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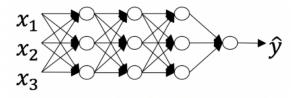
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Which of the following are true? (Check all that apply.)	1 / 1 point
$a_3^{[2]}$ denotes the activation vector of the second layer for the third example. $a^{[2]}$ denotes the activation vector of the second layer.	
\checkmark Correct Yes. In our convention $a^{[j]}$ denotes the activation function of the j-th layer.	
$\stackrel{[4]}{\sim} w_3^{[4]}$ is the column vector of parameters of the fourth layer and third neuron.	
\checkmark Correct Yes. The vector $w_j^{[i]}$ is the column vector of parameters of the i-th layer and j-th neuron of that layer.	
$\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ $	
$igsqcup w_3^{[4]}$ is the column vector of parameters of the third layer and fourth neuron.	
$\boxed{ a^{[3](2)}}$ denotes the activation vector of the second layer for the third example.	
✓ Correct Great, you got all the right answers.	
In which of the following cases is the linear (identity) activation function most likely used?	1 / 1 point
As activation function in the hidden layers.	
When working with regression problems.	
For binary classification problems. The linear activation function is never used.	
∠ [∞] Expand	
Correct Yes. In problems such as predicting the price of a house it makes sense to use the linear activation function as output.	

3. Which of the following represents the activation output of the second neuron of the third layer applied to the fourth example?

1 / 1 point



 $a_2^{[3](4)}$

2.

- $\bigcirc \ a_2^{[4](3)}$
- $\bigcirc \ \ a_4^{[3](2)}$
- $\bigcirc \ \ a_3^{[4]2}$

Z Expand

✓ Correct

Yes. The superscript in brackets indicates the layer number, the superscript in parenthesis represents the number of examples, and the subscript the number of the neuron.

alaid		
sigmoid		
Leaky ReLU		
tanh		
ReLU		
∠ [™] Expand		
You can classify as 0 if	a value between 0 and 1 which makes it a very good choice for binary classification. f the output is less than 0.5 and classify as 1 if the output is more than 0.5. It can be all but it is less convenient as the output is between -1 and 1.	
Consider the following code	e:	1 / 1 poin
#+begin_src python		, .
x = np.random.rand(3, 2)		
	limes True	
y = np.sum(x, axis=0, keepdi	illis=True)	
#+end_src		
What will be y.shape?		
(3, 1)		
(3,)		
(1, 2)		
(2,)		
	axis=0 the sum is computed over each column of the array, thus the resulting array is ntries. Since the option keepdims=True is used the first dimension is kept, thus (1, 2).	
Suppose you have built a ne following statements is true	eural network. You decide to initialize the weights and biases to be zero. Which of the e?	1 / 1 poin
		, ,
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∠⁷ Expand



Yes, Logistic Regression doesn't have a hidden layer. If you initialize the weights to zeros, the first example x fed into the logistic regression will output zero but the derivatives of the Logistic Regression depend on the input x (because there's no hidden layer) which is not zero. So at the second iteration, the weights' values follow x's distribution and are different from each other if x is not a constant vector.

8. Which of the following are true about the tanh function?

0 / 1 point

For large values the slope is larger.

For large values the slope is close to zero.

The tanh is mathematically a shifted version of the sigmoid function.

✓ Corr

Yes. You can see the shape of both is very similar but tanh passes through the origin.

The slope is zero for negative values.

 $\begin{tabular}{|c|c|c|c|c|}\hline & The derivative at $c=0$ is not well defined. \end{tabular}$

This should not be selected

No. The slope of the tangent line of the tanh function is well defined at 0, moreover the slope is 1.

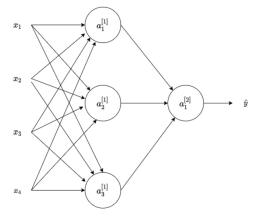


(X) Incorrec

You didn't select all the correct answers

9. Consider the following 1 hidden layer neural network:

1 / 1 point



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

✓ Correc

Yes. The number of rows in $W^{[k]}$ is the number of neurons in the k-th layer and the number of columns is the number of inputs of the layer.

✓ Correct

Yes. $b^{[k]}$ is a column vector and has the same number of rows as neurons in the k-th layer.

 $b^{[1]}$ will have shape (1, 3)

 $\ \ \ \ \ b^{[2]}$ will have shape (3, 1)

 $\stackrel{ imes}{\smile}$ *E: $b^{[2]}$ will have shape (1,1)

✓ Correct

Yes. $b^{[k]}$ is a column vector and has the same number of rows as neurons in the k-th layer.

 $\qquad \qquad W^{[1]}$ will have shape (4, 3).



\bigcirc Correct

Great, you got all the right answers.



- $\bigcirc \ \ Z^{[1]}$ and $A^{[1]}$ are (4,m)
- $igotimes Z^{[1]}$ and $A^{[1]}$ are (4,1)
- $\bigcirc \hspace{0.1in} Z^{[1]}$ and $A^{[1]}$ are (1,4)
- $\bigcirc \hspace{0.1in} Z^{[1]}$ and $A^{[1]}$ are (4,2)



(X) Incorrect

Remember that $Z^{[1]}$ and $A^{[1]}$ are quantities computed over a batch of training examples, not only 1.