

# Artificial Intelligence Tutorial 6 - Answers

1. The nodes in a multi-layer neural network often contain sigmoid units, which perform the following calculation for a given weighted sum  $S$ :

$$\sigma(S) = \frac{1}{1 + e^{-S}}$$

1a) Calculate the output from a sigmoid unit which takes the set  $\{0.1, 0.8, 0.8, 0.3\}$  as input.

1b) Is this unit “firing”?

1a) The weighted sum coming into the node is  $0.1 + 0.8 + 0.8 + 0.3 = 2$ .  $e^{-2}$  is 0.135, so  $1/(1+e^{-2})$  is  $1/(1+0.135) = 0.88$ .

1b) This output is nearer to 1 than 0, so it can be thought of as firing.

Suppose we have a multi-layer network with two output nodes, and the target output for example  $E$  from output unit 1 is 1 and for output unit 2 is 0, yet the observed value produced for  $E$  was 0.3 for output unit 1 and 0.7 for output unit 2. The error term for an output unit  $O_k$  is calculated as:

$$\delta_{O_k} = o_k(E)(1 - o_k(E))(t_k(E) - o_k(E))$$

1c) What is the error term for  $O_1$  and  $O_2$ ?

1c) Remembering that  $o_k(E)$  is the observed output from output unit  $k$  for training example  $E$ , and  $t_k(E)$  is the target output from output unit  $k$  for  $E$ , the calculation is fairly straightforward:

$$d_{o_1} = o_1(E)(1-o_1(E))(t_1(E)-o_1(E)) = 0.3*(1-0.3)(1-0.3) = 0.3*0.7*0.7 = 0.147$$

$$d_{o_2} = o_2(E)(1-o_2(E))(t_2(E)-o_2(E)) = 0.7*(1-0.7)(0-0.7) = 0.7*0.3*-0.7 = -0.147$$

Suppose, in the ANN discussed in (b), the weight from hidden node  $H_1$  to  $O_1$  was 0.25 and from  $H_1$  to  $O_2$  it was 0.4. Suppose further that the output from  $H_1$  for example  $E$  was 0.9.

1d) Use the following formula to calculate the error term of  $H_1$  with respect to  $E$ :

$$\delta_{H_k} = h_k(E)(1 - h_k(E)) \sum_{i \in \text{outputs}} w_{ki} \delta_{O_i}$$

1d) To use this formula, we have to remember what each of the symbols represents. Firstly, in our case,  $k$  is 1, because we’re dealing with the first hidden node (counting from top to bottom). Also,  $h_k(E)$  is the observed output from hidden unit  $k$  when training example  $E$  is propagated through the network. Finally,  $w_{ki}$  is the weight between hidden unit  $k$  and output unit  $i$  and  $d_{oi}$  is the error term for output unit  $i$ , as calculated in part (b). The big sigma sign means that we add up all the values calculated for the different  $i$ ’s, where  $i$  ranges over the output units. We will deal first with the

summation. There are two output nodes, and the error terms for them were 0.147 and  $-0.147$  respectively, with the weights between hidden unit 1 and them being 0.25 and 0.4 respectively (as specified in the question). Hence, the summation is:

$$0.25 * 0.147 + 0.4 * (-0.147) = -0.02205$$

Next, we can calculate that  $h_1(E)(1-h_1(E))$  is  $0.9 * (1-0.9) = 0.9 * 0.1 = 0.09$ . Finally, we can put the two halves of the calculation together to give:

$$d_{hk} = -0.2205 * 0.09 = -0.0019845$$

Suppose in the last epoch of training using example E, the weight change for  $h_1$  was 0.004. Suppose further that we are using a learning rate of 0.1 and a momentum of 0.2 in training the network.

1e) What will be the change for the weight between  $h_1$  and  $o_1$  using example E to train it in the current epoch?

1e) The weight change is calculated by multiplying the error term for the output unit by the learning rate (given as 0.1), then multiplying the answer by the output from the hidden unit for example E. We have calculated the error rate in part (b) to be 0.147, and we also know that the output from H1 for E was 0.7. Therefore, the weight change is:

$$\Delta_{11} = 0.1 * 0.147 * 0.9 = 0.01323$$

Momentum is a heuristic used to get over local minimas, and it works by adding on a fraction of the previous weight change during the current weight change. The fraction is called the momentum, and in our case it was 0.2. Hence, to alter this weight change using momentum, we need to add on 0.2 times the previous weight change, which we were told was 0.004. Hence, our final weight change is:

$$\Delta_{11} = 0.01323 + 0.2 * 0.004 = 0.01403$$

2. Suppose you know one thing in life:

(i) all people who smoke are stupid

You've also observed that

(ii) people who smoke and are smelly are ugly.

2a) Use the absorption rule to induce a hypothesis about stupid, smelly, ugly people (i.e., a rule not involving smoking).

2a) The absorption rule of inductive inference can be portrayed like this:

$$\frac{q \leftarrow A \ \& \ p \leftarrow A, B}{q \leftarrow A \ \& \ p \leftarrow q, B}$$

$$q \leftarrow A \ \& \ p \leftarrow q, B$$

Where the commas represent conjunction between (sets of) literals, p and q are single literals and A



Hence, we see that given (i) and (H) as true, we can deduce using resolution that people who smoke and are smelly are ugly, which is exactly what we observed and wrote down in sentence (ii).

In English, we have done the following: we stated that we knew that people who smoke are stupid. We didn't know why, but we've noticed that smokers who are smelly are also ugly. This could possibly be because stupid, smelly people are ugly. If this were true, then because smokers are known to be stupid, then smelly smokers are stupid smelly people, and, by our conjecture are ugly – so the hypothesis explains our observation.