

3)
 Data: $(x^{(1)}, y^{(1)}), \dots, (x^{(m)}, y^{(m)})$, where $x^{(j)} \in \mathbb{R}^n$
 $y^{(j)} \in \{1, \dots, c\}$
 $j = 1, \dots, m$

m : sample size

n : # of features

$\theta = \{w_i, b_i\}_{i=1, \dots, c}$

$$\tilde{x} = \begin{bmatrix} x \\ 1 \end{bmatrix}, \quad \tilde{w}_i = \begin{bmatrix} w_i \\ b_i \end{bmatrix}$$

$$a_i(x) = \tilde{w}_i^T \tilde{x}$$

$$\text{softmax}_i(x) = \frac{e^{w_i^T x + b_i}}{\sum_{k=1}^c e^{w_k^T x + b_k}}$$

$$\begin{aligned} p(x^{(1)}, \dots, x^{(m)}, y^{(1)}, \dots, y^{(m)} | \theta) &= \prod_{i=1}^m p(x^{(i)}, y^{(i)} | \theta) \\ &= \prod_{i=1}^m p(x^{(i)} | \theta) \underbrace{p(y^{(i)} | x^{(i)}, \theta)}_{\text{softmax}_j(x^{(i)})} \end{aligned}$$

$$\begin{aligned} &\arg \max_{\theta} \prod_{i=1}^m p(x^{(i)} | \theta) p(y^{(i)} | x^{(i)}, \theta) \\ &\downarrow \\ &= \arg \max_{\theta} \prod_{i=1}^m p(y^{(i)} | x^{(i)}, \theta) \end{aligned}$$

Take log:

$$\arg \max_{\theta} \sum_{i=1}^m \log \left[\frac{e^{a_{y^{(i)}}(x^{(i)})}}{\sum_{j=1}^c e^{a_j(x^{(i)})}} \right]$$

$$\arg \max_{\theta} f(\theta) = \arg \min_{\theta} -f(\theta)$$

$$= \arg \min_{\theta} \frac{1}{m} \sum_{i=1}^m \left[\log \left(\sum_{j=1}^c e^{a_j(x^{(i)})} \right) - a_{y^{(i)}}(x^{(i)}) \right]$$

$$\begin{aligned}
& \nabla_{\tilde{w}_i} \left(\log \sum_{j=1}^C e^{a_j(\tilde{x})} \right) \\
&= \nabla_{\tilde{w}_i} \left(\log \left[e^{w_1^T \tilde{x}} + e^{w_2^T \tilde{x}} + \dots + e^{w_C^T \tilde{x}} \right] \right) \\
&= \frac{1}{\sum_{j=1}^C e^{a_j(\tilde{x})}} e^{\tilde{w}_i^T \tilde{x}} \tilde{x}, \text{ by chain rule} \\
&= \frac{e^{\tilde{w}_i^T \tilde{x}}}{\sum_{j=1}^C e^{a_j(\tilde{x})}} \tilde{x} = \frac{e^{a_i(\tilde{x})}}{\sum_{j=1}^C e^{a_j(\tilde{x})}} \tilde{x}
\end{aligned}$$

$$\nabla_{w_i} a_{y(k)}(x) \Rightarrow \nabla_{\tilde{w}_i} a_{y(k)}(x) \quad \begin{array}{l} \text{if } i = y(k) \\ 0 \quad \text{if } i \neq y(k) \end{array}$$

$$\text{if } i = y(k)$$

$$\nabla_{\tilde{w}_i} \tilde{w}_i^T \tilde{x} = \tilde{x}$$

$$\nabla_{\tilde{w}_i} \mathcal{L}(\tilde{w}_i) = \frac{1}{n} \sum_{j=1}^n \left[\frac{e^{a_i(x^{(j)})}}{\sum_{k=1}^C e^{a_k(x^{(j)})}} - \delta_{y^{(j)}, i} \right] \tilde{x}^{(j)}$$

$$\nabla_{w_i} \mathcal{L}(w_i, b_i) = \frac{1}{n} \sum_{j=1}^n \left[\frac{e^{a_i(x^{(j)})}}{\sum_{k=1}^C e^{a_k(x^{(j)})}} - \delta_{y^{(j)}, i} \right] x^{(j)}$$

$$\nabla_{b_i} \mathcal{L}(w_i, b_i) = \frac{1}{n} \sum_{j=1}^n \left[\frac{e^{a_i(x^{(j)})}}{\sum_{k=1}^C e^{a_k(x^{(j)})}} - \delta_{y^{(j)}, i} \right]$$

4)

$$\mathcal{D} = \{(x^{(1)}, y^{(1)})\}, \dots, (x^{(k)}, y^{(k)})\}$$

$$x^{(i)} \in \mathbb{R}^d, y^{(i)} \in \{-1, 1\}$$

$$\tilde{w} = \begin{bmatrix} w \\ 1 \end{bmatrix}$$

$$\tilde{x}^{(i)} = \begin{bmatrix} x^{(i)} \\ 1 \end{bmatrix}$$

$$\mathcal{L}(w, b) = \frac{1}{k} \sum_{i=1}^k \max(0, 1 - y^{(i)} (w^T x^{(i)} + b))$$

$$\frac{\partial \text{hinge}_{y^{(i)}}(x^{(i)})}{\partial \tilde{w}} = \begin{cases} 0 & \text{if } y_i (\tilde{w}^T \tilde{x}^{(i)}) \geq 1 \\ -y_i \tilde{x}^{(i)} & \text{if } y_i (\tilde{w}^T \tilde{x}^{(i)}) < 1 \end{cases}$$

$$\frac{\partial \mathcal{L}}{\partial \tilde{w}} = \frac{1}{k} \sum_{i=1}^k \frac{\partial \text{hinge}_{y^{(i)}}(x^{(i)})}{\partial \tilde{w}} = \frac{1}{k} \sum_{i=1}^k \mathbb{I}_{y_i (\tilde{w}^T \tilde{x}^{(i)}) < 1} (-y_i \tilde{x}^{(i)})$$

$$\frac{\partial \mathcal{L}}{\partial w} = \frac{1}{k} \sum_{i=1}^k \mathbb{I}_{y_i (w^T x^{(i)} + b) < 1} (-y_i x^{(i)})$$

$$\frac{\partial \mathcal{L}}{\partial b} = \frac{1}{k} \sum_{i=1}^k \mathbb{I}_{y_i (w^T x^{(i)} + b) < 1} (-y_i)$$