Congratulations! You passed!

Grade received 80% | Latest Submission Grade 80% | To pass 80% or higher

Go to next item

1. We use the "cache" in our implementation of forward and backward propagation to pass useful values to the next layer in the forward propagation. True/False? **1 / 1 point**

- (•) False
- ( ) True

Expand

Correct
Correct. The "cache" is used in our implementation to store values computed during forward propagation to be used in backward propagation.

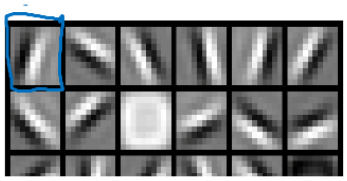
2. During the backpropagation process, we use gradient descent to change the hyperparameters. True/False? **0 / 1 point**

- (•) True
- ( ) False

Expand

Incorrect
Incorrect. During backpropagation, we use gradient descent to compute new values of $W^{[l]}$ and $b^{[l]}$. These are the parameters of the network.

3. Which of the following is more likely related to the early layers of a deep neural network? **1 / 1 point**

- (•) 

Expand

Correct
Yes. The early layer of a neural network usually computes simple features such as edges and lines.

4. Vectorization allows us to compute $a^{[l]}$ for all the examples on a batch at the same time without using a for loop. True/False? **1 / 1 point**

- (•) True
- ( ) False

Expand

Correct
Correct. Vectorization allows us to compute the activation for all the training examples at the same time, avoiding the use of a for loop.

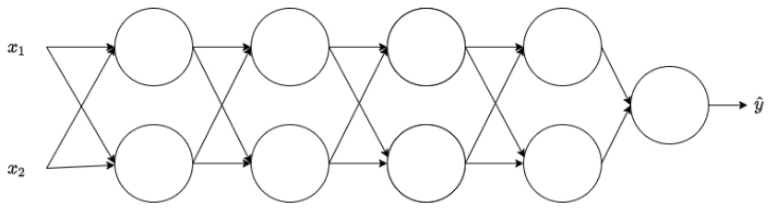
5. Assume we store the values for $n^{[l]}$ in an array called layer_dims, as follows: layer_dims = [n_x, 4,3,2,1]. So layer 1 has four hidden units, layer 2 has 3 hidden units, and so on. Which of the following for-loops will allow you to initialize the parameters for the model? **0 / 1 point**

- for i in range(len(layer_dims)-1):
  parameter['W' + str(i+1)] = np.random.randn(layer_dims[i+1], layer_dims[i]) * 0.01
  parameter['b' + str(i+1)] = np.random.randn(layer_dims[i+1], 1) * 0.01
- for i in range(1, len(layer_dims)/2):
  parameter['W' + str(i)] = np.random.randn(layer_dims[i], layer_dims[i-1]) * 0.01
  parameter['b' + str(i)] = np.random.randn(layer_dims[i], 1) * 0.01
- for i in range(len(layer_dims)):
  parameter['W' + str(i+1)] = np.random.randn(layer_dims[i+1], layer_dims[i]) * 0.01
  parameter['b' + str(i+1)] = np.random.randn(layer_dims[i+1], 1) * 0.01
- for i in range(len(layer_dims)-1):
  parameter['W' + str(i+1)] = np.random.randn(layer_dims[i], layer_dims[i+1]) * 0.01
  parameter['b' + str(i+1)] = np.random.randn(layer_dims[i+1], 1) * 0.01

Expand

Incorrect
No. This exceeds the number of layers on the neural network.

6. Consider the following neural network: **1 / 1 point**



How many layers does this network have?

- The number of layers L is 6
- The number of layers L is 2.
- The number of layers L is 4.
- The number of layers L is 5.

Expand

Correct
Yes. The number of layers is the number of hidden layers + 1.

7. During forward propagation, in the forward function for a layer l you need to know what is the activation function in a layer (sigmoid, tanh, ReLU, etc.). During backpropagation, the corresponding backward function also needs to know what is the activation function for layer l, since the gradient depends on it. True/False? **1 / 1 point**

- False
- True

Expand

Correct
Yes, as you've seen in week 3 each activation has a different derivative. Thus, during backpropagation you need to know which activation was used in the forward propagation to be able to compute the correct derivative.

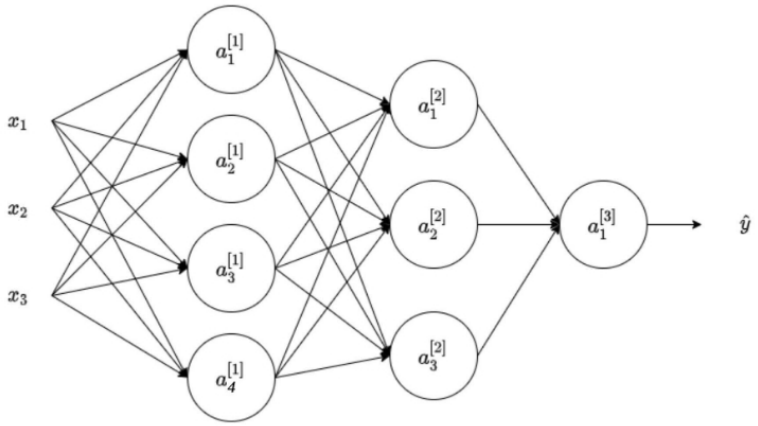
8. For any mathematical function you can compute with an L-layered deep neural network with N hidden units there is a shallow neural network that requires only $\log N$ units, but it is very difficult to train. **1 / 1 point**

- (•) False
- ( ) True

Expand

Correct
Correct. On the contrary, some mathematical functions can be computed using an L-layered neural network and a given number of hidden units; but using a shallow neural network the number of necessary hidden units grows exponentially.

9. Consider the following 2 hidden layers neural network: **1 / 1 point**



Which of the following statements is true? (Check all that apply).

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

  Correct
  Yes. More generally, the shape of $b^{[l]}$ is $(n^{[l]}, 1)$.

- [ ] $W^{[1]}$ will have shape (3, 4)
- [ ] $$b^{[1]}$$ will have shape (3, 1)
- [ ] $$W^{[2]}$$ will have shape (3, 1)
- [x] $$W^{[2]}$$ will have shape (3, 4)

  Correct
  Yes. More generally, the shape of $$W^{[l]}$$ is ($$n^{[l]}$$, $$n^{[l-1]}$$).

- [ ] $$W^{[3]}$$ will have shape (4, 3)

$$W^{[2]}$$ will have shape (4, 3)

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

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

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

Correct

Yes. More generally, the shape of $$W^{[l]}$$ is ($$n^{[l]}$$, $$n^{[l-1]}$$)

Expand

Correct

Great, you got all the right answers.

10. Whereas the previous question used a specific network, in the general case what is the dimension of $b^{[l]}$, the bias vector associated with layer l? **1 / 1 point**

- $b^{[l]}$ has shape $(n^{[l+1]}, 1)$
- $b^{[l]}$ has shape $(1, n^{[l-1]})$
- $b^{[l]}$ has shape $(1, n^{[l]})$
- $b^{[l]}$ has shape $(n^{[l]}, 1)$

Expand

Correct

True. $b^{[l]}$ is a column vector with the same number of rows as units in the respective layer.