

Problem Set 1

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1. Problem 1

a)

Let xl denote $\frac{\partial l}{\partial x}$, and according to the question, we know $l = f(y, z) = f(g(x), h(x))$

According to calculus, we have.

$$\frac{\partial l}{\partial x} = \frac{\partial f(g(x), h(x))}{\partial x} = \frac{\partial f(g(x), h(x))}{\partial g(x)} * \frac{\partial g(x)}{\partial x} + \frac{\partial f(g(x), h(x))}{\partial h(x)} * \frac{\partial h(x)}{\partial x} = yl * g'(x) + zl * h'(x) \quad (1-1)$$

Now we calculate $\frac{\partial l}{\partial x}$ based on backpropagation:

Set $x.grad = y.grad = z.grad = 0$

$u.grad = 1$

$$y.grad += u.grad * \frac{\partial f}{\partial y}$$

$$z.grad += u.grad * \frac{\partial f}{\partial z}$$

$$x.grad += y.grad * \frac{\partial g(x)}{\partial x}$$

$$x.grad += z.grad * \frac{\partial h(x)}{\partial x}$$

Calculate the formula above one by one, we have:

$$y.grad = 0 + 1 * \frac{\partial f(y, z)}{\partial y} = \frac{\partial f(y, z)}{\partial y} = yl$$

$$z.grad = 0 + 1 * \frac{\partial f(y, z)}{\partial z} = \frac{\partial f(y, z)}{\partial z} = zl$$

$$x.grad = 0 + yl * g'(x)$$

$$x.grad = yl * g'(x) + zl * h'(x) = yl * g'(x) + zl * h'(x) \quad (1-2)$$

We can see that (1-1) is equal to (1-2), which proves back propagation correctly calculates xl .

b)

Let xl denote $\frac{\partial l}{\partial x}$, Let xl' denote $\frac{\partial^2 l}{\partial x^2}$

According to calculus,

$$xl' = \frac{\partial(\frac{\partial l}{\partial x})}{\partial x} = \left(\frac{\partial f(g(x), h(x))}{\partial g(x)} * g'(x) + \frac{\partial f(g(x), h(x))}{\partial h(x)} * h'(x) \right)' = yl' * g'(x)^2 + yl * g''(x) + zl' * h'(x)^2 + zl * h''(x) \quad (1-3)$$

However, according to naïve backpropagation, we have the result

$$yl' * g''(x) + zl' * h''(x) \quad (1-4)$$

We can see that equation (1-3) and (1-4) have different results, which proves $xl' \neq yl' * g''(x) + zl' * h''(x)$

2. Problem 2

Let \mathbf{z} denote the input to the softmax function, \mathbf{h} denote the output of the softmax function, l denote the loss, we have,

$$\mathbf{h} = \text{softmax}(\mathbf{z}) \quad (2-1)$$

We can expand (2-1) as,

$$h_j = \frac{e^{z_j}}{\sum_i e^{z_i}} \quad (2-2)$$

Based on (2-2), we can have the derivative,

$$\frac{\partial h_i}{\partial z_j} = h_j(1 - h_i) \quad : i = j \quad (2-3)$$

$$\frac{\partial h_i}{\partial z_j} = -h_i h_j \quad : i \neq j \quad (2-4)$$

We can combine (2-3) and (2-4) using Kronecker delta,

$$\frac{\partial h_i}{\partial z_j} = h_j(\delta_{i,j} - h_i) \quad (2-5)$$

Where

$$\delta_{i,j} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \quad (2-6)$$

Based on (2-5), we can have,

$$\frac{\partial l}{\partial z_j} = \sum_i \frac{\partial l}{\partial h_i} \frac{\partial h_i}{\partial z_j} = \sum_i \frac{\partial l}{\partial h_i} h_j(\delta_{i,j} - h_i) = \sum_i h_j \left(\frac{\partial l}{\partial h_i} \delta_{i,j} - \frac{\partial l}{\partial h_i} h_i \right) = h_j \sum_i \left(\frac{\partial l}{\partial h_i} \delta_{i,j} - \frac{\partial l}{\partial h_i} h_i \right) \quad (2-7)$$

Based on (2-6) and (2-7), we can have,

$$\frac{\partial l}{\partial z_j} = h_j \left(\frac{\partial l}{\partial h_j} - \sum_i \left(\frac{\partial l}{\partial h_i} h_i \right) \right) \quad (2-8)$$

Based on (2-8), we can have

$$\frac{\partial l}{\partial \mathbf{z}} = \mathbf{h} \left(\frac{\partial l}{\partial \mathbf{h}} - \frac{\partial l}{\partial \mathbf{h}} * \mathbf{h} \right) \quad (\text{The } * \text{ here refers to vector dot product}) \quad (2-9)$$

Now let's have a look at the code, we can see that the code and the formula are consistent.

$\frac{\partial l}{\partial \mathbf{h}} * \mathbf{h}$ refers to the code `"np.dot(self.grad, self.value)"`

$\mathbf{h} \left(\frac{\partial l}{\partial \mathbf{h}} - \frac{\partial l}{\partial \mathbf{h}} * \mathbf{h} \right)$ refers to the code `"self.value * (self.grad - gvdot)"`

Now we have proved the correctness of the code.