}^n w_l X_{l\mu} \right) m_{j \rightarrow \mu}(w_j)$$

relaxed-BP equation

approximate $m_{i \rightarrow \mu}$ only TWO moments

Central Limit Theory

$$z_\mu = X_{\mu i} w_i + \sum_{j \neq i} X_{\mu j} w_j \quad \omega_{\mu \rightarrow i} = \sum_{j \neq i} X_{\mu j} \hat{w}_{j \rightarrow \mu} \quad \hat{w}_{i \rightarrow \mu} \equiv \int dw_i m_{i \rightarrow \mu}(w_i) w_i$$

$$\sum_{j \neq i} X_{\mu j} w_j \sim \mathcal{N}(\omega_{\mu \rightarrow i}, V_{\mu \rightarrow i}) \quad V_{\mu \rightarrow i} = \sum_{j \neq i} X_{\mu j}^2 v_{j \rightarrow \mu} \quad v_{i \rightarrow \mu} \equiv \int dw_i m_{i \rightarrow \mu}(w_i) w_i^2 - \hat{w}_{i \rightarrow \mu}^2$$

$$m_{\mu \rightarrow i}(w_i) \propto \int dz_\mu P_{\text{out}}(y_\mu | z_\mu) \exp \left\{ -\frac{(z_\mu - \omega_{\mu \rightarrow i} - X_{\mu i} w_i)^2}{2V_{\mu \rightarrow i}} \right\}$$

$$\mathcal{H}(\mathbf{x}; \mathbf{Y}, \Phi) := - \sum_{\mu=1}^M \ln P_{\text{out}} \left(Y_\mu \mid \frac{1}{\sqrt{N}} [\Phi \mathbf{x}]_\mu \right)$$

$$E(\mathbf{x}) = - \sum_a \ln f_a(\mathbf{x}_a)$$

$$P_{a \rightarrow i}(x_i) = \sum_{\mathbf{x}_j : j \in \partial a \setminus i} f_a(\mathbf{x}_a) \prod_{j \in \partial a \setminus i} P_{j \rightarrow a}(x_j)$$

$$P_{i \rightarrow a}(x_i) = \frac{1}{Z_{i \rightarrow a}} \prod_{b \in \partial i \setminus a} P_{b \rightarrow i}(x_i).$$

$$\begin{aligned}
m_{\mu \rightarrow i}(w_i) &\propto \int dz_\mu P_{\text{out}}(y_\mu | z_\mu) \exp \left\{ -\frac{(z - \omega_{\mu \rightarrow i} - X_{\mu i} w_i)^2}{2V_{\mu \rightarrow i}} \right\} \\
&\quad \exp \left\{ -\frac{(z - \omega_{\mu \rightarrow i} - X_{\mu i} w_i)^2}{2V_{\mu \rightarrow i}} \right\} \\
&= \exp \left\{ -\frac{(z - \omega_{\mu \rightarrow i})^2 + X_{\mu i}^2 w_i^2 - 2(z - \omega_{\mu \rightarrow i}) X_{\mu i} w_i}{2V_{\mu \rightarrow i}} \right\} \\
&= \exp \left\{ -\frac{(z - \omega_{\mu \rightarrow i})^2}{2V_{\mu \rightarrow i}} \right\} \exp \left\{ -\frac{X_{\mu i}^2 w_i^2 - 2(z - \omega_{\mu \rightarrow i}) X_{\mu i} w_i}{2V_{\mu \rightarrow i}} \right\} \\
&= \exp \left\{ -\frac{(z - \omega_{\mu \rightarrow i})^2}{2V_{\mu \rightarrow i}} \right\} \left(1 + X_{\mu i}^2 w_i^2 - 2(z - \omega_{\mu \rightarrow i}) X_{\mu i} w_i + \frac{1}{2}(z - \omega_{\mu \rightarrow i})^2 X_{\mu i}^2 w_i^2 + \mathcal{O}\left(\frac{1}{n}\right) \right)
\end{aligned}$$

$$m_{\mu \rightarrow i}(w_i) \propto \int dz_\mu P_{\text{out}}(y_\mu | z_\mu) \exp \left\{ -\frac{(z - \omega_{\mu \rightarrow i})^2}{2V_{\mu \rightarrow i}} \right\} \times \left(1 + X_{\mu i}^2 w_i^2 - 2(z - \omega_{\mu \rightarrow i}) X_{\mu i} w_i + \frac{1}{2} (z - \omega_{\mu \rightarrow i})^2 X_{\mu i}^2 w_i^2 + \mathcal{O}\left(\frac{1}{n}\right) \right)$$

define

$$f_{\text{out}}(\omega, y, V) \equiv \frac{\int dz P_{\text{out}}(y|z)(z - \omega)e^{-\frac{(z-\omega)^2}{2V}}}{V \int dz P_{\text{out}}(y|z)e^{-\frac{(z-\omega)^2}{2V}}}$$

$$\partial_\omega f_{\text{out}}(\omega, y, V) = \frac{\int dz P_{\text{out}}(y|z)(z - \omega)^2 e^{-\frac{(z-\omega)^2}{2V}}}{V^2 \int dz P_{\text{out}}(y|z) e^{-\frac{(z-\omega)^2}{2V}}} - \frac{1}{V} - f_{\text{out}}^2(\omega, y, V)$$

$$A_{\mu \rightarrow i}^t = -X_{\mu i}^2 \partial_\omega f_{\text{out}}(\omega_{\mu \rightarrow i}^t, y_\mu, V_{\mu \rightarrow i}^t)$$

$$B_{\mu \rightarrow i}^t = X_{\mu i} f_{\text{out}}(\omega_{\mu \rightarrow i}^t, y_\mu, V_{\mu \rightarrow i}^t)$$

$$\begin{aligned}
& V], \\
&] - f_w f_w^\top. \\
& \boxed{B_{\mu \rightarrow i}^t \equiv \frac{X_{\mu i}}{\sqrt{n}} g_{\text{out}}(\omega_{i\mu}^t, Y_\mu, V_{i\mu}^t),} \\
& \boxed{A_{\mu \rightarrow i}^t \equiv -\frac{X_{\mu i}^2}{n} \partial_\omega g_{\text{out}}(\omega_{i\mu}^t, Y_\mu, V_{i\mu}^t)} \\
& , Y_\mu, V_{i\mu}^t) + \frac{1}{2} \frac{X_{\mu i}^2}{n} W_i^\top g_{\text{out}} g_{\text{out}}^\top (\omega_{i\mu}^t, Y_\mu, V_{i\mu}^t) W_i + \\
& \quad \text{why omit?} \\
& \left. \right\} = \frac{1}{Z_{\mu \rightarrow i}} \left\{ 1 + W_i^\top B_{\mu \rightarrow i}^t + \boxed{\frac{1}{2} W_i^\top B_{\mu \rightarrow i}^t (B_{\mu \rightarrow i}^t)^\top (W_i)} - \frac{1}{2} W_i^\top A_{\mu \rightarrow i}^t W_i \right\} \\
& = \sqrt{\frac{\det(A_{\mu \rightarrow i}^t)}{(2\pi)^K}} \exp \left(-\frac{1}{2} (W_i^\top - (A_{\mu \rightarrow i}^t)^{-1} B_{\mu \rightarrow i}^t)^\top A_{\mu \rightarrow i}^t (W_i^\top - (A_{\mu \rightarrow i}^t)^{-1} B_{\mu \rightarrow i}^t) \right)
\end{aligned}$$

$$m_{i \rightarrow \mu}(w_i) \propto P_0(w_i) e^{-\frac{(w_i - R_{i \rightarrow \mu})^2}{2\Sigma_{i \rightarrow \mu}}}$$

define $f_w \equiv \frac{\int dw w P_0(w) e^{-\frac{(w-R)^2}{2\Sigma}}}{\int dw P_0(w) e^{-\frac{(w-R)^2}{2\Sigma}}}$

$$\Sigma_{i \rightarrow \mu}^t = \left(\sum_{\nu \neq \mu} A_{\nu \rightarrow i}^t \right)^{-1}$$

$$R_{i \rightarrow \mu}^t = \Sigma_{i \rightarrow \mu}^t \left(\sum_{\nu \neq \mu} B_{\nu \rightarrow i}^t \right)$$

$$\hat{w}_{i \rightarrow \mu} \equiv \int dw_i m_{i \rightarrow \mu}(w_i) w_i$$

$$v_{i \rightarrow \mu} \equiv \int dw_i m_{i \rightarrow \mu}(x_i) w_i^2 - \hat{w}_{i \rightarrow \mu}^2$$

$\rightarrow \hat{w}_{\mu \rightarrow i} = f_w(\Sigma, R)$

$$v_{\mu \rightarrow i} = \partial_R f_w(\Sigma, R)$$

r-BP Algorithm

Algorithm 1 relaxed Belief-Propagation (r-BP)

Input: y

Initialize: $\mathbf{a}_{i \rightarrow \mu}(t=0), \mathbf{v}_{i \rightarrow \mu}(t=0), t=1$

repeat

r-BP Update of $\{\omega_{\mu \rightarrow i}, V_{\mu \rightarrow i}\}$

$$V_{\mu \rightarrow i}(t) \leftarrow \sum_{j \neq i} F_{\mu j}^2 v_{j \rightarrow \mu}(t-1)$$

$$\omega_{\mu \rightarrow i}(t) \leftarrow \sum_{j \neq i} F_{\mu j} a_{j \rightarrow \mu}(t-1)$$

r-BP Update of $\{A_{\mu \rightarrow i}, B_{\mu \rightarrow i}\}$

$$B_{\mu \rightarrow i}(t) \leftarrow g_{\text{out}}(\omega_{\mu \rightarrow i}(t), y_\mu, V_{\mu \rightarrow i}(t)) F_{\mu i},$$

$$A_{\mu \rightarrow i}(t) \leftarrow -\partial_\omega g_{\text{out}}(\omega_{\mu \rightarrow i}(t), y_\mu, V_{\mu \rightarrow i}(t)) F_{\mu i}^2$$

r-BP Update of $\{R_{\mu \rightarrow i}, \Sigma_{\mu \rightarrow i}\}$

$$\Sigma_{i \rightarrow \mu}(t) \leftarrow \frac{1}{\sum_{\nu \neq \mu} A_{\nu \rightarrow i}(t)}$$

$$R_{i \rightarrow \mu}(t) \leftarrow \Sigma_{i \rightarrow \mu}(t) \sum_{\nu \neq \mu} B_{\nu \rightarrow i}(t)$$

AMP Update of the estimated partial marginals $\mathbf{a}_{i \rightarrow \mu}(t), \mathbf{v}_{i \rightarrow \mu}(t)$

$$a_{i \rightarrow \mu}(t) \leftarrow f_a(\Sigma_{i \rightarrow \mu}(t), R_{i \rightarrow \mu}(t)),$$

$$v_{i \rightarrow \mu}(t) \leftarrow f_v(\Sigma_{i \rightarrow \mu}(t), R_{i \rightarrow \mu}(t)).$$

$t \leftarrow t + 1$

until Convergence on $\mathbf{a}_{i \rightarrow \mu}(t), \mathbf{v}_{i \rightarrow \mu}(t)$

output: Estimated marginals mean and variances:

$$a_i \leftarrow f_a \left(\frac{1}{\sum_\nu A_{\nu \rightarrow i}}, \frac{\sum_\nu B_{\nu \rightarrow i}}{\sum_\nu A_{\nu \rightarrow i}} \right),$$

$$v_i \leftarrow f_v \left(\frac{1}{\sum_\nu A_{\nu \rightarrow i}}, \frac{\sum_\nu B_{\nu \rightarrow i}}{\sum_\nu A_{\nu \rightarrow i}} \right).$$

AMP



$$\omega_{\mu \rightarrow i} = \sum_{j \neq i} X_{\mu j} \hat{w}_{j \rightarrow \mu}$$

$$V_{\mu \rightarrow i} = \sum_{j \neq i} X_{\mu j}^2 v_{j \rightarrow \mu}$$

$$\boxed{XXX}_{\mu \rightarrow i} \rightarrow \boxed{XXX}_\mu$$

$$\omega_\mu = \sum_i X_{\mu i} \hat{w}_{i \rightarrow \mu}$$

$$V_\mu = \sum_i X_{\mu i}^2 v_{i \rightarrow \mu}$$

$$\Sigma_\mu^{t+1} = \frac{1}{\sum_\mu A_{\mu \rightarrow i}^{t+1}}$$

$$R_\mu^{t+1} = \frac{\sum_\mu B_{\mu \rightarrow i}^{t+1}}{\sum_\mu A_{\mu \rightarrow i}^t}$$

$$V_\mu^{t+1} = \sum_i X_{\mu i}^2 v_{i \rightarrow \mu}^t \approx \sum_i X_{\mu i}^2 v_i^t$$

$$\omega_{\mu \rightarrow i} = \sum_{j \neq i} X_{\mu j} \hat{w}_{j \rightarrow \mu}$$

$$B_{\mu \rightarrow i}^t = X_{\mu i} f_{\text{out}}(\omega_{\mu \rightarrow i}^t, y_\mu, V_{\mu \rightarrow i}^t)$$

$$A_{\mu \rightarrow i}^t = -X_{\mu i}^2 \partial_\omega f_{\text{out}}(\omega_{\mu \rightarrow i}^t, y_\mu, V_{\mu \rightarrow i}^t)$$

$$(\Sigma_i)^{t+1} \approx \left[- \sum_{\mu} X_{\mu i}^2 \partial_{\omega} f_{\text{out}} (\omega_{\mu}^{t+1}, y_{\mu}, V_{\mu}^{t+1}) \right]^{-1}$$

$$R_i^{t+1} = \left[-\sum_{\mu} X_{\mu i}^2 \partial_{\omega} f_{\text{out}}(\omega_{\mu}^{t+1}, y_{\mu}, V_{\mu}^{t+1}) \right]^{-1} \times \left[\sum_{\mu} X_{\mu i} f_{\text{out}}(\omega_{\mu \rightarrow i}^{t+1}, y_{\mu}, V_{\mu \rightarrow i}^{t+1}) \right]$$

输入: y 、 X 初始化 \hat{w}^0 、 v^0 、 f_{out}^0 设置迭代次数 $t = 1$, 最大迭代次数 T

$$\bullet \quad f_{\text{out}}(\omega_{\mu \rightarrow i}^{t+1}, y_\mu, V_{\mu \rightarrow i}^{t+1})$$

$$\approx f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1}) - X_{\mu i} \hat{w}_i^t \partial_\omega f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1})$$

$$\approx f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1}) - X_{\mu i} \hat{w}_i^t \partial_\omega f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1})$$

$$\bullet \quad R_i^{t+1}$$

$$= (\Sigma_i)^{t+1} \times \left[\sum_\mu X_{\mu i} f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1}) - X_{\mu i}^2 \hat{w}_i^t \partial_\omega f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1}) \right]$$

$$= \hat{w}_i^t + (\Sigma_i)^{t+1} \sum_\mu X_{\mu i} f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1})$$

$$\bullet \quad \hat{w}_{i \rightarrow \mu}^t = f_w(R_{i \rightarrow \mu}^t, \Sigma_{i \rightarrow \mu}) \approx f_w(R_{i \rightarrow \mu}^t, \Sigma_i)$$

$$\approx f_w(R_i^t, \Sigma_i) - B_{\mu \rightarrow i}^t \partial_R f_w(R_i^t, \Sigma_i)$$

$$\approx \hat{w}_i^t - f_{\text{out}}(\omega_\mu^t, y_\mu, V_\mu^t) X_{\mu i} v_i^t$$

$$\hat{w}_i^{t+1} = \frac{\Sigma_i^{t+1}}{1 + R_i^{t+1}}$$

$$\bullet \quad \omega_\mu^{t+1} = \sum_i X_{\mu i} \hat{w}_i^t - \sum_i f_{\text{out}}(\omega_\mu^t, y_\mu, V_\mu^t) X_{\mu i}^2 v_i^t$$

$$= \sum_i X_{\mu i} \hat{w}_i^t - V_\mu^t f_{\text{out}}(\omega_\mu^t, y_\mu, V_\mu^t)$$

$$v_i^{t+1} = \frac{1}{1 + R_i^{t+1}}$$

1 **while** $t < T$ **do**2 计算 ω 、 V

$$\omega_\mu^{t+1} \leftarrow \frac{1}{\sqrt{n}} \sum_i X_{\mu i} \hat{w}_i^t - V_\mu^t f_{\text{out}}(\omega_\mu^t, y_\mu, V_\mu^t)$$

$$V_\mu^{t+1} \leftarrow \frac{1}{n} \sum_i X_{\mu i}^2 v_i^t$$

3 计算 f_{out}

$$f_{\text{out}}^{t+1} \leftarrow f_{\text{out}}(y, \omega^{t+1}, V^{t+1})$$

4 计算 Σ 、 R

$$\Sigma_i^{t+1} \leftarrow \left[-\frac{1}{n} \sum_\mu X_{\mu i}^2 \partial_\omega f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1}) \right]^{-1}$$

$$R_i^{t+1} \leftarrow \hat{w}_i^t + \frac{1}{\sqrt{n}} (\Sigma_i)^{t+1} \sum_\mu X_{\mu i} f_{\text{out}}(\omega_\mu^{t+1}, y_\mu, V_\mu^{t+1})$$

5 计算 \hat{w} 、 v

$$\hat{w}_i^{t+1} \leftarrow \frac{\Sigma_i^{t+1}}{1 + R_i^{t+1}}$$

if \hat{w} 、 v 不再变化 **then**

$$v_i^{t+1} \leftarrow \frac{1}{1 + R_i^{t+1}}$$

停止迭代

end $t \leftarrow t + 1$

模型出发点：

$$\omega_{\mu \rightarrow i} = \frac{1}{\sqrt{n}} \sum_{j \neq i} X_{\mu i} \hat{w}_i$$

$$z_{\mu \rightarrow i} = \frac{1}{\sqrt{n}} \sum_{j \neq i} X_{\mu i} w_{i \rightarrow j}^*$$

$$V_\mu = \frac{1}{n} \sum_i X_{\mu i}^2 v_i$$

算法出发点：

$$\Sigma_i = \frac{1}{\sum_\mu A_{\mu \rightarrow i}}$$

$$R_i = \frac{\sum_\mu B_{\mu \rightarrow i}}{\sum_\mu A_{\mu \rightarrow i}}$$

定义以下序参量：

$$\hat{q} = \alpha \mathbb{E}_{\omega, z} [f_{\text{out}}^2(\omega, \text{sign}[z], V)]$$

$$\hat{m} = \alpha \mathbb{E}_{\omega, z} [\partial_z f_{\text{out}}(\omega, \text{sign}[z], V)]$$



$$\frac{R_i}{\Sigma_i} = \mathcal{N}(0, 1) \sqrt{\hat{q}} + w_i^* \hat{m}$$

闭合方程：

$$q = \mathbb{E}_{w^*} \mathbb{E}_{R, \Sigma} [f_w^2(\Sigma, R)]$$

$$m = \mathbb{E}_{w^*} \mathbb{E}_{R, \Sigma} [w^* f_w(\Sigma, R)]$$



$$q = \mathbb{E}[\omega^2] = \mathbb{E}[\hat{w}^2]$$

$$m = \mathbb{E}[z\omega] = \mathbb{E}[w^* \hat{w}]$$

$$f_w(\Sigma, R) \equiv \frac{\int dw w P_0(w) e^{-\frac{(w-R)^2}{2\Sigma}}}{\int dw P_0(w) e^{-\frac{(w-R)^2}{2\Sigma}}}$$

$$f_{\text{out}}(\omega, y, V) \equiv \frac{\int dz P_{\text{out}}(y|z)(z - \omega) e^{-\frac{(z-\omega)^2}{2V}}}{V \int dz P_{\text{out}}(y|z) e^{-\frac{(z-\omega)^2}{2V}}}$$

$$\frac{R_i}{\Sigma_i} = \sum_\mu B_{\mu \rightarrow i}$$

$$= \sum_\mu X_{\mu i} f_{\text{out}}(\omega_{\mu \rightarrow i}, y_\mu, V_{\mu \rightarrow i})$$

$$= \sum_\mu X_{\mu i} f_{\text{out}}(\omega_{\mu \rightarrow i}, \text{sign}[\sum_{j \neq i} X_{\mu j} w_j^* + X_{\mu i} w_i^*], V)$$

$$= \sum_\mu X_{\mu i} f_{\text{out}}(\omega_{\mu \rightarrow i}, \text{sign}[\sum_{j \neq i} X_{\mu j} w_j^*], V) + \sum_\mu X_{\mu i} f_{\text{out}}(\omega_{\mu \rightarrow i}, \text{sign}[X_{\mu i} w_i^*], V)$$

SE

$$q = \mathbb{E}_{w^*} \mathbb{E}_{R,\Sigma} [f_w^2(\Sigma, R)]$$

$$m = \mathbb{E}_{w^*} \mathbb{E}_{R,\Sigma} [w^* f_w(\Sigma, R)]$$

$$\hat{q} = \alpha \mathbb{E}_{\omega,z} [f_{\text{out}}^2(\omega, \text{sign}[z], V)]$$

$$\hat{m} = \alpha \mathbb{E}_{\omega,z} [\partial_z f_{\text{out}}(\omega, \text{sign}[z], V)]$$

Nishimori condition: q=m

Bayes optimal

$$q = m = \mathbb{E}_{w^*} \mathbb{E}_{R,\Sigma} [w^* f_w(\Sigma, R)]$$

$$\hat{q} = \hat{m} = \alpha \mathbb{E}_{\omega,z} [\partial_z f_{\text{out}}(\omega, \text{sign}[z], V)]$$

显式表达:

$$q^{t+1} = \int dx P_X(x) \int d\xi \frac{e^{-\frac{\xi^2}{2}}}{\sqrt{2\pi}} f_{w^*}^2\left(\frac{1}{\hat{q}^t}, x + \frac{\xi}{\sqrt{\hat{q}^t}}\right)$$

$$\hat{q}^t = - \int dp \int dz \frac{e^{-\frac{p^2}{2m^t}} e^{-\frac{(z-p)^2}{2(1-m^t)}}}{2\pi \sqrt{m^t(1-m^t)}} \partial_p f_{\text{out}}(p, \text{sign}[z], 1-m^t)$$

$$q = \frac{\hat{q}}{1 + \hat{q}}$$

$$\hat{q} = \frac{2}{\pi} \frac{\alpha}{1-q} \int D\xi \frac{\exp\left\{-\frac{q\xi^2}{1-q}\right\}}{1 + \operatorname{erf}\left(\frac{\sqrt{q}\xi}{\sqrt{2(1-q)}}\right)}$$

same as replica

简单并不断重复:

$$\int_{-\infty}^{\infty} e^{-x^2} dx = \sqrt{\pi}$$

$$\int_{-\infty}^{\infty} x e^{-x^2} dx = 0$$

$$\int_{-\infty}^{\infty} x^2 e^{-x^2} dx = \frac{\sqrt{\pi}}{2}$$

$$\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt$$

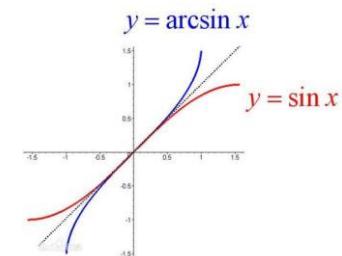
Asymptotic solution $\alpha \rightarrow \infty, q \rightarrow 1$

$$\int D\xi \frac{e^{-\frac{q_b \xi^2}{1-q_b}}}{\left(1 + \operatorname{erf}\left(\frac{\sqrt{q_b} \xi}{\sqrt{2(1-q_b)}}\right)\right)} = \int d\xi \frac{\frac{\xi^{2(q_b+1)}}{-e^{\frac{-\xi^2}{2(1-q_b)}}}}{\sqrt{2\pi} \left(1 + \operatorname{erf}\left(\frac{\sqrt{q_b} \xi}{\sqrt{2(1-q_b)}}\right)\right)} \simeq \int d\xi \frac{\frac{\xi^2}{\sqrt{2\pi}}}{\left(1 + \operatorname{erf}\left(\frac{\xi}{\sqrt{2(1-q_b)}}\right)\right)}$$

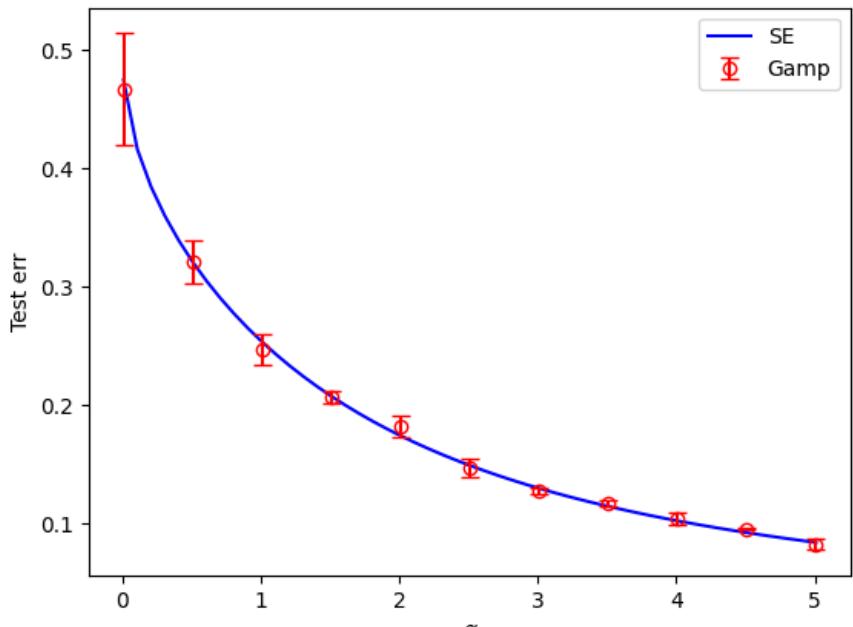
$$= \frac{\sqrt{1-q_b}}{\sqrt{2\pi}} \int d\eta \frac{e^{-\eta^2}}{1 + \operatorname{erf}\left(\frac{\eta}{\sqrt{2}}\right)} = \frac{c_0}{\sqrt{2\pi}} \sqrt{1-q_b}$$

$$c_0 \equiv \int d\eta \frac{e^{-\eta^2}}{1 + \operatorname{erf}\left(\frac{\eta}{\sqrt{2}}\right)} \simeq 2.83748.$$

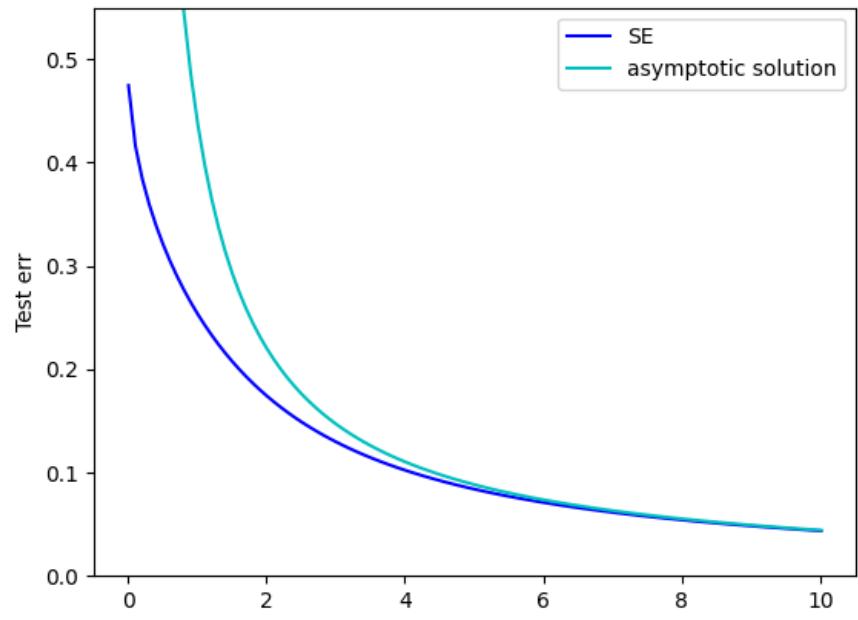
$$q_b = \frac{1}{2} \left(\alpha k \sqrt{\alpha^2 k^2 + 4} - \alpha^2 k^2 \right) \underset{\alpha \rightarrow \infty}{\simeq} 1 - \frac{1}{\alpha^2 k^2} \quad k \equiv \frac{2c_0}{\pi \sqrt{2\pi}} \simeq 0.720647$$



Conclusion



$$\varepsilon_g^{bayes}(\alpha) = \frac{1}{\pi} \arccos\left(\sqrt{q^T}\right)$$



$$\varepsilon_g^{bayes}(\alpha) \underset{\alpha \rightarrow \infty}{\simeq} \frac{1}{k\pi} \frac{1}{\alpha} \simeq \frac{0.4417}{\alpha}$$

Replica

$$P(\mathbf{w}|\mathbf{y}, \mathbf{X}) = \frac{P(\mathbf{y}|\mathbf{X}, \mathbf{w})P(\mathbf{w})}{P(\mathbf{y}, \mathbf{X})} = \frac{1}{\mathcal{Z}} P(\mathbf{y}|\mathbf{X}, \mathbf{w})P(\mathbf{w})$$

partition function

$$\mathcal{Z}(\mathbf{y}, \mathbf{X}) = P(\mathbf{y}, \mathbf{X}) = \int d\mathbf{w} P(\mathbf{w}, \mathbf{y}, \mathbf{X}) = \int d\mathbf{w} P(\mathbf{y}|\mathbf{w}, \mathbf{X})P(\mathbf{w})$$

$$= \int d\mathbf{z} P(\mathbf{y}|\mathbf{z}) \int d\mathbf{w} P(\mathbf{w}) \delta\left(\mathbf{z} - \frac{1}{\sqrt{n}}\mathbf{w}\mathbf{X}\right)$$

$$\Phi = \frac{1}{n} \mathbb{E}_{\mathbf{y}, \mathbf{X}} \log \mathcal{Z}(\mathbf{y}, \mathbf{X}) \xrightarrow{\text{Replica}} \Phi = \frac{1}{n} \lim_{r \rightarrow 0} \frac{\partial \log \mathbb{E}_{\mathbf{y}, \mathbf{X}} [\mathcal{Z}(\mathbf{y}, \mathbf{X})^r]}{\partial r}$$

$$\begin{aligned} \mathbb{E}_{\mathbf{y}, \mathbf{X}} [\mathcal{Z}(\mathbf{y}, \mathbf{X})^r] &= \mathbb{E}_{\mathbf{w}^*, \mathbf{X}} \left[\prod_{a=1}^r \int_{\mathbb{R}^n} d\mathbf{z}^a P_{\text{out}^a}(\mathbf{y} | \mathbf{z}^a) \int_{\mathbb{R}^d} d\mathbf{w}^a P_{\mathbf{w}^a}(\mathbf{w}^a) \delta\left(\mathbf{z}^a - \frac{1}{\sqrt{d}} \mathbf{X} \mathbf{w}^a\right) \right] \\ &= \mathbb{E}_{\mathbf{X}} \int_{\mathbb{R}^n} d\mathbf{y} P(\mathbf{y} | \mathbf{X}) \int_{\mathbb{R}^n} d\mathbf{z}^a P_{\text{out}^a}(\mathbf{y} | \mathbf{z}^a) \int_{\mathbb{R}^d} d\mathbf{w}^a P_{\mathbf{w}^a}(\mathbf{w}^a) \delta\left(\mathbf{z}^a - \frac{1}{\sqrt{d}} \mathbf{X} \mathbf{w}^a\right) \\ &= \boxed{\mathbb{E}_{\mathbf{X}} \int_{\mathbb{R}^n} d\mathbf{y} \int_{\mathbb{R}^n} d\mathbf{z}^* P_{\text{out}^*}(\mathbf{y} | \mathbf{z}^*) \int_{\mathbb{R}^d} d\mathbf{w}^* P_{\mathbf{w}^*}(\mathbf{w}^*) \delta\left(\mathbf{z}^* - \frac{1}{\sqrt{d}} \mathbf{X}^* \mathbf{w}^*\right)} \quad \text{Average over } \mathbf{y} \\ &\quad P(\mathbf{y} | \mathbf{X}) \\ &\times \left[\prod_{a=1}^r \int_{\mathbb{R}^n} d\mathbf{z}^a P_{\text{out}^a}(\mathbf{y} | \mathbf{z}^a) \int_{\mathbb{R}^d} d\mathbf{w}^a P_{\mathbf{w}^a}(\mathbf{w}^a) \delta\left(\mathbf{z}^a - \frac{1}{\sqrt{d}} \mathbf{X} \mathbf{w}^a\right) \right] \\ &= \mathbb{E}_{\mathbf{X}} \int_{\mathbb{R}^n} d\mathbf{y} \prod_{a=0}^r \int_{\mathbb{R}^n} d\mathbf{z}^a P_{\text{out}^a}(\mathbf{y} | \mathbf{z}^a) \int_{\mathbb{R}^d} d\mathbf{w}^a P_{\mathbf{w}^a}(\mathbf{w}^a) \delta\left(\mathbf{z}^a - \frac{1}{\sqrt{d}} \mathbf{X} \mathbf{w}^a\right) \end{aligned}$$

Replica

Assuming X is i.i.d, according to the central limit theorem

$$z_\mu^a = \frac{1}{\sqrt{n}} \sum_{i=1}^n x_i^{(\mu)} w_i^a \sim \mathcal{N} \left(\mathbb{E}_X [z_\mu^a], \mathbb{E}_X [z_\mu^a z_\mu^b] \right) \quad a, b = 0..r$$

$$\mathbb{E}_X [z_\mu^a] = \frac{1}{\sqrt{n}} \sum_{i=1}^n \mathbb{E}_X [x_i^{(\mu)}] w_i^a = 0$$

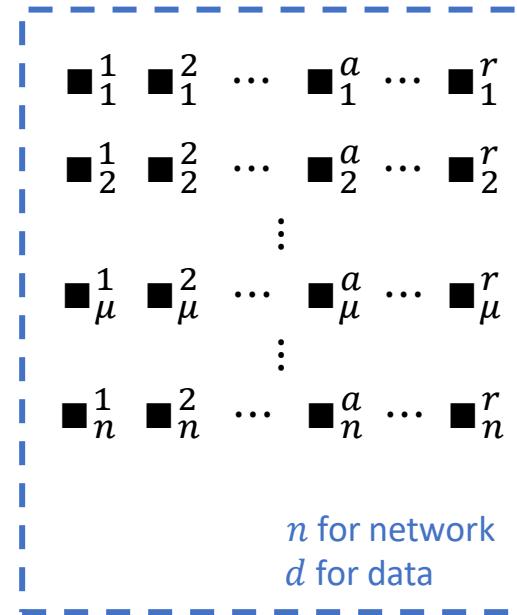
$$\mathbb{E}_X \left[z_\mu^a z_\mu^b \right] = \frac{1}{n} \sum_{ij} \mathbb{E}_X \left[x_i^{(\mu)} x_j^{(\mu)} \right] w_i^a w_j^b = \frac{1}{n} \sum_{ij} \delta_{ij} w_i^a w_j^b = \frac{1}{n} \mathbf{w}^a \cdot \mathbf{w}^b \equiv Q$$

The integration of column vectors → row vectors.

$$\tilde{\mathbf{z}}_\mu \equiv (z_\mu^a)_{a=0\dots r}, \quad \tilde{\mathbf{w}}_i \equiv (w_i^a)_{a=0\dots r}$$

$$\tilde{\mathbf{z}}_\mu \sim P_{\tilde{\mathbf{z}}}(\tilde{\mathbf{z}}; Q) = \mathcal{N}_{\tilde{\mathbf{z}}}(\mathbf{0}_{r+1}, Q) \quad P_{\tilde{\mathbf{w}}}(\tilde{\mathbf{w}}) = \prod_{a=0}^r P_{\mathbf{w}}(\tilde{w}^a)$$

$$\begin{aligned} \mathbb{E}_{\mathbf{y}, \mathbf{X}} [\mathcal{Z}(\mathbf{y}, \mathbf{X})^r] &= \mathbb{E}_{\mathbf{X}} \int d\mathbf{y} \prod_{a=0}^r \int d\mathbf{z}^a P_{\text{out}^a}(\mathbf{y} \mid \mathbf{z}^a) \int d\mathbf{w}^a P_{\mathbf{w}^a}(\mathbf{w}^a) \delta\left(\mathbf{z}^a - \frac{1}{\sqrt{d}} \mathbf{X} \mathbf{w}^a\right) \\ &= \left[\int dy \int d\tilde{\mathbf{z}} P_{\text{out}}(y \mid \tilde{\mathbf{z}}) P_{\tilde{\mathbf{z}}}(\tilde{\mathbf{z}}; Q(\tilde{\mathbf{w}})) \right]^d \left[\int d\tilde{\mathbf{w}} P_{\tilde{\mathbf{w}}}(\tilde{\mathbf{w}}) \right]^n \end{aligned}$$



Replica

Introduce Fourier transform of Dirac δ function

$$\begin{aligned} 1 &= \int dQ \prod_{a \leq b} \delta \left(nQ_{ab} - \sum_{i=1}^n w_i^a w_i^b \right) \\ &\propto \int dQ \int d\hat{Q} \prod_{a \leq b} \exp \left\{ -\hat{Q}_{ab} \left(nQ_{ab} - \sum_{i=1}^n w_i^a w_i^b \right) \right\} \\ &\propto \int dQ \int d\hat{Q} \exp \left\{ - \sum_{a \leq b} \hat{Q}_{ab} \left(nQ_{ab} - \sum_{i=1}^n w_i^a w_i^b \right) \right\} \\ &\propto \int dQ \int d\hat{Q} \exp(-n \text{Tr}[Q\hat{Q}]) \exp \left(\frac{1}{2} \sum_{i=1}^n \tilde{\mathbf{w}}_i^\top \hat{Q} \tilde{\mathbf{w}}_i \right) \end{aligned}$$

$$\delta(x) = \frac{1}{2i\pi} \int_{i\mathbb{R}} d\hat{x} e^{-\hat{x}x}$$

$$tr(\mathbf{AB}) = \sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{ji}$$

$a > b :$

$$\delta^2(x) = \frac{b-a}{2\pi} \delta(x), \quad x \in [a, b]$$

Insert it into the partition function

$$\begin{aligned} \mathbb{E}_{\mathbf{y}, \mathbf{X}} [\mathcal{Z}(\mathbf{y}, \mathbf{X})^r] &\propto \int dQ \int d\hat{Q} \exp(-n \text{Tr}[Q\hat{Q}]) \exp \left(\frac{1}{2} \sum_{i=1}^n \tilde{\mathbf{w}}_i^\top \hat{Q} \tilde{\mathbf{w}}_i \right) \\ &\quad \left[\int dy \int d\tilde{\mathbf{z}} P_{\text{out}}(y | \tilde{\mathbf{z}}) P_{\tilde{\mathbf{z}}}(\tilde{\mathbf{z}}; Q(\tilde{\mathbf{w}})) \right]^d \left[\int d\tilde{\mathbf{w}} P_{\tilde{\mathbf{w}}}(\tilde{\mathbf{w}}) \right]^n \\ &\propto \iint dQ d\hat{Q} e^{n\Phi^{(r)}(Q, \hat{Q})} \end{aligned}$$

$$\Phi = \frac{1}{n} \lim_{r \rightarrow 0} \frac{\partial \log \mathbb{E}_{\mathbf{y}, \mathbf{X}} [\mathcal{Z}(\mathbf{y}, \mathbf{X})^r]}{\partial r}$$

where

$$\Phi^{(r)}(Q, \hat{Q}) = -\text{Tr}[Q\hat{Q}] + \log \Psi_{\mathbf{w}}^{(r)}(\hat{Q}) + \alpha \log \Psi_{\text{out}}^{(r)}(Q)$$

$$\Psi_{\mathbf{w}}^{(r)}(\hat{Q}) = \int d\tilde{\mathbf{w}} P_{\tilde{\mathbf{w}}}(\tilde{\mathbf{w}}) e^{\frac{1}{2} \tilde{\mathbf{w}}^\top \hat{Q} \tilde{\mathbf{w}}}$$

$$\Psi_{\text{out}}^{(r)}(Q) = \int dy \int d\tilde{\mathbf{z}} P_{\tilde{\mathbf{z}}}(\tilde{\mathbf{z}}; Q) P_{\text{out}}(y | \tilde{\mathbf{z}})$$

 Laplace approximation

$$\Phi(\alpha) = \text{extr}_{Q, \hat{Q}} \left\{ \lim_{r \rightarrow 0} \frac{\partial \Phi^{(r)}(Q, \hat{Q})}{\partial r} \right\}$$

Replica

Replica symmetric ansatz

$$Q_{\text{rs}} = \begin{pmatrix} Q^0 & m & \dots & m \\ m & Q & \dots & \dots \\ \dots & \dots & \dots & q \\ m & \dots & q & Q \end{pmatrix} \quad \text{and} \quad \hat{Q}_{\text{rs}} = \begin{pmatrix} \hat{Q}^0 & \hat{m} & \dots & \hat{m} \\ \hat{m} & -\frac{1}{2}\hat{Q} & \dots & \dots \\ \dots & \dots & \dots & \hat{q} \\ \hat{m} & \dots & \hat{q} & -\frac{1}{2}\hat{Q} \end{pmatrix}$$

$$\begin{aligned} m &= \frac{1}{n} \mathbf{w}^a \cdot \mathbf{w}^\star \\ q &= \frac{1}{n} \mathbf{w}^a \cdot \mathbf{w}^b \\ Q &= \frac{1}{n} \|\mathbf{w}^a\|_2^2 \\ Q^0 &= \rho_{\mathbf{w}^\star} = \frac{1}{n} \|\mathbf{w}^\star\|_2^2 \end{aligned}$$

$$\Phi(\alpha) = \text{extr}_{Q, \hat{Q}} \left\{ \lim_{r \rightarrow 0} \frac{\partial \Phi^{(r)}(Q, \hat{Q})}{\partial r} \right\}$$

$$\Phi^{(r)}(Q, \hat{Q}) = -\text{Tr}[Q\hat{Q}] + \log \Psi_w^{(r)}(\hat{Q}) + \alpha \log \Psi_{\text{out}}^{(r)}(Q)$$

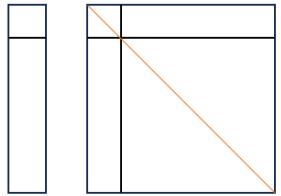
- $\text{Tr}(Q\hat{Q}) \Big|_{\text{rs}} = Q^0\hat{Q}^0 + rm\hat{m} - \frac{1}{2}rQ\hat{Q} + \frac{r(r-1)}{2}q\hat{q}$

$$tr(\mathbf{AB}) = \sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{ji}$$

$$\begin{aligned} &\text{extr} \left\{ \lim_{r \rightarrow 0} \frac{\partial}{\partial r} \left(-\text{Tr}[Q\hat{Q}] \right) \right\} \\ &= \text{extr} \left\{ \lim_{r \rightarrow 0} \frac{\partial}{\partial r} \left(-Q^0\hat{Q}^0 - rm\hat{m} + \frac{1}{2}rQ\hat{Q} - \frac{r(r-1)}{2}q\hat{q} \right) \right\} \\ &= \text{extr} \left\{ \lim_{r \rightarrow 0} \left(-m\hat{m} + \frac{1}{2}Q\hat{Q} - \left(r - \frac{1}{2} \right) q\hat{q} \right) \right\} \\ &= \text{extr} \left\{ -m\hat{m} + \frac{1}{2}Q\hat{Q} + \frac{1}{2}q\hat{q} \right\} \end{aligned}$$

Replica

- $\Psi_w^{(r)}(\hat{Q}) = \int d\tilde{\mathbf{w}} P_{\tilde{\mathbf{w}}}(\tilde{\mathbf{w}}) e^{\frac{1}{2}\tilde{\mathbf{w}}^\top \hat{Q} \tilde{\mathbf{w}}}$



$$\tilde{\mathbf{w}}^\top \hat{Q}_{rs} \tilde{\mathbf{w}} = w^\star \hat{Q}^0 w^\star + 2 \sum_{a=1}^r w^\star \hat{m} w^a - \left(\hat{Q} + \hat{q} \right) \sum_{a=1}^r (w^a)^2 + \hat{q} \left(\sum_{a=1}^r w^a \right)^2$$

$$\begin{aligned} \Psi_w^{(r)}(\hat{Q}) \Big|_{rs} &= \int d\tilde{\mathbf{w}} P_{\tilde{\mathbf{w}}}(\tilde{\mathbf{w}}) e^{\frac{1}{2}\tilde{\mathbf{w}}^\top \hat{Q}_{rs} \tilde{\mathbf{w}}} \\ &= \mathbb{E}_{w^\star} e^{\frac{1}{2}\hat{Q}^0(w^\star)^2} \int d\tilde{\mathbf{w}} P_{\tilde{\mathbf{w}}}(\tilde{\mathbf{w}}) e^{w^\star \hat{m} \sum_{a=1}^r w^a - \frac{1}{2}(\hat{Q} + \hat{q}) \sum_{a=1}^r (\tilde{w}^a)^2 + \frac{1}{2}\hat{q}(\sum_{a=1}^r w^a)^2} \\ &= \mathbb{E}_{\xi, w^\star} e^{\frac{1}{2}\hat{Q}^0(w^\star)^2} \left[\mathbb{E}_w \exp \left(\hat{m} w^\star w - \frac{1}{2}(\hat{Q} + \hat{q}) w^2 + \hat{q}^{1/2} \xi w \right) \right]^r \end{aligned}$$

H-S transformation
 $\mathbb{E}_\xi \exp(\sqrt{a}\xi) = e^{\frac{a}{2}}$

$$\begin{aligned} \Psi_w(\hat{Q}) &= \text{extr} \left\{ \lim_{r \rightarrow 0} \frac{\partial}{\partial r} \left(\log \Psi_w^{(r)}(\hat{Q}) \right) \right\} \\ &= \text{extr} \left\{ \lim_{r \rightarrow 0} \frac{\partial}{\partial r} \mathbb{E}_{\xi, w^\star} \log \left[\mathbb{E}_w \exp \left(\hat{m} w^\star w - \frac{1}{2}(\hat{Q} + \hat{q}) w^2 + \hat{q}^{1/2} \xi w \right) \right] \right\} \\ &= \text{extr} \left\{ \mathbb{E}_{\xi, w^\star} \log \left[\mathbb{E}_w \exp \left(\hat{m} w^\star w - \frac{1}{2}(\hat{Q} + \hat{q}) w^2 + \hat{q}^{1/2} \xi w \right) \right] \right\} \\ &= \text{extr} \left\{ \mathbb{E}_{\xi, w^\star} \exp \left(-\frac{1}{2}\hat{q}^{-1}\hat{m}^2(w^\star)^2 + \xi \hat{q}^{-\frac{1}{2}}\hat{m} w^\star \right) \log \left[\mathbb{E}_w \exp \left(-\frac{1}{2}(\hat{Q} + \hat{q}) w^2 + \hat{q}^{1/2} \xi w \right) \right] \right\} \end{aligned}$$

decouple the teacher and student expectations

$$\xi \leftarrow \xi + \hat{q}^{-\frac{1}{2}}\hat{m} w^\star$$

Replica

$$\mathbb{E}_{\xi, w^*} \exp \left(-\frac{1}{2} \hat{q}^{-1} \hat{m}^2 (w^*)^2 + \xi \hat{q}^{-\frac{1}{2}} \hat{m} w^* \right) \log \left[\mathbb{E}_w \exp \left(-\frac{1}{2} (\hat{Q} + \hat{q}) w^2 + \hat{q}^{1/2} \xi w \right) \right]$$

define $\mathcal{Z}_w(\gamma, \Lambda) \equiv \mathbb{E}_{w \sim P_w} \left[e^{-\frac{1}{2} \Lambda w^2 + \gamma w} \right] \xrightarrow{P_w \sim \mathcal{N}(0, 1)} \frac{e^{\frac{\gamma^2}{2(\Lambda+1)}}}{\sqrt{\Lambda+1}}$

Bayesian optimization $\mathcal{Z}_w = \mathcal{Z}_{w^*}$

$$\boxed{\Psi_w(\hat{Q}, \hat{m}, \hat{q}) \equiv \mathbb{E}_\xi \left[\mathcal{Z}_{w^*} \left(\hat{m} \hat{q}^{-1/2} \xi, \hat{m} \hat{q}^{-1} \hat{m} \right) \log \mathcal{Z}_w \left(\hat{q}^{1/2} \xi, \hat{Q} + \hat{q} \right) \right]}$$

- $\Psi_{\text{out}}^{(r)}(Q) = \int dy \int d\tilde{\mathbf{z}} P_{\tilde{\mathbf{z}}}(y; Q) P_{\text{out}}(y | \tilde{\mathbf{z}})$

$$P_{\tilde{\mathbf{z}}}(\tilde{\mathbf{z}}; Q) = \frac{e^{-\frac{1}{2} \tilde{\mathbf{z}}^\top Q^{-1} \tilde{\mathbf{z}}}}{\det(2\pi Q)^{1/2}}$$

$$Q_{\text{rs}}^{-1} = \begin{bmatrix} Q_{00}^{-1} & Q_{01}^{-1} & Q_{01}^{-1} & Q_{01}^{-1} \\ Q_{01}^{-1} & Q_{11}^{-1} & Q_{12}^{-1} & Q_{12}^{-1} \\ Q_{01}^{-1} & Q_{12}^{-1} & Q_{11}^{-1} & Q_{12}^{-1} \\ Q_{01}^{-1} & Q_{12}^{-1} & Q_{12}^{-1} & Q_{11}^{-1} \end{bmatrix}$$

$$\begin{aligned} Q_{00}^{-1} &= (Q^0 - rm(Q + (r-1)q)^{-1}m)^{-1} \\ Q_{01}^{-1} &= -(Q^0 - rm(Q + (r-1)q)^{-1}m)^{-1} m(q + (r-1)q)^{-1} \\ Q_{11}^{-1} &= (Q - q)^{-1} - (Q + (r-1)q)^{-1} q(Q - q)^{-1} \\ &\quad + (Q + (r-1)q)^{-1} m (Q^0 - rm(Q + (r-1)q)^{-1}m)^{-1} m(Q + (r-1)q)^{-1} \\ Q_{12}^{-1} &= -(Q + (r-1)q)^{-1} q(Q - q)^{-1} \\ &\quad + (Q + (r-1)q)^{-1} m (Q - rm(Q + (r-1)q)^{-1}m)^{-1} m(Q + (r-1)q)^{-1} \end{aligned}$$

$$\det Q_{\text{rs}} = (Q - q)^{r-1} (Q + (r-1)q) (Q^0 - rm(Q + (r-1)q)^{-1}m)$$

Replica

$$\begin{aligned}
\Psi_{\text{out}}^{(r)}(Q) \Big|_{\text{rs}} &= \int dy \int d\tilde{\mathbf{z}} e^{-\frac{1}{2}\tilde{\mathbf{z}}^\top Q_{\text{rs}}^{-1}\tilde{\mathbf{z}} - \frac{1}{2}\log(\det(2\pi Q_{\text{rs}}))} P_{\text{out}}(y \mid \tilde{\mathbf{z}}) \\
&= \mathbb{E}_{y,\xi} e^{-\frac{1}{2}\log(\det(2\pi Q_{\text{rs}}))} \\
&\times \int dz^* P_{\text{out}^*}(y \mid z^*) e^{-\frac{1}{2}Q_{00}^{-1}(z^*)^2} \left[\int dz P_{\text{out}}(y \mid z) e^{-Q_{01}^{-1}z^*z - \frac{1}{2}(Q_{11}^{-1} - Q_{12}^{-1})z^2 - Q_{12}^{-1/2}\xi z} \right]^r
\end{aligned}$$

↓ similar operation

$$\Psi_{\text{out}}(Q, m, q; \rho_{w^*}) \equiv \mathbb{E}_{y,\xi} \left[\mathcal{Z}_{\text{out}^*} \left(y, mq^{-1/2}\xi, \rho_{w^*} - mq^{-1}m \right) \log \mathcal{Z}_{\text{out}} \left(y, q^{1/2}\xi, Q - q \right) \right]$$

$$\begin{aligned}
\mathcal{Z}_{\text{out}}(y, \omega, V) &= \int dz \frac{1}{\sqrt{2\pi\Delta}} \exp \left(\frac{y - \text{sign}(z)}{2\Delta} \right) \frac{1}{\sqrt{2\pi V}} \exp \left(-\frac{(z - \omega)^2}{2V} \right) \\
&= \int_0^\infty dz \frac{1}{\sqrt{2\pi\Delta}} \exp \left(\frac{y - 1}{2\Delta} \right) \frac{1}{\sqrt{2\pi V}} \exp \left(-\frac{(z - \omega)^2}{2V} \right) \\
&+ \int_{-\infty}^0 dz \frac{1}{\sqrt{2\pi\Delta}} \exp \left(\frac{y + 1}{2\Delta} \right) \frac{1}{\sqrt{2\pi V}} \exp \left(-\frac{(z - \omega)^2}{2V} \right) \\
&= \mathcal{N}_y(1, \Delta^*) \left(1 + \text{erf} \left(\frac{\omega}{\sqrt{2V}} \right) \right) + \mathcal{N}_y(-1, \Delta^*) \frac{1}{2} \left(1 - \text{erf} \left(\frac{\omega}{\sqrt{2V}} \right) \right)
\end{aligned}$$

Finally, the replica symmetric solution of free energy is obtained as follows

$$\Phi_{\text{rs}}(\alpha) = \text{extr}_{Q, \hat{Q}, q, \hat{q}, m, \hat{m}} \left\{ -m\hat{m} + \frac{1}{2}Q\hat{Q} + \frac{1}{2}q\hat{q} + \Psi_w(\hat{Q}, \hat{m}, \hat{q}) + \alpha\Psi_{\text{out}}(Q, m, q; \rho_{w^*}) \right\}$$

↓ Nishimori condition $Q = \rho_{w^*}, \quad m = q = q, \quad \hat{Q} = 0, \quad \hat{m} = \hat{q} = \hat{q}$

$$\Phi(\alpha) = \text{extr}_{q, \hat{q}} \left\{ -\frac{1}{2}q\hat{q} + \Psi_w(\hat{q}) + \alpha\Psi_{\text{out}}(q; \rho_{w^*}) \right\}$$

Replica

$$\begin{aligned}\hat{q} &= -2\alpha \partial_q \Psi_{\text{out}} \\ q &= -2\partial_{\hat{q}} \Psi_{\text{w}}\end{aligned}$$

define

$$f_{\text{w}^*}(\gamma, \Lambda) \equiv \partial_\gamma \log \mathcal{Z}_{\text{w}^*}(\gamma, \Lambda) = \frac{\gamma}{1 + \Lambda}.$$

$$f_{\text{out}^*}(y, \omega, V) \equiv \partial_\omega \log \mathcal{Z}_{\text{out}^*}(y, \omega, V) = \frac{\mathcal{N}_y(1, \Delta^*) - \mathcal{N}_y(-1, \Delta^*)}{\mathcal{Z}_{\text{out}^*}(y, \omega, V)} \mathcal{N}_\omega(0, V)$$

obtain

$$\begin{aligned}\hat{q} &= \alpha \mathbb{E}_{y, \xi} \left[\mathcal{Z}_{\text{out}^*} \left(y, q^{1/2} \xi, \rho_{\text{w}^*} - q \right) f_{\text{out}^*} \left(y, q^{1/2} \xi, \rho_{\text{w}^*} - q \right)^2 \right] \\ q &= \mathbb{E}_\xi \left[\mathcal{Z}_{\text{w}^*} \left(\hat{q}^{1/2} \xi, \hat{q} \right) f_{\text{w}^*} \left(\hat{q}^{1/2} \xi, \hat{q} \right)^2 \right]\end{aligned}$$

Analytic solution

$$q = \frac{\hat{q}}{1 + \hat{q}}$$

$$\hat{q} = \alpha \mathbb{E}_{y, \xi} \left[\mathcal{Z}_{\text{out}^*} \left(y, q^{1/2} \xi, 1 - q \right) f_{\text{out}^*} \left(y, q^{1/2} \xi, 1 - q \right)^2 \right]$$

$$= 2\alpha \int D\xi y^2 \frac{\mathcal{N}_{\sqrt{q}\xi}(0, 1-q)^2}{\frac{1}{2} \left(1 + \operatorname{erf} \left(\frac{\sqrt{q}\xi}{\sqrt{2(1-q)}} \right) \right)}$$

$$= \frac{2}{\pi} \frac{\alpha}{1-q} \int D\xi \frac{e^{-\frac{q_b \xi^2}{1-q}}}{\left(1 + \operatorname{erf} \left(\frac{\sqrt{q}\xi}{\sqrt{2(1-q)}} \right) \right)}$$

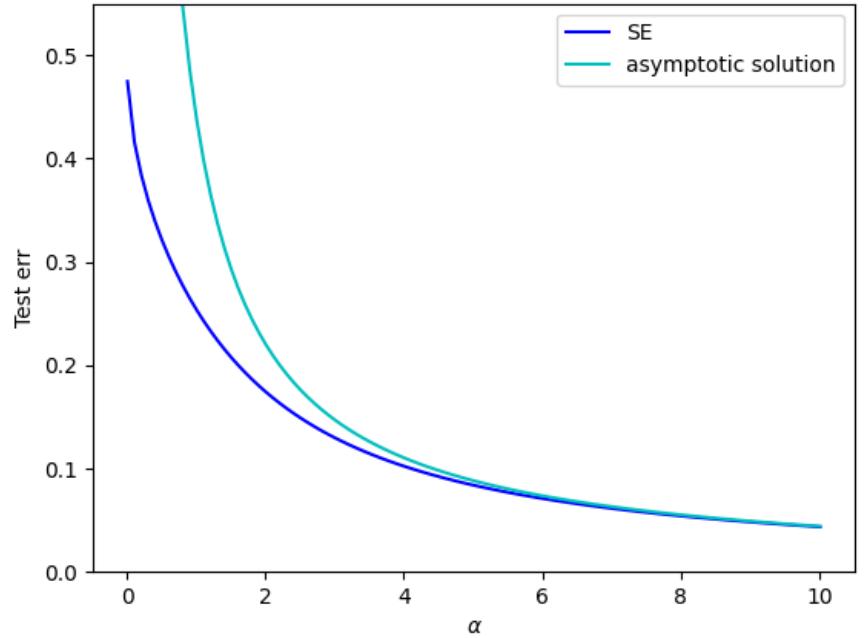
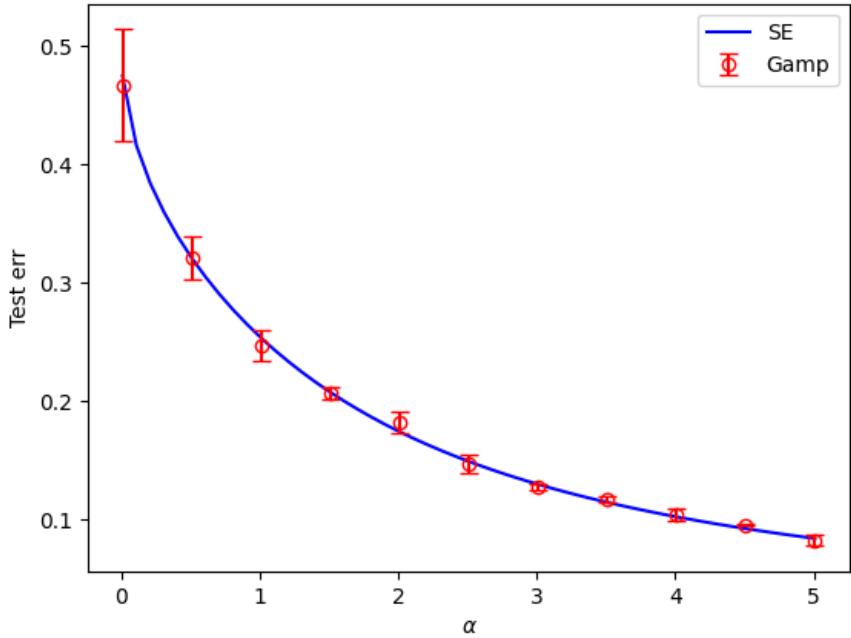
$$\begin{aligned}\Psi_{\text{w}}(\hat{q}) &= \mathbb{E}_\xi \left[\mathcal{Z}_{\text{w}^*} \left(\hat{q}^{1/2} \xi, \hat{q} \right) \log \mathcal{Z}_{\text{w}^*} \left(\hat{q}^{1/2} \xi, \hat{q} \right) \right], \\ \Psi_{\text{out}}(q; \rho_{\text{w}^*}) &= \mathbb{E}_{y, \xi} \left[\mathcal{Z}_{\text{out}^*} \left(y, q^{1/2} \xi, \rho_{\text{w}^*} - q \right) \log \mathcal{Z}_{\text{out}^*} \left(y, q^{1/2} \xi, \rho_{\text{w}^*} - q \right) \right] \\ \mathcal{Z}_{\text{w}}(\gamma, \Lambda) &\equiv \mathbb{E}_{w \sim P_{\text{w}}} \left[e^{-\frac{1}{2} \Lambda w^2 + \gamma w} \right] = \frac{e^{\frac{\gamma^2}{2(\Lambda+1)}}}{\sqrt{\Lambda+1}}, \\ \mathcal{Z}_{\text{out}}(y, \omega, V) &= \int dz \frac{1}{\sqrt{2\pi\Delta}} \exp \left(\frac{y - \operatorname{sign}(z)}{2\Delta} \right) \frac{1}{\sqrt{2\pi V}} \exp \left(-\frac{(z-\omega)^2}{2V} \right) \\ &= \mathcal{N}_y(1, \Delta^*) \left(1 + \operatorname{erf} \left(\frac{\omega}{\sqrt{2V}} \right) \right) + \mathcal{N}_y(-1, \Delta^*) \frac{1}{2} \left(1 - \operatorname{erf} \left(\frac{\omega}{\sqrt{2V}} \right) \right)\end{aligned}$$

equivalent to the definition in AMP

same as SE equation

Conclusion

$$e_g^{\text{bayes}}(\alpha) = \frac{1}{\pi} \arccos(\sqrt{q_b}) \underset{\alpha \rightarrow \infty}{\simeq} \frac{1}{k\pi} \frac{1}{\alpha} \simeq \frac{0.4417}{\alpha}$$



Asymptotic solution $\alpha \rightarrow \infty, q \rightarrow 1$

$$\begin{aligned} \int D\xi \frac{e^{-\frac{q_b \xi^2}{1-q_b}}}{\left(1 + \operatorname{erf}\left(\frac{\sqrt{q_b} \xi}{\sqrt{2(1-q_b)}}\right)\right)} &= \int d\xi \frac{\frac{\xi^2 (q_b+1)}{\sqrt{2\pi}}}{\left(1 + \operatorname{erf}\left(\frac{\sqrt{q_b} \xi}{\sqrt{2(1-q_b)}}\right)\right)} \simeq \int d\xi \frac{\frac{-e^{\frac{\xi^2}{1-q_b}}}{\sqrt{2\pi}}}{\left(1 + \operatorname{erf}\left(\frac{\xi}{\sqrt{2(1-q_b)}}\right)\right)} \\ &= \frac{\sqrt{1-q_b}}{\sqrt{2\pi}} \int d\eta \frac{e^{-\eta^2}}{1 + \operatorname{erf}\left(\frac{\eta}{\sqrt{2}}\right)} = \frac{c_0}{\sqrt{2\pi}} \sqrt{1-q_b} \end{aligned}$$

$$q_b = \frac{1}{2} \left(\alpha k \sqrt{\alpha^2 k^2 + 4} - \alpha^2 k^2 \right) \underset{\alpha \rightarrow \infty}{\simeq} 1 - \frac{1}{\alpha^2 k^2}, \quad \hat{q}_b = k^2 \alpha^2 \quad k \equiv \frac{2c_0}{\pi \sqrt{2\pi}} \simeq 0.720647$$