

$$① \epsilon_w \sim N(0,1) \text{ for weights}$$

$$② \sigma_w = \ln(1 + e^{\mu_w}) \text{ for weights}$$

$$③ w = \mu_w + \ln(1 + e^{\mu_w}) \otimes \epsilon_w$$

$$④ \frac{\partial w}{\partial \mu_w} = 1$$

$$⑤ \frac{\partial w}{\partial \mu_w} = \epsilon_w \otimes \frac{1}{1 + e^{\mu_w}} \otimes e^{\mu_w}$$

$$⑥ \text{sigmoid}(k) = \frac{1}{1 + e^{-k}}$$

$$⑦ \frac{\partial \text{sigmoid}(k)}{\partial k} = (-1) \cdot \frac{1}{(1 + e^{-k})^2} \cdot e^{-k} = \frac{1}{1 + e^{-k}} \cdot \frac{-e^{-k}}{1 + e^{-k}} = \text{sigmoid}(k) \cdot (1 - \text{sigmoid}(k))$$

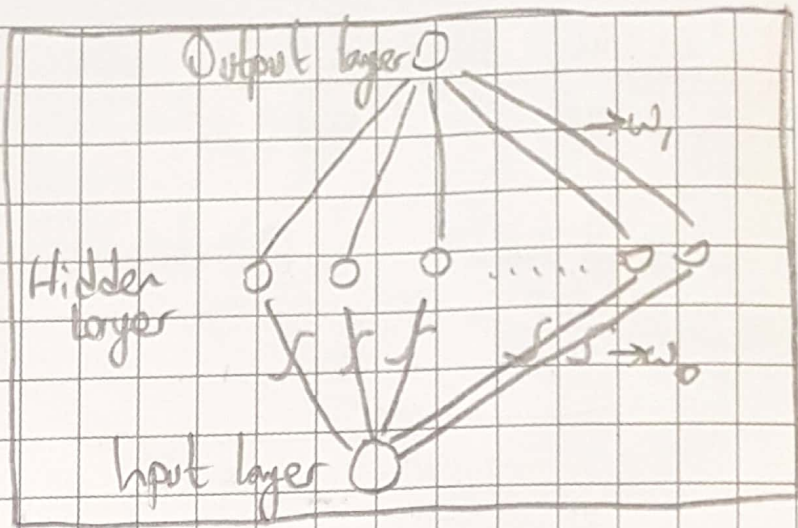
$$⑧ \text{ Say } m \sim N(\mu, \sigma^2), \text{ then}$$

$$f(m) = \frac{1}{\sqrt{2\pi}\sigma} \cdot e^{\frac{-(m-\mu)^2}{2\sigma^2}} \rightarrow \text{pdf of normal dist.}$$

$$\ln(f(m)) = -\ln(\sqrt{2\pi}) - \ln(\sigma) - \frac{(m-\mu)^2}{2\sigma^2}$$

$$⑨ \text{ Loss} = F(w, \theta) = \underbrace{\ln(q(w|\theta))}_{\text{logarithm of variational posterior probability}} - \underbrace{\ln(P(w))}_{\text{logarithm of prior probability}} - \underbrace{\ln(P(D|w))}_{\text{logarithm of likelihood}}, \text{ where } \theta = (\mu, \sigma)$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i \hat{y}_i)^2 \text{ where } N \text{ is the sample size}$$



$$q(w|\theta) \sim N(\mu_w, \sigma_w^2)$$

$$\ln(q(w|\theta)) = -\ln\sqrt{2\pi} - \ln\sigma_w - \frac{(w - \mu_w)^2}{2\sigma_w^2}$$

$$= -\ln\sqrt{2\pi} - \ln(\ln(1+e^{\mu_w})) - \frac{(\mu_w + \ln(1+e^{\mu_w}) \otimes \epsilon_w - \mu_w)^2}{2 \cdot (\ln(1+e^{\mu_w}))^2}$$

$$= -\ln\sqrt{2\pi} - \ln(\ln(1+e^{\mu_w})) - \frac{\epsilon_w \otimes \epsilon_w}{2}$$

$$P(w) \sim N(0, 1)$$

$$\ln(P(w)) = -\ln\sqrt{2\pi} - \cancel{\ln 1} - \frac{(w-0)^2}{2 \cdot 1^2}$$

$$= -\ln\sqrt{2\pi} - \frac{w^2}{2}$$

$$= -\ln\sqrt{2\pi} - \frac{(\mu_w + \ln(1+e^{\mu_w}) \otimes \epsilon_w)^2}{2}$$

$$P(D|w) \sim N(\hat{y}, \text{tol}) \quad \text{where } \hat{y} = \text{sigmoid}(x \cdot w_0^T) \cdot w_1^T$$

$$\ln(P(D|w)) = -\ln\sqrt{2\pi} - \ln(\text{tol}) - \frac{(y - \hat{y})^2}{2\text{tol}^2}$$

$$= -\ln\sqrt{2\pi} - \ln(\text{tol}) - \frac{(y - \text{sigmoid}(x \cdot w_0^T) \cdot w_1^T)^2}{2\text{tol}^2}$$

$$= -\ln\sqrt{2\pi} - \ln(\text{tol}) - \frac{[y - \text{sigmoid}(x \cdot (\mu_w + \ln(1+e^{\mu_w}) \otimes \epsilon_w)^T) \cdot (\mu_w + \ln(1+e^{\mu_w}) \otimes \epsilon_w)]^2}{2\text{tol}^2}$$

$$(10) \frac{\partial \ln(P(D|w))}{\partial \hat{y}} = \frac{-2(y - \hat{y})}{2\sigma^2} \cdot (+1) = -\frac{y - \hat{y}}{\sigma^2}$$

$$(11) \frac{\partial \hat{y}}{\partial w_1} = \text{sigmoid}(x \cdot w_0^T)$$

$$(12) \frac{\partial \text{Loss}}{\partial \mu_{w_1}} = \frac{\partial \log\text{-var_post}}{\partial \mu_{w_1}} - \frac{\partial \log\text{-prior}}{\partial \mu_{w_1}} - \frac{\partial \log\text{-likelihood}}{\partial \mu_{w_1}}$$

$$= \frac{\partial \ln(q(w_1|\theta))}{\partial \mu_{w_1}} - \frac{\partial \ln(P(w_1))}{\partial \mu_{w_1}} - \frac{\partial \ln(P(D|w_1))}{\partial \mu_{w_1}}$$

$$\frac{\partial \ln(q(w_1|\theta))}{\partial \mu_{w_1}} = 0$$

$$\frac{\partial \ln(P(w_1))}{\partial \mu_{w_1}} = -\frac{2(\mu_{w_1} + \ln(1 + e^{\mu_{w_1}}) \otimes E_{w_1})}{2} \otimes 1 = -w_1$$

$$\frac{\partial \ln(P(D|w_1))}{\partial \mu_{w_1}} = \frac{\partial \ln(P(D|w_1))}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} \cdot \frac{\partial w_1}{\partial \mu_{w_1}}$$

$$= \frac{y - \hat{y}}{\sigma^2} \cdot \text{sigmoid}(x \cdot w_0^T) \otimes 1$$

$$(13) \frac{\partial \text{Loss}}{\partial \mu_{w_0}} = \frac{\partial \ln(q(w_0|\theta))}{\partial \mu_{w_0}} - \frac{\partial \ln(P(w_0))}{\partial \mu_{w_0}} - \frac{\partial \ln(P(D|w_0))}{\partial \mu_{w_0}}$$

$$\frac{\partial \ln(q(w_0|\theta))}{\partial \mu_{w_0}} = 0$$

$$\frac{\partial \ln(P(w_0))}{\partial \mu_{w_0}} = -\frac{2(\mu_{w_0} + \ln(1 + e^{\mu_{w_0}}) \otimes E_{w_0})}{2} \otimes 1 = -w_0$$

$$\frac{\partial \ln(P(D|w_0))}{\partial \mu_{w_0}} = \frac{\partial \ln(P(D|w_0))}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial h} \cdot \frac{\partial h}{\partial z} \cdot \frac{\partial z}{\partial w_0} \cdot \frac{\partial w_0}{\partial \mu_{w_0}}$$

where $\hat{y} = \underbrace{\text{sigmoid}(x \cdot w_0^T)}_h \cdot w_1^T$

$$= \frac{y - \hat{y}}{\frac{1}{2}} \cdot w_1 \otimes [\text{sigmoid}(x \cdot w_0^T) \cdot (1 - \text{sigmoid}(x \cdot w_0^T))] \cdot x \otimes 1$$

$$\textcircled{14} \frac{\partial \text{Loss}}{\partial w_1} = \frac{\partial \ln(p(w_1|\theta))}{\partial w_1} - \frac{\partial \ln(P(w_1))}{\partial w_1} - \frac{\partial \ln(P(D|w_1))}{\partial w_1}$$

$$\frac{\partial \ln(p(w_1|\theta))}{\partial w_1} = -\frac{1}{\ln(1+e^{w_1})} \otimes \frac{1}{1+e^{w_1}} \otimes e^{w_1}$$

$$\frac{\partial \ln(P(w_1))}{\partial w_1} = -\frac{2(\mu_{w_1} + \ln(1+e^{w_1}) \otimes \epsilon_{w_1})}{2} \otimes \frac{\partial w_1}{\partial \mu_1}$$

$$= -w_1 \otimes \left[\frac{1}{1+e^{w_1}} \otimes e^{w_1} \otimes \epsilon_{w_1} \right]$$

$$\frac{\partial \ln(P(D|w_1))}{\partial w_1} = \frac{\partial \ln(P(D|w_1))}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_1} \cdot \frac{\partial w_1}{\partial \mu_1}$$

$$= \frac{(y - \hat{y})}{\frac{1}{2}} \cdot \text{sigmoid}(x \cdot w_0^T) \otimes \left[\frac{1}{1+e^{w_1}} \otimes e^{w_1} \otimes \epsilon_{w_1} \right]$$

$$(15) \frac{\partial \text{Loss}}{\partial \mu_{w_0}} = \frac{\partial \ln(q(w_0|\theta))}{\partial \mu_{w_0}} - \frac{\partial \ln(P(w_0))}{\partial \mu_{w_0}} - \frac{\partial \ln(P(D|w_0))}{\partial \mu_{w_0}}$$

$$\frac{\partial \ln(q(w_0|\theta))}{\partial \mu_{w_0}} = -\frac{1}{\ln(1+e^{\mu_{w_0}})} \otimes \frac{1}{1+e^{\mu_{w_0}}} \otimes \mu_{w_0}$$

$$\begin{aligned} \frac{\partial \ln(P(w_0))}{\partial \mu_{w_0}} &= \frac{-2(\mu_{w_0} + \ln(1+e^{\mu_{w_0}}) \otimes E_{w_0})}{2} \otimes \frac{\partial \mu_{w_0}}{\partial \mu_{w_0}} \\ &= -w_0 \otimes \left[\frac{1}{1+e^{\mu_{w_0}}} \otimes e^{\mu_{w_0}} \otimes E_{w_0} \right] \end{aligned}$$

$$\frac{\partial \ln(P(D|w_0))}{\partial \mu_{w_0}} = \frac{\partial \ln(P(D|w_0))}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial h} \cdot \frac{\partial h}{\partial z} \cdot \frac{\partial z}{\partial w_0} \cdot \frac{\partial w_0}{\partial \mu_{w_0}}$$

$$\text{where } \hat{y} = \text{sigmoid}(\underbrace{\kappa \cdot w_0^T}_{h}) \cdot w_1^T$$

$$= \frac{y - \hat{y}}{\ln 2} \cdot w_1 \otimes \left[\text{sigmoid}(\kappa \cdot w_0^T) \otimes (1 - \text{sigmoid}(\kappa \cdot w_0^T)) \right] \cdot \kappa \otimes \left[\frac{e^{\mu_{w_0}}}{1+e^{\mu_{w_0}}} \otimes E_{w_0} \right]$$

$$(16) \mu_{w_1} = \mu_{w_1} - \alpha \cdot \frac{\partial \text{Loss}}{\partial \mu_{w_1}}$$

$$\mu_{w_0} = \mu_{w_0} - \alpha \cdot \frac{\partial \text{Loss}}{\partial \mu_{w_0}}$$

$$\mu_{w_1} = \mu_{w_1} - \alpha \cdot \frac{\partial \text{Loss}}{\partial \mu_{w_1}}$$

$$\mu_{w_0} = \mu_{w_0} - \alpha \cdot \frac{\partial \text{Loss}}{\partial \mu_{w_0}}$$

where α is the learning rate

$$(17) \hat{y} = \text{sigmoid}(\kappa \cdot w_0^T) \cdot w_1^T$$

$$(18) y = 10 \cdot \sin(2\pi k) + \epsilon$$