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Assignment-1

1) $x = \text{torch.tensor}([0.1, 0, 0.2, 1], \text{dtype} = \text{torch.FloatTensor}, \text{requires_grad} = \text{True})$
 $z = \text{torch.tensor}([-1, 1, -1, 0], \text{dtype} = \text{torch.FloatTensor}, \text{requires_grad} = \text{True})$

$$a = x + 10 \times 4 + z$$

$$b = a^{**} (4 \times x)$$

$$c = (b + 3) \times 5$$

$$y = c.\text{mean}()$$

$$y.\text{backward}()$$

 $i = 1, 2, 3, 4$

$$\frac{\delta y}{\delta z_i} = \frac{\delta y}{\delta c_i} \cdot \frac{\delta c_i}{\delta b_i} \cdot \frac{\delta b_i}{\delta a_i} \cdot \frac{\delta a_i}{\delta z_i}$$

$$\frac{\delta a_i}{\delta z_i} = 1$$

$$b_i = a_i^{4x_i} \Rightarrow \ln b_i = 4x_i \ln a_i$$

$$\Rightarrow \frac{1}{b_i} \frac{\delta b_i}{\delta z_i} = \frac{4x_i}{a_i} \cdot \frac{\delta a_i}{\delta z_i}$$

$$\Rightarrow \frac{\delta b_i}{\delta z_i} = 4x_i a_i$$

$$\frac{\delta c_i}{\delta b_i} = 1$$

$$\frac{\delta y}{\delta c_i} = \frac{1}{4} \times 5 \times 4x_i a_i^{4x_i-1}$$

$$\therefore \frac{\delta y_i}{\delta z_i} = 5x_i a_i^{4x_i-1}$$

Substituting the values of a_i, x_i we get,

$$\therefore z.\text{grad} = [0.4722, 0.0000, 0.8642, 0.135.0000]$$

$$\frac{\partial y}{\partial x_i} = \frac{\partial y}{\partial c_i} \cdot \frac{\partial c_i}{\partial b_i} \cdot \frac{\partial b_i}{\partial x_i}$$

$$y = \frac{1}{4}(c_1 + c_2 + c_3 + c_4).$$

$$\frac{\partial y}{\partial c_i} = \frac{1}{4}$$

$$\frac{\partial c_i}{\partial b_i} = 5.$$

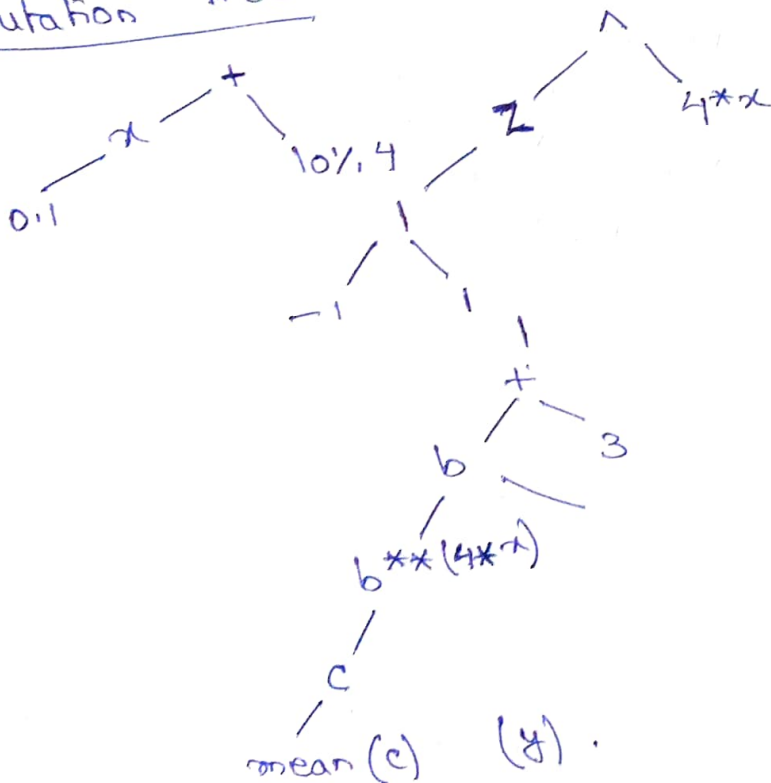
$$b = a^{4x_i}$$

$$\frac{\partial b_i}{\partial x_i} = 4x_i a_i^{4x_i-1} + 4a_i^{4x_i} \ln a_i$$

$$\therefore x_i \text{ grad} = \sum \left[5 (x_i a_i^{4x_i-1}) + a_i^{4x_i} \ln a_i \right] \quad i=1,2,3,4.$$

$$= ([0.9673, 5.4931, 2.0190, 579.9380])$$

computation Tree:-



$$2a) \text{ TSS} = \frac{1}{2} [(t_1 - o_1)^2 + (t_2 - o_2)^2]$$

$$\Delta w_{11} = -\eta \frac{\delta \text{TSS}}{\delta w_{11}}$$

$$\frac{\delta \text{TSS}}{\delta w_{11}} = \frac{\delta \text{TSS}}{\delta o_1} \cdot \frac{\delta o_1}{\delta \text{net}} \cdot \frac{\delta \text{net}}{\delta w_{11}}$$

$$\frac{\delta \text{TSS}}{\delta o_1} = -(t_1 - o_1) \dots (i)$$

$$o_1 = \frac{1}{1 + e^{-\text{net}}}$$

$$\frac{\delta o_1}{\delta \text{net}} = o_1(1 - o_1) \dots (ii)$$

$$\text{net} = \sum_{i=0}^n w_{ij} x_i$$

$$\frac{\delta \text{net}}{\delta w_{11}} = x_1 \dots (iii)$$

$$\begin{aligned} \therefore \Delta w_{11} &= -\eta \left[\frac{\delta \text{TSS}}{\delta o_1} \cdot \frac{\delta o_1}{\delta \text{net}} \cdot \frac{\delta \text{net}}{\delta w_{11}} \right] \\ &= -\eta (-t_1 + o_1) \cdot o_1(1 - o_1) \cdot x_1 \\ &= \eta (t_1 - o_1) \cdot o_1(1 - o_1) \cdot x_1 \end{aligned}$$

2b) Problem of Vanishing Gradient:-

① Large Non-normalized input values:- If the input values are (x_i) very large or small, the weighted sum at the hidden neuron can quickly move away from 0 during the forward pass. This leads to a near zero derivative (σ') for the sigmoid activation fn, resulting in vanishing gradients during backpropagation.

① Activation function:- If the network gets stuck in a state where the outputs are close to 0 or 1 due to bias or other factors. The error signal $(t_1 - o_1)$ will be very

Small. This can also lead to vanishing gradients, as the small error signal gets multiplied by the small derivative (σ') during backpropagation.