

Nathan Inkawhich

Homework 1

Questions 1 + 5

$$\boxed{L}$$

Logistic Regression

$$X \in \mathbb{R}^{1 \times M}$$

$$W \in \mathbb{R}^{M \times 1}$$

$$h, a, y, b \in \mathbb{R}$$

$$h = XW + b$$

$$a = \sigma(h)$$

$$L = -y \log a - (1-y) \log(1-a)$$

$$\text{Need } \frac{\partial L}{\partial W}, \frac{\partial L}{\partial b}$$

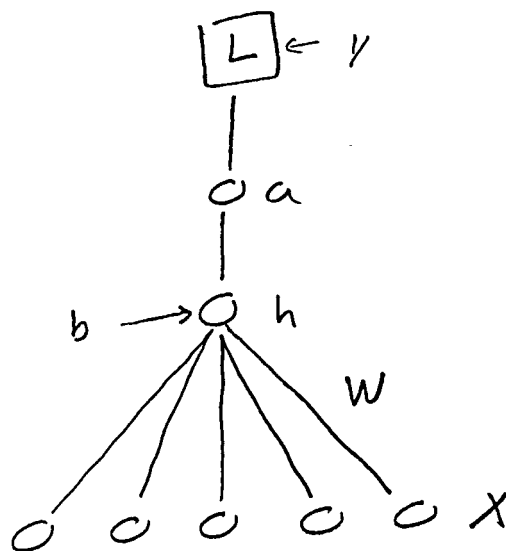
$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial h} \frac{\partial h}{\partial W} = X^T \frac{\partial L}{\partial h}$$

$$\frac{\partial L}{\partial h} = \frac{\partial L}{\partial a} \frac{\partial a}{\partial h}$$

$$\begin{aligned} \frac{\partial L}{\partial a} &= -\frac{y}{a} + \frac{1-y}{1-a} = \frac{y(1-a) + a(1-y)}{a(1-a)} \\ &= \frac{a-y}{a(1-a)} \end{aligned}$$

$$\frac{\partial a}{\partial h} = \sigma(h)(1-\sigma(h)) = a(1-a)$$

$$\frac{\partial L}{\partial h} = \frac{a-y}{a(1-a)} \cdot a(1-a) = a-y$$



$$\boxed{\frac{\partial L}{\partial w} = \overset{\mathbb{R}^m}{X^T} \cdot \overset{\mathbb{R}}{(a-y)}}$$

$$\in \mathbb{R}^m \quad \checkmark$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial h} \frac{\partial h}{\partial b}$$

$$\frac{\partial h}{\partial b} = 1$$

$$\boxed{\frac{\partial L}{\partial b} = \overset{\mathbb{R}}{a-y}}$$

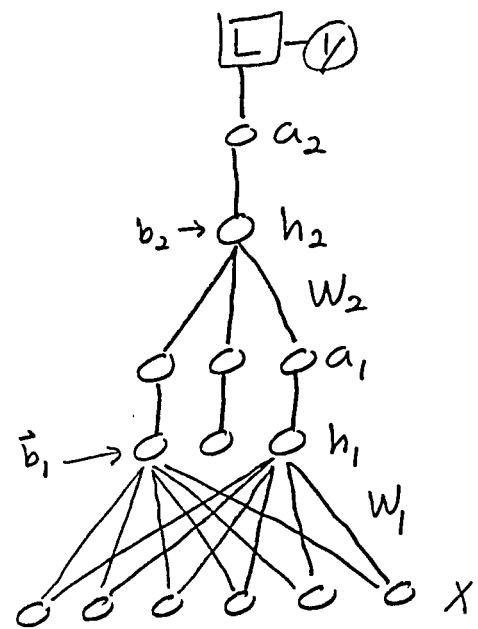
$$\in \mathbb{R}$$

\checkmark

1b

1-Hidden Layer
MLP w/ binary
output

$$\begin{aligned}
 X &\in \mathbb{R}^{1 \times M} \\
 W_1 &\in \mathbb{R}^{M \times N} \\
 a_1, h_1, b_1 &\in \mathbb{R}^{1 \times N} \\
 W_2 &\in \mathbb{R}^{N \times 1} \\
 a_2, h_2, b_2 &\in \mathbb{R}
 \end{aligned}$$



$$h_1 = X W_1 + b_1$$

$$a_1 = \sigma(h_1)$$

$$h_2 = a_1 W_2 + b_2$$

$$a_2 = \sigma(h_2)$$

$$L = -y \log a_2 - (1-y) \log (1-a_2)$$

From 1a. $\frac{\partial L}{\partial h_2} = a_2 - y$

Need: $\frac{\partial L}{\partial W_1}, \frac{\partial L}{\partial b_1}, \frac{\partial L}{\partial W_2}, \frac{\partial L}{\partial b_2}$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial h_1} \frac{\partial h_1}{\partial w_1} = X^T \frac{\partial L}{\partial h_1}$$

$$\frac{\partial L}{\partial h_1} = \frac{\partial L}{\partial h_2} \frac{\partial h_2}{\partial a_1} \frac{\partial a_1}{\partial h_1}$$

$$\frac{\partial L}{\partial h_2} = a_2 - y \in \mathbb{R}$$

$$\frac{\partial h_2}{\partial a_1} = W_2^T$$

$$\frac{\partial a_1}{\partial h_1} = \sigma(h_1) \odot (1 - \sigma(h_1)) = a_1 \odot (1 - a_1)$$

$$\frac{\partial L}{\partial h_1} = \underbrace{(a_2 - y)}_{\mathbb{R}} \cdot \underbrace{\left(\underbrace{W_2^T}_{\mathbb{R}^{1 \times N}} \odot \underbrace{(a_1 \odot (1 - a_1))}_{\mathbb{R}^{1 \times N}} \right)}_{\mathbb{R}^{1 \times N}} \in \mathbb{R}^{1 \times N}$$

$$\boxed{\frac{\partial L}{\partial w_1} = X^T \left((a_2 - y) \cdot (W_2^T \odot (a_1 \odot (1 - a_1))) \right)} \in \mathbb{R}^{M \times N} \checkmark$$

$\mathbb{R}^{M \times 1} \quad \mathbb{R}^{1 \times N}$

$$\boxed{\frac{\partial L}{\partial b_1} = (a_2 - y) \cdot (W_2^T \odot (a_1 \odot (1 - a_1)))} \in \mathbb{R}^{1 \times N} \checkmark$$

$$\frac{2L}{2w_2} = \frac{2L}{2h_2} \frac{2h_2}{2w_2} = a_1^T \frac{2L}{2h_2}$$

$$\boxed{\frac{2L}{2w_2} = a_1^T \cdot (a_2 - \gamma)}$$

$\mathbb{R}^{N \times 1} \quad - \quad \mathbb{R}$

$$\in \mathbb{R}^{N \times 1} \quad \checkmark$$

$$\frac{2L}{2b_2} = \frac{2L}{2h_2} \frac{2h_2}{2b_2}$$

$$\frac{2h_2}{2b_2} = 1$$

$$\boxed{\frac{2L}{2b_2} = a_2 - \gamma}$$

$$\in \mathbb{R} \quad \checkmark$$

$$L - \text{result (a)}$$

$L = \# \text{ of classes}$

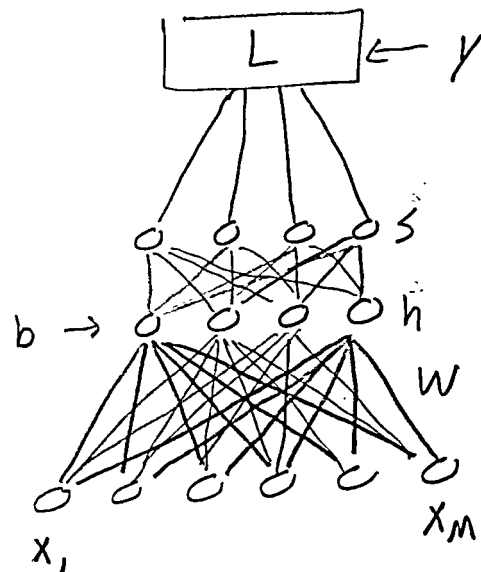
$$X \in \mathbb{R}^{1 \times M}$$

$$W \in \mathbb{R}^{M \times L}$$

$$b, s, y \in \mathbb{R}^{1 \times L}$$

$$h = XW + b$$

$$s = \text{softmax}(\vec{h}) = \frac{e^{h_i}}{\sum_{j=1}^L e^{h_j}}$$



$$L(\vec{y}, \vec{s}) = - \sum_{i=1}^L 1_{(y_i=1)} \log(s_i) = -\vec{y} \cdot \log(\vec{s}) \quad \text{because } \vec{y} \text{ is one-hot}$$

$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial s} \frac{\partial s}{\partial h} \frac{\partial h}{\partial W}$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial s} \frac{\partial s}{\partial h} \frac{\partial h}{\partial b}$$

$$\frac{\partial L}{\partial \vec{s}} = \frac{\partial}{\partial \vec{s}} \left(-\vec{y} \cdot \log(\vec{s}) \right) = -\frac{\vec{y}}{\vec{s}} \in \mathbb{R}^{1 \times L}$$

$$\frac{\partial \vec{s}_i}{\partial \vec{h}_j} = \frac{\partial}{\partial \vec{h}_j} \left(\frac{e^{h_i}}{\sum_{k=1}^L e^{h_k}} \right)$$

So two cases, when $i=j$
and when $i \neq j$

When $i = j$

$$\frac{\partial \vec{s}_i}{\partial h_j} = \frac{\partial}{\partial h_j} \left(\frac{e^{h_i}}{\sum_k e^{h_k}} \right)$$

$$= \frac{e^{h_i} \sum - e^{h_i} e^{h_j}}{\sum^2}$$

$$= \frac{e^{h_i} (\sum - e^{h_j})}{\sum^2}$$

$$= \frac{e^{h_i}}{\sum} \cdot \frac{\sum - e^{h_j}}{\sum} = \boxed{s_i (1 - s_j) \text{ when } i = j}$$

quotient rule

$$f(x) = \frac{g(x)}{h(x)}$$

$$f'(x) = \frac{g'(x)h(x) - g(x)h'(x)}{(h(x))^2}$$

let \sum represent $\sum_{k=1}^L e^{h_k}$

$$g(x) = e^{h_i} \quad h(x) = \sum$$

When $i \neq j$

$$\frac{\partial s_i}{\partial h_j} = \frac{\partial}{\partial h_j} \left(\frac{e^{h_i}}{\sum} \right) = \frac{0 \sum - e^{h_i} e^{h_j}}{\sum^2}$$

$$= -\frac{e^{h_i}}{\sum} \cdot \frac{e^{h_j}}{\sum}$$

$$= \boxed{-s_i s_j \text{ when } i \neq j}$$

So define Q as a $L \times L$ square matrix
with $s_i(1-s_j)$ along the diagonal
and $-s_i s_j$ elsewhere.

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial h} \frac{\partial h}{\partial w} = X^T \frac{\partial L}{\partial h}$$

$$\frac{\partial L}{\partial h} = \frac{\partial L}{\partial s} \frac{\partial s}{\partial h} = \frac{-y}{s} Q \in \mathbb{R}^{1 \times L}$$

$\mathbb{R}^{1 \times L} \cdot \mathbb{R}^{L \times L}$

$$\boxed{\frac{\partial L}{\partial w} = X^T \left(\frac{-y}{s} Q \right)}$$

$\mathbb{R}^{M \times 1} \quad \mathbb{R}^{1 \times L}$

$$\in \mathbb{R}^{M \times L} \quad \checkmark$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial h} \frac{\partial h}{\partial b}$$

$$\frac{\partial h}{\partial b} = 1$$

$$\boxed{\frac{\partial L}{\partial b} = \frac{-y}{s} Q}$$

$\mathbb{R}^{1 \times L} \quad \mathbb{R}^{L \times L}$

$$\in \mathbb{R}^{1 \times L} \quad \checkmark$$

L - result (b)

$$X \in \mathbb{R}^{1 \times M}$$

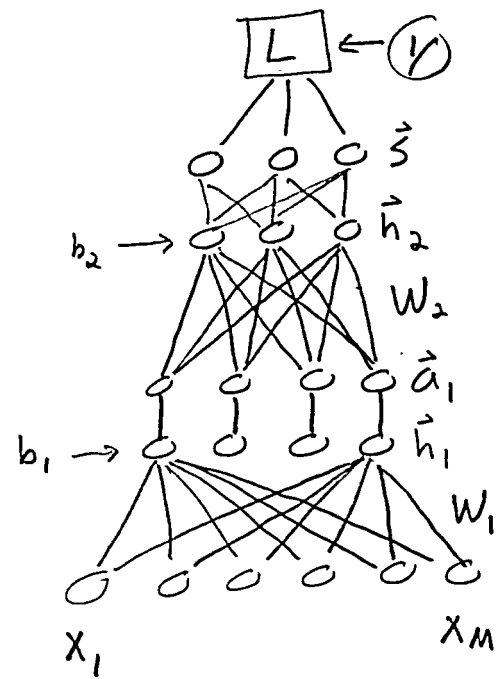
$$W_1 \in \mathbb{R}^{M \times L}$$

$$h_1, a_1, b_1 \in \mathbb{R}^{1 \times N}$$

$$W_2 \in \mathbb{R}^{N \times L}$$

$$y, h_2, b_2, s \in \mathbb{R}^{1 \times L}$$

$$Q \in \mathbb{R}^{L \times L}$$



$$\vec{h}_1 = XW_1 + b_1$$

$$a_1 = \sigma(\vec{h}_1)$$

$$\vec{h}_2 = a_1 W_2 + b_2$$

$$\vec{s} = \text{softmax}(\vec{h}_2) = \frac{e^{h_{2i}}}{\sum_k e^{h_{2k}}}$$

Need $\frac{\partial L}{\partial W_2}, \frac{\partial L}{\partial b_2}, \frac{\partial L}{\partial W_1}, \frac{\partial L}{\partial b_1}$

For $\frac{\partial s}{\partial h_2}$ use same Q matrix with $s_i(1-s_i)$ on diagonal and $-s_i s_j$ elsewhere

$$\frac{\partial L}{\partial W_2} = \frac{\partial L}{\partial s} \frac{\partial s}{\partial h_2} \frac{\partial h_2}{\partial W_2} = a_1^T \left(\frac{-y}{s} Q \right) \in \mathbb{R}^{N \times 1} (\mathbb{R}^{1 \times L} \mathbb{R}^{L \times L}) = \mathbb{R}^{N \times L} \checkmark$$

$$\frac{\partial L}{\partial b_2} = \frac{-y}{s} Q \in \mathbb{R}^{1 \times L} \checkmark$$

$$\frac{\partial L}{\partial W_1} = \frac{\partial L}{\partial s} \frac{\partial s}{\partial h_2} \frac{\partial h_2}{\partial a_1} \frac{\partial a_1}{\partial h_1} \frac{\partial h_1}{\partial W_1} \Rightarrow X^T \left(\frac{-y}{s} Q W_2^T \odot (a_1 \odot (1-a_1)) \right) \in \mathbb{R}^{M \times 1} \checkmark$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial L}{\partial s} \frac{\partial s}{\partial h_2} \frac{\partial h_2}{\partial a_1} \frac{\partial a_1}{\partial h_1} \frac{\partial h_1}{\partial b_1} \Rightarrow \frac{-y}{s} Q W_2^T \odot (a_1 \odot (1-a_1)) \in \mathbb{R}^{1 \times N} \checkmark$$

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- a) Yes, I was able to run on the cluster
 - b) This assignment took 15 - 20 hours
 - c) I adhered to the Duke Community standard in the completion of this assignment
- NAI