Reference Solutions to the Quiz 7

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1 Lecture 23

1). Please derive the updating rule, if we use ReLU as the activation function.

Sol: Before proceeding, we introduce the indicator function $\mathbb{I}(\cdot)$, meaning if condition \cdot is met, then return 1; otherwise, return 0.

In the backward pass, we consider changes in any w_i , i = 1, ..., n affecting the total error E. This is achieved by simply applying the chain rule, i.e.,

$$\frac{\partial E}{\partial w_i} = \sum_d \frac{\partial E}{\partial o_d} \frac{\partial o_d}{\partial \text{net}_d} \frac{\partial \text{net}_d}{\partial w_i}
= \sum_d (o_d - t_d) \mathbb{I}(\text{net}_d \ge 0) x_{d,i},$$
(1)

where we use the fact that the derivative of ReLU function is the defined indicator function above. We hence update the weights as follows

$$w_{i} = w_{i} - \eta \frac{\partial E}{\partial w_{i}}$$

$$= w_{i} - \eta \sum_{d} (o_{d} - t_{d}) \mathbb{I}(\text{net}_{d} \ge 0) x_{d,i}.$$
(2)

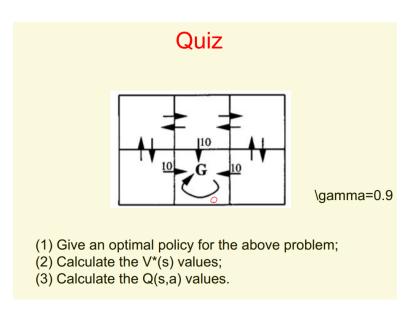
2). Compare the difference between the error gradients of the sigmoid function and the ReLU function.

Sol: The error gradients of the sigmoid function reads

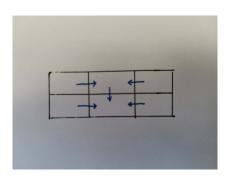
$$\frac{\partial E}{\partial w_i} = \sum_d \frac{\partial E}{\partial o_d} \frac{\partial o_d}{\partial \text{net}_d} \frac{\partial \text{net}_d}{\partial w_i}
= \sum_d (o_d - t_d) o_d (1 - o_d) x_{d,i}.$$
(3)

We first note that the backward updating is a gradient-based learning method. From (3), we observe that the derivative of the sigmoid function is always smaller than 1 (i.e., consider $o_d(1 - o_d)$). Indeed, it is at most 0.25. This would cause significant side effects if you have many layers as the product of many smaller than 1 values goes to zero very quickly. However, RELU activation fixes the vanishing gradients problem because it only saturates in one direction.

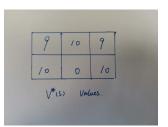
2 Lecture 24



Sol:



(1)



(2)

(3)

