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1. When building a ConvNet, typically you start with some POOL layers followed by some CONV layers. True/False?

1 / 1 point

- ☒ False
- ☐ True

[↗ Expand](#)

✓ **Correct**

Correct. It is typical for ConvNets to use a POOL layer after some Conv layers; sometimes even one POOL layer after each CONV layer; but is not common to start with POOL layers.

2. In LeNet - 5 we can see that as we get into deeper networks the number of channels increases while the height and width of the volume decreases. True/False?

1 / 1 point

- ☒ True
- ☐ False

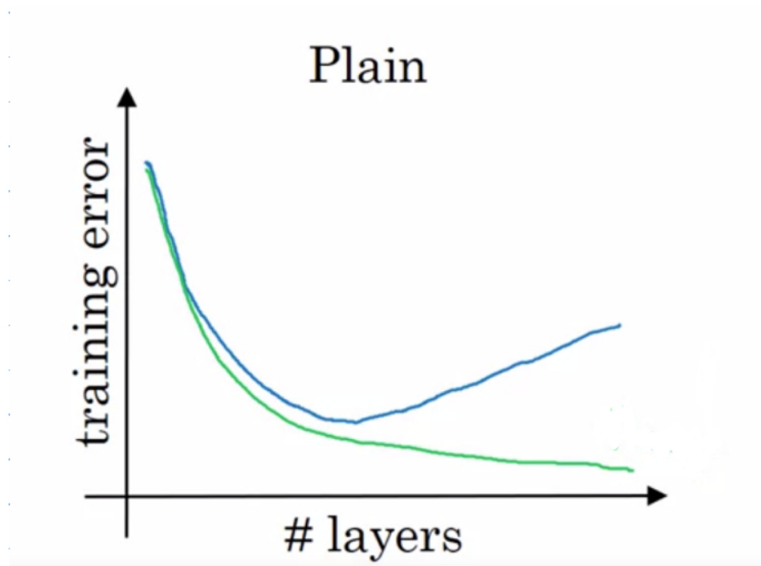
[↗ Expand](#)

✓ **Correct**

Correct, since in its implementation only valid convolutions were used, without padding, the height and width of the volume were reduced at each convolution. These were also reduced by the POOL layers, whereas the number of channels was increased from 6 to 16.

3. Based on the lectures, in the following picture, which curve corresponds to the expected behavior in theory, and which one corresponds to the behavior we get in practice? This when using plain neural networks.

1 / 1 point



- ☐ The green one depicts the results in theory, and also in practice.

- ☐ The blue one depicts the theory, and the green one the reality.
- ☒ The green one depicts the results in theory, and the blue one the reality.
- ☐ The blue one depicts the results in theory, and also in practice.

↗ Expand

✓ **Correct**

Yes, in theory, we expect that as we increase the number of layers the training error decreases; but in practice after a certain number of layers the error increases.

4. The computation of a ResNet block is expressed in the equation:

0 / 1 point

$$a^{[l+2]} = g \left(\underbrace{W^{[l+2]}}_C g \left(\underbrace{W^{[l+1]} a^{[l]} + \underbrace{b^{[l+1]}}_A \right) + b^{[l+2]} + \underbrace{a^{[l]}}_B \right)$$

Which part corresponds to the skip connection?

- ☐ The equation of ResNet.
- ☒ The term in the red box, marked as C .
- ☐ The term in the orange box, marked as B .
- ☐ The term in the blue box, marked as A .

↗ Expand

✗ **Incorrect**

No, this corresponds to the weights of the $l + 2$ layer.

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

0 / 1 point

- ☐ The performance of the networks doesn't get hurt since the ResNet block can easily approximate the identity function.
- ☐ 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.
- ☒ It shifts the behavior of the network to be more like the identity function.

↗ Expand

✗ **Incorrect**

No, the ResNet block can easily approximate the identity function, but doesn't shift the whole net to become the identity function.

6. Suppose you have an input volume of dimension $n_H \times n_W \times n_C$. Which of the following statements do you agree with? (Assume that the "1x1 convolutional layer" below always uses a stride of 1 and no padding.)

1 / 1 point

- ☒ You can use a 2D pooling layer to reduce n_H , n_W , but not n_C .

✓ **Correct**

This is correct.

- ☒ You can use a 1x1 convolutional layer to reduce n_C but not n_H and n_W .

✓ **Correct**

Yes, a 1x1 convolutional layer with a small number of filters is going to reduce n_C but will keep the dimensions n_H and n_W .

- ☐ You can use a 2D pooling layer to reduce n_H , n_W , and n_C .
- ☐ You can use a 1x1 convolutional layer to reduce n_H , n_W , and n_C .

[Expand](#)

✓ **Correct**

Great, you got all the right answers.

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

1 / 1 point

- ☐ The bottleneck layer has a more powerful regularization effect than Dropout layers.
- ☒ The use of bottlenecks doesn't seem to hurt the performance of the network.

✓ **Correct**

Yes, although it reduces the computational cost significantly.

- ☒ By adding these layers we can reduce the computational cost in the inception modules.

✓ **Correct**

Yes, by using the 1×1 convolutional layers we can reduce the depth of the volume and help reduce the computational cost of applying other convolutional layers with different filter sizes.

- ☐ Bottleneck layers help to compress the 1x1, 3x3, 5x5 convolutional layers in the inception network.

[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

- ☒ It is a convenient way to get working with an implementation of a complex ConvNet architecture.

✓ **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.

[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 produce distributed representations with distributed representations

☒ They combine depthwise convolutions with pointwise convolutions.

✓ **Correct**

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

☐ They are just a combination of a normal convolution and a bottleneck layer.

↗ **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

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

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

☐ $32 \times 32 \times 32$ $32 \times 32 \times 32$

☒ $64 \times 64 \times 32$ $64 \times 64 \times 32$

↗ **Expand**

✓ **Correct**

Correct, the size of the input and output volume of the depthwise convolution is determined by the number of filters in the expansion.