EE 628
Deep Learning
Fall 2019

Lecture 7

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STEVENS
INSTITUTE of TECHNOLOGY
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Overview

- Last lecture we covered
  - More on Optimization Algorithms
  - Convolutional layers
- Today, we will cover
  - More on convolutional layers
  - Convolutional neural networks

Multiple Input Channels

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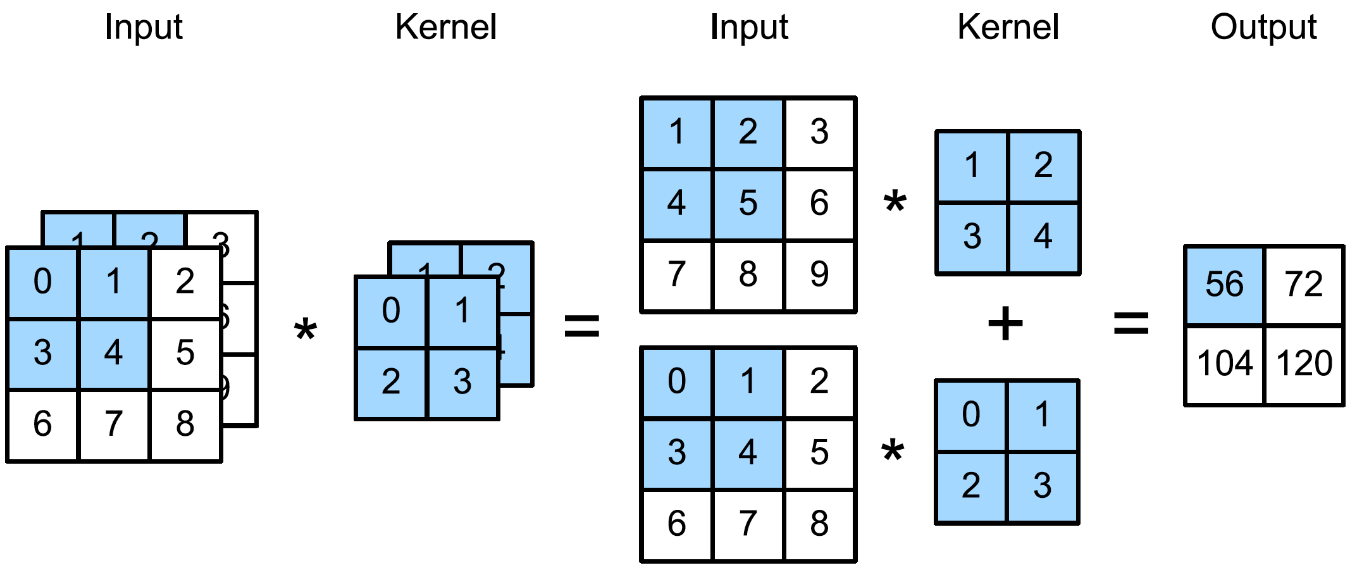
- When the input data contains multiple channels, we need to construct a convolution kernel with the same number of input channels as the input data



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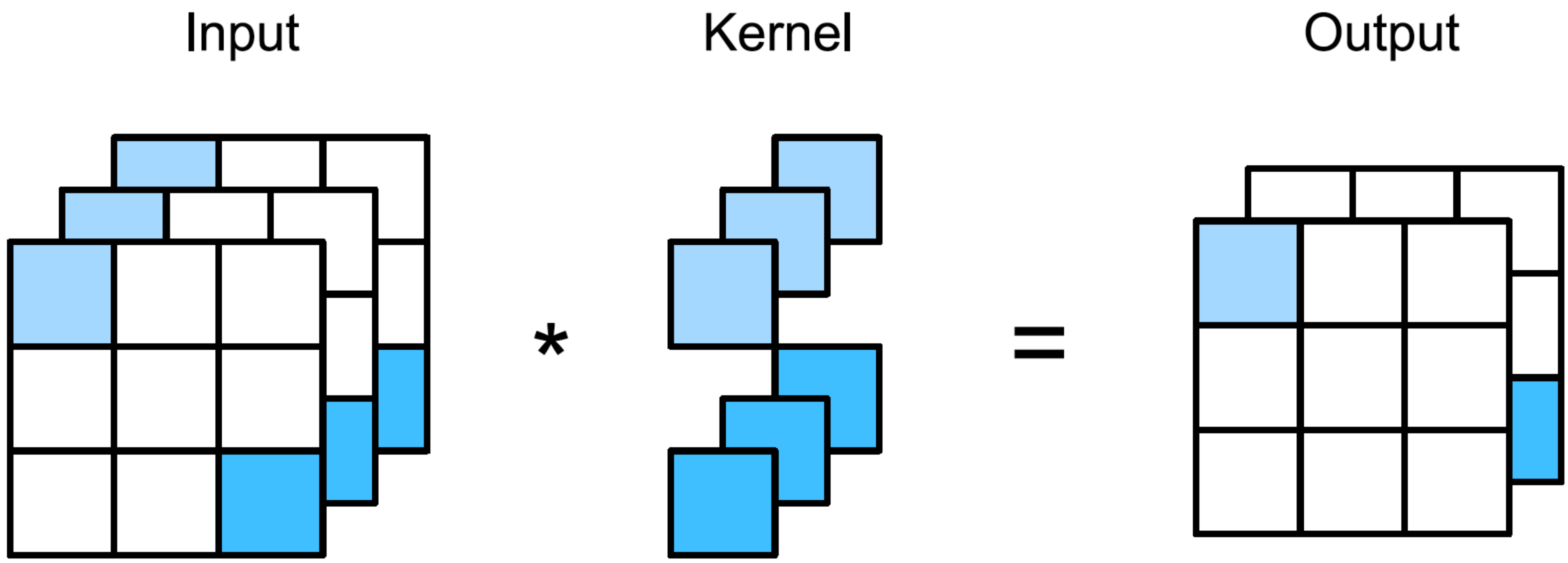
- We concatenate them on the output channel dimension, so that the shape of the convolution kernel is $c_o \times c_i \times k_h \times k_w$.

Multiple Input and Output Channels

- The figure below shows the cross-correlation computation using the 1 1 convolution kernel with 3 input channels and 2 output channels



Pooling

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- Pooling layers serve the dual purposes
  - of mitigating the sensitivity of convolutional layers to location and
  - of spatially downsampling representations

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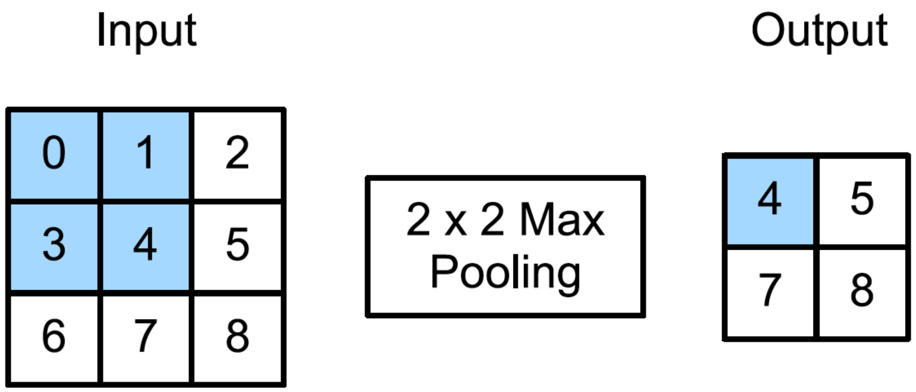
- However, the pooling layer contains no parameters.
- Instead, pooling operators are deterministic, typically calculating either the maximum or the average value of the elements in the pooling window. These operations are called *maximum pooling* (max pooling for short) and *average pooling*, respectively.



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  - This means that the number of output channels for the pooling layer is the same as the number of input channels.

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- The first published convolutional neural networks whose benefit was

first demonstrated by Yann Lecun is LeNet5

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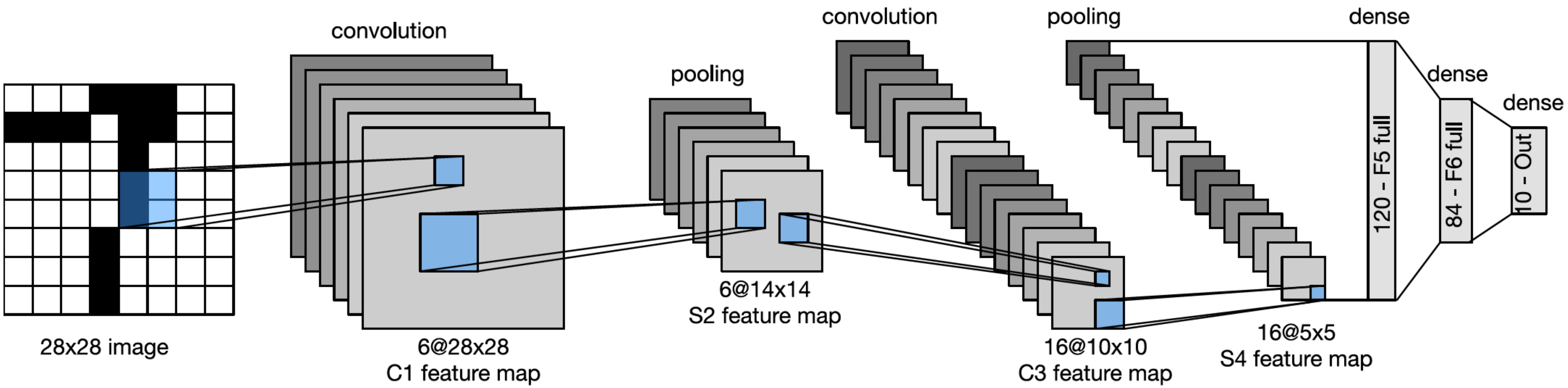

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- Start IN_CLASS_convolutional_neural_networks.ipynb

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  - Densely connected networks (**DenseNet**): expensive to compute but have set some recent benchmarks.

Deep Convolutional Neural Networks (AlexNet)

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    1. Obtain an interesting dataset
    2. Preprocess the dataset with hand-crafted features based on some knowledge of optics, geometry, other analytic tools
    3. Feed the data through a standard set of feature extractions
    4. Dump the resulting representations into your favorite classifier, likely a linear model or kernel method, to learn a classifier
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- Ultimately, the final hidden state learns a compact representation of the image that summarizes its contents such that the data belonging to different categories can be separated easily.

Image filters learned by the first layer of AlexNet

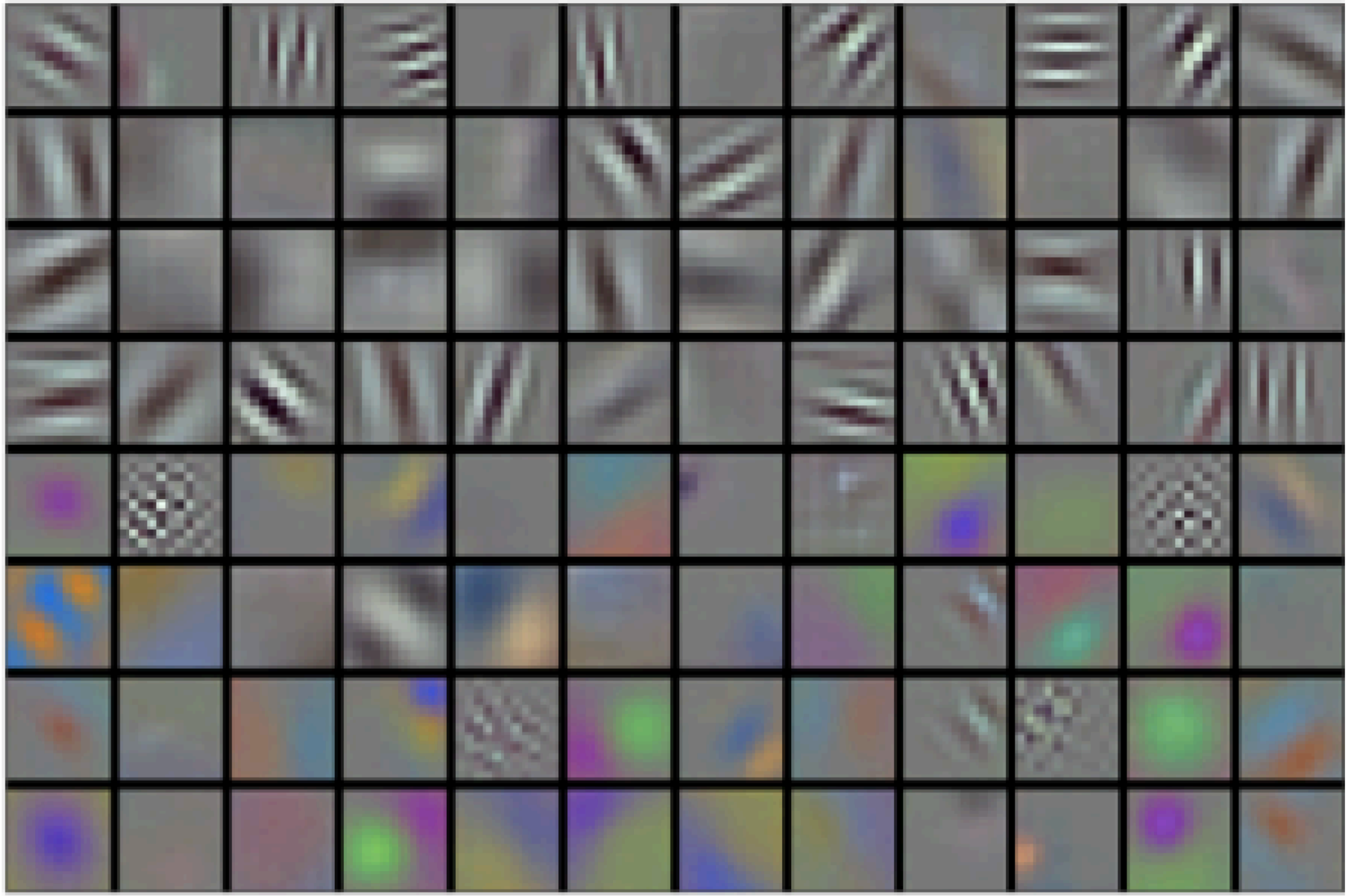

Fig. 9.1.1: Image filters learned by the first layer of AlexNet

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- Missing Ingredients – Hardware:
  - DL models demand expensive computations
  - GPUs proved to be a game changer

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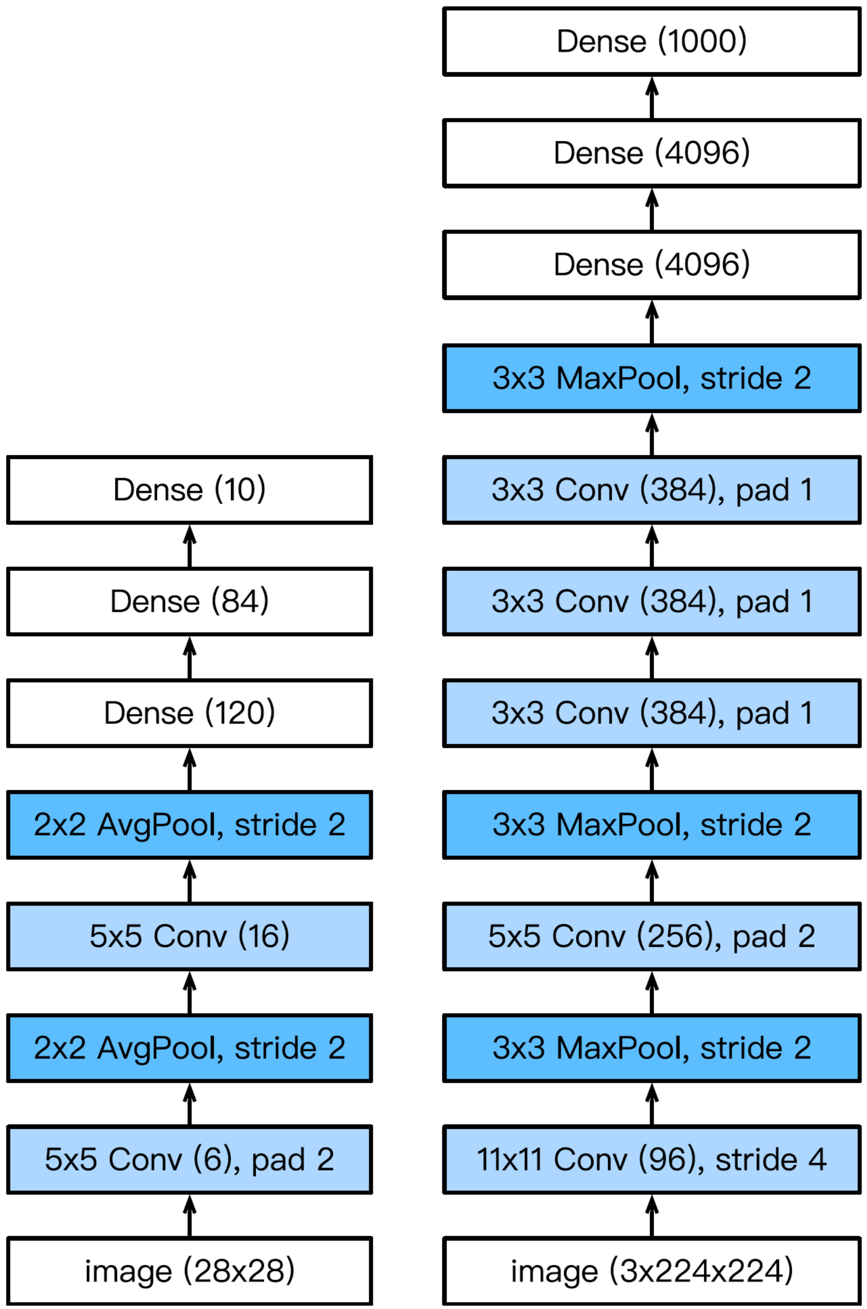
  - AlexNet used the ReLU instead of the sigmoid as its activation function.

AlexNet - Architecture

- Compared to LeNet, AlexNet
  - has larger convolution window,
  - has three more convolution layers,
  - adds max pooling layers and
  - has ten times more convolution channels.



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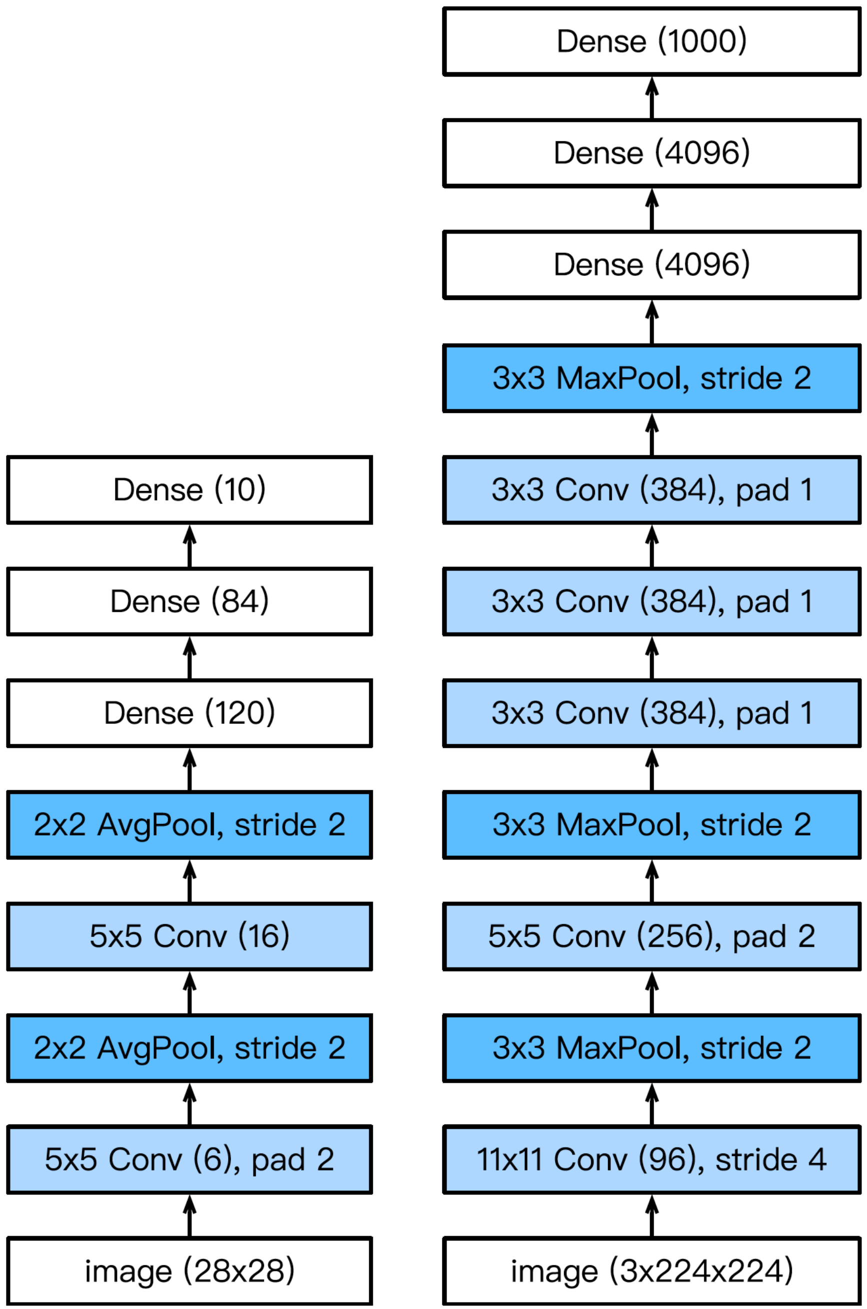

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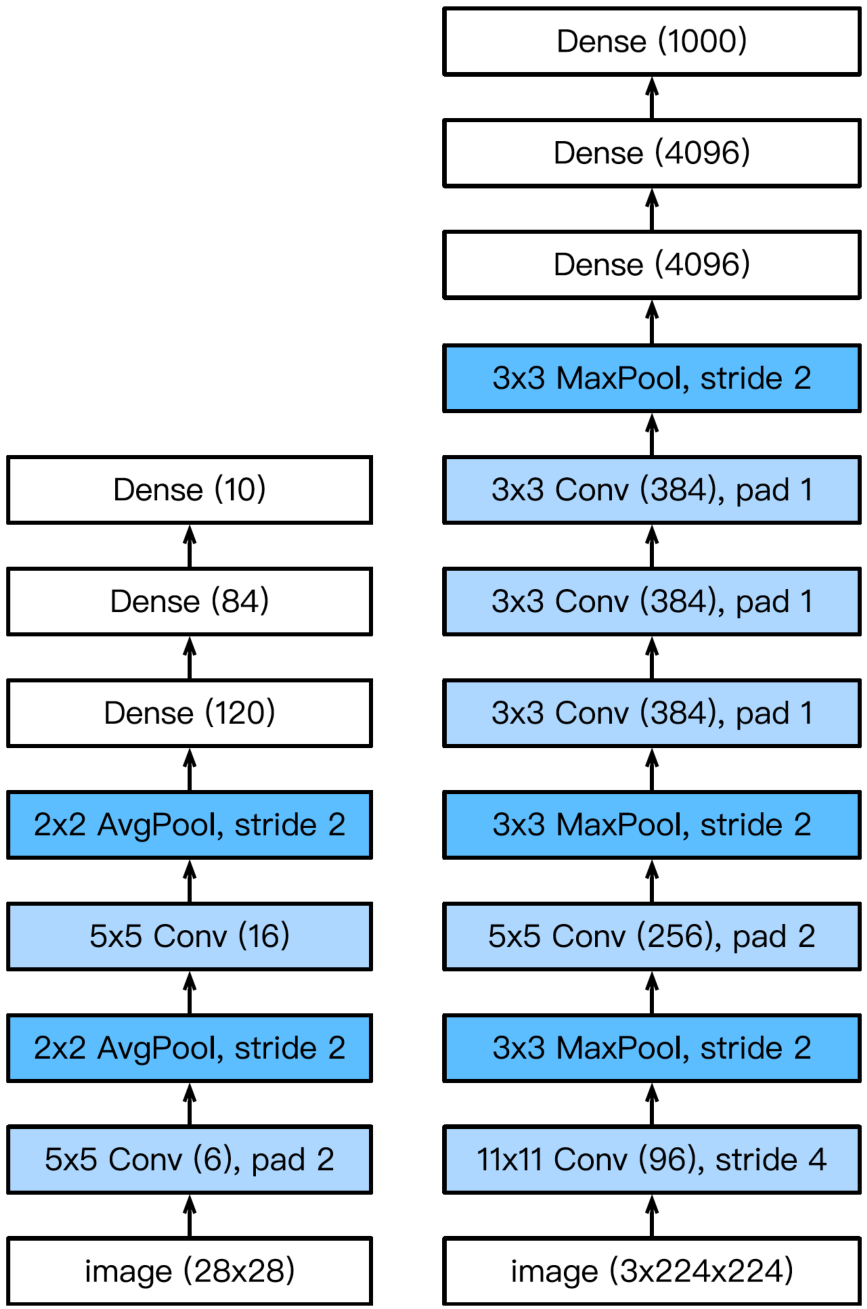
- Fortunately, GPU memory is comparatively abundant now, so we rarely need to break up models across GPUs these days.



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  - However, if the model parameters are not initialized properly, the sigmoid function may obtain a gradient of almost 0 so that the model cannot be effectively trained.

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- This makes the model more robust and the larger sample size effectively reduces overfitting.

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- The idea of using blocks first emerged from the Visual Geometry Group120 (VGG) at Oxford University.
- In their VGG network, it’s easy to implement these repeated structures in code with any modern deep learning framework by using loops and subroutines.

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- One VGG block consists of a sequence of convolutional layers, followed by a max pooling layer for spatial downsampling.

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- Since this network uses 8 convolutional layers and 3 fully-connected layers, it is often called VGG-11.

VGG Network

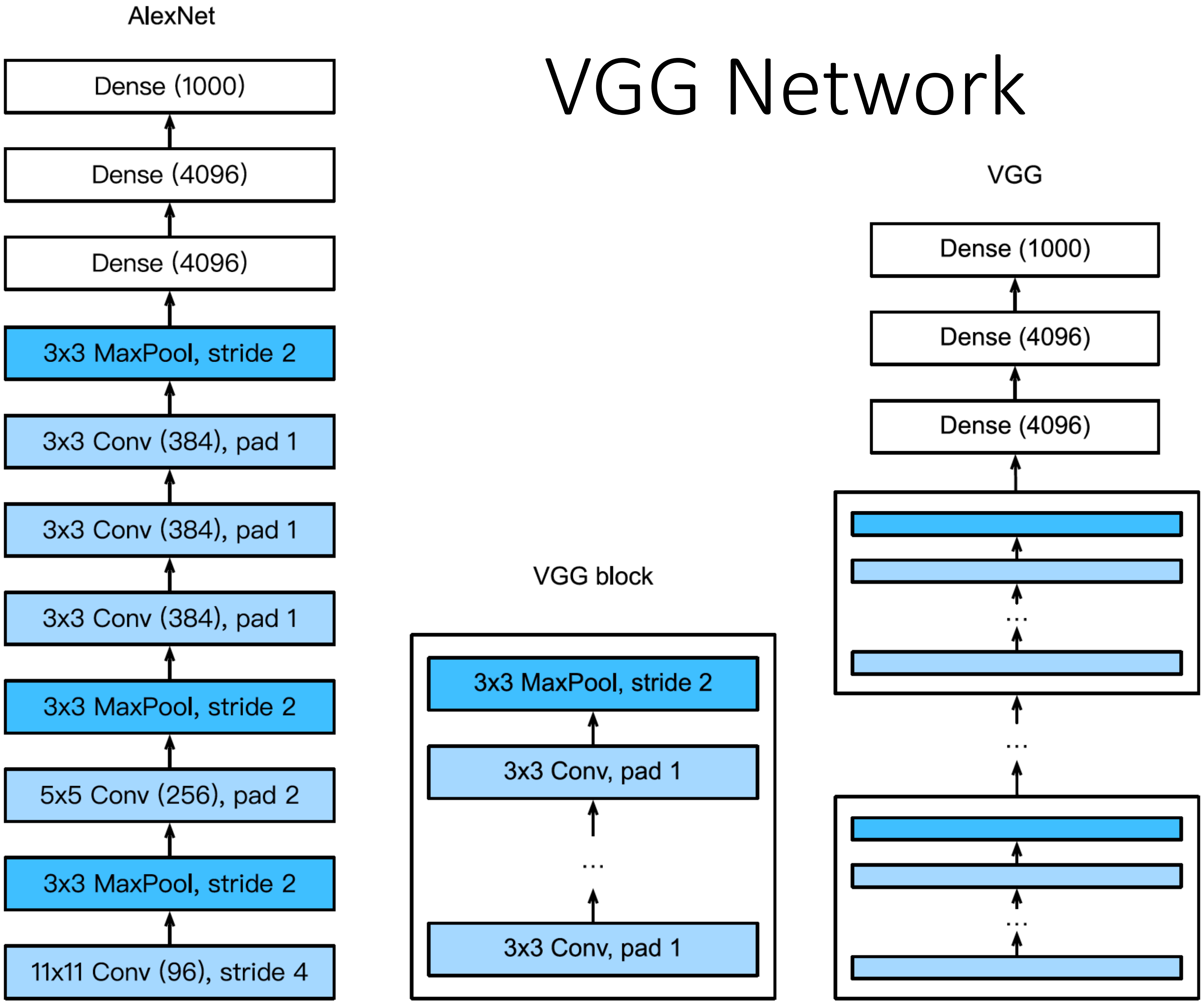

Fig. 9.2.1: Designing a network from building blocks

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- NiN blocks were proposed to use an MLP on the channels for each pixel separately.

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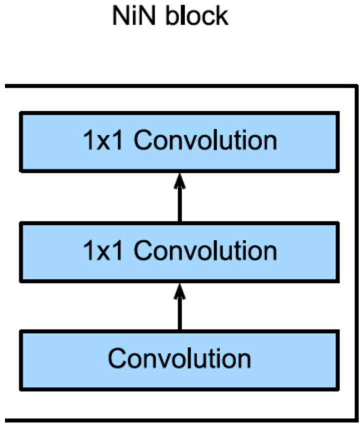
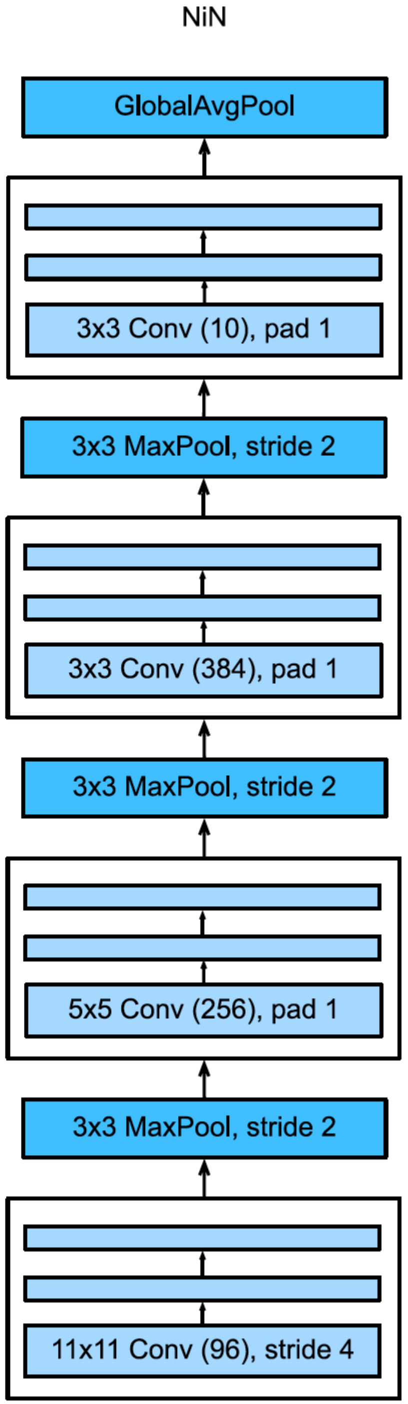
- We could think of this as a 1x1 convolutional layer or as a fully-connected layer acting independently on each pixel location.
- Another way to view this is to think of each element in the spatial dimension (height and width) as equivalent to an example and the channel as equivalent to a feature.

NiN models

- The NiN block consists of one convolutional layer followed by two 1x1 convolutional layers that act as per-pixel fully-connected layers with ReLU activations. The convolution width of the first layer is typically set by the user. The subsequent widths are fixed to 1 x 1.





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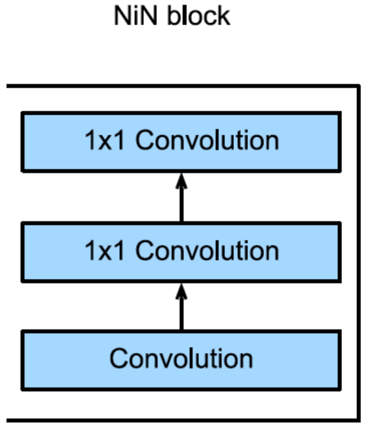
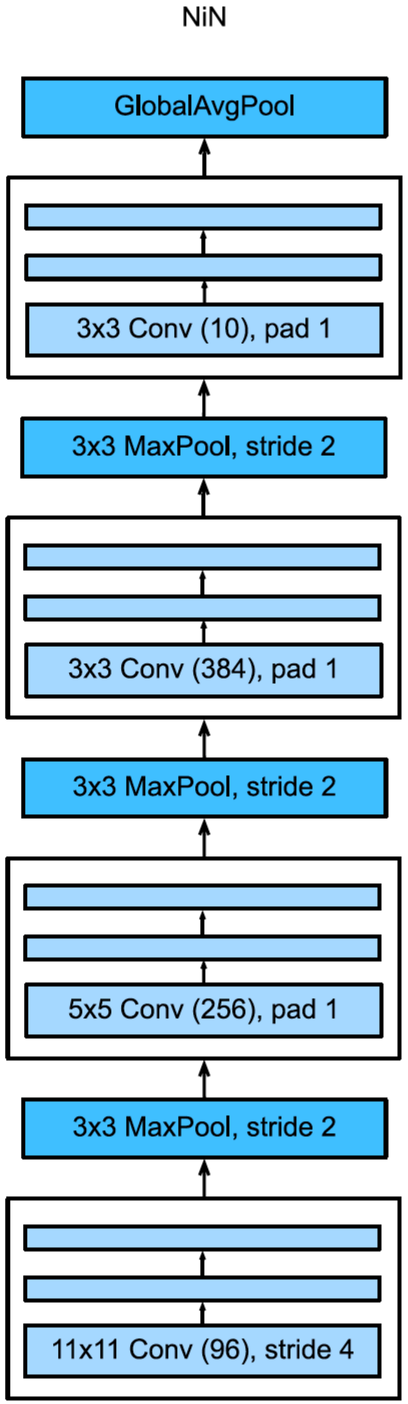
- Once significant difference between NiN and AlexNet is that NiN avoids dense connections altogether. Instead, NiN uses an NiN block with a number of output channels equal to the number of label classes, followed by a global average pooling layer, yielding a vector of logits.





Networks with Parallel Concatenations (GoogleNet)

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- One focus of the paper was to address the question of which sized convolutional kernels are best.
- One insight in this paper was that sometimes it can be advantageous to employ a combination of variously-sized kernels.

Inception Blocks

- The basic convolutional block in GoogLeNet is called an Inception block.

https://knowyourmeme.com/memes/we-need-to-go-deeper

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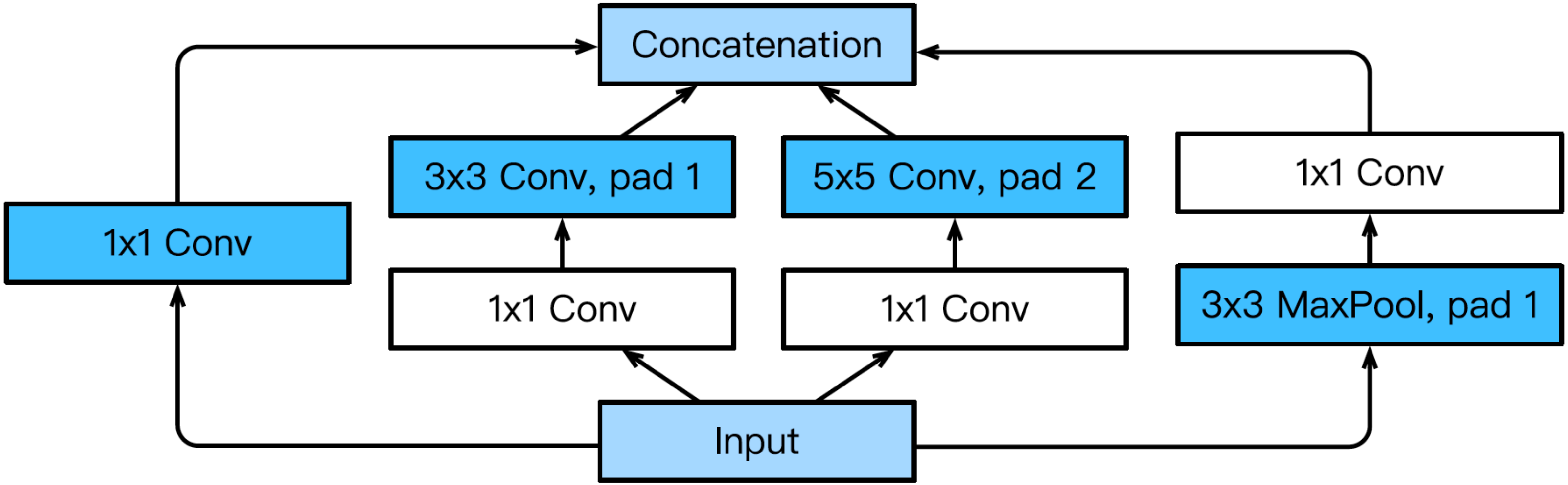
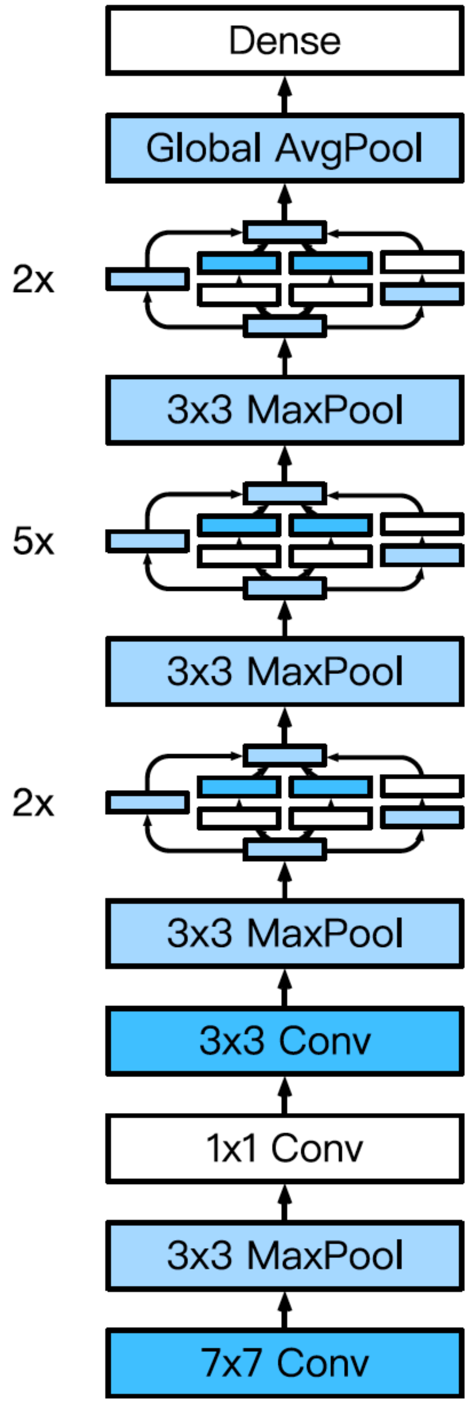


GoogleLeNet Model

- GoogLeNet uses a stack of a total of 9 inception blocks and global average pooling to generate its estimates.



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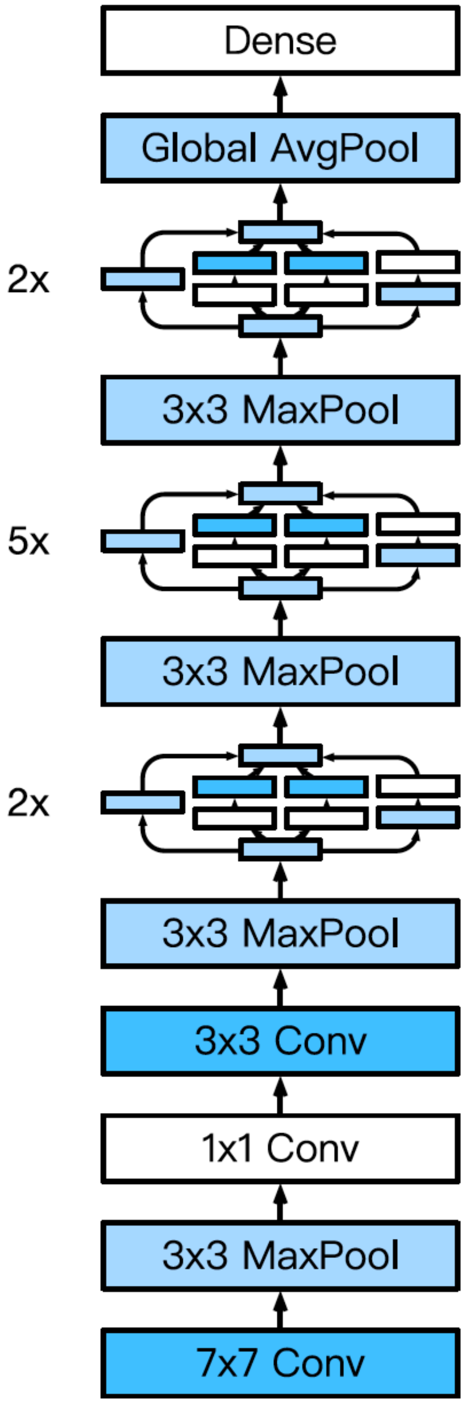

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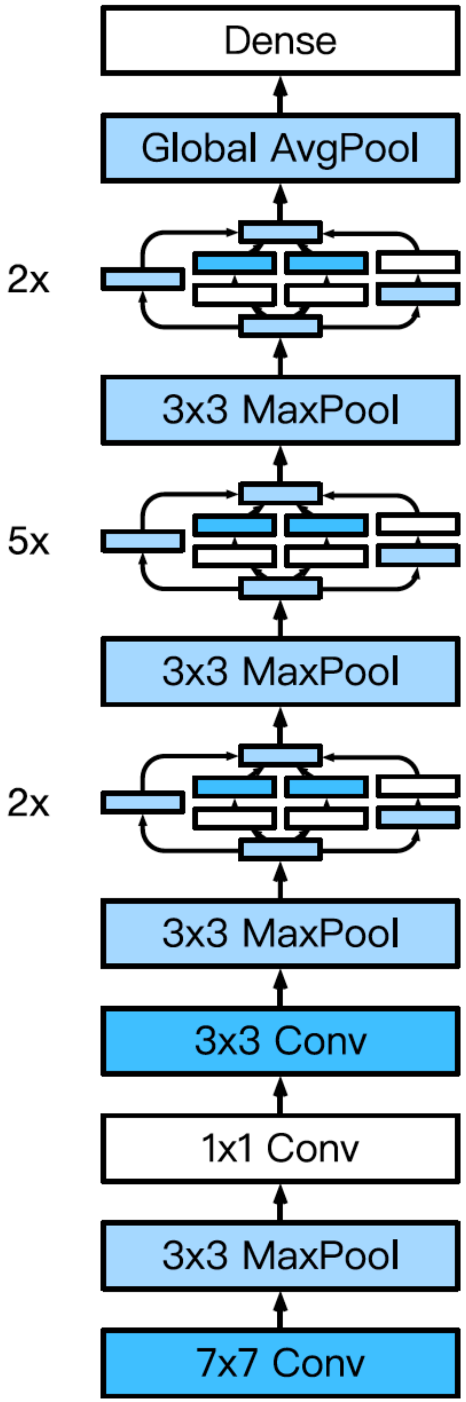
- Maximum pooling between inception blocks reduced the dimensionality.
- The first part is identical to AlexNet and LeNet, the stack of blocks is inherited from VGG and the global average pooling avoids a stack of fully-connected layers at the end.



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- Deeper networks are complex and easily capable of overfitting. This means that regularization becomes more critical. Empirically, we note that even with dropout, models can overfit badly and we might benefit from other regularization heuristics.

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- Consequently, the activations for intermediate layers cannot diverge any longer: we are actively rescaling them back to a given order of magnitude via μ and σ.

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- To remedy this problem BN uses only the current minibatch for estimating mean and variance.

$$\hat{\mu}_{\mathcal{B}} \leftarrow \frac{1}{|\mathcal{B}|} \sum_{\mathbf{x} \in \mathcal{B}} \mathbf{x} \text{ and } \hat{\sigma}_{\mathcal{B}}^2 \leftarrow \frac{1}{|\mathcal{B}|} \sum_{\mathbf{x} \in \mathcal{B}} (\mathbf{x} - \mu_{\mathcal{B}})^2 + \epsilon$$

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- Consequently, BN behaves differently during training and at test time.

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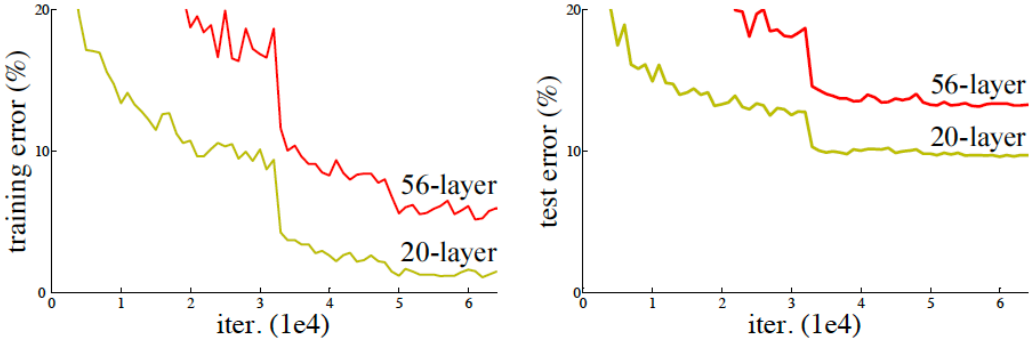

Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena

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- There exists a solution by construction to the deeper model: the added layers are identity mapping, and the other layers are copied from the learned shallower model.
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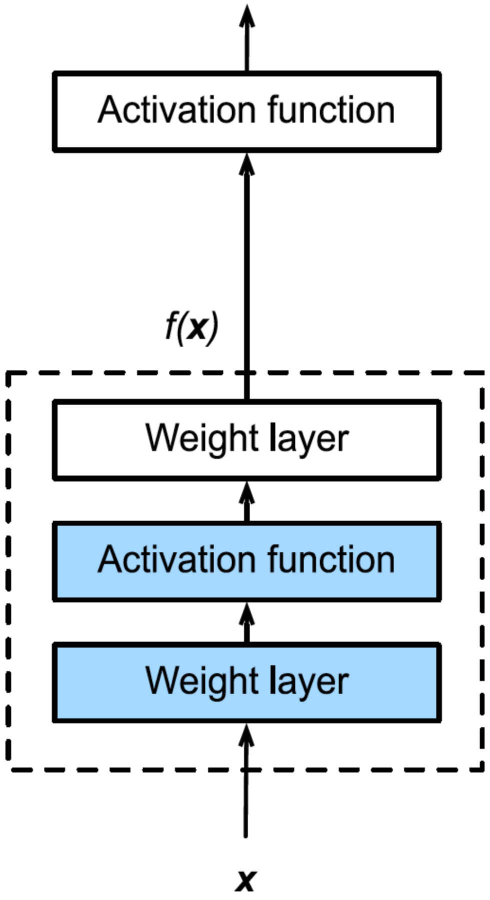

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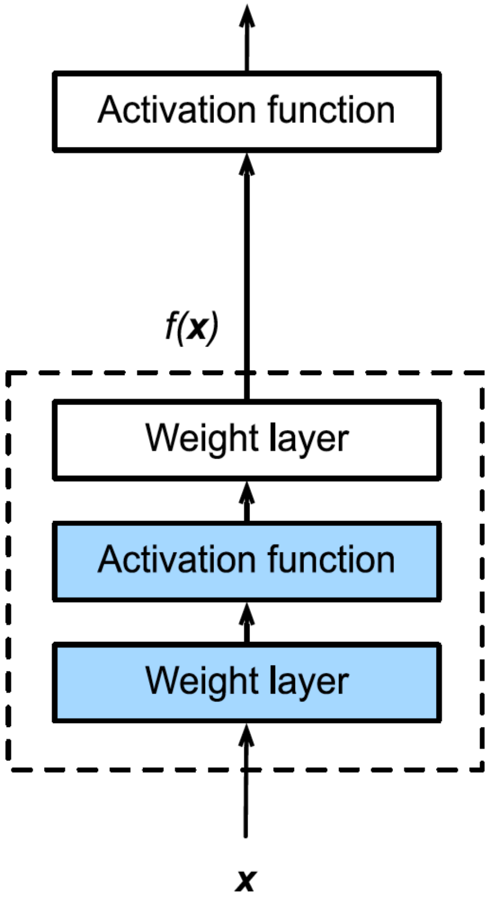

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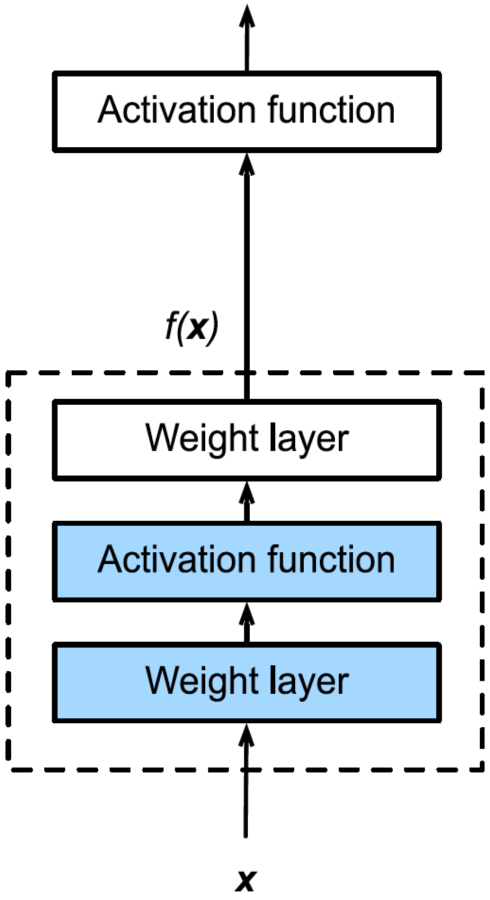

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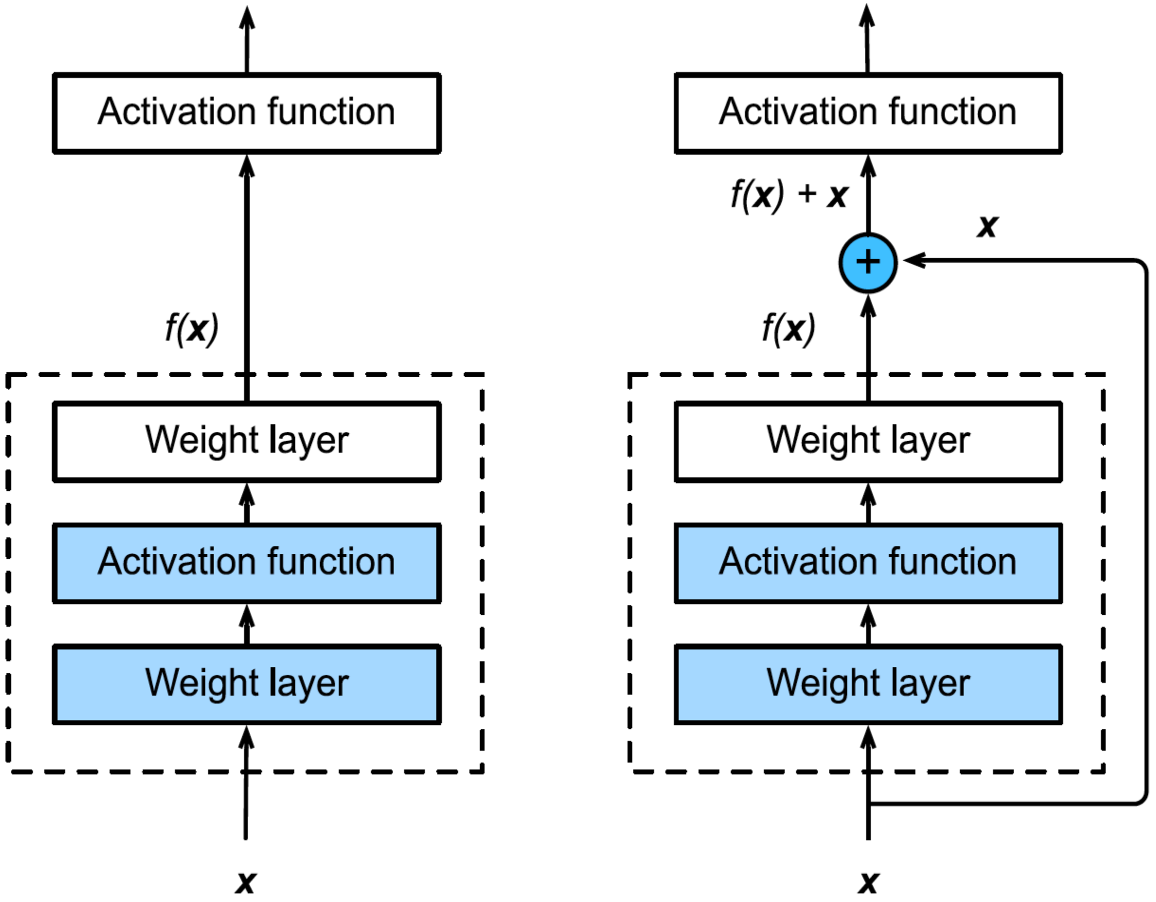

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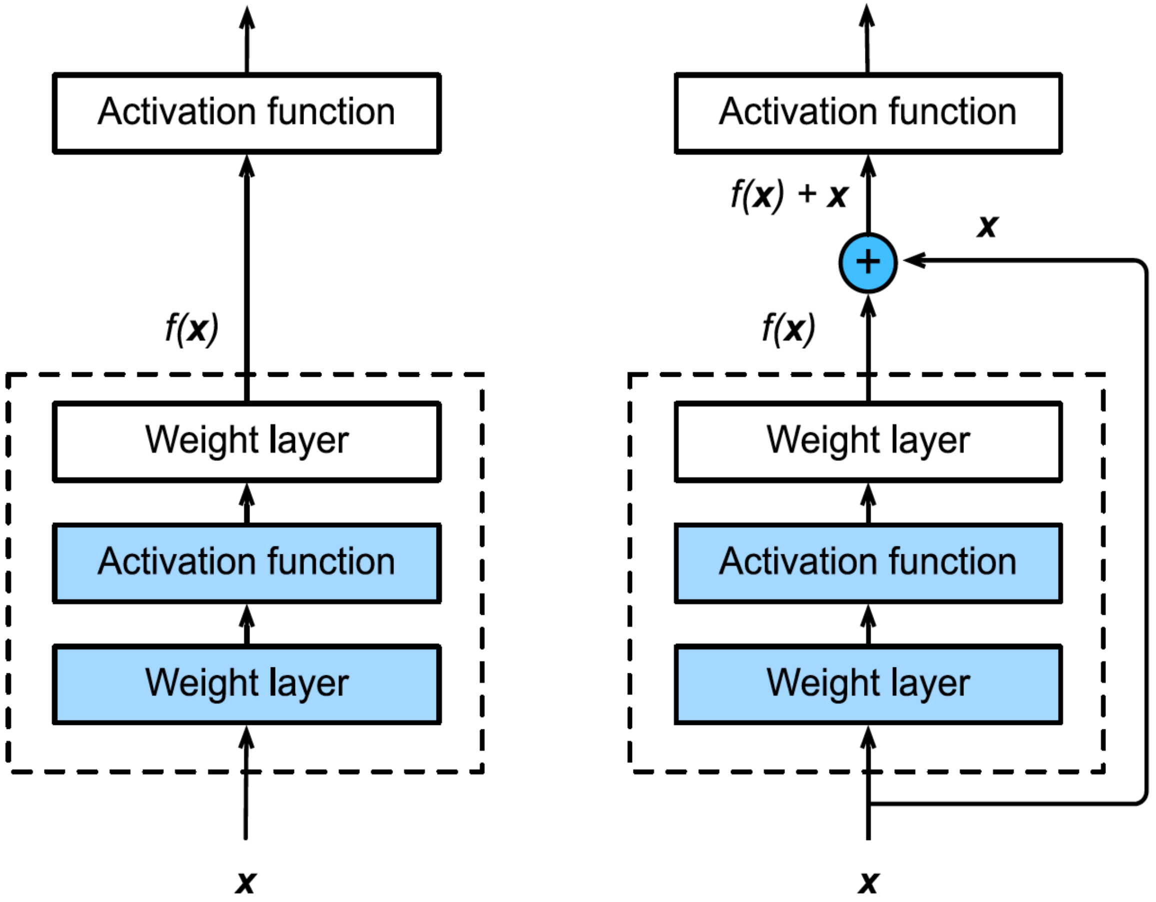
- In practice, the residual mapping is often easier to optimize.



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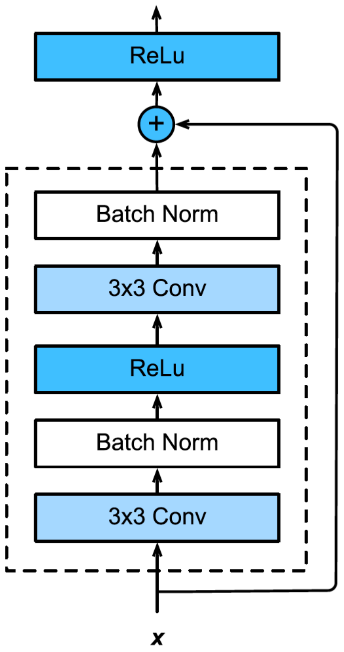

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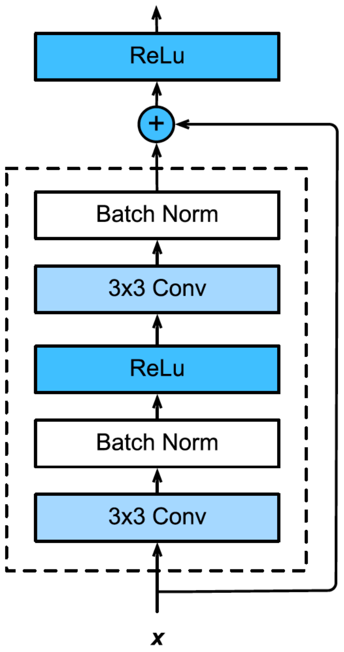

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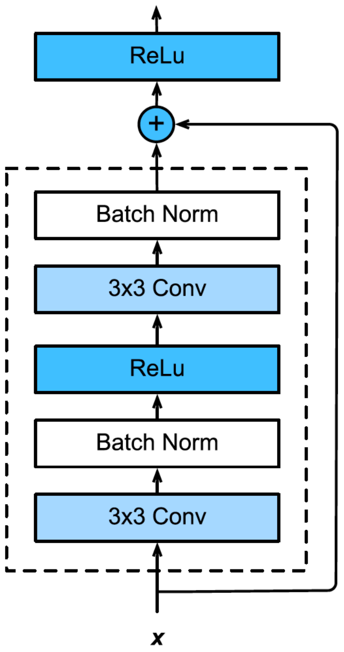

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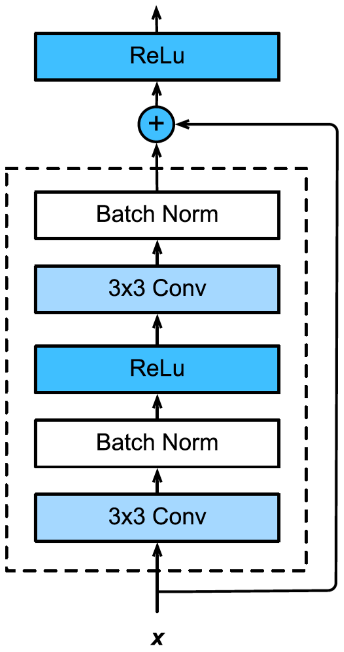
- The residual block has two 3 x 3 convolutional layers with the same number of output channels.
- Each convolutional layer is followed by a batch normalization layer and a ReLU activation function.
- Then, we skip these two convolution operations and add the input directly before the final ReLU activation function.



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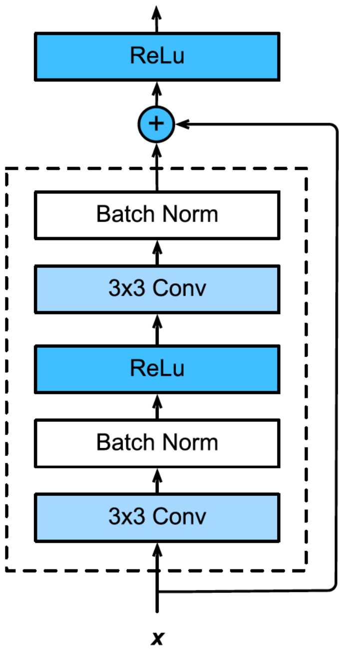

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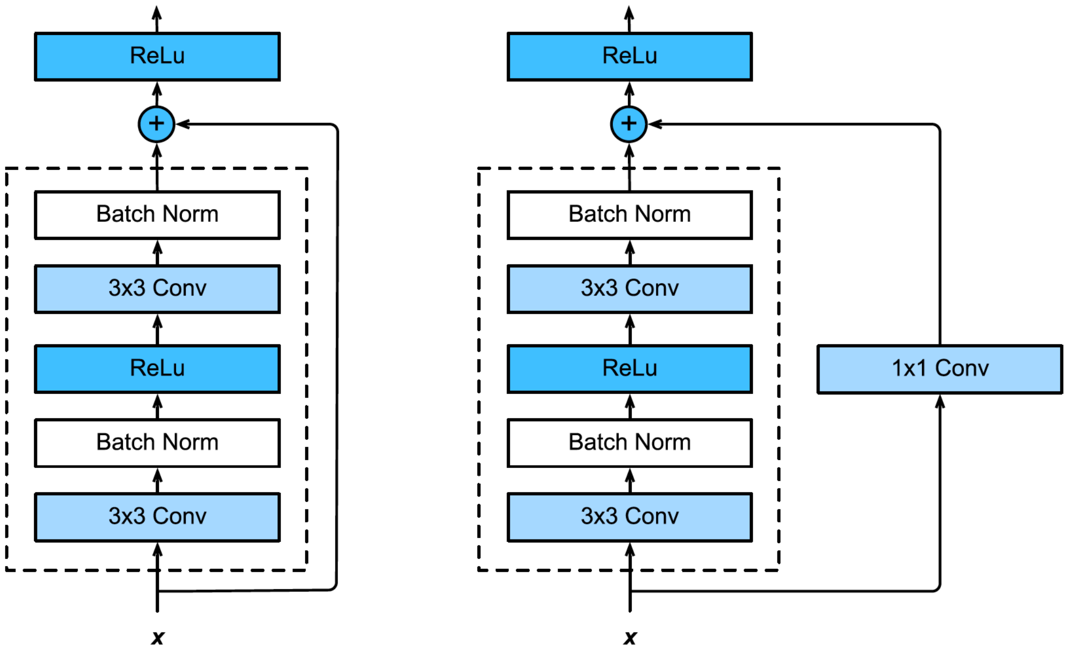
- If we want to change the number of channels or the stride, we need to introduce an additional 1x1 convolutional layer to transform the input into the desired shape for the addition operation.



ResNet Model

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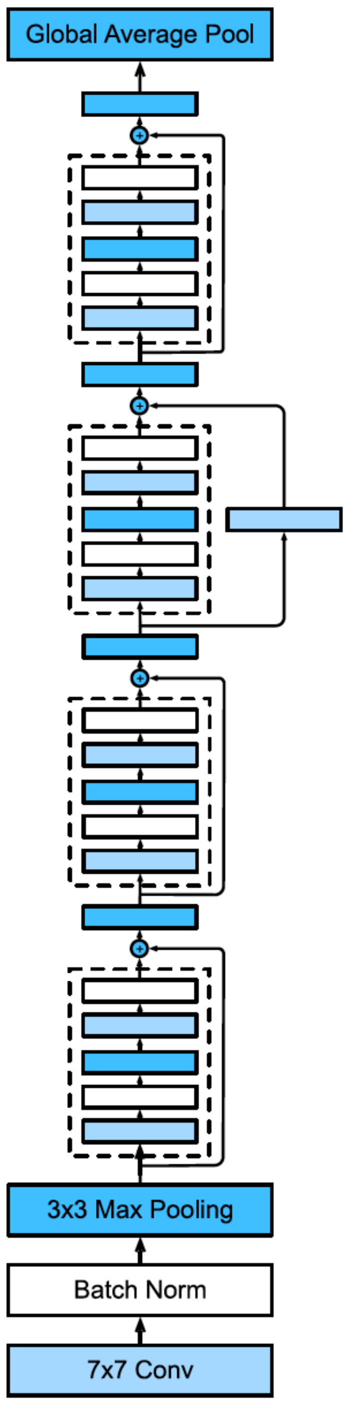

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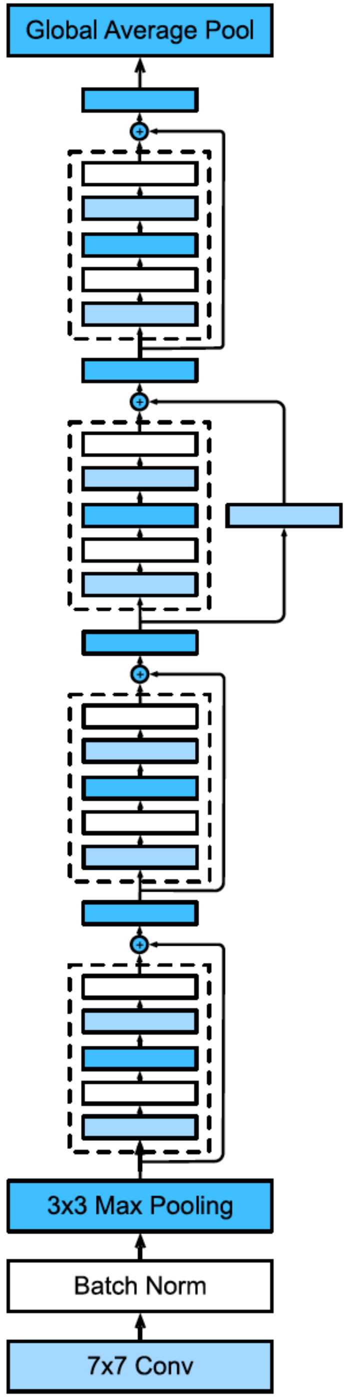

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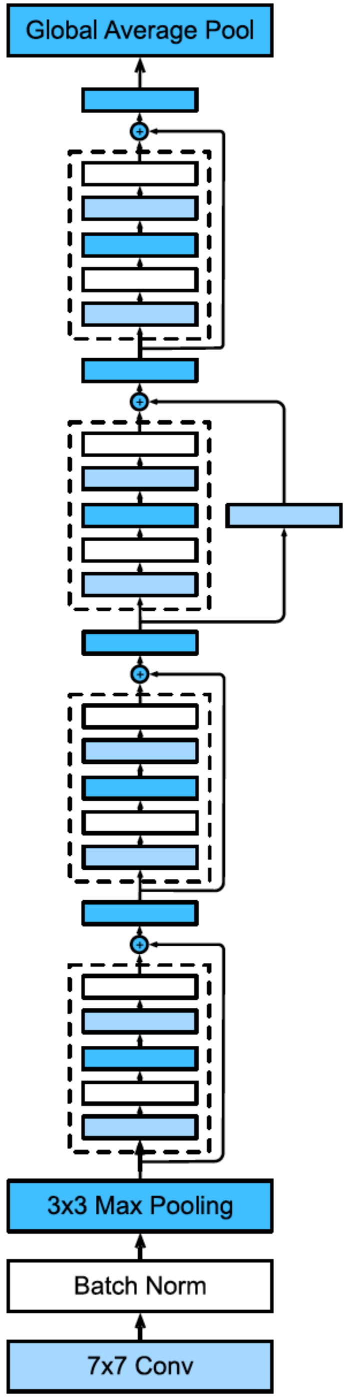

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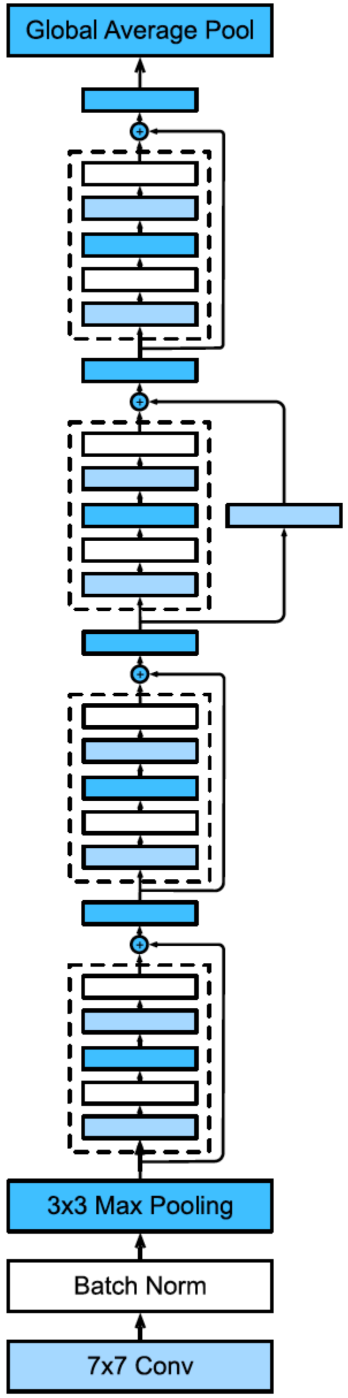
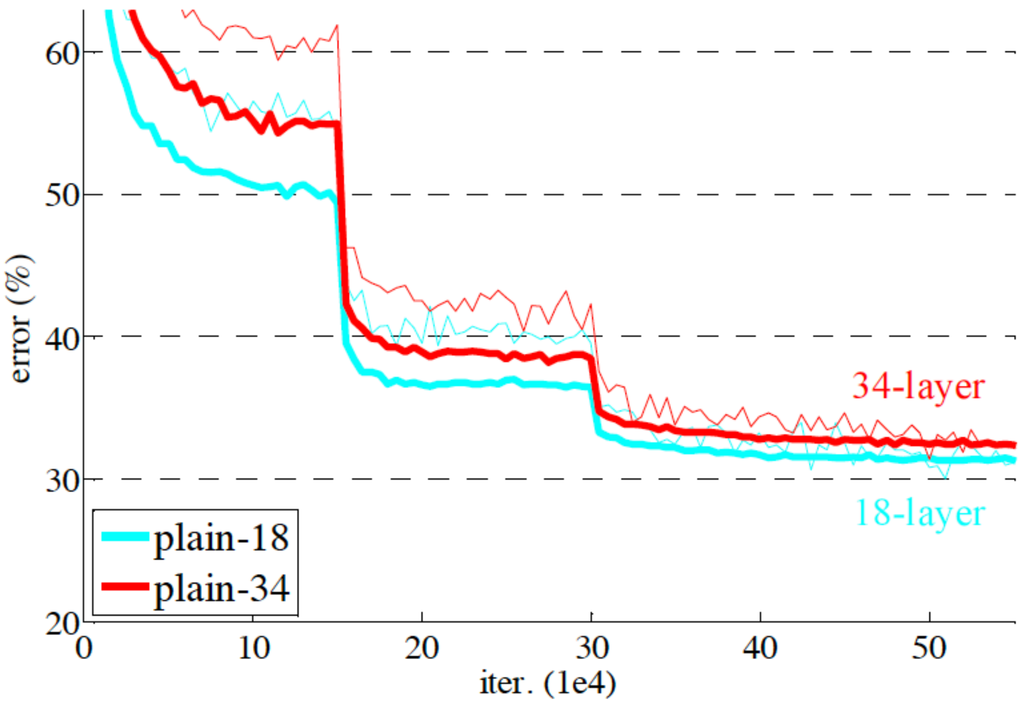
- There are 4 convolutional layers in each module (excluding the 1 1 convolutional layer). Together with the first convolutional layer and the final fully connected layer, there are 18 layers in total.



Results Using ResNet



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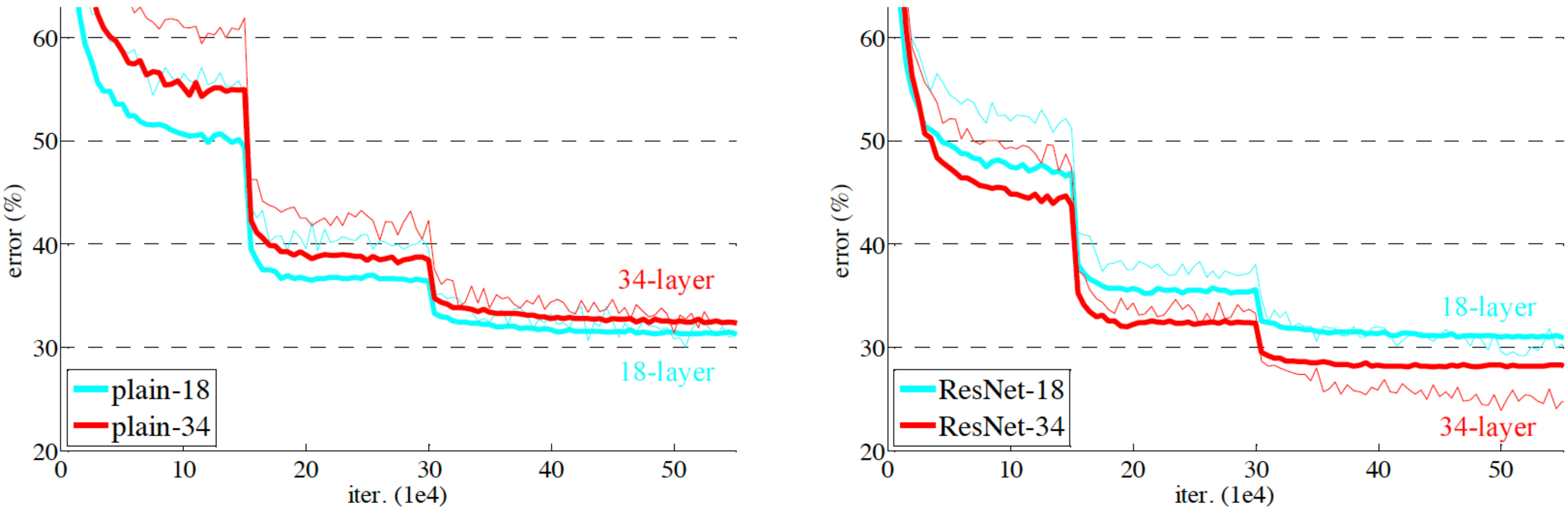

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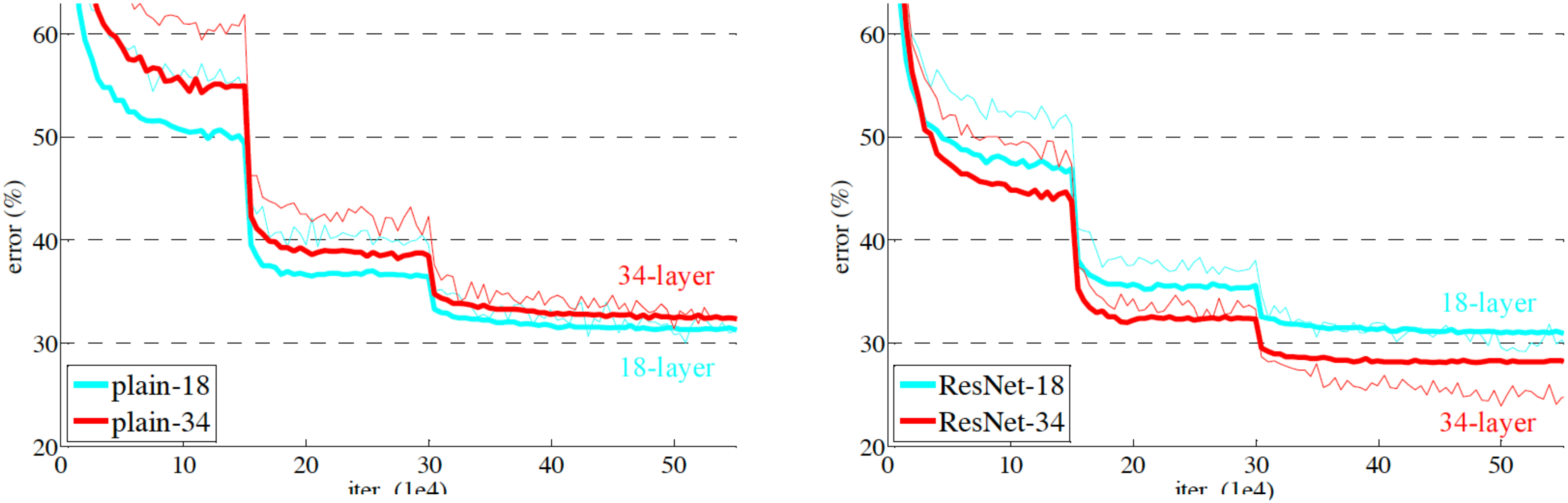

	plain	ResNet
18 layers	27.94	27.88
34 layers	28.54	**25.03**

Table 2. Top-1 error (%, 10-crop testing) on ImageNet validation. Here the ResNets have no extra parameter compared to their plain counterparts. Fig. 4 shows the training procedures.

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- A solution was proposed by the paper: https://arxiv.org/pdf/1608.06993.pdf

Densely Connected Networks (DenseNet)

- The key difference between ResNet and DenseNet is that in the latter case outputs are concatenated rather than added.

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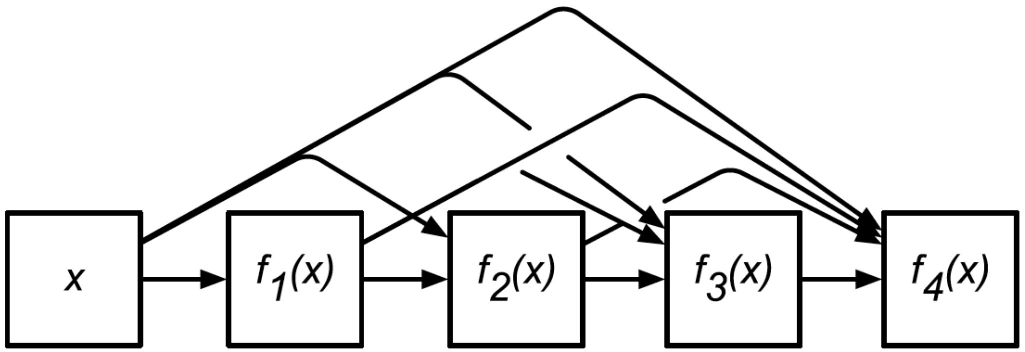

Fig. 9.7.2: Dense connections in DenseNet

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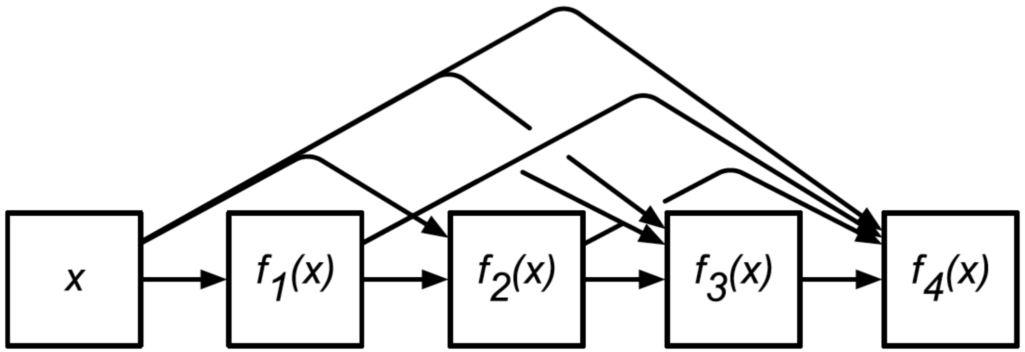

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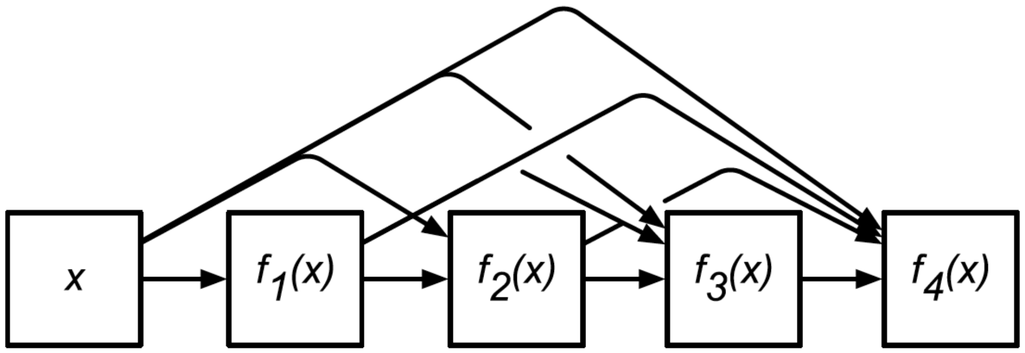

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- In the end, all these functions are combined in an MLP to reduce the number of features again.
- The main components that compose a DenseNet are dense blocks and transition layers. The former defines how the inputs and outputs are concatenated, while the latter controls the number of channels so that it is not too large.

DenseNet Model

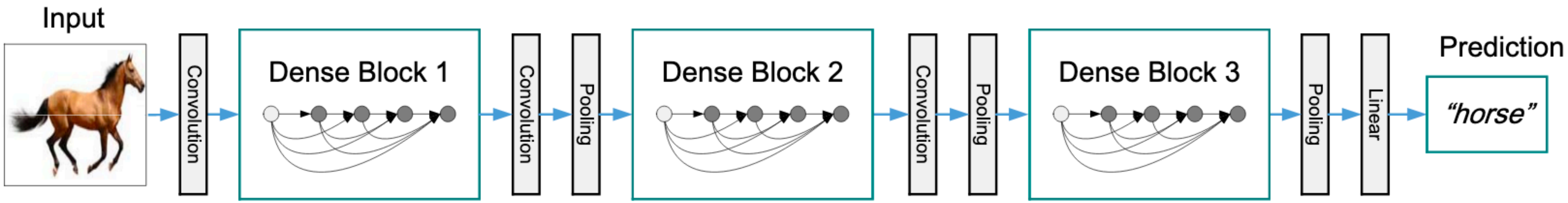

Figure 2: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.