Residual Network

Computer Vision Group

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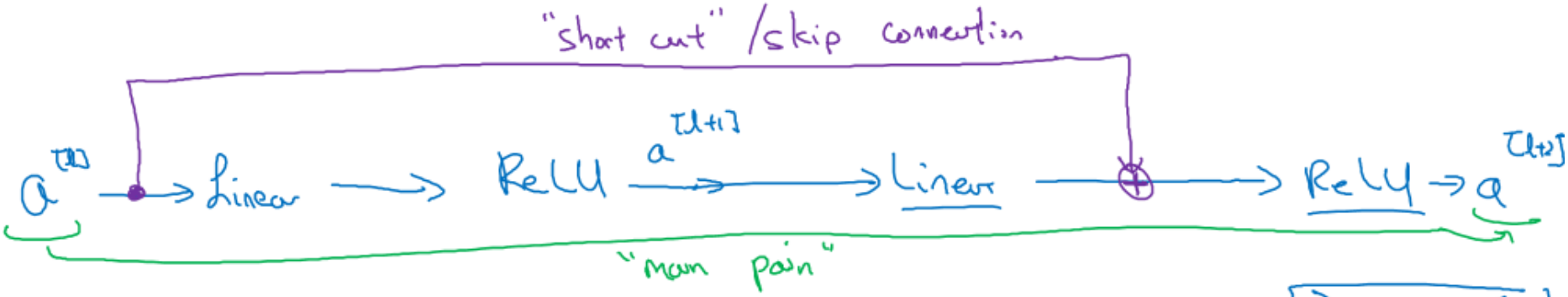
Residual Block

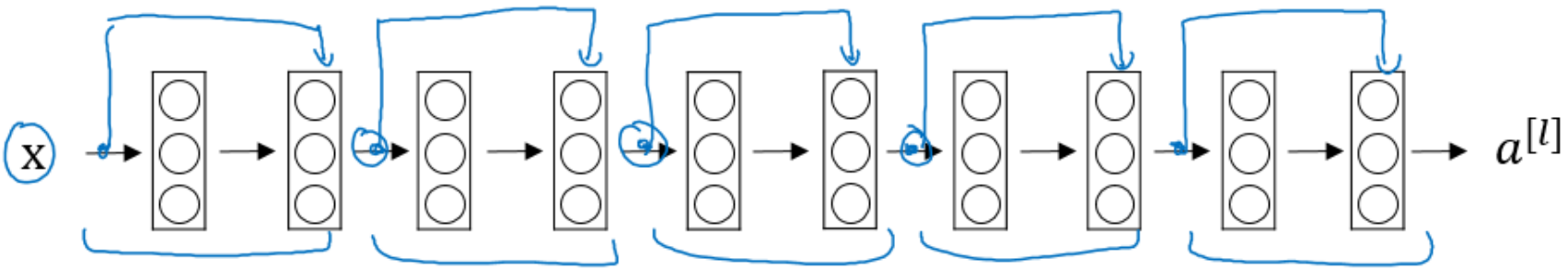
- Very, very deep NNs are difficult to train because of vanishing and exploding gradients problems.
- Residual network also be know as skip connection.
- skip connection makes you take the activation from one layer and suddenly feed it to another layer even much deeper in NN which allows you to train large NNs even with layers greater than 100.

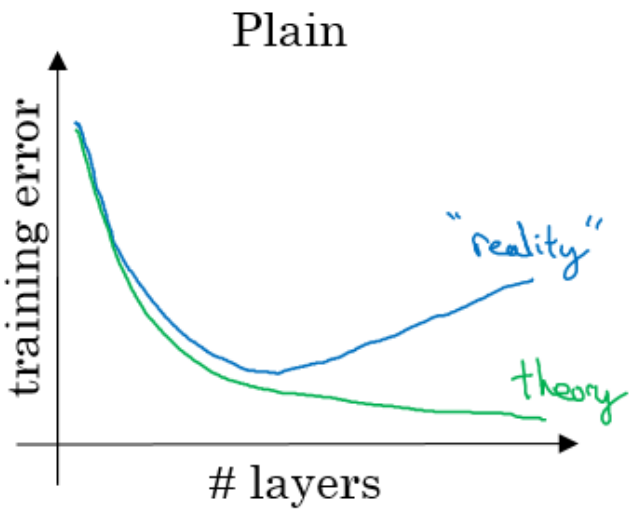


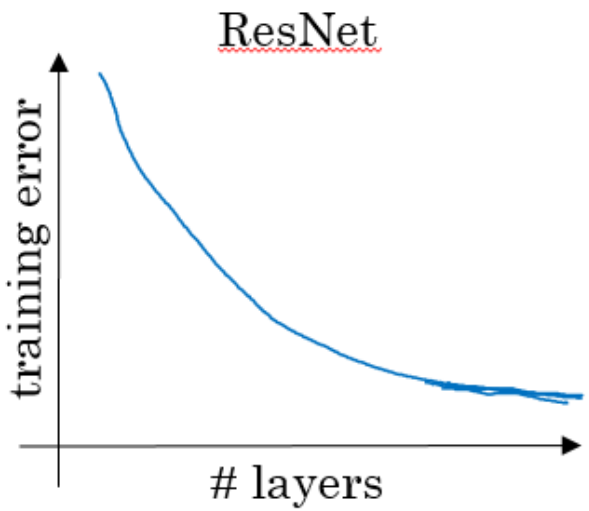
$$z^{[l+1]} = W^{[l+1]}\, a^{[l]} + b^{[l+1]} \qquad a^{[l+1]} = g(z^{[l+1]}) \qquad z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]} \qquad a^{[l+2]} = g(z^{[l+2]})$$

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

Residual Network




Plain
training error
"reality"
theory
layers


ResNet
training error
layers

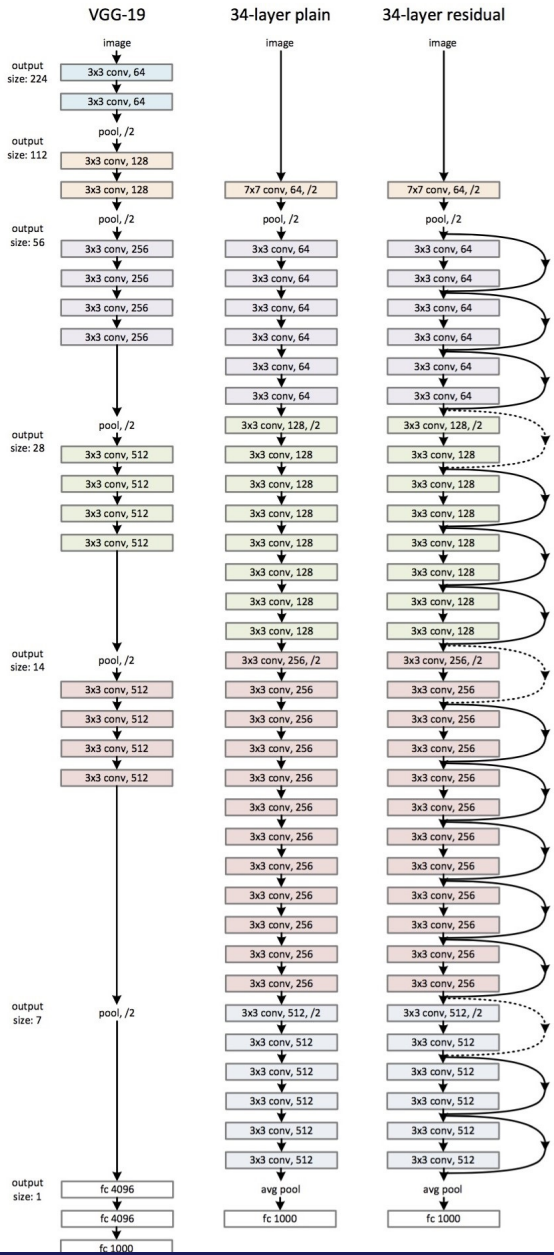
$$
\begin{aligned}
a[l+2] &= g(z[l+2] + a[l]) && (1)\\
&= g(W[l+2]a[l+1] + b[l+2] + a[l]) && (2)
\end{aligned}
$$

We we apply L2 regularization we obtain :

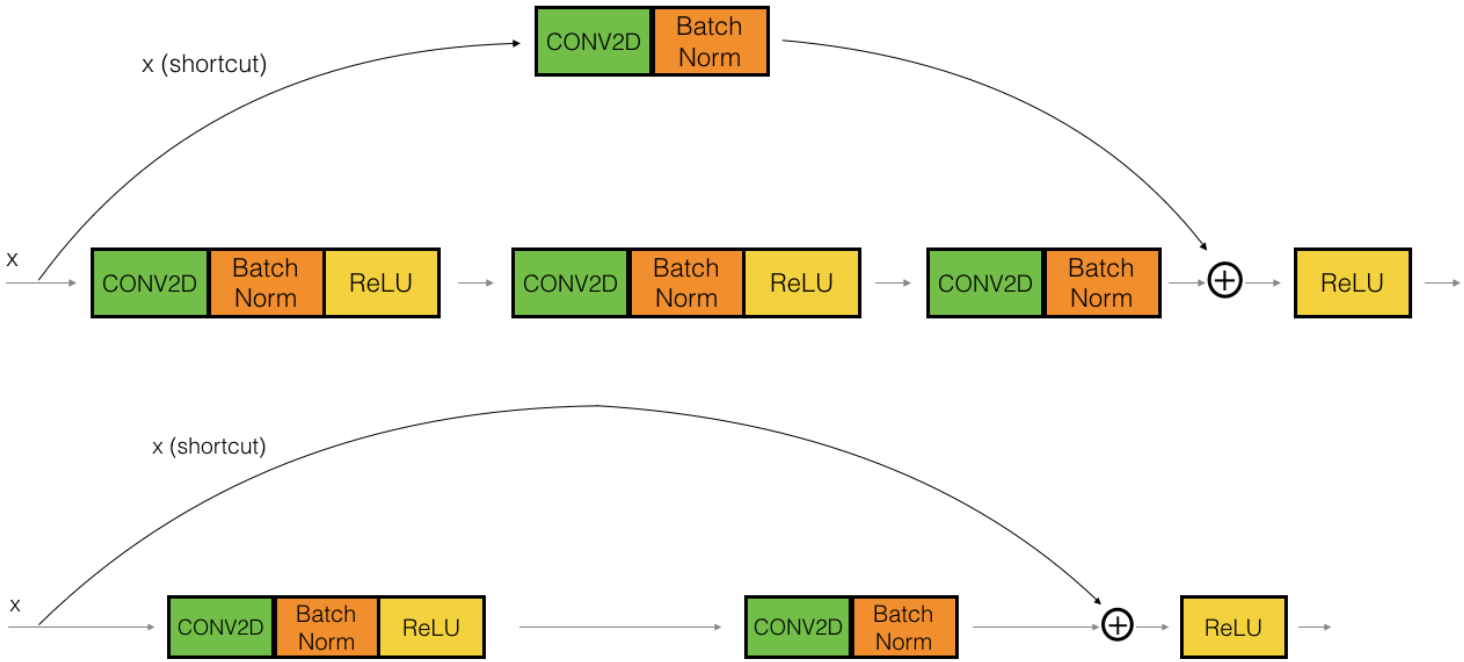
$$a[l+2] = g(a[l]) = a[l] \quad (3)$$

• This show that identity function is easy for a residual block to learn. And that why it can train deeper NNs.
• ResNets or Skip connections can be used to solved the vanishing and exploding gradient problem.

ResNet-34


VGG-19
34-layer plain
34-layer residual
image
output size: 224
3x3 conv, 64
3x3 conv, 64
pool, /2
output size: 112
3x3 conv, 128
3x3 conv, 128
pool, /2
output size: 56
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
pool, /2
output size: 28
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
pool, /2
output size: 14
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
pool, /2
output size: 7
fc 4096
fc 4096
output size: 1
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 256, /2
3x3 conv, 256
3x3 conv, 512, /2
3x3 conv, 512
avg pool
fc 1000

Implementation of Residual Network



https://www.cs.toronto.edu/~kriz/cifar.html