

## ✓ Congratulations! You passed!

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1. Which of the following do you typically see in a ConvNet? (Check all that apply.)

1 / 1 point

☒ FC layers in the last few layers

✓ **Correct**

True, fully-connected layers are often used after flattening a volume to output a set of classes in classification.

☒ Multiple CONV layers followed by a POOL layer

✓ **Correct**

True, as seen in the case studies.

☐ Multiple POOL layers followed by a CONV layer

☐ FC layers in the first few layers

[↗ Expand](#)

✓ **Correct**

Great, you got all the right answers.

2. LeNet - 5 made extensive use of padding to create valid convolutions, to avoid increasing the number of channels after every convolutional layer. True/False?

1 / 1 point

☐ True

☒ False

[↗ Expand](#)

✓ **Correct**

Yes, back in 1998 when the corresponding paper of LeNet - 5 was written padding wasn't used.

3. The motivation of Residual Networks is that very deep networks are so good at fitting complex functions that when training them we almost always overfit the training data. True/False?

1 / 1 point

☐ True

☒ False

[↗ Expand](#)

✓ **Correct**

Correct, very deep neural networks are hard to train and a deeper network does not always imply lower training error. Residual Networks allow us to train very deep neural networks.

4. Which of the following equations captures the computations in a ResNet block?

1 / 1 point

- ☐  $a^{[l+2]} = g\left(W^{[l+2]}g\left(W^{[l+1]}a^{[l]} + b^{[l+1]}\right) + b^{[l+2]}\right) + a^{[l]}$
- ☐  $a^{[l+2]} = g\left(W^{[l+2]}g\left(W^{[l+1]}a^{[l]} + b^{[l+1]}\right) + b^{[l+2]} + a^{[l]}\right) + a^{[l+1]}$
- ☒  $a^{[l+2]} = g\left(W^{[l+2]}g\left(W^{[l+1]}a^{[l]} + b^{[l+1]}\right) + b^{[l+2]} + a^{[l]}\right)$
- $a^{[l+2]} = g\left(W^{[l+2]}g\left(W^{[l+1]}a^{[l]} + b^{[l+1]}\right) + b^{[l+2]} + a^{[l]}\right)$
- ☐  $a^{[l+2]} = g\left(W^{[l+2]}g\left(W^{[l+1]}a^{[l]} + b^{[l+1]}\right) + b^{[l+2]} + a^{[l]}\right)$

[Expand](#)

☒ **Correct**

Correct. This expresses the computations of a ResNet block, where the last term  $a^{[l]}$  is the shortcut connection.

5. Adding a ResNet block to the end of a network makes it deeper. Which of the following is true?

1 / 1 point

- ☐ The performance of the networks is hurt since we make the network harder to train.
- ☐ The number of parameters will decrease due to the shortcut connections.
- ☒ The performance of the networks doesn't get hurt since the ResNet block can easily approximate the identity function.
- ☐ It shifts the behavior of the network to be more like the identity function.

[Expand](#)

☒ **Correct**

Yes, as noted in the lectures in a ResNet block the computations are given by  $a^{[l+2]} = g(W^{[l+2]}(a^{[l+1]} + b^{[l+2]} + a^{[l]}))$  thus if  $W^{[l+2]}$  and  $b^{[l+2]}$  are zero then we get the identity function.

6.  $1 \times 1$  convolutions are the same as multiplying by a single number. True/False?

1 / 1 point

- ☐ True
- ☒ False

[Expand](#)

☒ **Correct**

Yes, a  $1 \times 1$  layer doesn't act as a single number because it makes a sum over the depth of the volume.

7. Which of the following are true about the inception Network? (Check all that apply)

1 / 1 point

- ☐ Making an inception network deeper won't hurt the training set performance.
- ☒ Inception blocks allow the use of a combination of  $1 \times 1$ ,  $3 \times 3$ ,  $5 \times 5$  convolutions and pooling by stacking up all the activations resulting from each type of layer.

☒ **Correct**

Correct. The use of several different types of layers and stacking up the results to get a single volume is at the heart of the inception network.

- ☒ One problem with simply stacking up several layers is the computational cost of it.

☒ **Correct**

Correct. That is why the bottleneck layer is used to reduce the computational cost.

- ☐ Inception blocks allow the use of a combination of  $1 \times 1$ ,  $3 \times 3$ ,  $5 \times 5$  convolutions, and pooling by applying one layer after the other.

Expand



Correct

Great, you got all the right answers.

8. Which of the following are common reasons for using open-source implementations of ConvNets (both the model and/or weights)? Check all that apply.

1 / 1 point

- ☒ Parameters trained for one computer vision task are often useful as pre-training for other computer vision tasks.



Correct

True

- ☐ The same techniques for winning computer vision competitions, such as using multiple crops at test time, are widely used in practical deployments (or production system deployments) of ConvNets.
- ☐ A model trained for one computer vision task can usually be used to perform data augmentation for a different computer vision task.
- ☒ It is a convenient way to get working with an implementation of a complex ConvNet architecture.



Correct

True

Expand



Correct

Great, you got all the right answers.

9. Which of the following are true about Depth wise-separable convolutions? (Choose all that apply)

1 / 1 point

- ☐ The result has always the same number of channels  $n_c$  as the input.
- ☒ They have a lower computational cost than normal convolutions.



Correct

Yes, as seen in the lectures the use of the depthwise and pointwise convolution reduces the computational cost significantly.

- ☐ They are just a combination of a normal convolution and a bottleneck layer.
- ☒ They combine depthwise convolutions with pointwise convolutions.



Correct

Correct, this combination is what we call depth wise separable convolutions.

Expand



Correct

Great, you got all the right answers.

10. Suppose that in a MobileNet v2 Bottleneck block the input volume has shape  $64 \times 64 \times 16$ . If we use 32 filters for the expansion and 16 filters for the projection. What is the size of the input and output volume of the depthwise convolution, assuming a pad='same'?

1 / 1 point

- ☐  $64 \times 64 \times 32$   $64 \times 64 \times 16$
- ☐  $32 \times 32 \times 32$   $32 \times 32 \times 32$
- ☐  $64 \times 64 \times 16$   $64 \times 64 \times 32$
- ☐  $32 \times 32 \times 32$   $64 \times 64 \times 32$

Typesetting math: 100%