



ResNet-34

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- Proposed in 2015

Deep Residual Learning for Image Recognition

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Abstract

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we

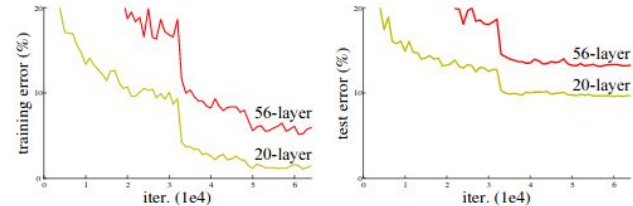


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer “plain” networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

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- It has 34 layers with learnable parameters



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 - 16 residual blocks

Analytics
Vidhya

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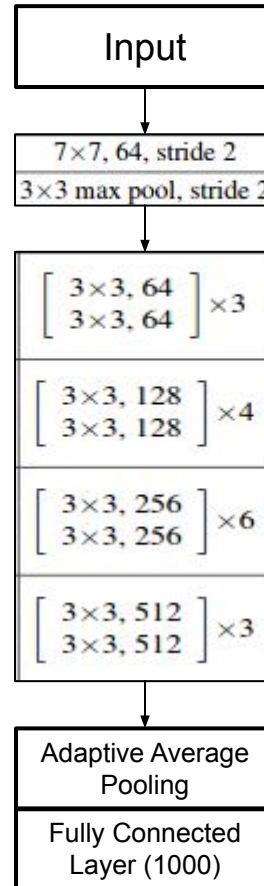
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 - Activation function: ReLU
- Trained on imagenet dataset

Architecture: ResNet-34



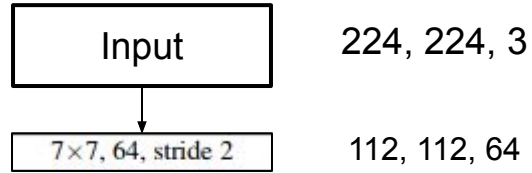
Architecture: ResNet-34

Input

224, 224, 3

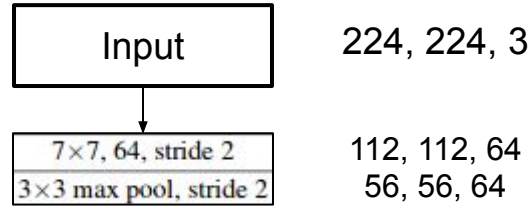


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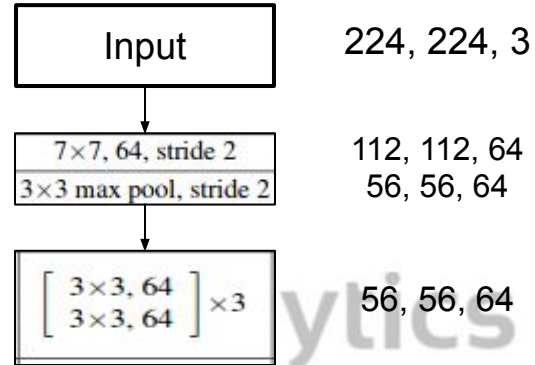
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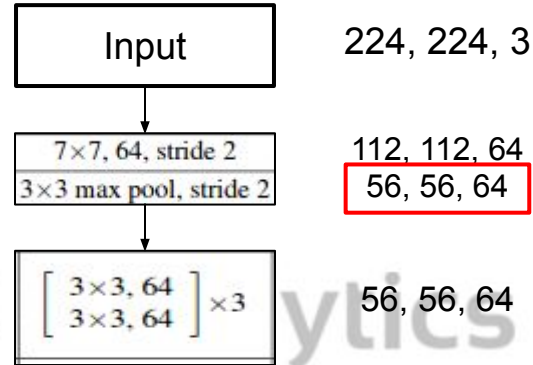
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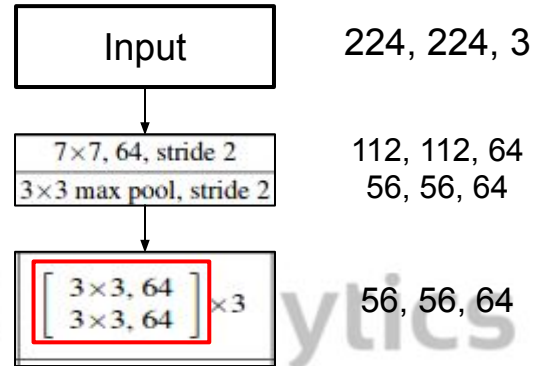
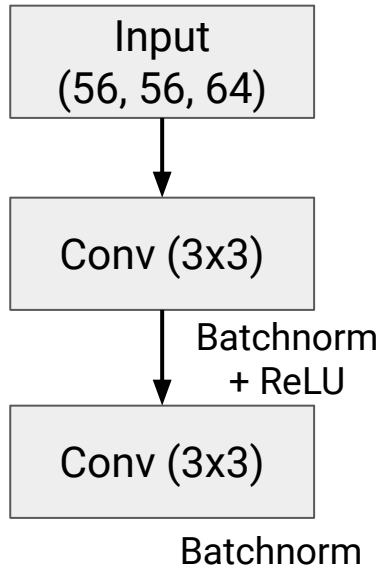


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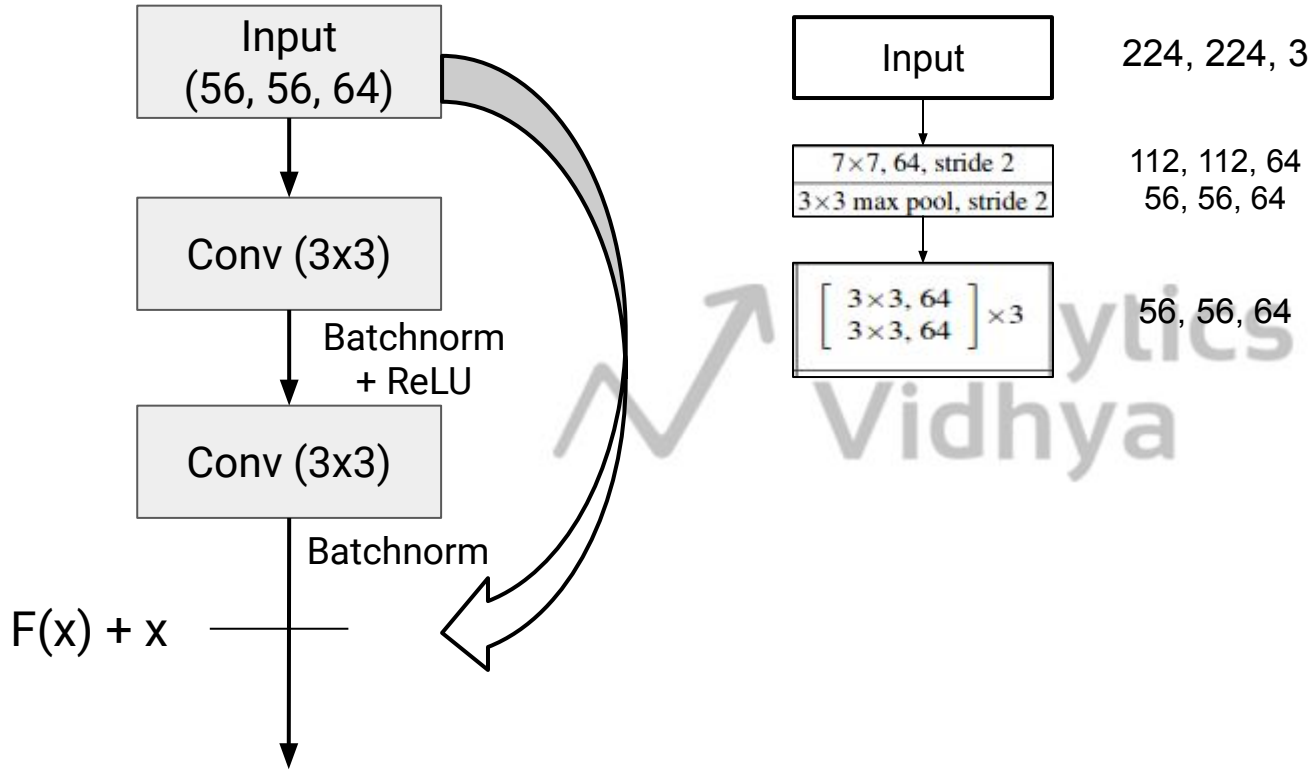
Input
(56, 56, 64)



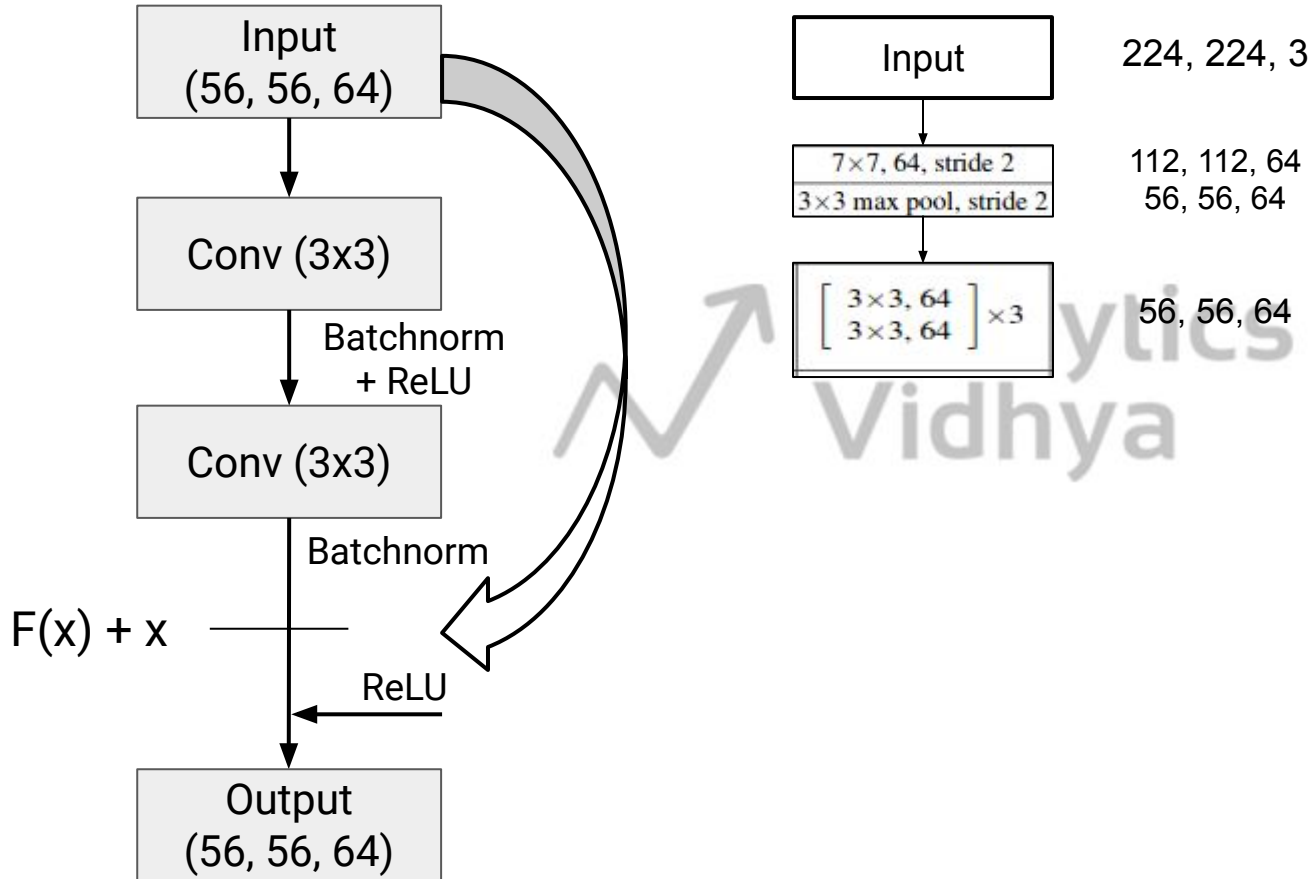
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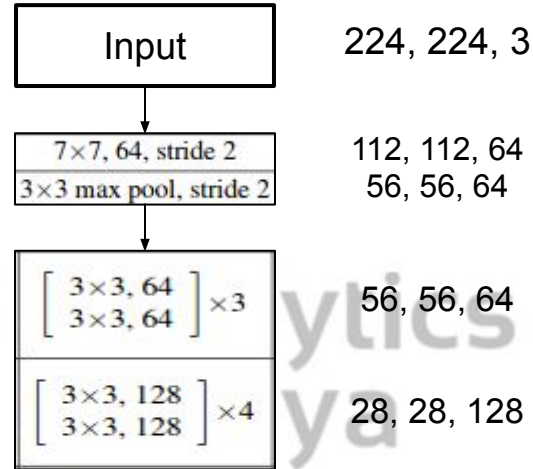
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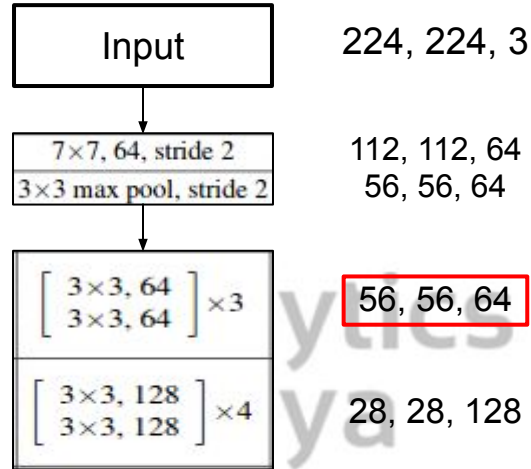


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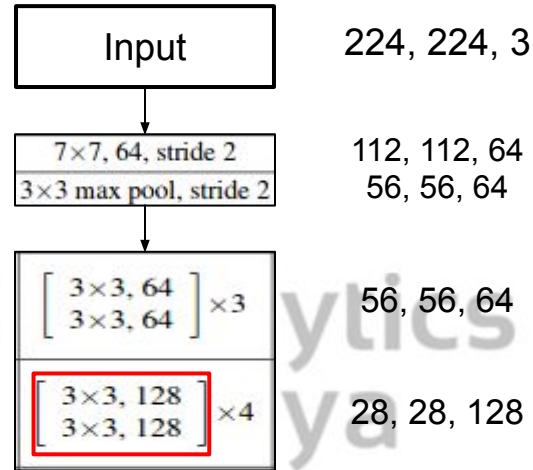
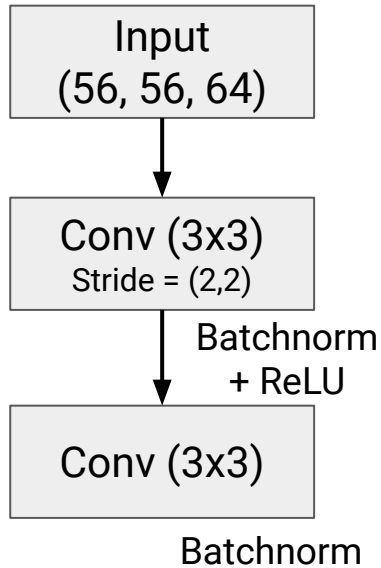


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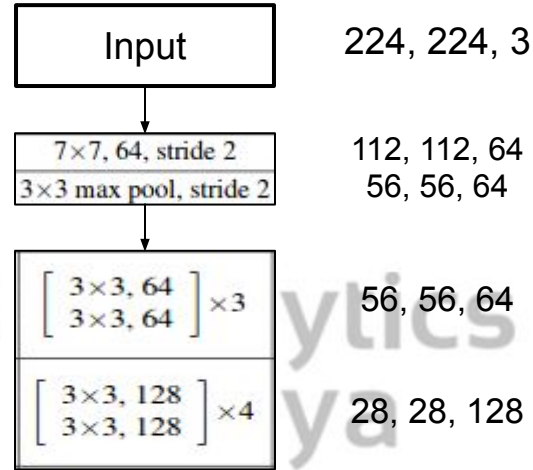
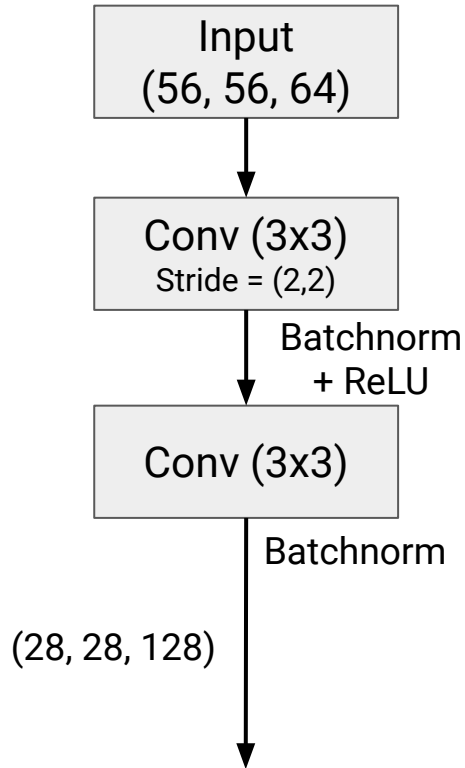
Input
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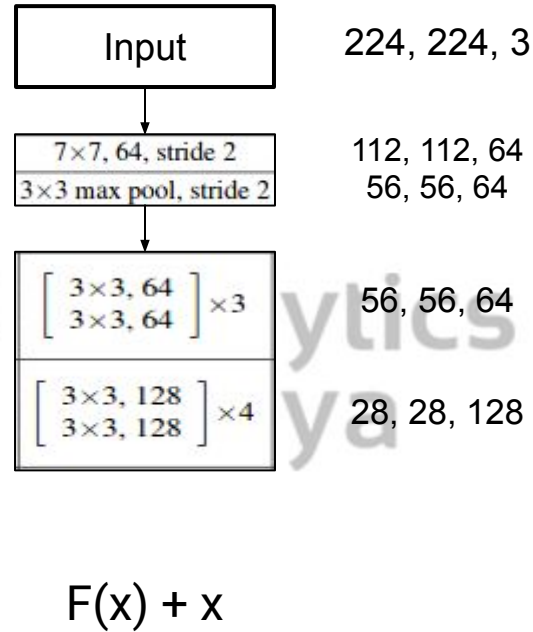
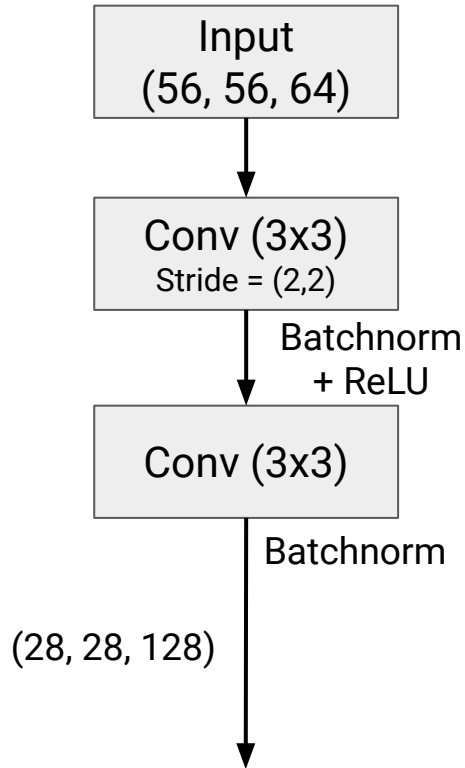
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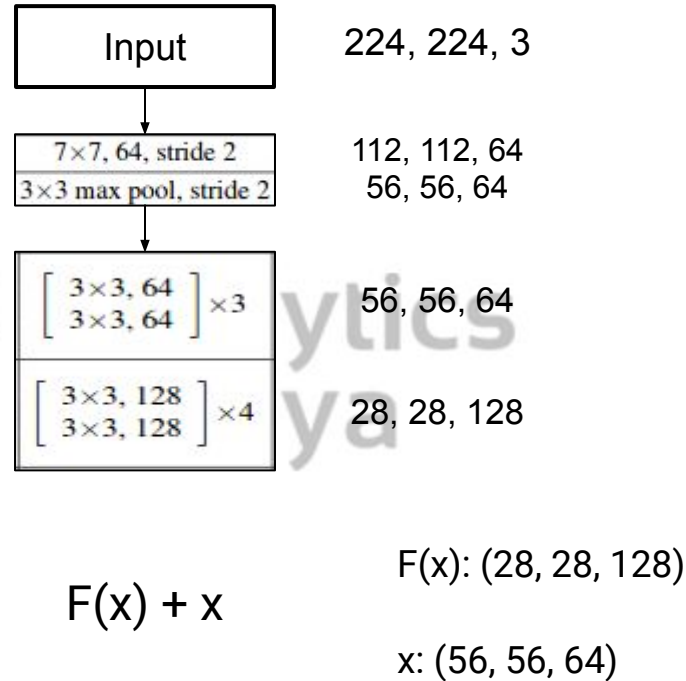
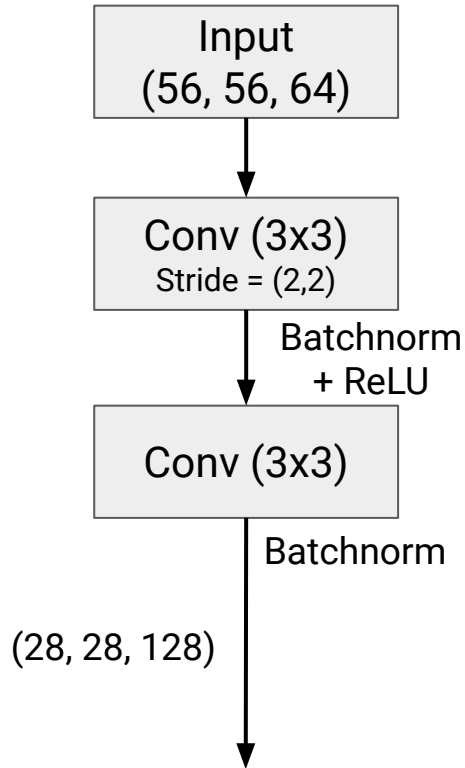
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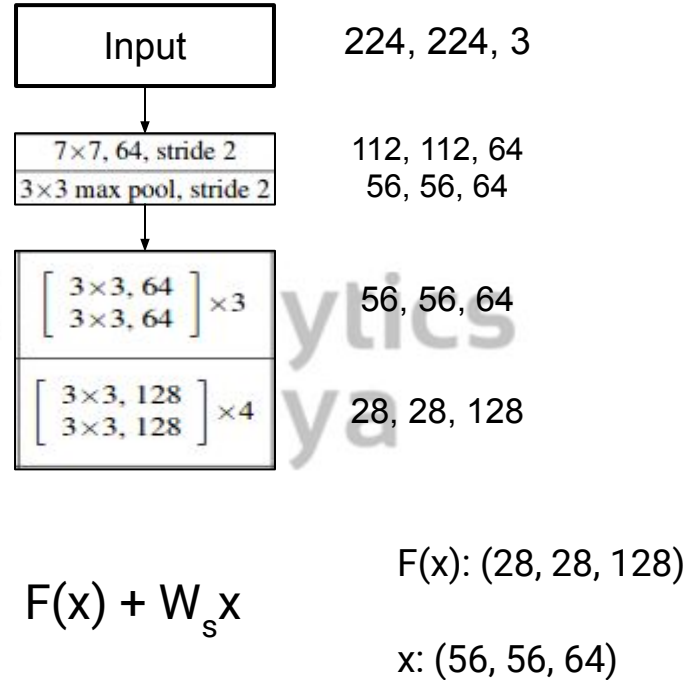
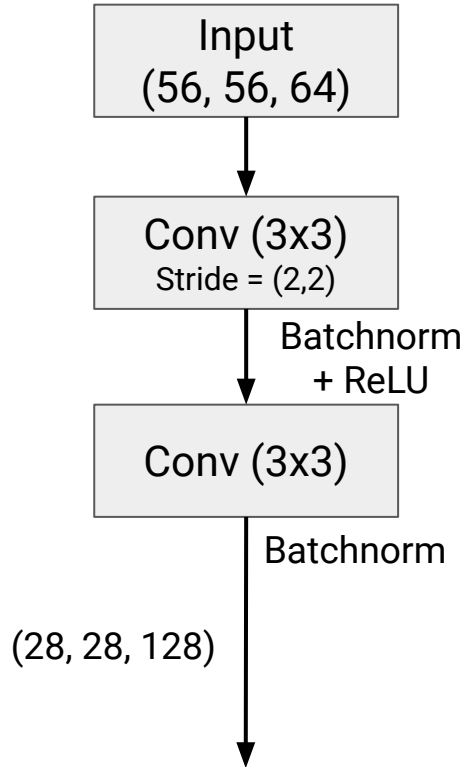
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$$F(x) + W_s x$$



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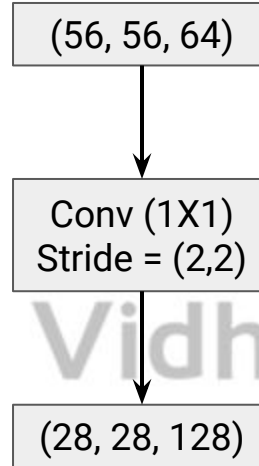
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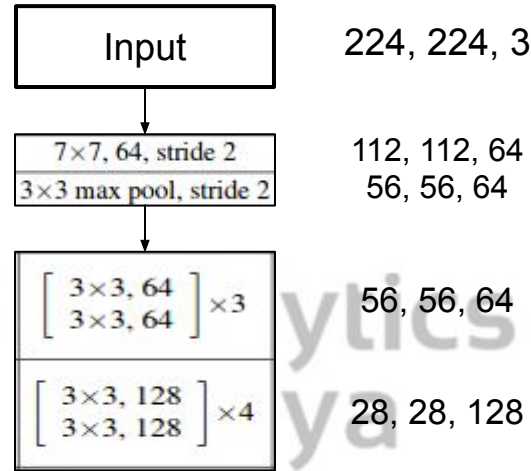
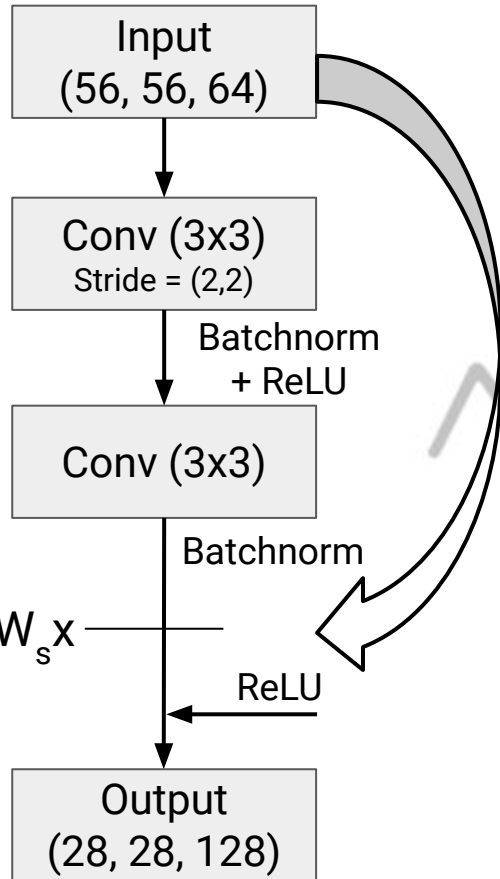
Conv (1X1)
Stride = (2,2)

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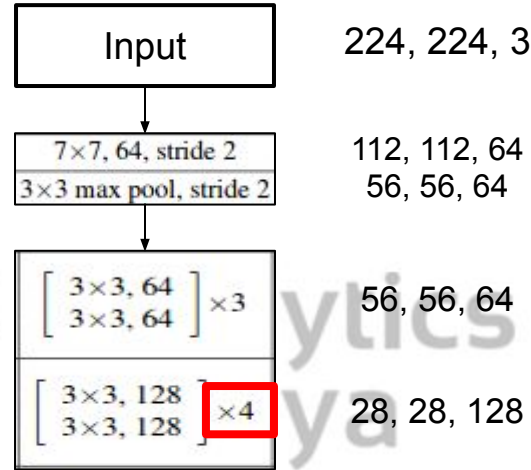
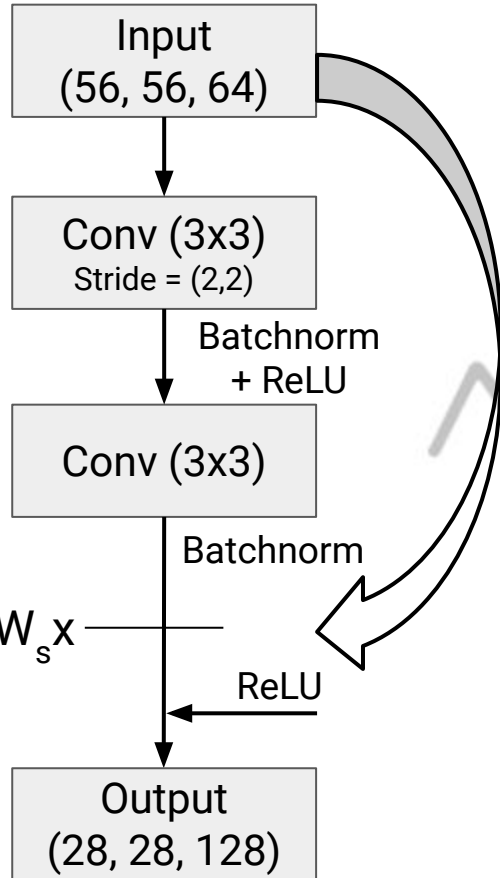
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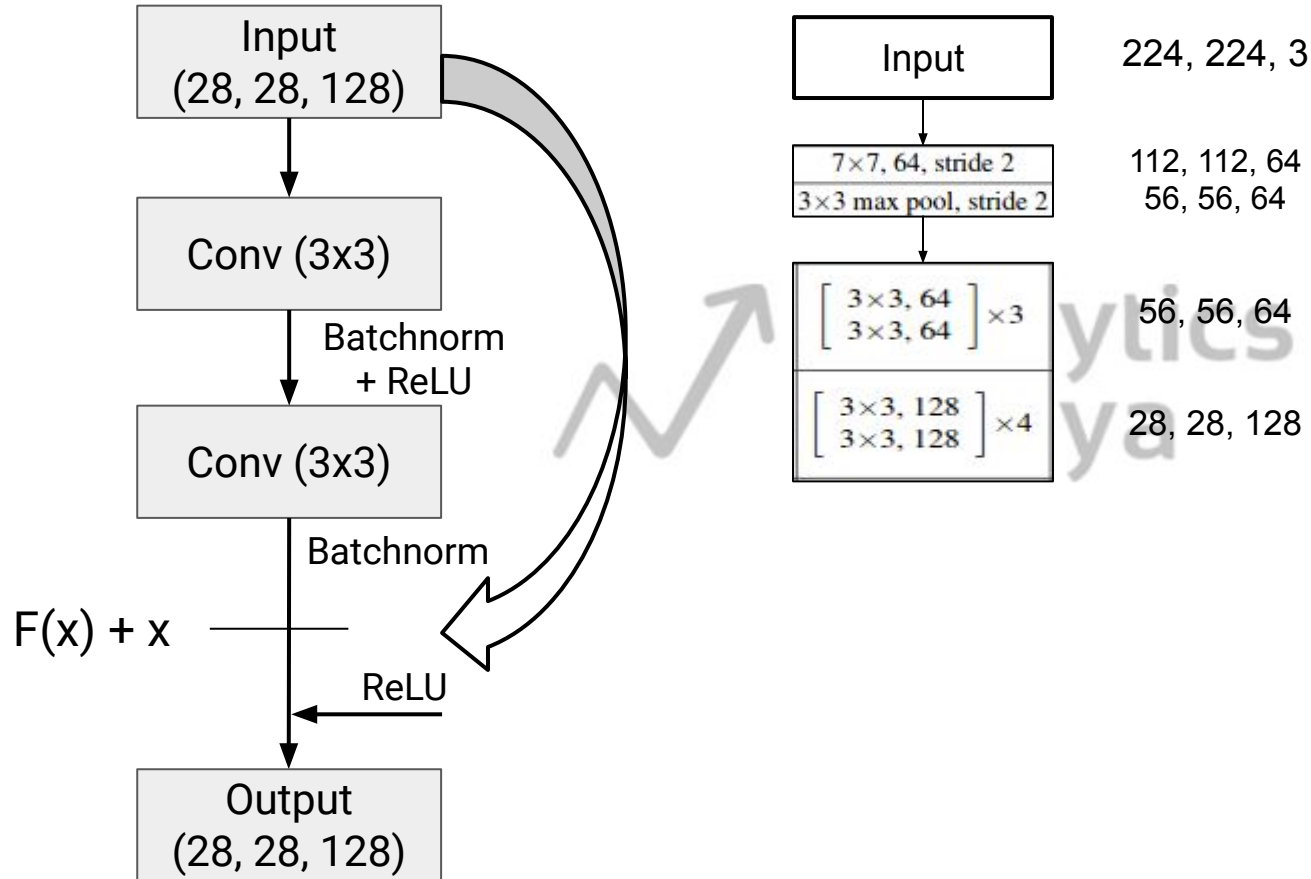
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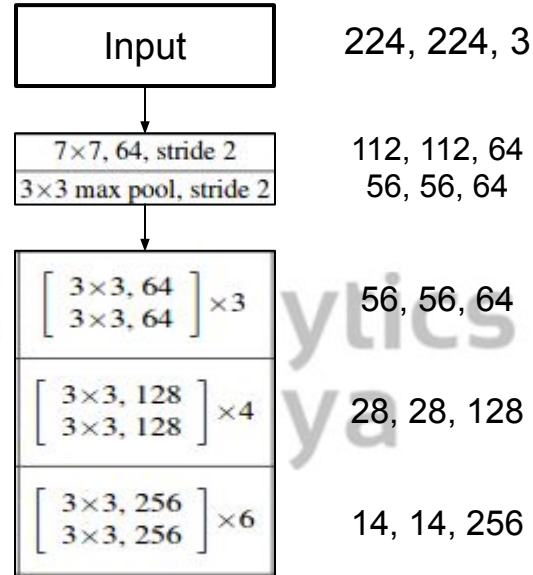
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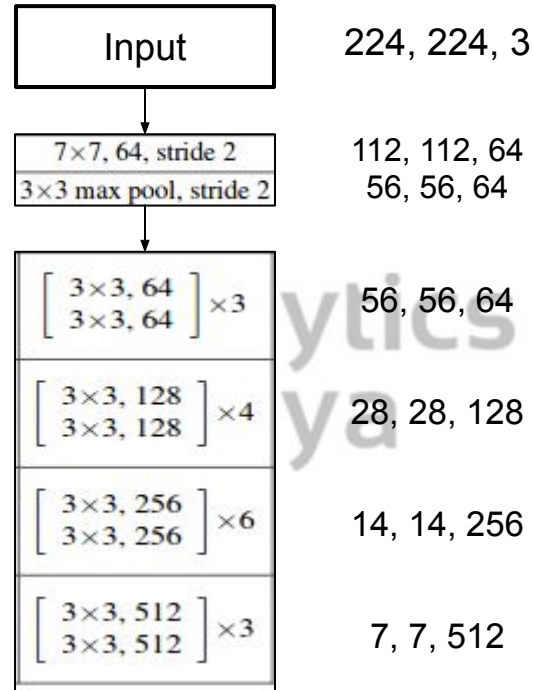
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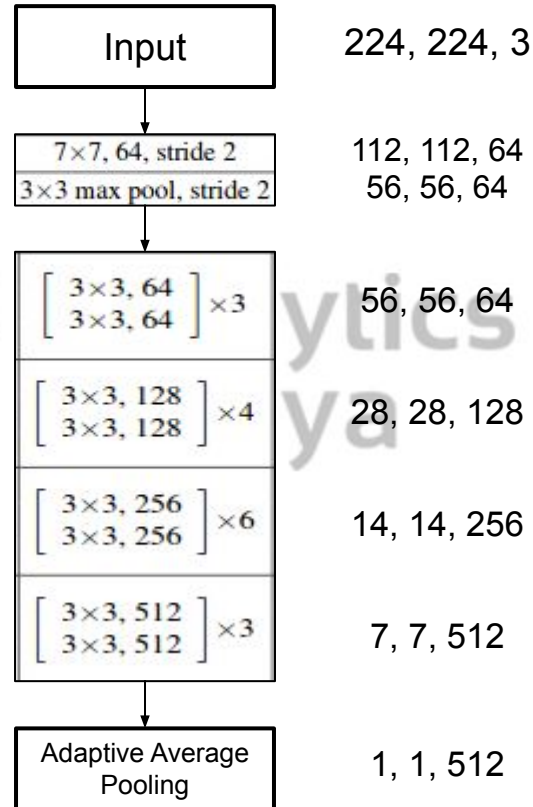
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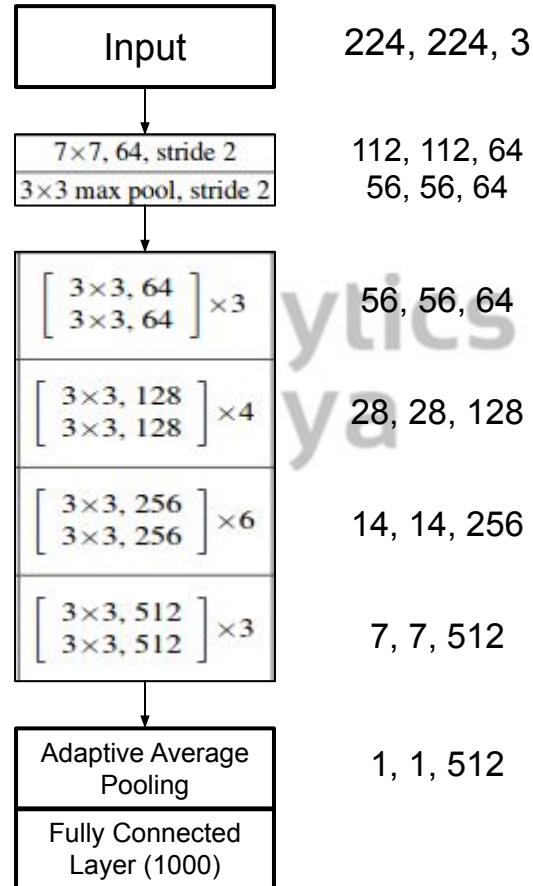
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Thank You