

10/10 points (100.00%)

Congratulations! You passed!	Next Item
1/1	
point .	
Vhich of the following are true? (Check all that apply.)	
$a_4^{[2]}$ is the activation output of the 2^{nd} layer for the 4^{th} training example	
Un-selected is correct	
$a_4^{[2]}$ is the activation output by the 4^{th} neuron of the 2^{nd} layer	
a_4 is the activation output by the Φ -fleuron of the Z -layer	
Correct	
igwedge X is a matrix in which each column is one training example.	
Correct	
X is a matrix in which each row is one training example.	
Un-selected is correct	
$a^{[2](12)}$ denotes activation vector of the 12^{th} layer on the 2^{nd} training example.	
Un-selected is correct	
$a^{[2](12)}$ denotes the activation vector of the 2^{nd} layer for the 12^{th} training example.	
Correct	
$a^{[2]}$ denotes the activation vector of the 2^{nd} layer.	
Correct	

The tanh activation usually works better than sigmoid activation function for hidden units because the mean of its output is closer to

https://www.coursera.org/learn/neural-networks-deep-learning/exam/7llnl/shallow-neural-networks

zero, and so it centers the data better for the next layer. True/False?



10/10 points (100.00%)

Correct

Yes. As seen in lecture the output of the tanh is between -1 and 1, it thus centers the data which makes the learning simpler for the next layer.

False



1/1 point

3

Which of these is a correct vectorized implementation of forward propagation for layer l, where $1 \le l \le L$?

- $\bigcirc \quad \bullet \ \ Z^{[l]} = W^{[l]} A^{[l-1]} + b^{[l]}$
 - $ullet \ A^{[l]} = g^{[l]}(Z^{[l]})$

Correct

- - $ullet \ A^{[l+1]} = g^{[l+1]}(Z^{[l]})$
- - $ullet \ A^{[l+1]} = g^{[l]}(Z^{[l]})$
- - $A^{[l]} = q^{[l]}(Z^{[l]})$



1/1 point

4.

You are building a binary classifier for recognizing cucumbers (y=1) vs. watermelons (y=0). Which one of these activation functions would you recommend using for the output layer?

- ReLU
- Leaky ReLU
- sigmoid

Correct

Yes. Sigmoid outputs a value between 0 and 1 which makes it a very good choice for binary classification. You can classify as 0 if the output is less than 0.5 and classify as 1 if the output is more than 0.5. It can be done with tanh as well but it is less convenient as the output is between -1 and 1.

- tanh
- 1/1 point

	ShallowiNgural Networks Quiz, 10 questions	10/10 points (100.00%)
1 2	<pre>A = np.random.randn(4,3) B = np.sum(A, axis = 1, keepdims = True)</pre>	
nat v	will be B.shape? (If you're not sure, feel free to run this in python to find out)	
	(4,)	
	(1, 3)	
	(4, 1)	
Corr	rect	
Yes,	we use (keepdims = True) to make sure that A.shape is (4,1) and not (4,). It	nakes our code more rigorous.
	(, 3)	
	1/1	
	point	
	sse you have built a neural network. You decide to initialize the weights and l	iases to be zero. Which of the following statem
ıppo		iases to be zero. Which of the following statem
ippo true		oiases to be zero. Which of the following statem
	? Each neuron in the first hidden layer will perform the same computation. S	o even after multiple iterations of gradient
true	?	o even after multiple iterations of gradient
true	? Each neuron in the first hidden layer will perform the same computation. See the descent each neuron in the layer will be computing the same thing as other.	o even after multiple iterations of gradient
true	? Each neuron in the first hidden layer will perform the same computation. See the descent each neuron in the layer will be computing the same thing as other.	to even after multiple iterations of gradient r neurons. In the first iteration. But after one iteration of
true	Each neuron in the first hidden layer will perform the same computation. Seech neuron in the layer will be computing the same thing as other rect Each neuron in the first hidden layer will perform the same computation in	to even after multiple iterations of gradient r neurons. If the first iteration. But after one iteration of twe "broken symmetry". The transfer of the compute different layers will compute different to ever the com
true	Each neuron in the first hidden layer will perform the same computation. Seect Each neuron in the first hidden layer will be computing the same thing as other seect Each neuron in the first hidden layer will perform the same computation in gradient descent they will learn to compute different things because we have been seen to the same thing, but neuron in the first hidden layer will compute the same thing, but neuron in the first hidden layer will compute the same thing, but neuron in the first hidden layer will compute the same thing, but neuron in the first hidden layer will compute the same thing, but neuron in the first hidden layer will compute the same thing, but neuron in the first hidden layer will compute the same thing.	to even after multiple iterations of gradient r neurons. If the first iteration. But after one iteration of the "broken symmetry". If the first iteration is a symmetry in the first iteration of the broken symmetry.
C	Each neuron in the first hidden layer will perform the same computation. Seect Each neuron in the layer will be computing the same thing as other rect Each neuron in the first hidden layer will perform the same computation in gradient descent they will learn to compute different things because we have a computed in the same thing, but neuron in the first hidden layer will compute the same thing, but neurons, thus we have accomplished "symmetry breaking" as described in least things, this we have accomplished "symmetry breaking" as described in least things.	to even after multiple iterations of gradient r neurons. If the first iteration. But after one iteration of the "broken symmetry". If the first iteration is a symmetry in the first iteration of the broken symmetry.
True	Each neuron in the first hidden layer will perform the same computation. Seect Each neuron in the layer will be computing the same thing as other rect Each neuron in the first hidden layer will perform the same computation in gradient descent they will learn to compute different things because we have a computed in the first hidden layer will compute the same thing, but neuthings, thus we have accomplished "symmetry breaking" as described in least things, this we have accomplished "symmetry breaking" as described in least things, thus we have accomplished "symmetry breaking" as described in least things, thus we have accomplished "symmetry breaking" as described in least things, thus we have accomplished "symmetry breaking" as described in least things, thus we have accomplished "symmetry breaking" as described in least things.	to even after multiple iterations of gradient r neurons. If the first iteration. But after one iteration of the "broken symmetry". If the first iteration is a symmetry in the first iteration of the broken symmetry.
Corr	Each neuron in the first hidden layer will perform the same computation. Seect Each neuron in the layer will be computing the same thing as other rect Each neuron in the first hidden layer will perform the same computation in gradient descent they will learn to compute different things because we have a computed in the first hidden layer will compute the same thing, but neuthings, thus we have accomplished "symmetry breaking" as described in lethings, this we have accomplished "symmetry breaking" as described in lethings, this we have accomplished in their own way.	to even after multiple iterations of gradient r neurons. If the first iteration. But after one iteration of ove "broken symmetry". It is the first iteration of the process of the symmetry
Corr	Each neuron in the first hidden layer will perform the same computation. I descent each neuron in the layer will be computing the same thing as other ect Each neuron in the first hidden layer will perform the same computation in gradient descent they will learn to compute different things because we have a complished "symmetry breaking" as described in least things, thus we have accomplished "symmetry breaking" as described in least hidden layer's neurons will perform different computations from parameters will thus keep evolving in their own way.	to even after multiple iterations of gradient r neurons. If the first iteration. But after one iteration of ove "broken symmetry". It is the first iteration of the process of the symmetry
Corr	Each neuron in the first hidden layer will perform the same computation. Second each neuron in the layer will be computing the same thing as other each neuron in the first hidden layer will perform the same computation in gradient descent they will learn to compute different things because we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, this we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished "symmetry breaking" as described in lethings, thus we have accomplished the symmetry breaking as described in lethings.	to even after multiple iterations of gradient r neurons. If the first iteration. But after one iteration of ove "broken symmetry". It is the first iteration of the process of the symmetry

Yes, Logistic Regression doesn't have a hidden layer. If you initialize the weights to zeros, the first example x fed in the logistic regression depend on the input x (because there's no hidden layer) with layer with lay

1/1 point

8.

You have built a network using the tanh activation for all the hidden units. You initialize the weights to relative large values, using np.random.randn(..,..)*1000. What will happen?

- It doesn't matter. So long as you initialize the weights randomly gradient descent is not affected by whether the weights are large or small.
- This will cause the inputs of the tanh to also be very large, thus causing gradients to also become large. You therefore have to set α to be very small to prevent divergence; this will slow down learning.
- This will cause the inputs of the tanh to also be very large, causing the units to be "highly activated" and thus speed up learning compared to if the weights had to start from small values.
- This will cause the inputs of the tanh to also be very large, thus causing gradients to be close to zero. The optimization algorithm will thus become slow.



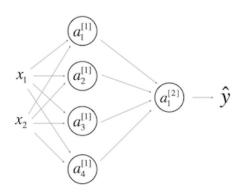
Yes. tanh becomes flat for large values, this leads its gradient to be close to zero. This slows down the optimization algorithm.



1/1 point

9

Consider the following 1 hidden layer neural network:



Which of the following statements are True? (Check all that apply).

 $igwedge W^{[1]}$ will have shape (2, 4)

Un-selected is correct

 $igcup b^{[1]}$ will have shape (4, 1)

Correct

 $W^{[1]}$ will have shape (4, 2)

← Correshallow Neural Networks Quiz, 10 questions	10/10 points (100.00%)				
$b^{[1]}$ will have shape (2, 1)					
Un-selected is correct					
$W^{[2]}$ will have shape (1, 4)					
Correct					
$b^{[2]}$ will have shape (4, 1)					
Un-selected is correct					
$W^{[2]}$ will have shape (4, 1)					
Un-selected is correct					
$b^{[2]}$ will have shape (1, 1)					
Correct					
1/1 point					
10. In the same network as the previous question, what are the dimensions of $Z^{[1]}$ and $A^{[1]}$?					
$igcup Z^{[1]}$ and $A^{[1]}$ are (4,2)					
$Z^{[1]}$ and $A^{[1]}$ are (4,m)					
Correct					
$igcup Z^{[1]}$ and $A^{[1]}$ are (4,1)					
$igcup Z^{[1]}$ and $A^{[1]}$ are (1,4)					

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