Very, very deep neural networks are difficult to train because of vanishing and exploding gradient types of problems.

2 - The Problem of Very Deep Neural Networks

Last week, you built your first convolutional neural networks: first manually with numpy, then using Tensorflow and Keras.

In recent years, neural networks have become much deeper, with state-of-the-art networks evolving from having just a few layers (e.g., AlexNet) to over a hundred layers.

- The main benefit of a very deep network is that it can represent very complex functions. It can also learn features at many different levels of abstraction, from edges (at the shallower layers, closer to the input) to very complex features (at the deeper layers, closer to the output).
- However, using a deeper network doesn't always help. A huge barrier to training them is vanishing gradients: very deep networks often have a gradient signal that goes to zero quickly, thus making gradient descent prohibitively slow.
- More specifically, during gradient descent, as you backpropagate from the final layer back to the first layer, you are multiplying by the weight matrix on each step, and thus the gradient can decrease exponentially quickly to zero (or, in rare cases, grow exponentially quickly and "explode," from gaining very large values).
- During training, you might therefore see the magnitude (or norm) of the gradient for the shallower layers decrease to zero very rapidly as training proceeds, as shown below:

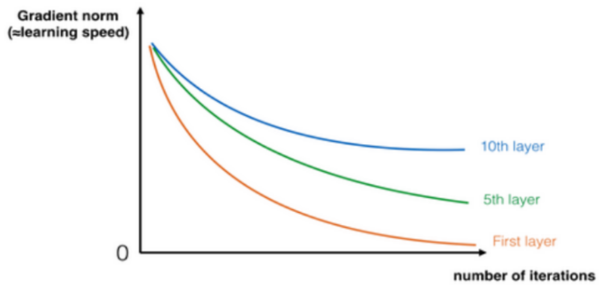
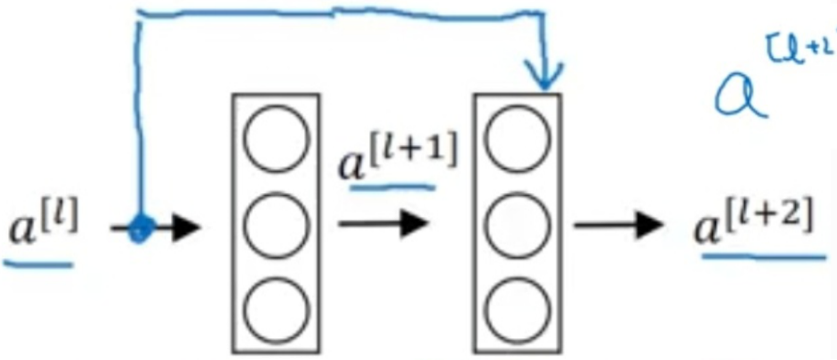


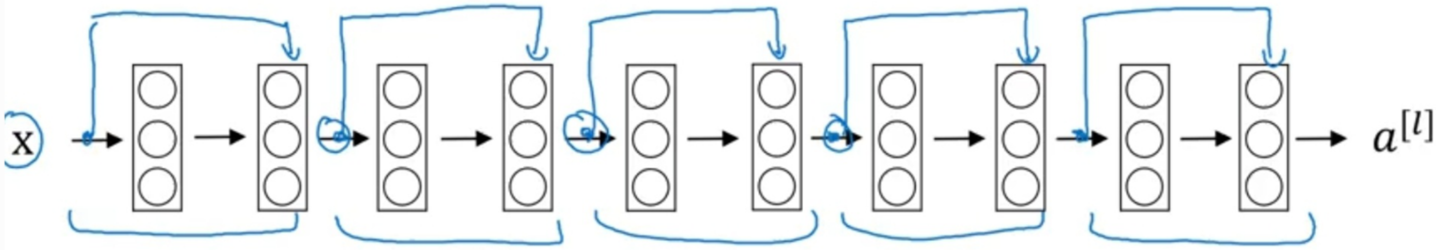
Figure 1 : **Vanishing gradient**
The speed of learning decreases very rapidly for the shallower layers as the network trains

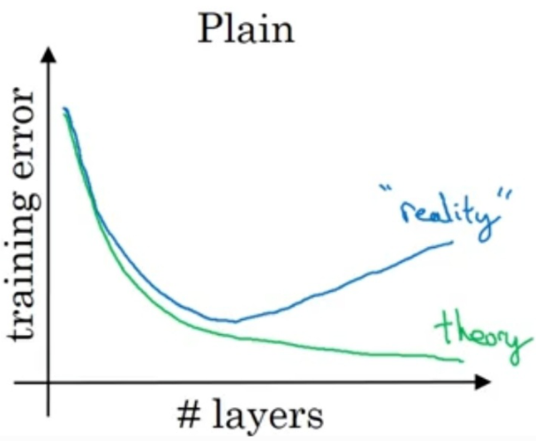
Not to worry! You are now going to solve this problem by building a Residual Network!

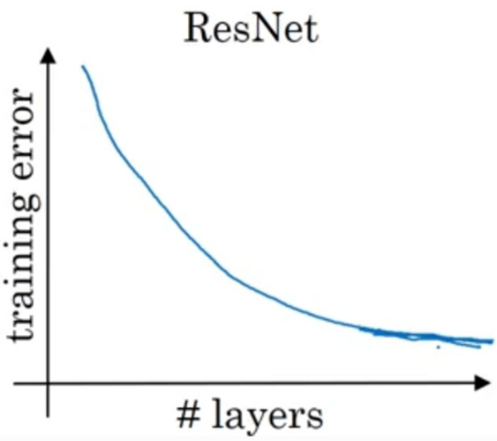
Residual block:



$$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$$







3 - Building a Residual Network

In ResNets, a "shortcut" or a "skip connection" allows the model to skip layers:

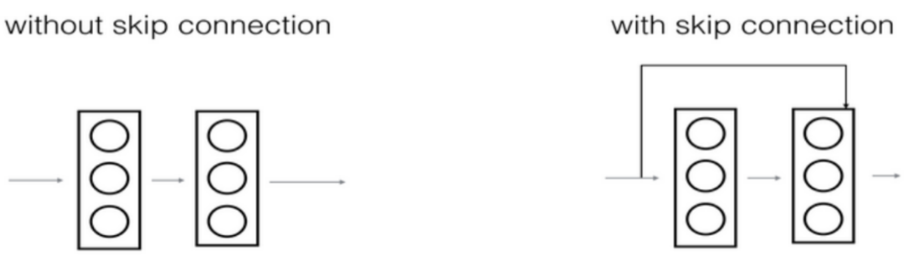


Figure 2 : A ResNet block showing a skip-connection

The image on the left shows the "main path" through the network. The image on the right adds a shortcut to the main path. By stacking these ResNet blocks on top of each other, you can form a very deep network.

The lecture mentioned that having ResNet blocks with the shortcut also makes it very easy for one of the blocks to learn an identity function. This means that you can stack on additional ResNet blocks with little risk of harming training set performance.

On that note, there is also some evidence that the ease of learning an identity function accounts for ResNets' remarkable performance even more than skip connections help with vanishing gradients.

Two main types of blocks are used in a ResNet, depending mainly on whether the input/output dimensions are the same or different. You are going to implement both of them: the "identity block" and the "convolutional block."

3.1 - The Identity Block

The identity block is the standard block used in ResNets, and corresponds to the case where the input activation (say $a^{[l]}$) has the same dimension as the output activation (say $a^{[l+2]}$). To flesh out the different steps of what happens in a ResNet's identity block, here is an alternative diagram showing the individual steps: