Feedback — Lecture 13 Quiz

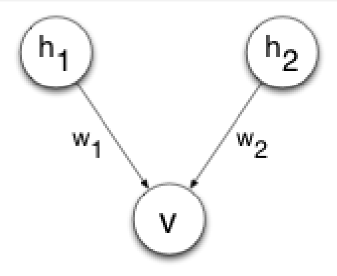
Help Center

You submitted this quiz on **Fri 1 Jul 2016 1:53 AM CEST**. You got a score of **0.00** out of **8.00**. However, you will not get credit for it, since it was submitted past the deadline.

Announcement, added on Thursday, November 15 2012, 18:28 UTC. You may find this explanation of SBNs helpful.

This quiz is going to take you through the details of Sigmoid Belief Networks (SBNs). The most relevant videos are the second video ("Belief Nets", especially from 11:44) and third video ("Learning sigmoid belief nets") of lecture 13.

We'll be working with this network:



The network has no biases (or equivalently, the biases are always zero), so it has only two parameters: w_1 (the weight on the connection from h_1 to v) and w_2 (the weight on the connection from h_2 to v).

Remember, the units in an SBN are all binary, and the logistic function (also known as the *sigmoid* function) figures prominently in the definition of SBNs. These binary units, with their logistic/sigmoid probability function, are in a sense the *stochastic* equivalent of the *deterministic* logistic hidden units that we've seen often in earlier lectures.

Let's start with $w_1 = -6.90675478$ and $w_2 = 0.40546511$. These numbers were chosen to ensure that the answer to many questions is a very simple answer, which might make it easier to understand more of what's going on. Let's also pick a complete configuration to focus on: $h_1 = 0, h_2 = 1, v = 1$ (we'll call that configuration C_{011}).

Question 1

What is $P(v = 1|h_1 = 0, h_2 = 1)$? Write your answer with four digits after the decimal point. Hint: the last three of those four digits are zeros. (If you're lost on this question, then I strongly recommend that you do whatever you need to do to figure it out, before proceeding with the rest of this quiz.)

You entered:

Your Answer		Score	Explanation
	✖	0.00	
Total		0.00 / 2.00	

Question Explanation

Pretend that this is a feed-forward neural network with two hidden units and a logistic output neuron. You're now calculating the output of the network given that the hidden units have taken on the values $h_1 = 0$ and $h_2 = 1$.

Question 2

What is the probability of that full configuration, i.e. $P(h_1 = 0, h_2 = 1, v = 1)$, which we called $P(C_{011})$? Write your answer with four digits after the decimal point. Hint: it's less than a half, and the last two of those four digits are zeros.

You entered:

Your Answer		Score	Explanation
	✖	0.00	
Total		0.00 / 1.00	

Question Explanation

We can use the rule of multiplication in order to obtain
$P(h_1 = 0, h_2 = 1, v = 1) = P(v = 1|h_1 = 0, h_2 = 1)P(h_1 = 0, h_2 = 1)$.
Question 1 deals with finding $P(v_1|h_1 = 0, h_2 = 1)$, now you need to find
$P(h_1 = 0, h_2 = 1)$. What does the picture given in the preamble tell you about the **marginal** independence of h_1 and h_2 (when we have not observed v)? Also, remember that h_1 and h_2 both have 0 total input, and that they are logistic neurons.

Question 3

Now let's talk about the gradient that we need for learning, i.e. $\frac{\partial \log P(C_{011})}{\partial w_i}$. There are two ways you can try to answer these questions, and I recommend that you do both and verify that the answer comes out the same way. The first way is to take the derivative yourself. The second one is to use the learning rule that was mentioned in the lecture.

What is $\frac{\partial \log P(C_{011})}{\partial w_1}$? Write your answer with at least three digits after the decimal point, and don't be too surprised if it's a very simple answer.

You entered:

Your Answer		Score	Explanation
	✖	0.00	
Total		0.00 / 1.00	

Question 4

What is $\frac{\partial \log P(C_{011})}{\partial w_2}$? Write your answer with at least three digits after the decimal point, and don't be too surprised if it's a very simple answer.

You entered:

Your Answer		Score	Explanation
	✖	0.00	
Total		0.00 / 1.00	

Question 5

As was explained in the lectures, the log likelihood gradient for a full configuration is just one part of the learning. The more difficult part is to get a handle on the posterior probability distribution over full configurations, given the state of the visible units. Explaining away is an important issue there.

Let's explore it with new weights: for the remainder of this quiz, $w_1 = 10$, and $w_2 = -4$. What is $P(h_2 = 1|v = 1, h_1 = 0)$? Give your answer with at least four digits after the decimal point. Hint: it's a fairly small number (and not a round number like for the earlier questions); try to intuitively understand why it's small. Second hint: you might find Bayes' rule useful, but even with that rule, this still requires some thought.

You entered:

Your Answer	Score	Explanation
✖	0.00	
Total	0.00 / 1.50	

Question Explanation

We can use Baye's rule to determine:

$$P(h_2 = 1|v = 1, h_1 = 0) = \frac{P(v=1|h_1=0,h_2=1)P(h_2=1)}{P(v=1|h_1=0,h_2=1)P(h_2=1)+P(v=1|h_1=0,h_2=0)P(h_2=0)}.$$

Question 6

What is $P(h_2 = 1|v = 1, h_1 = 1)$? Give your answer with at least four digits after the decimal point. Hint: it's quite different from the answer to the previous question; try to understand why. The fact that those two are different shows that, conditional on the state of the visible units, the hidden units have a strong effect on each other, i.e. they're not independent. That is what we call explaining away, and the earthquake vs. truck network is another example of that.

You entered:

Your Answer	Score	Explanation
✖	0.00	
Total	0.00 / 1.50	