

# CMPS 142 - Homework 5

Aidan Gadberry, Christopher Hsiao, Tom Burch  
{agadberr, chhsiao, tburch1}@ucsc.edu

June 8, 2017

## 1 Back Propagation

### 1.1 Feed Foward

First, we will perform the feed forward process to calculate the output of our neural network:  $z_5$ . Note that we will be using  $\sigma(a_j)$  to represent the logistic sigmoid function on the activations of nodes  $j = 1 \dots 5$ .

#### Input Layer - 1, 2

Given an input of  $(1, 2)$ ,  $a_1 = 1$  and  $a_2 = 2$ , we can calculate the outputs:

$$z_1 = \sigma(a_1) = \sigma(1) \approx 0.73$$

$$z_2 = \sigma(a_2) = \sigma(2) \approx 0.88$$

#### Hidden Layer - 3, 4

First, we'll calculate the activations  $a_3, a_4$  for the hidden nodes.

$$a_3 = z_1 w_{3,1} + z_2 w_{3,2} \approx 0.536$$

$$a_4 = z_1 w_{4,1} + z_2 w_{4,2} \approx 0.536$$

And we can now calculate the outputs of these nodes:

$$z_3 = \sigma(a_3) = \sigma(0.536) \approx 0.631$$

$$z_4 = \sigma(a_4) = \sigma(0.536) \approx 0.631$$

#### Output - 5

And now to calculate the output activation  $a_5$ . Recall that for the output node,  $a_5 = z_5$ .

$$a_5 = z_3 w_{5,3} + z_4 w_{5,4} = 0$$

$$\text{thus, } a_5 = z_5 = 0$$

## 1.2 Backpropagation

Now we'll begin calculating the  $\frac{\delta E}{\delta a_j}$  values, which we'll represent as  $\delta_j$ , starting with  $\delta_5$ .

**Output Node:  $\delta_5$**

Since the error function is:

$$E = \frac{1}{2}(a_5 - t)^2$$

then...

$$\delta_5 = \frac{\delta E}{\delta a_5} = (a_5 - t) = (1 - 2) = -1$$

Now, recall that the general equation for other  $\delta_j$  values is:

$$\frac{\delta E}{\delta a_j} = \delta_j = \left( \sum_{k \in U_j} \delta_k w_{k,j} \right) z_j (1 - z_j)$$

Where  $U_j$  represented outgoing arcs from node  $j$ .

### Hidden Layer - 3, 4

Using  $\delta_5$ , we'll use the equation above to calculate  $\delta_4$  and  $\delta_3$ .

$$\delta_4 = (-1 \cdot 1)(0.631)(0.369) \approx -0.233$$

$$\delta_3 = (-1 \cdot -1)(0.631)(0.369) \approx 0.233$$

### Input Layer - 1, 2

And now to find  $\delta_1$  and  $\delta_2$ .

$$\delta_2 = \left[ \left( \delta_3 \cdot \frac{1}{3} \right) + \left( \delta_4 \cdot \frac{1}{3} \right) \right] (0.88)(1 - 0.88) = 0$$

$$\delta_1 = \left[ \left( \delta_3 \cdot \frac{1}{3} \right) + \left( \delta_4 \cdot \frac{1}{3} \right) \right] (0.73)(1 - 0.73) = 0$$

### Updating the Weights - $w_{j,i}$ 's

Recall that the full step/update equation in SGD for each weight is:

$$w_{j,i} := w_{j,i} - \eta \frac{\delta E}{\delta w_{j,i}}$$

$$\text{where: } \frac{\delta E}{\delta w_{j,i}} = \delta_j z_i$$

Thus, the updates for the weights are as follows:

$$w_{5,3} = -1 - (0.1)(-1)(0.631) = -0.937$$

$$w_{5,4} = 1 - (0.1)(-1)(0.631) = 1.063$$

$$w_{4,1} = \frac{1}{3} - (0.1)(-0.233)(0.73) = 0.35$$

$$w_{4,2} = \frac{1}{3} - (0.1)(-0.233)(0.88) = 0.354$$

$$w_{3,1} = \frac{1}{3} - (0.1)(0.233)(0.73) = 0.316$$

$$w_{3,2} = \frac{1}{3} - (0.1)(0.233)(0.88) = 0.313$$

## 2 Clustering

Given: 1, 3, 6, 10, 15, 21, 28, 36, K=3, Given mean=1,3,6

Iteration	K1	K1-mean	K2	K2-mean	K3	K3-mean
#1	1	1	3	3	6, 10, 15, 21, 28, 36	19.3
#2	1,3	1.5	6	6	10, 15, 21, 28, 36	22
#3	1,3,6	3.3	10	10	15, 21, 28, 36	25
#4	1,3,6,10	5	15	15	21, 28, 36	28.3
#5	1,3,6,10,15	7	21	21	28, 36	32
#6	1,3,6,10,15,21	9.3	28	28	36	36

Given: 1, 3, 6, 10, 15, 21, 28, 36, K=3, Given mean=21,28,36

Iteration	K1	K1-mean	K2	K2-mean	K3	K3-mean
#1	1,3,6,10,15,21	9.3	28	28	36	36

Yes, we believe starting with the same given set 1, 3, 6, 10, 15, 21, 28, 36, the K-cluster algorithm will output the same clustering when comparing the initial means [1,3,6] and [21,28,36]. Although the final clustering is identical, the difference is the execution of the K-means cluster algorithm, where for the first set of initial means will result in the algorithm processing 6 iterations, while the the second set of means will allow the algorithm to complete in one iteration.