Generalized equations for finding the weight and bias gradients

$$\frac{dJ}{dW_2} = \frac{dJ}{dA_2} \frac{dA_2}{dZ_2} \frac{dZ_2}{dW_2}$$

$$\frac{dJ}{db_2} = \frac{dJ}{dA_2} \frac{dA_2}{dZ_2} \frac{dZ_2}{db_2}$$

$$\frac{dJ}{dW_1} = \frac{dJ}{dA_2} \frac{dA_2}{dA_2} \frac{dA_2}{dA_1} \frac{dA_2}{dA_1} \frac{dA_1}{dA_2} \frac{dA_2}{dW_1}$$

$$\frac{dS}{db_1} = \frac{dJ}{dA_2} \frac{dA_2}{dZ_2} \frac{dZ_2}{dA_1} \frac{dA_1}{dZ_1} \frac{dZ_1}{db_1}$$

#### Update Rules

$$W_{\ell} := W_{\ell} - \alpha \frac{JJ}{JW_{\ell}}$$

$$b_{\ell} := b_{\ell} - \lambda \frac{JJ}{Jb}$$

$$J = (a_{2} - y)^{2}$$

$$J_{W_{3}} = a_{1}^{T} \cdot 2(a_{2} - y) \cdot 2_{2}$$

$$J_{W_{3}} = 2(a_{3} - y)$$

$$\frac{\partial J}{\partial \omega_{i}} = X^{T} \cdot \lambda (a_{2} - y) \cdot \lambda_{2} \cdot \omega_{2}^{T} \cdot g'(a_{1})$$

$$\frac{\partial J}{\partial b_{i}} = \lambda (a_{2} - y) \cdot \lambda_{2} \cdot \omega_{2}^{T} \cdot g'(a_{1})$$

Now that we have our gradients, we're ready to train.

## Step 1: Forward Pass

$$Z_1 = W_1 X + b_1$$
  
 $\alpha_1 = \sigma(Z_1)$ 

$$\frac{2}{4} = \omega_{\lambda} a_{1} + b_{2}$$

$$a_{2} = \sigma(2_{2})$$

#### Step 2: Back Propagation

update weights and biases

based on the loss, learning rate, and gradients. Do this until the error converges.

We := 
$$We - \alpha \frac{JJ}{JWe}$$
 where  $\alpha$  is learning rate
$$b_{\ell} := b_{\ell} - \lambda \frac{JJ}{Jb}$$

### Step3: Test Model

Use the optimized weights and biases on the X-test data and see how the outputs compare to the Y-test data.

In my case, I ended with a loss of 79 as mentioned in question 2 of the homework.

# How Is This Update Different From Log Loss?

This update rule is very similar. There are minor differences in the gradients. For log loss update rules:

$$\frac{JJ}{J\omega_2} = (\alpha_2 - y) \cdot \alpha_1^T$$

$$\frac{\partial J}{\partial b_2} = (a_2 - y)$$

$$\frac{\partial J}{\partial w_1} = (\alpha_2 - y) \cdot w_2 \cdot g'(z_1) \cdot X$$

$$\frac{\partial}{\partial b_1} = (a_2 - y) \cdot \omega_2 \cdot g'(z_1)$$

The binary cross entropy cost function is used when doing binary classification problems.

As you can see above, the main differences between the update rules is that the cost function is different. When the cost function changes, all of the partial derivative and gradients will change too.