

CSCI567 – Machine Learning

Assignment 2

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Question 1-1

$$\frac{\partial l}{\partial u} = -[W^{(2)T} \frac{\partial l}{\partial a}] \cdot * H(u)$$

$$\frac{\partial l}{\partial a} = [\text{diag}(z) - zz^T] [-y \cdot * \frac{1}{z}]$$

$$\frac{\partial l}{\partial W^{(1)}} = \frac{\partial l}{\partial u} x^T$$

$$\frac{\partial l}{\partial b^{(1)}} = \frac{\partial l}{\partial u}$$

$$\frac{\partial l}{\partial W^{(2)}} = \frac{\partial l}{\partial a} h^T$$

Question 1-2

$$W^{(2)} = 0 \Rightarrow \frac{\partial l}{\partial u} = 0 \Rightarrow \frac{\partial l}{\partial W^{(1)}} = \frac{\partial l}{\partial b^{(1)}} = 0$$

$$W^{(1)} = b^{(1)} = 0 \rightarrow u = W^{(1)}x + b^{(1)} = 0 \Rightarrow h = \max(0, u) = \mathbf{0} \Rightarrow \frac{\partial l}{\partial W^{(2)}} = \frac{\partial l}{\partial a} h^T = \mathbf{0}$$

We have shown that the initial value for these parameters and the change on them (derivative) is zero, this is why they will not get updated and remain zero forever.

Question 1-3

$$\begin{aligned} a &= W^{(2)}u + b^{(2)} = W^{(2)}(W^{(1)}x + b^{(1)}) + b^{(2)} = \\ &= W^{(2)}W^{(1)}x + W^{(2)}b^{(1)} + b^{(2)} = \mathbf{U}x + \mathbf{v} \Rightarrow \\ &\quad \mathbf{U} = W^{(2)}W^{(1)} \\ &\quad \mathbf{v} = W^{(2)}b^{(1)} + b^{(2)} \end{aligned}$$

Question 2-1

$$\begin{aligned}
J(w) &= \sum l(w^T \phi(x_n), y_n) + \frac{\lambda}{2} \|w\|^2 \Rightarrow \min J(w) \Rightarrow \frac{\partial J}{\partial w} = 0 \\
&\Rightarrow \sum l'(w^T \phi(x_n), y_n) \cdot \phi(x_n) + \lambda w = 0 \\
&\Rightarrow w^* = \frac{-1}{\lambda} \sum l'(w^T \phi(x_n), y_n) \cdot \phi(x_n) \\
&\quad \text{note : } l' = \frac{\partial l(w)}{\partial w}
\end{aligned}$$

Question 2-2

$$\begin{aligned}
\alpha_n &= \frac{-1}{\lambda} l'(w^T \phi(x_n), y_n) \Rightarrow w^* = \sum \alpha_n \phi(x_n) = \Phi^T \alpha \\
\Rightarrow J(\alpha) &= \sum l(\alpha^T \Phi \phi(x_n), y_n) + \frac{\lambda}{2} \|\Phi^T \alpha\|^2 = \sum l(\alpha^T \Phi \phi(x_n), y_n) + \frac{\lambda}{2} \alpha^T \Phi \Phi^T \alpha \\
&\rightarrow J(\alpha) = \sum l(\alpha^T K_n, y_n) + \frac{\lambda}{2} \alpha^T K \alpha,
\end{aligned}$$

$$K_n = \begin{bmatrix} \phi(x_1)^T \cdot \phi(x_n) \\ \phi(x_2)^T \cdot \phi(x_n) \\ \phi(x_3)^T \cdot \phi(x_n) \\ \dots \\ \dots \\ \phi(x_N)^T \cdot \phi(x_n) \end{bmatrix}$$