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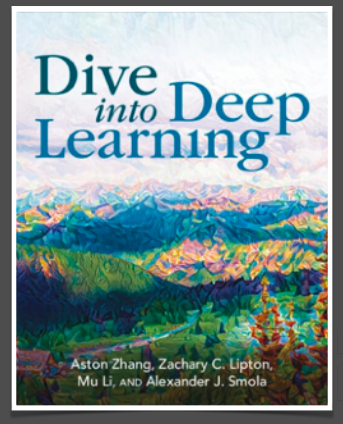
Introduction to Deep Learning

Convolutional Neural Networks

Sungjoon Choi, Korea University



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Convolution Operation

Fully Connected to Convolutions

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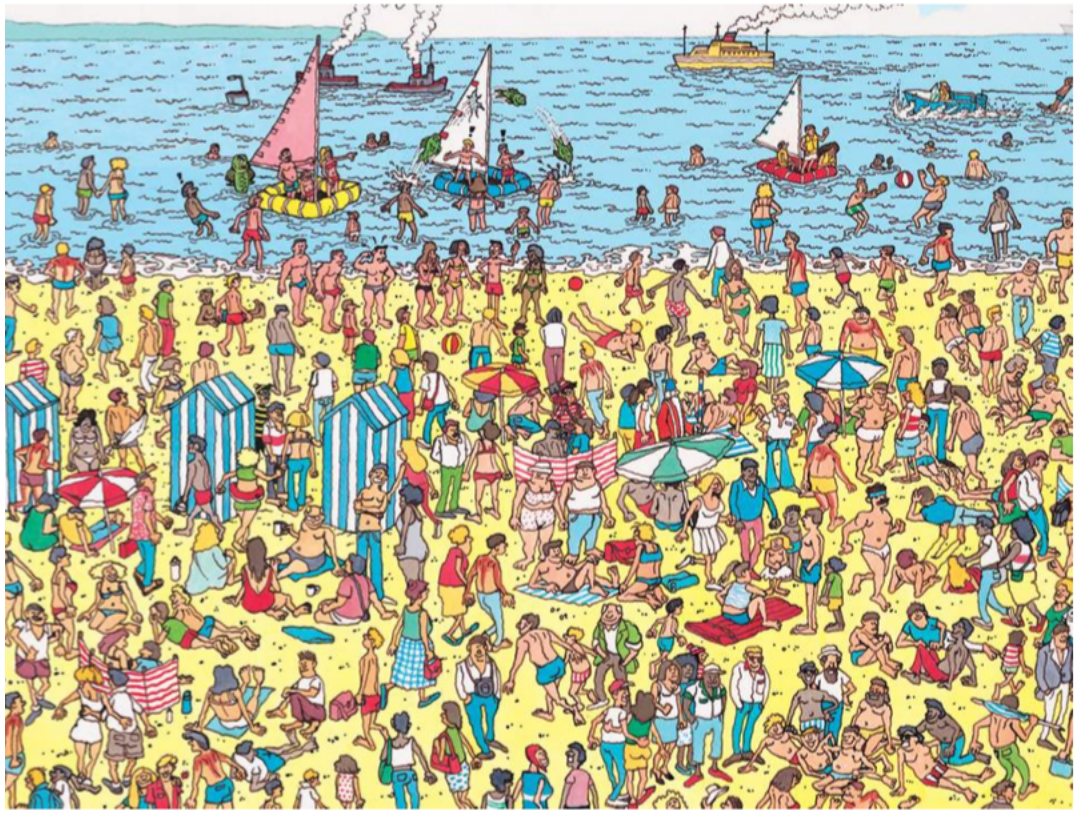
Why do convolutional neural networks (CNNs) more appropriate than MLPs in image domains?

Invariance



- Imagine that we want to detect an object in an image (Wheres Waldo).
- It seems reasonable that whatever method we use, the precise location of the object in the image should not be overly concerned.

Invariance

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- Despite Waldo's characteristic outfit, what Waldo looks like does not depend upon where is located.
- We could sweep the image with a Waldo detector that could assign a score to each patch, indicating the likelihood that the patch contains Waldo.
- Convolutional neural networks (CNNs) systematize this idea of spatial invariance, exploiting it to learn useful representations with fewer parameters.

Convolutions (in signal processings)

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- In mathematics, the convolution between two functions, say f and g, is defined as

$$(f * g)(\mathbf{x}) = \int f(\mathbf{z})g(\mathbf{x} - \mathbf{z})d\mathbf{z}.$$

- That is, we measure the overlap between f and g when on function if flipped and shifted by $\mathbf{x}$ (i.e., $g(\mathbf{x} - \mathbf{z})$).
- When we have discrete objects in two-dimensional spaces:

$$(f * g)(i, j) = \sum_a \sum_b f(a, b)g(i - a, j - b).$$

Convolutions (in CNNs)

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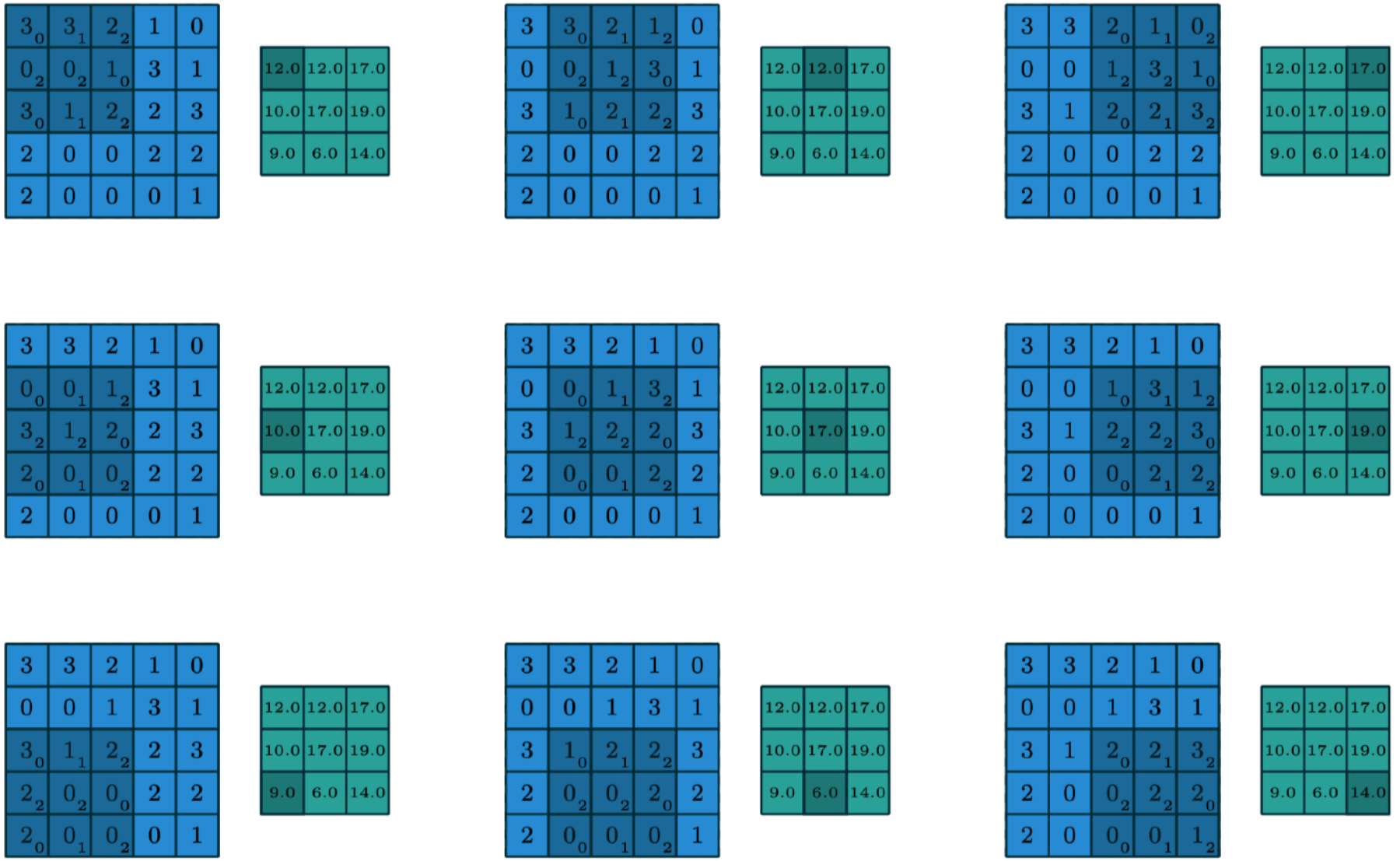
- To exploit the translation invariance, an output of a convolutional layer is computed as:

$$[\mathbf{H}]_{i,j} = u + \sum_{a=-\triangle}^{\triangle} \sum_{b=-\triangle}^{\triangle} [\mathbf{V}]_{a,b} [\mathbf{X}]_{i+a,j+b}$$

  where $\mathbf{V}$ is referred to as a convolution kernel or a filter.

- The number of parameters for the layer is $4\triangle^2$.
- This operation is more properly described as a cross-correlation.

Convolution



"A guide to convolution arithmetic for deep learning," 2018

Convolution (Padding and Strides)

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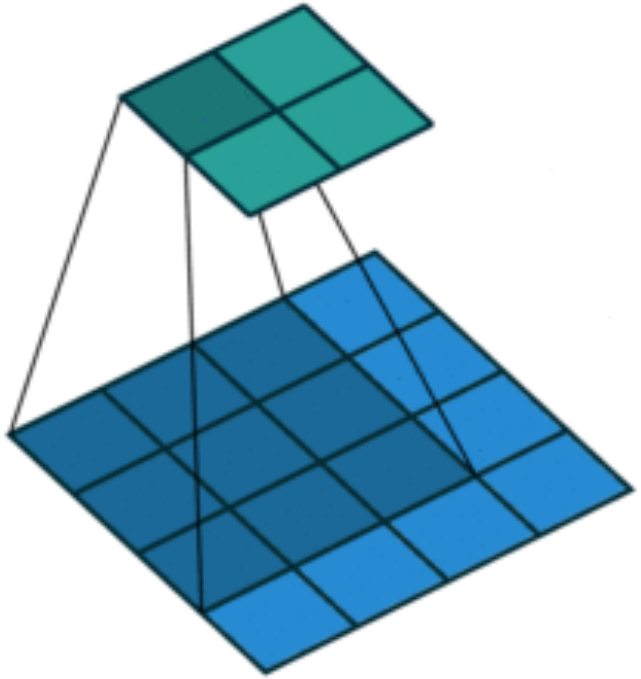
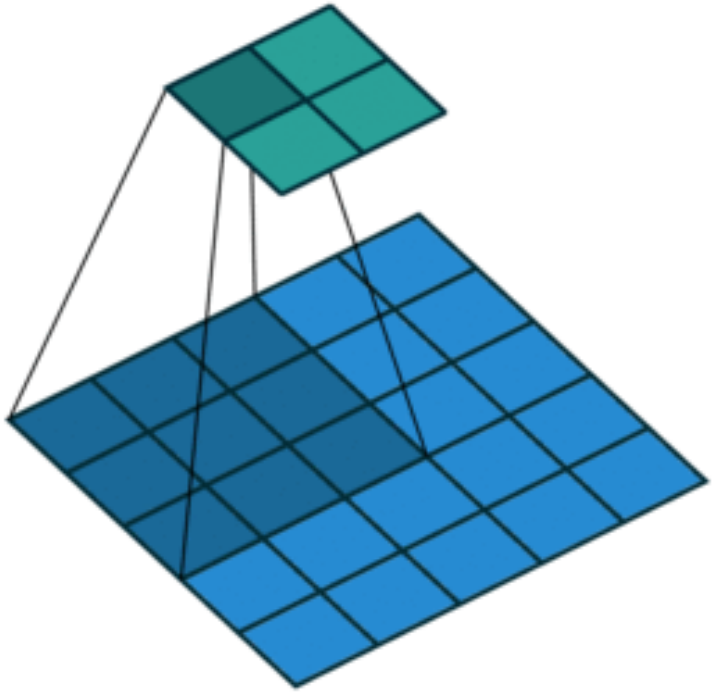


padding=0 and stride=1



padding=0 and stride=2

Blue maps are inputs and cyan maps are outputs.

https://github.com/vdumoulin/conv_arithmetic

Convolution (Padding and Strides)

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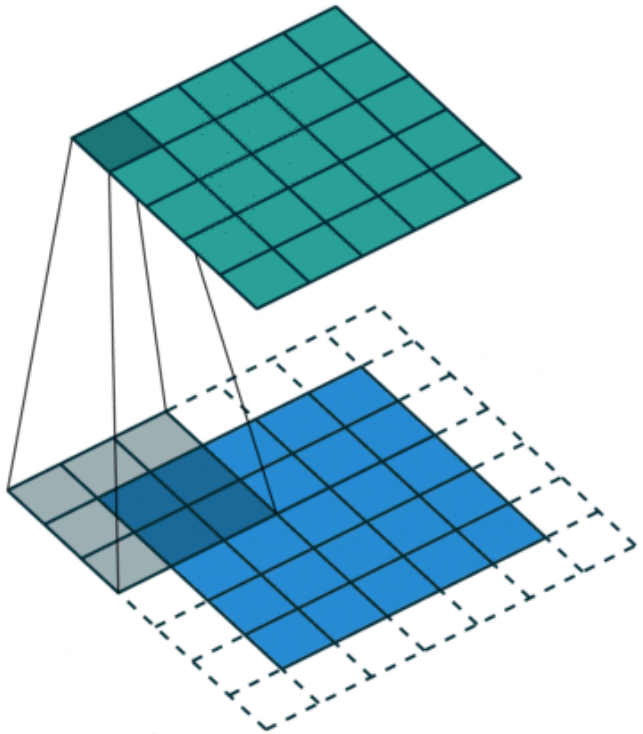
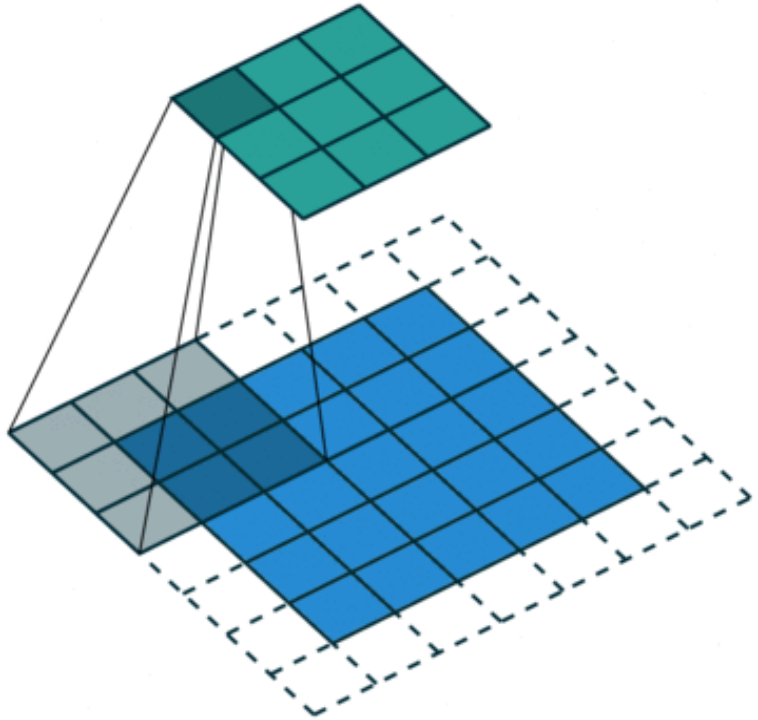


padding=1 and stride=1



padding=1 and stride=2

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Convolution (Padding and Strides)

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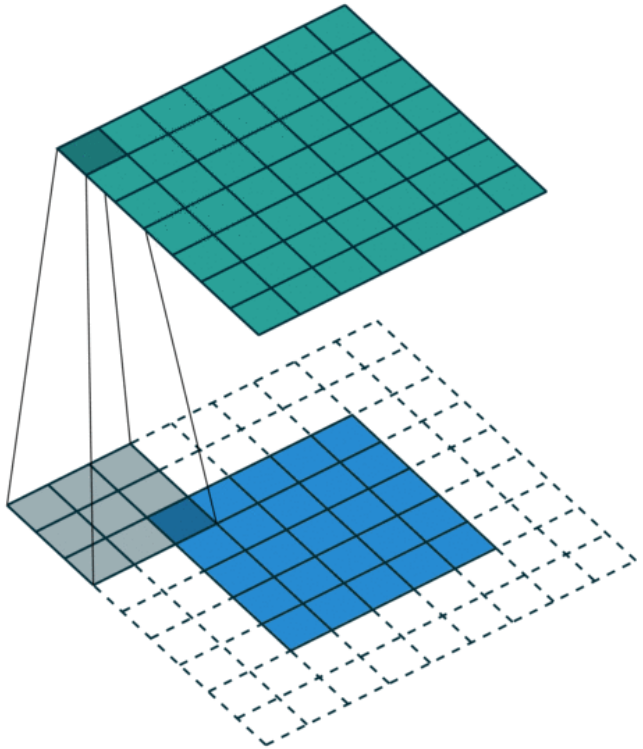
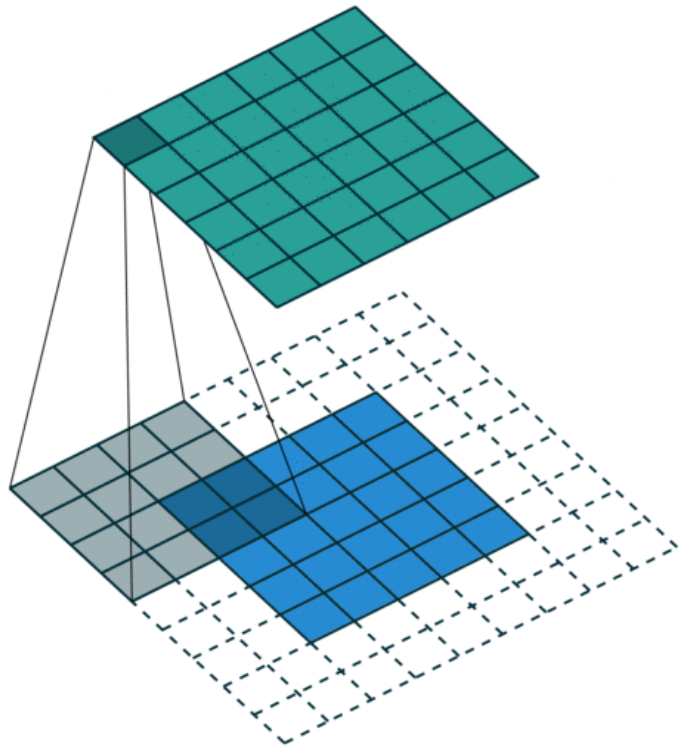


padding=2 and stride=1



padding=2 and stride=1

Note that the sizes of the output features vary!

https://github.com/vdumoulin/conv_arithmetic

Transposed Convolution (Padding and Strides)

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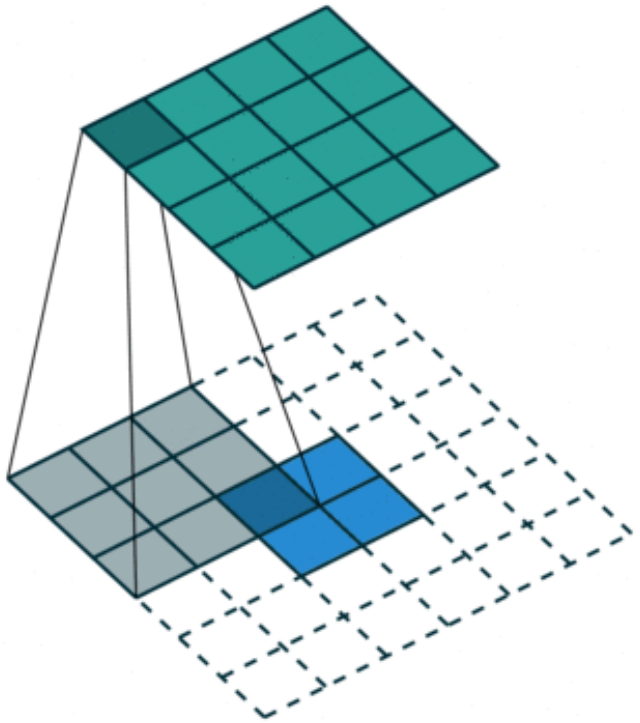
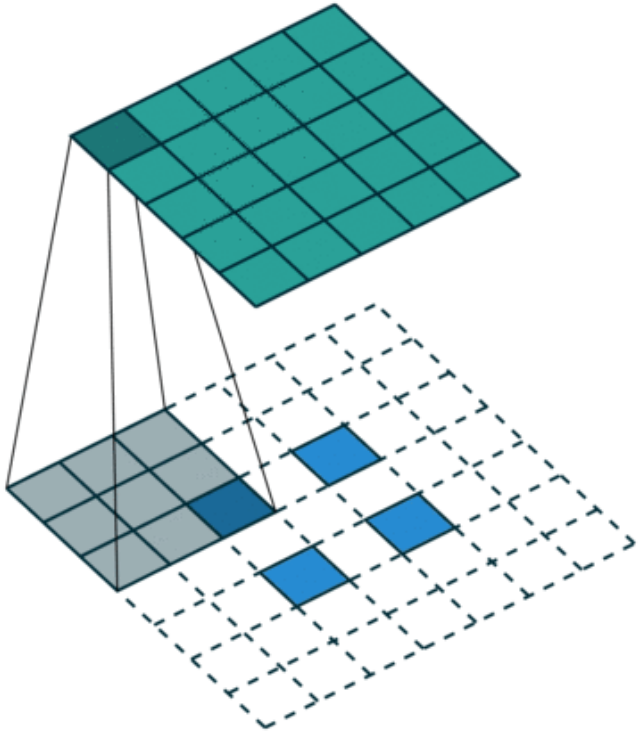


padding=0 and stride=0

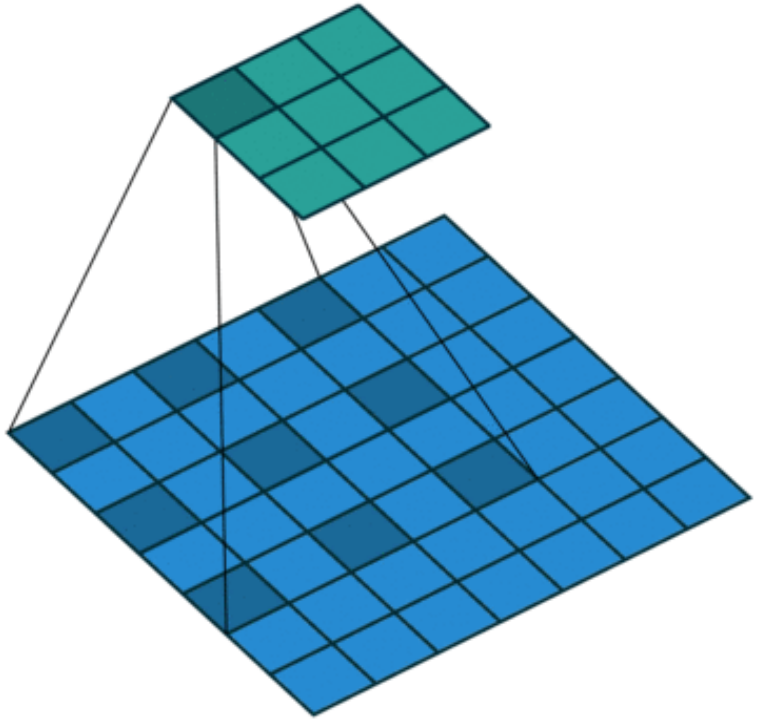


padding=0 and stride=1

Blue maps are inputs and cyan maps are outputs.

https://github.com/vdumoulin/conv_arithmetic

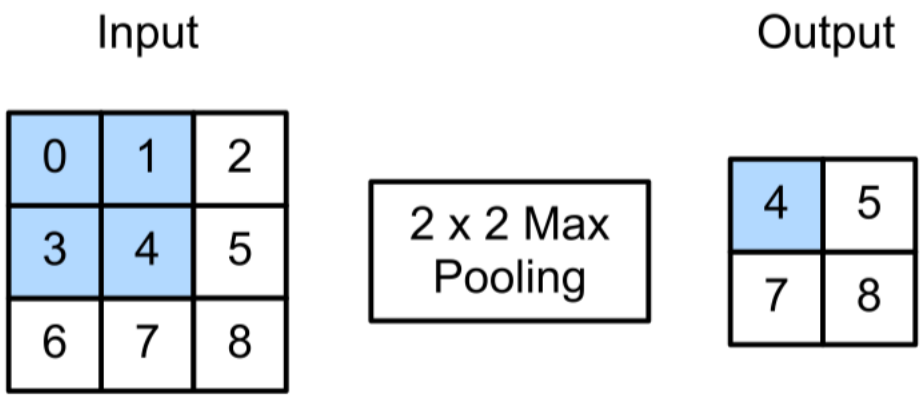
Dilated Convolution (Padding and Strides)



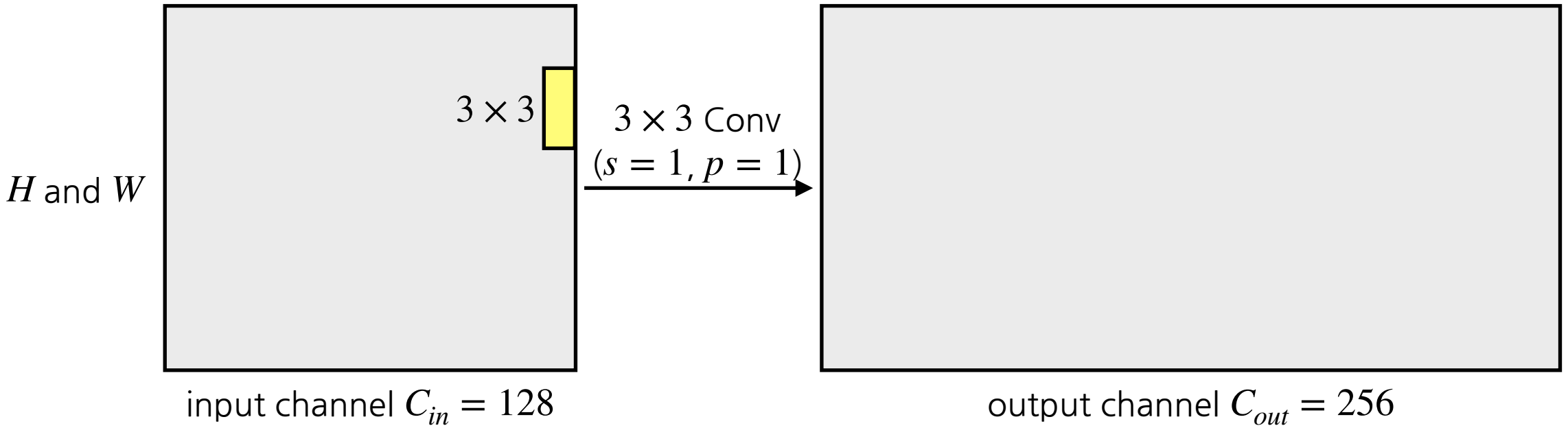
padding=0 and stride=1

https://github.com/vdumoulin/conv_arithmetic

Pooling

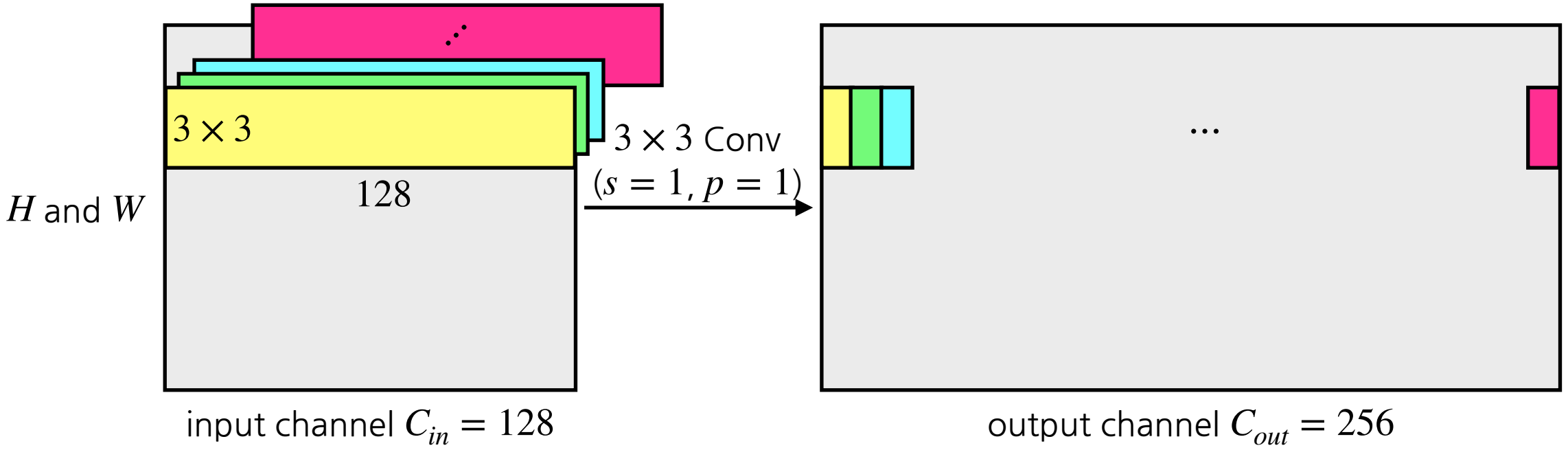


Channel



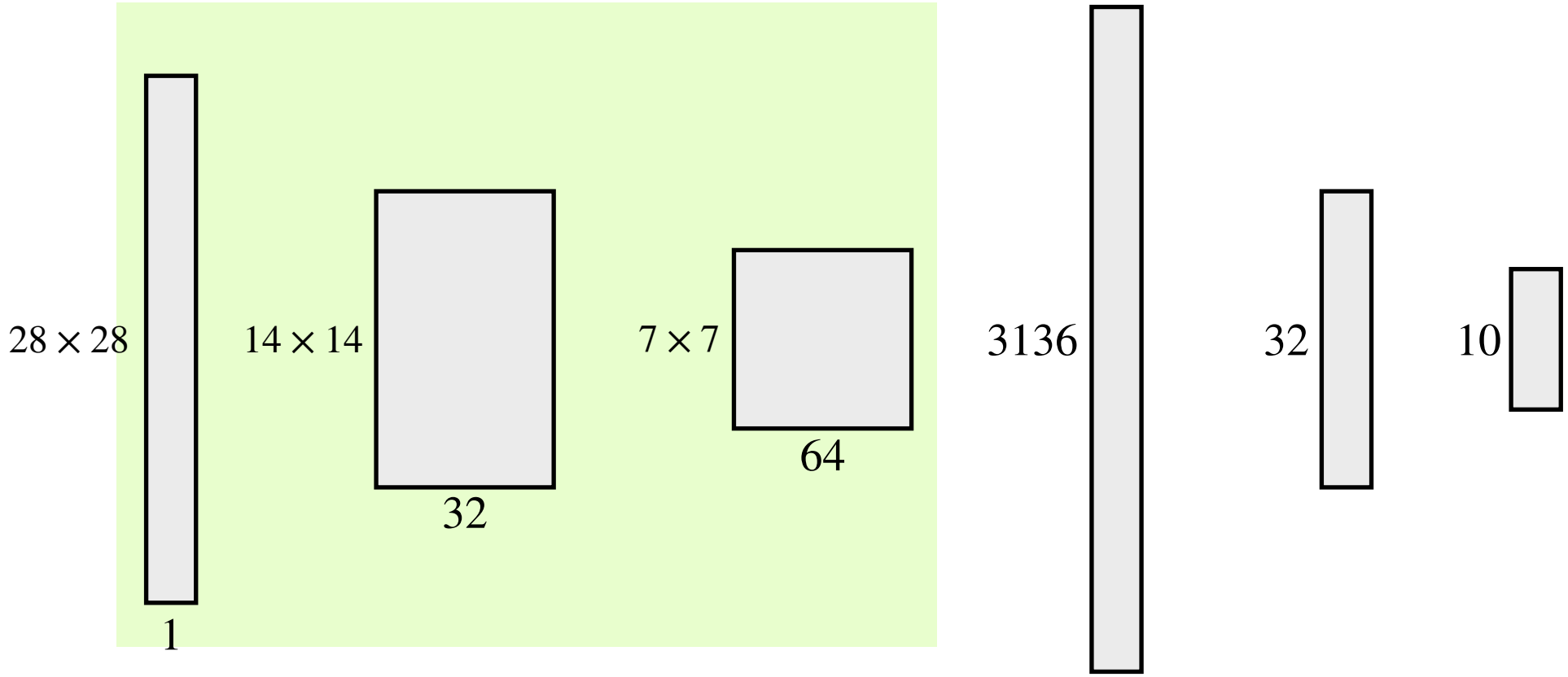
- What is the number of parameters of this 3×3 convolution layer?

Channel



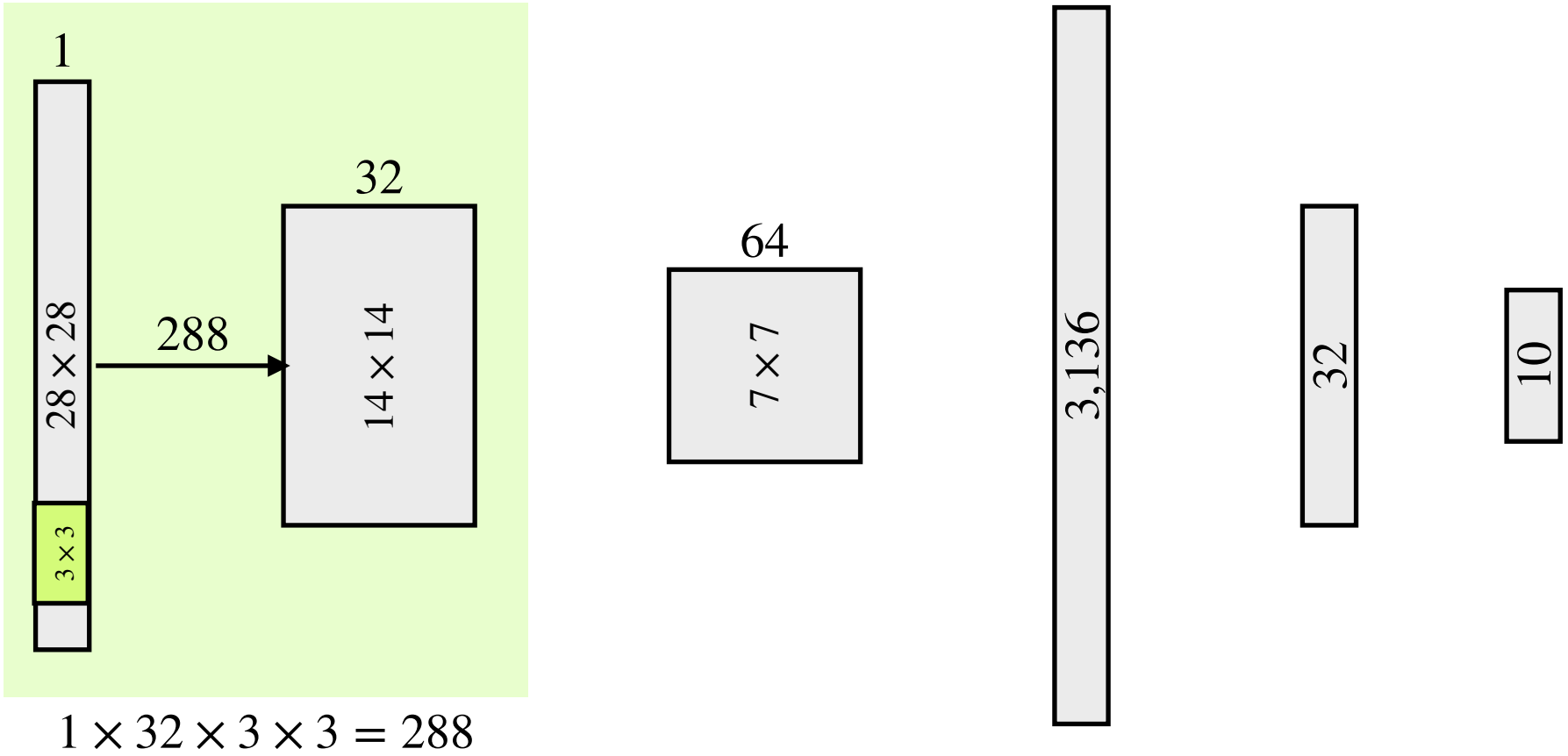
- What is the number of parameters of this 3×3 convolution layer?
  - Each kernel has a dimension of $128 \times 3 \times 3$
  - And we have 256 kernels.
  - The number of parameters is $128 \times 256 \times 3 \times 3 = 294{,}912$

Convolutional Neural Network

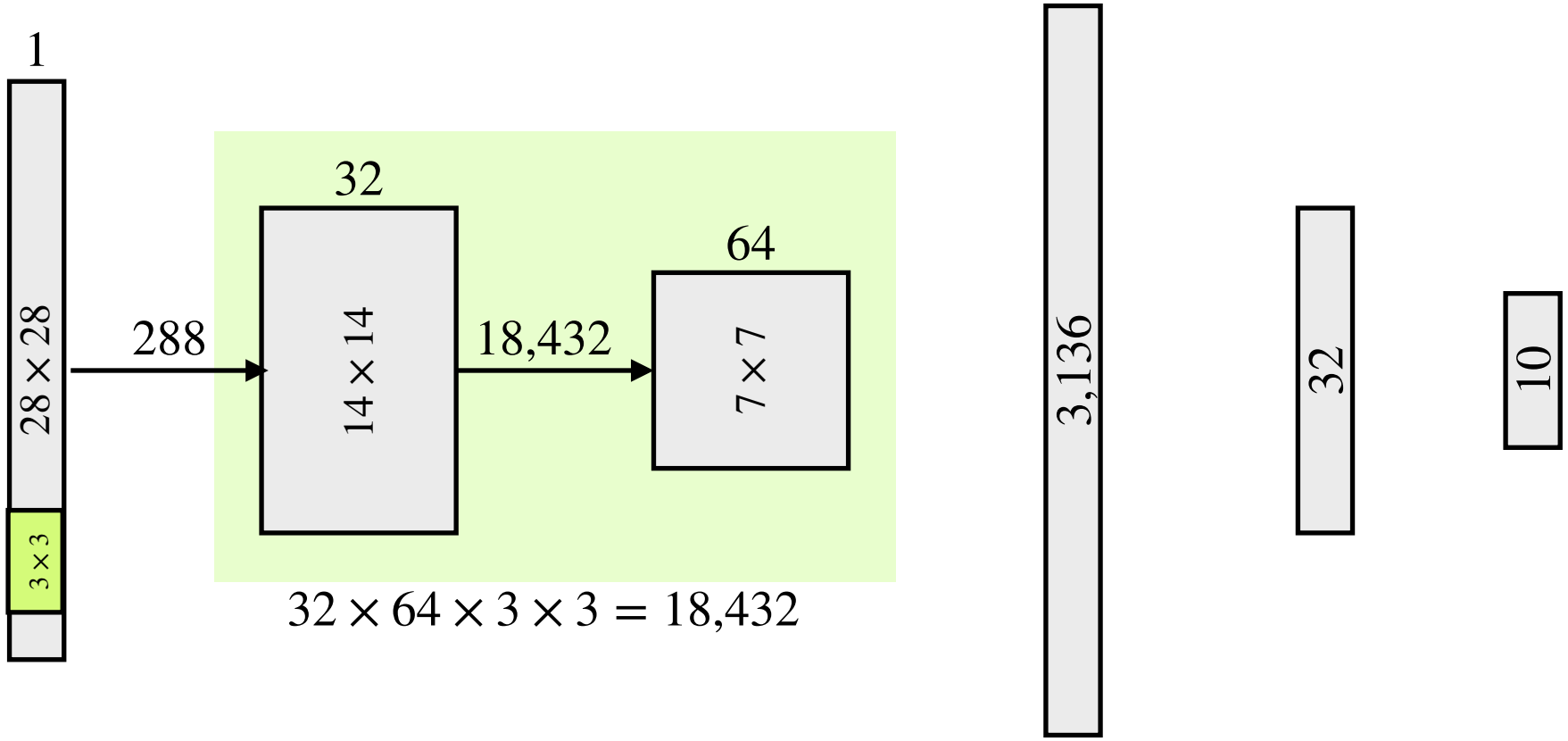


- Convolutions with 3×3 kernels, stride is two, and padding is one.
- Max-pooling with 2×2 kernels.

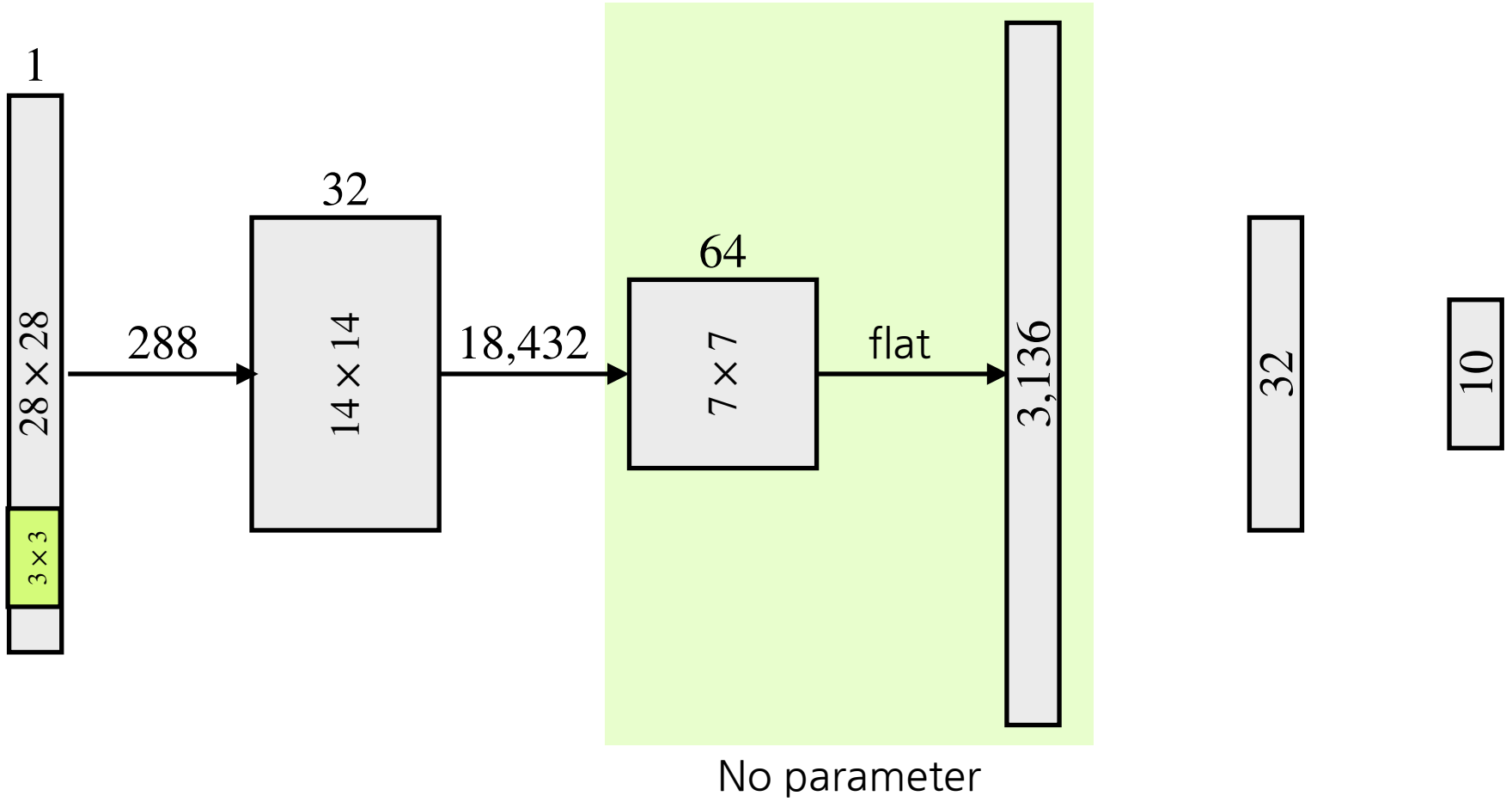
Convolutional Neural Network



Convolutional Neural Network

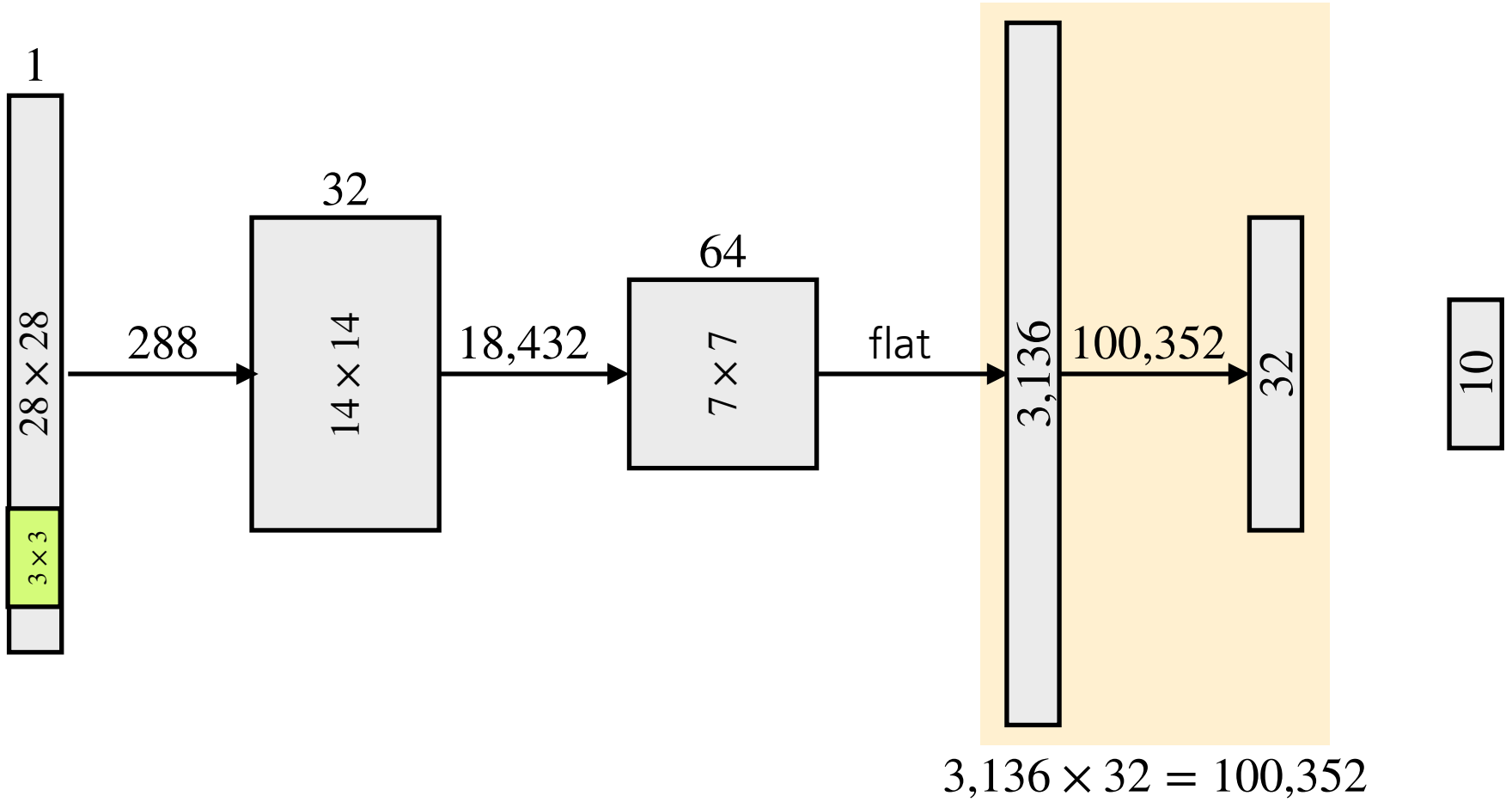


Convolutional Neural Network

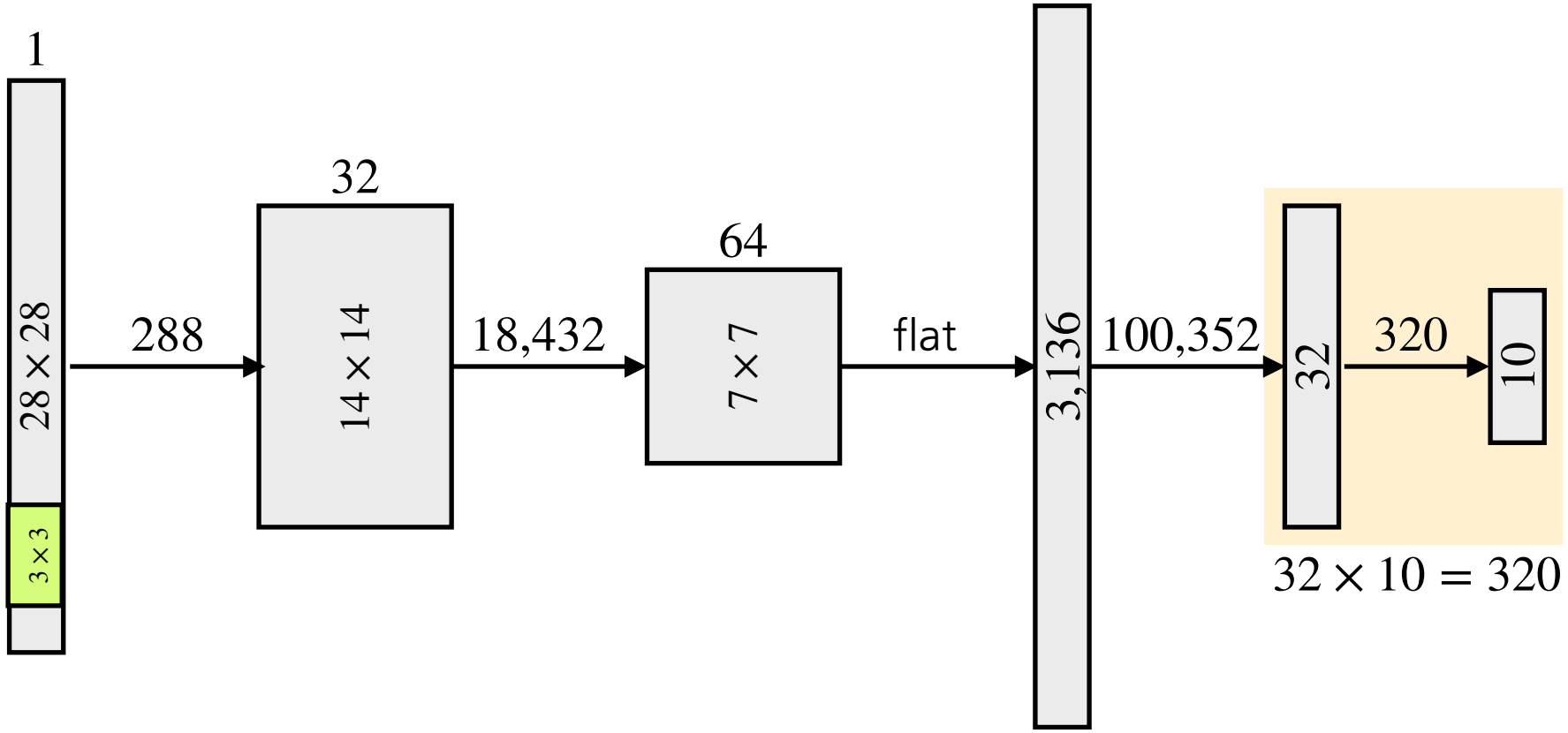


No parameter

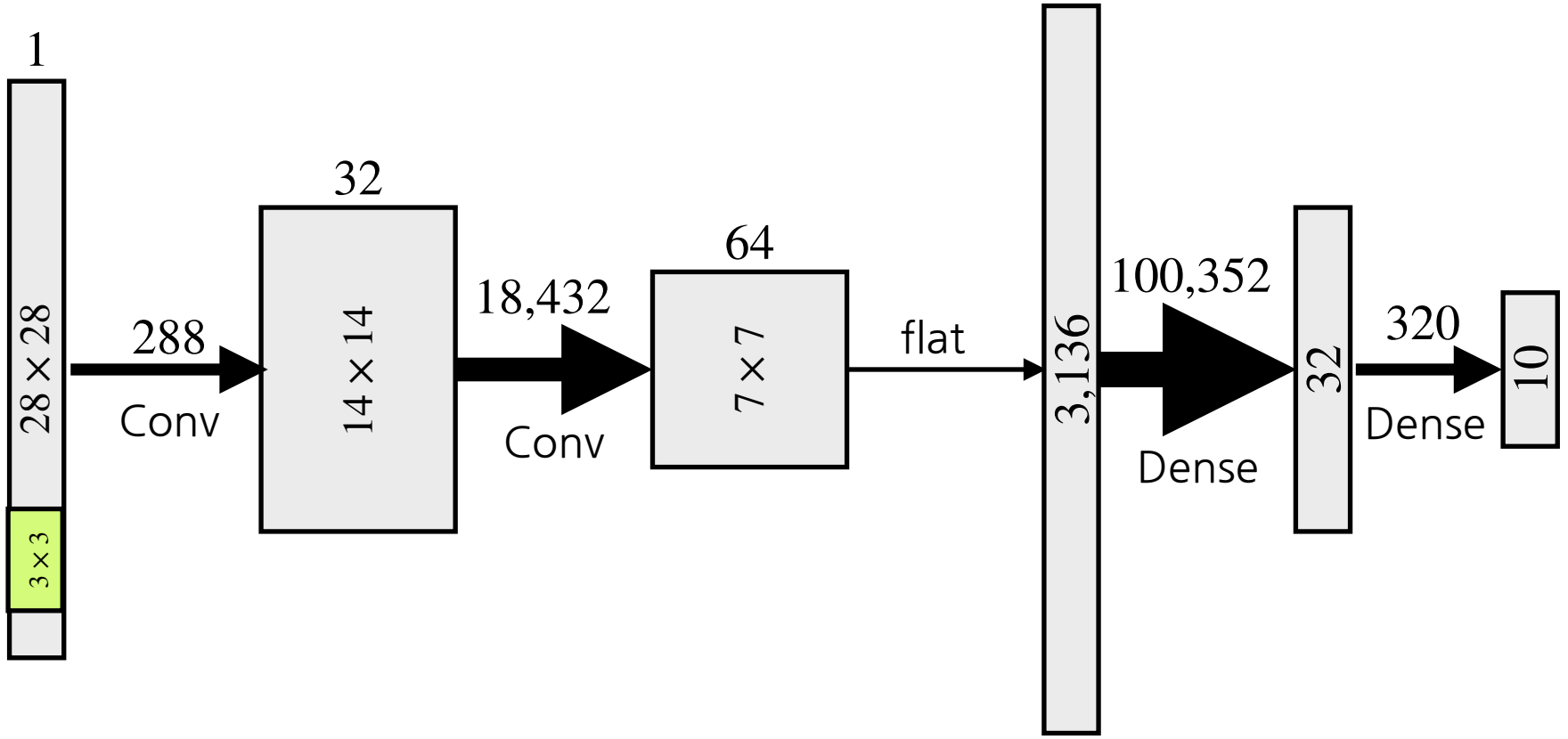
Convolutional Neural Network



Convolutional Neural Network



Convolutional Neural Network



PyTorch Implementation

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https://github.com/sjchoi86/yet-another-pytorch-tutorial-v2

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Modern CNNs

History

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- The introduction of LeNet in 1995 introduced CNNs to computer vision and machine learning communities.
- However, CNNs did not immediately dominate the field until AlexNet in 2012.
- Back in the day, classical pipelines looked more like this:
  - Obtain an interesting dataset.
    - For instance, the Apple QuickTake 100 of 1994 supported 640x480 resolution (VGA), capable of storing up to 8 images, for the price of $1,000.
  - Preprocess the dataset with hand-crafted features based on some knowledge of optics and geometry and occasionally on the serendipitous discoveries of lucky graduate students.
    - SIFT (scale-invariant feature transform) or SURF (speeded-up robust features)
  - Dump the resulting representation into your favorite classifier
    - A linear model or kernel method

Apple QuickTake 100

Representation Learning

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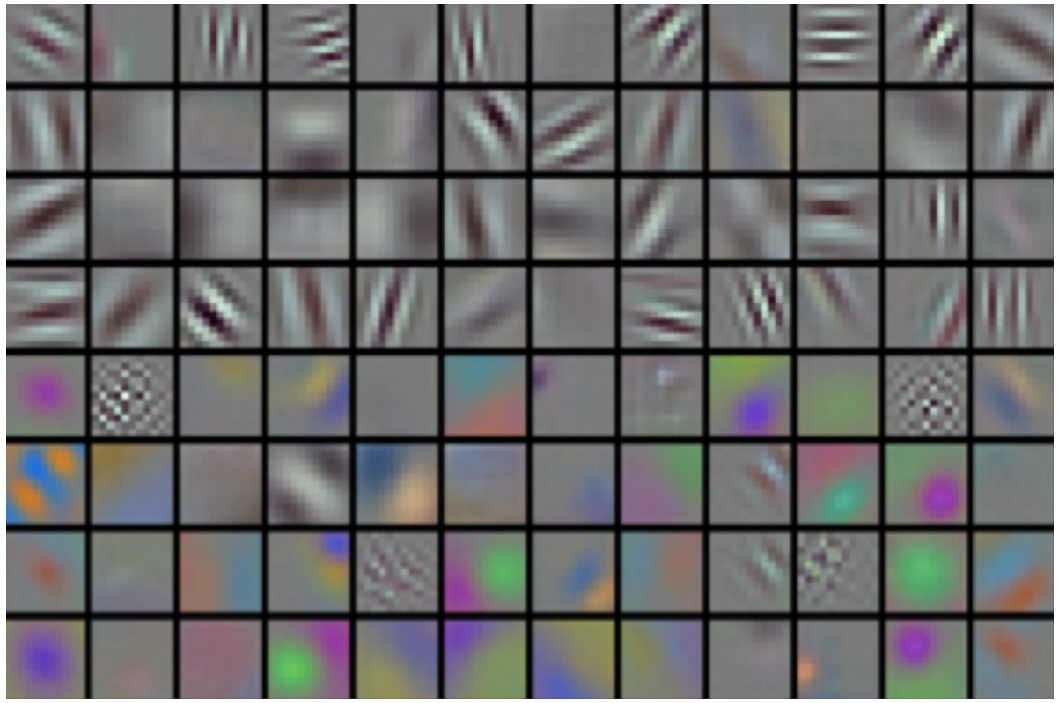

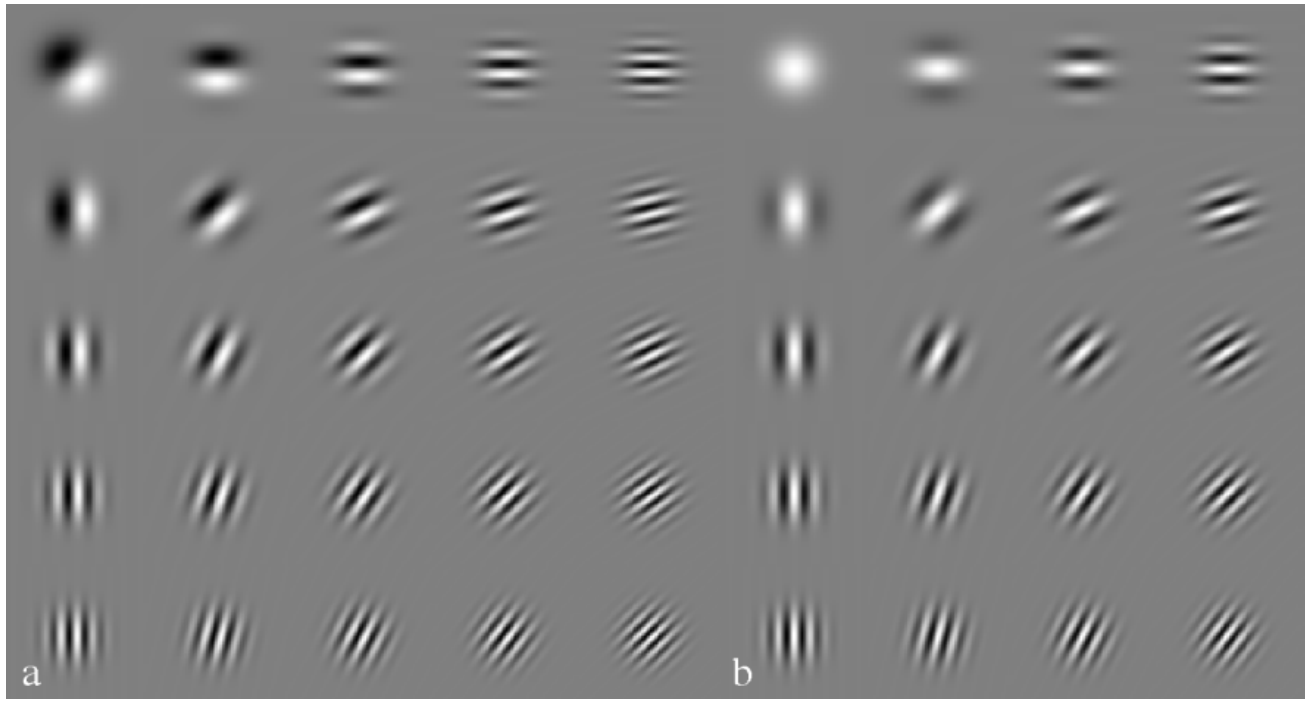

- The left figure shows image filters learned by the first layer of AlexNet.
- Interestingly, in the lowest layers of the network, the model learned feature extractors that resembled some traditional filters, as shown in the right figure.

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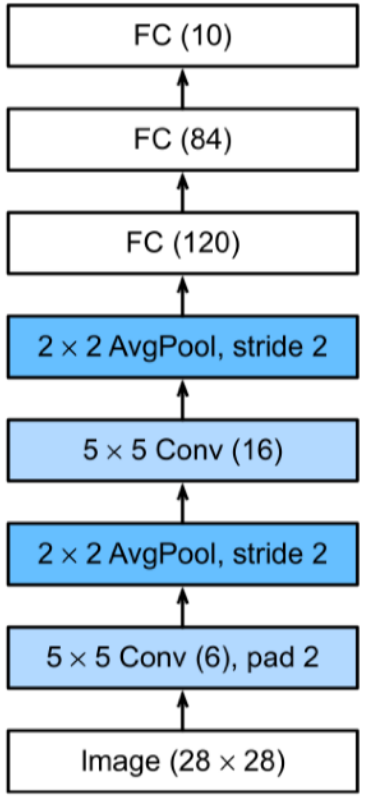
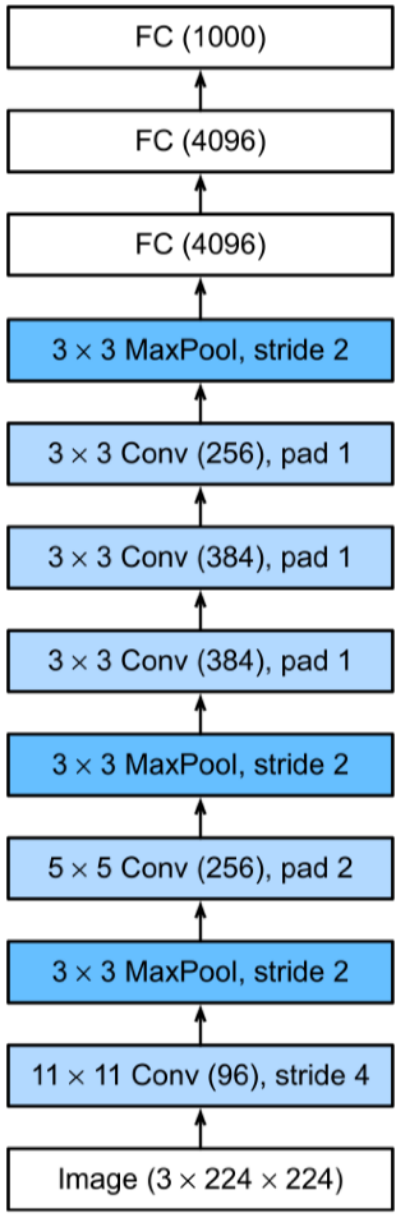
AlexNet

"ImageNet Classification with Deep Convolutional Neural Networks," 2012

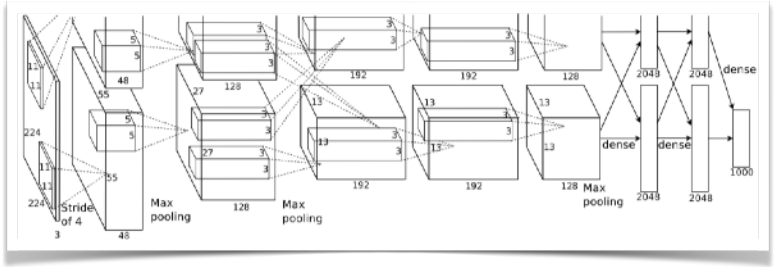
Architecture



LeNet



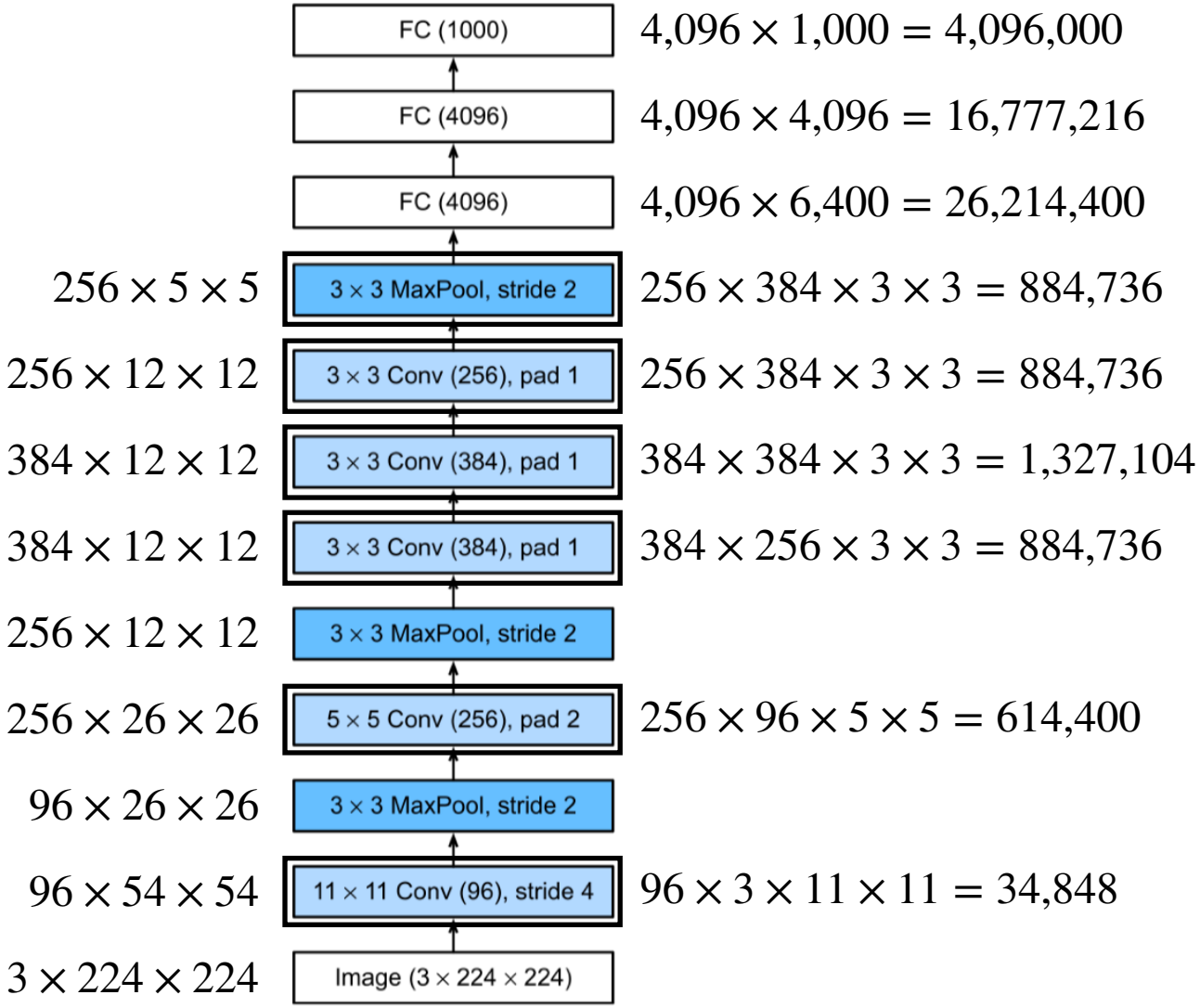
AlexNet



(Original) AlexNet

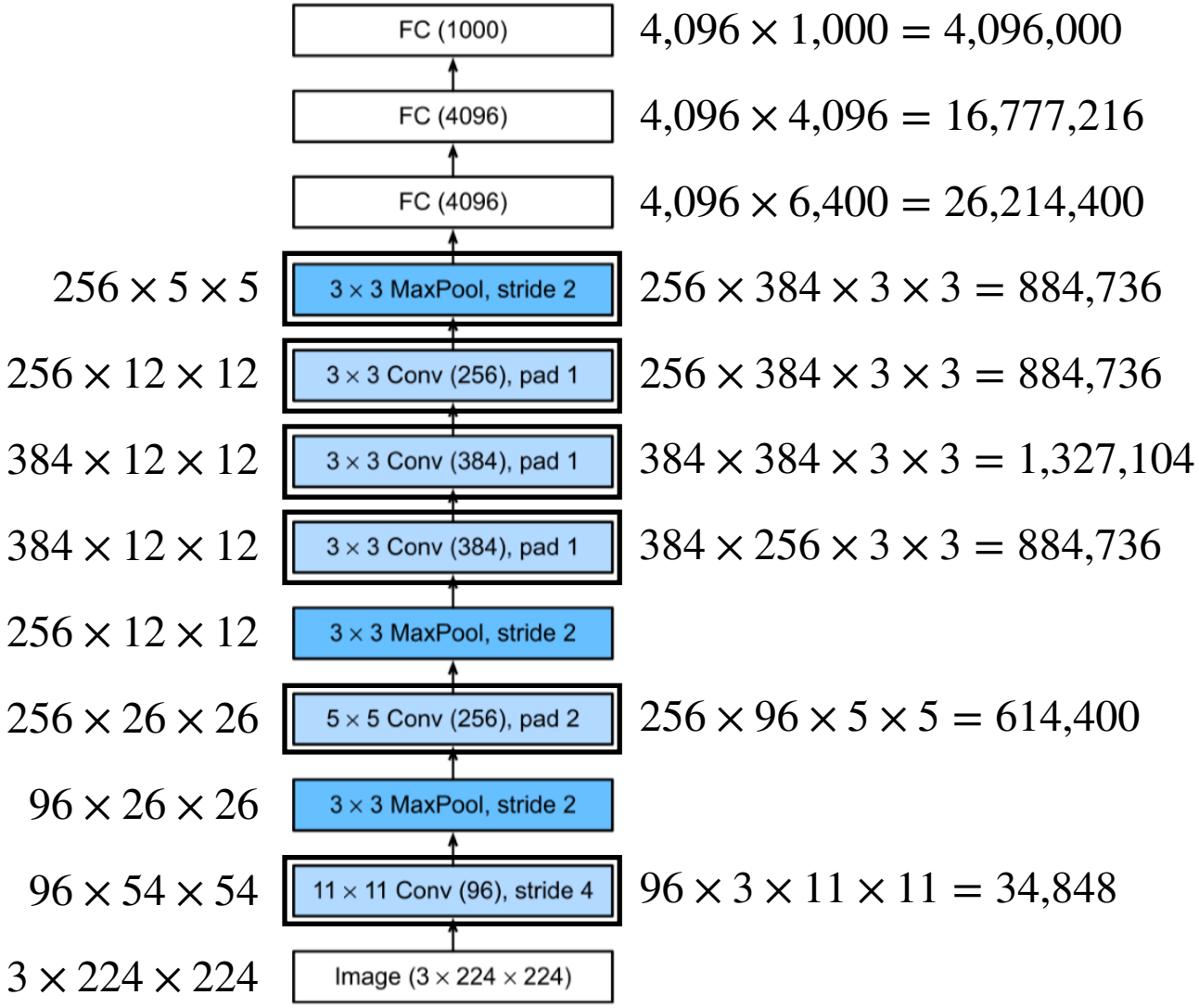
Architecture

- Kernel: [out_channels x in_channels x kernel_height x kernel_width]



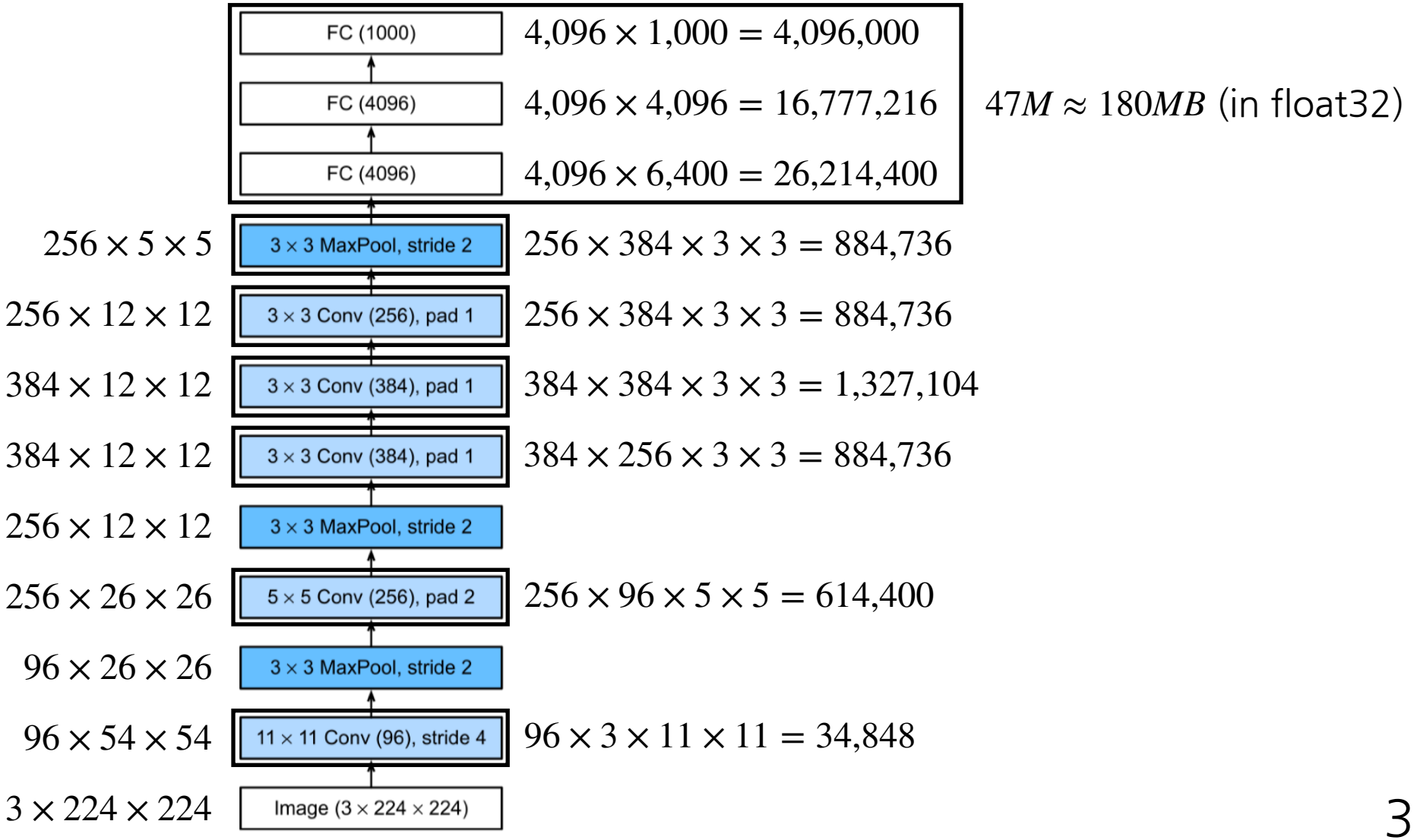
Architecture

- Kernel: [out_channels x in_channels x kernel_height x kernel_width]



Architecture

- Kernel: [out_channels x in_channels x kernel_height x kernel_width]



Implementation Details

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- For activation functions, the ReLU activation function is used.
- Data augmentation is based on perturbing RGB pixel values.
- Dropout is used.
- The amount of parameters to be trained (40 million) by far exceeds the amount of training data.
    - However, there is hardly any overfitting.. why?

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VGG

"Very Deep Convolutional Networks for Large-Scale Image Recognition," 2015

VGG

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Visual **G**eometry **G**roup (VGG) at Oxford University

VGG Blocks

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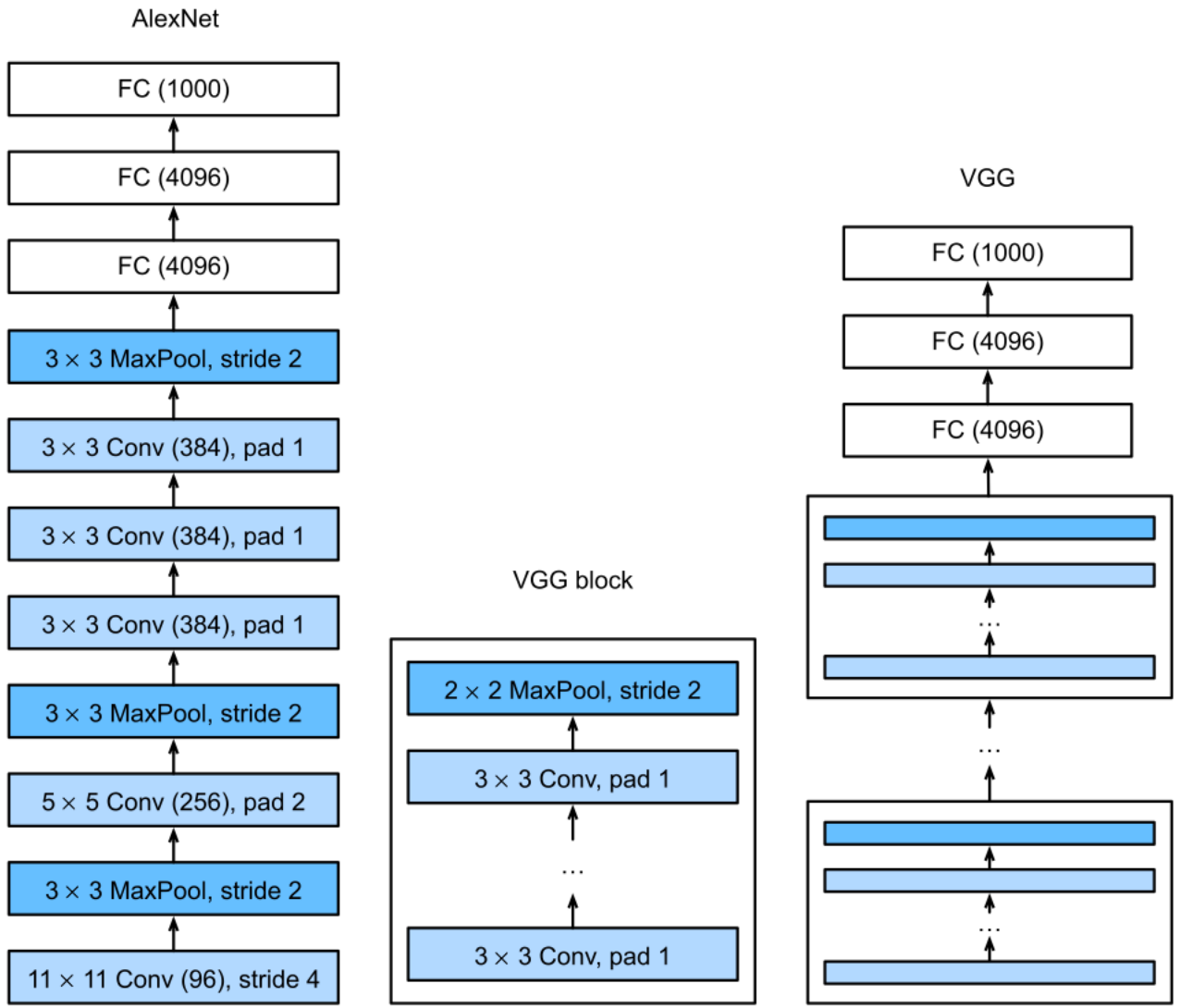
- Basic building blocks
  - a convolutional layer with padding to maintain the resolution
  - a nonlinearity such as a ReLU
  - a pooling layer such as max-pooling to reduce the resolution
- The key idea of VGG was to use multiple convolutions in between downsampling via max-pooling in the form of a block.

VGG Networks



Contribution

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- While AlexNet introduced many of the components of what makes deep learning effective at scale, it is VGG that arguably introduced key properties such as blocks of multiple convolutions and a preference for deep and narrow networks.
- It is also the first network that is actually an entire family of similarly parametrized models, giving the practitioner ample trade-off between complexity and speed.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

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GoogLeNet

"Going Deeper with Convolutions," 2015


THAT'S NOT ENOUGH
WE HAVE TO GO DEEPER

Multi-Branch Networks

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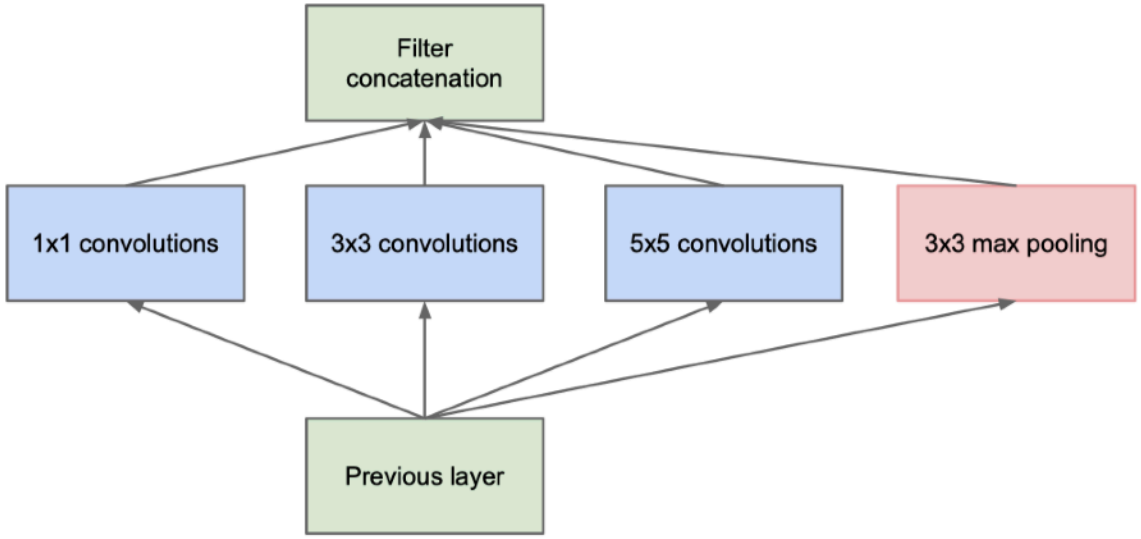
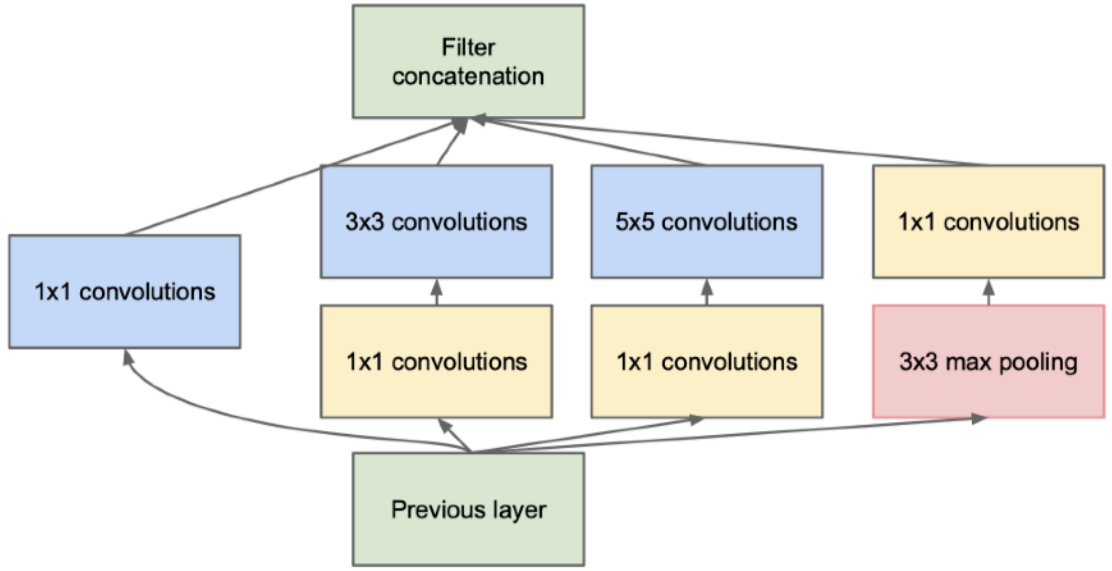
- In 2014, GooLeNet won the ImageNet Challenge.
- It is arguably also the first network that exhibits a clear distinction among the stem (data ingest), body (data processing), and head (prediction) in a CNN.
  - The **stem** is given by the first 2-3 convolutions that operate on the image
  - This is followed by a **body** of convolutional blocks.
  - Finally, the **head** maps the feature obtained so far to the required problem (e.g., classification or detection).
- The key contribution in GoogLeNet was the design of the **network body**.

Inception Blocks

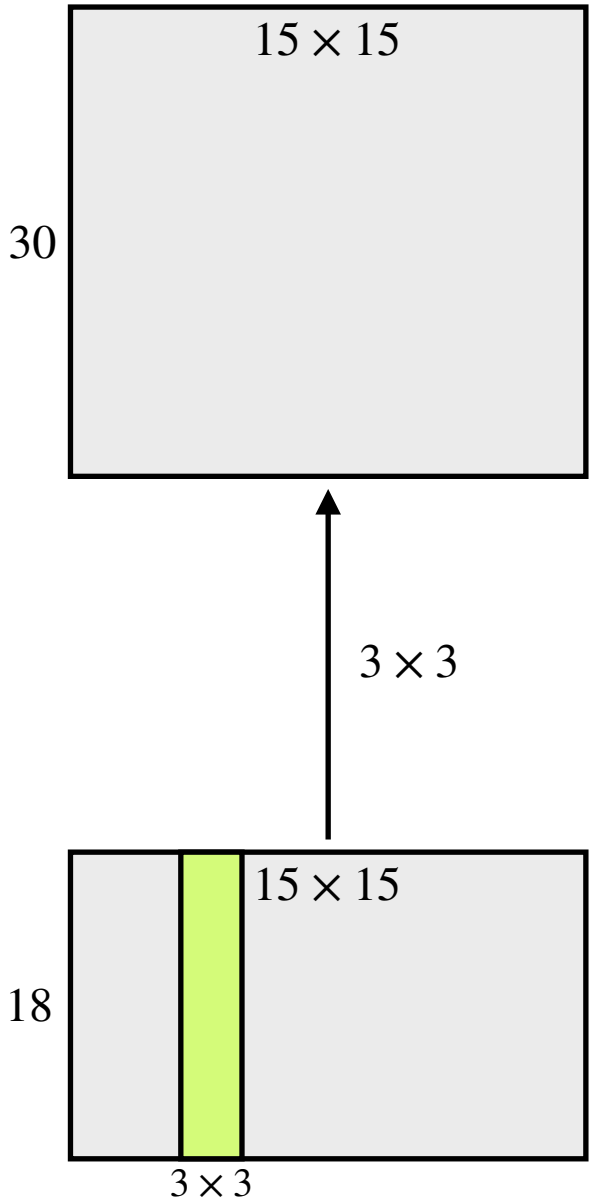


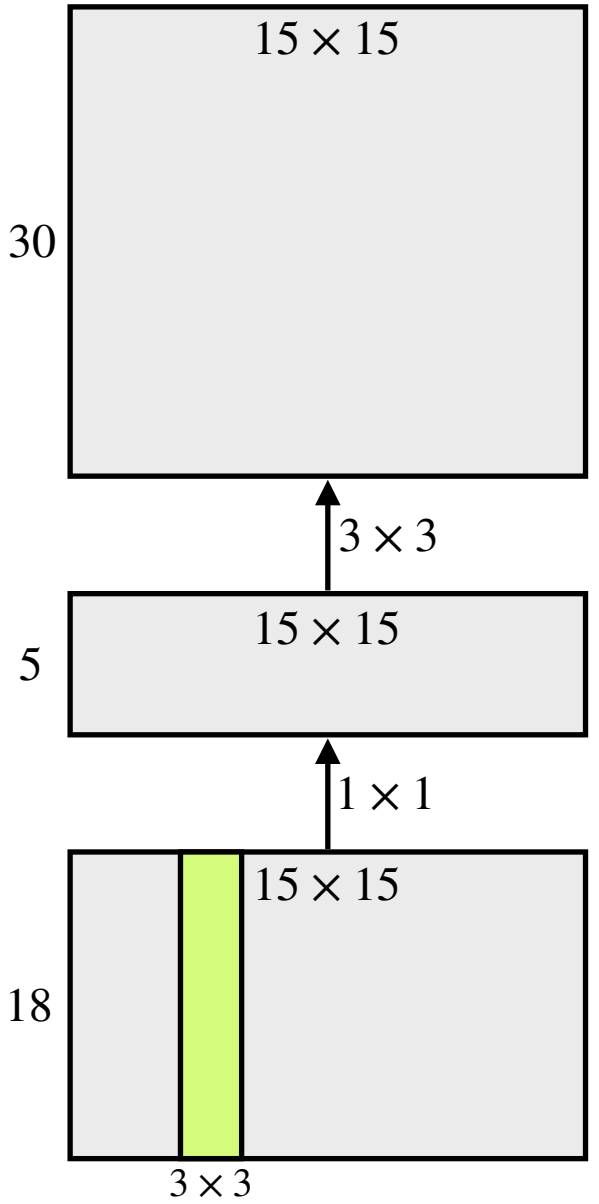
(a) Inception module, naïve version



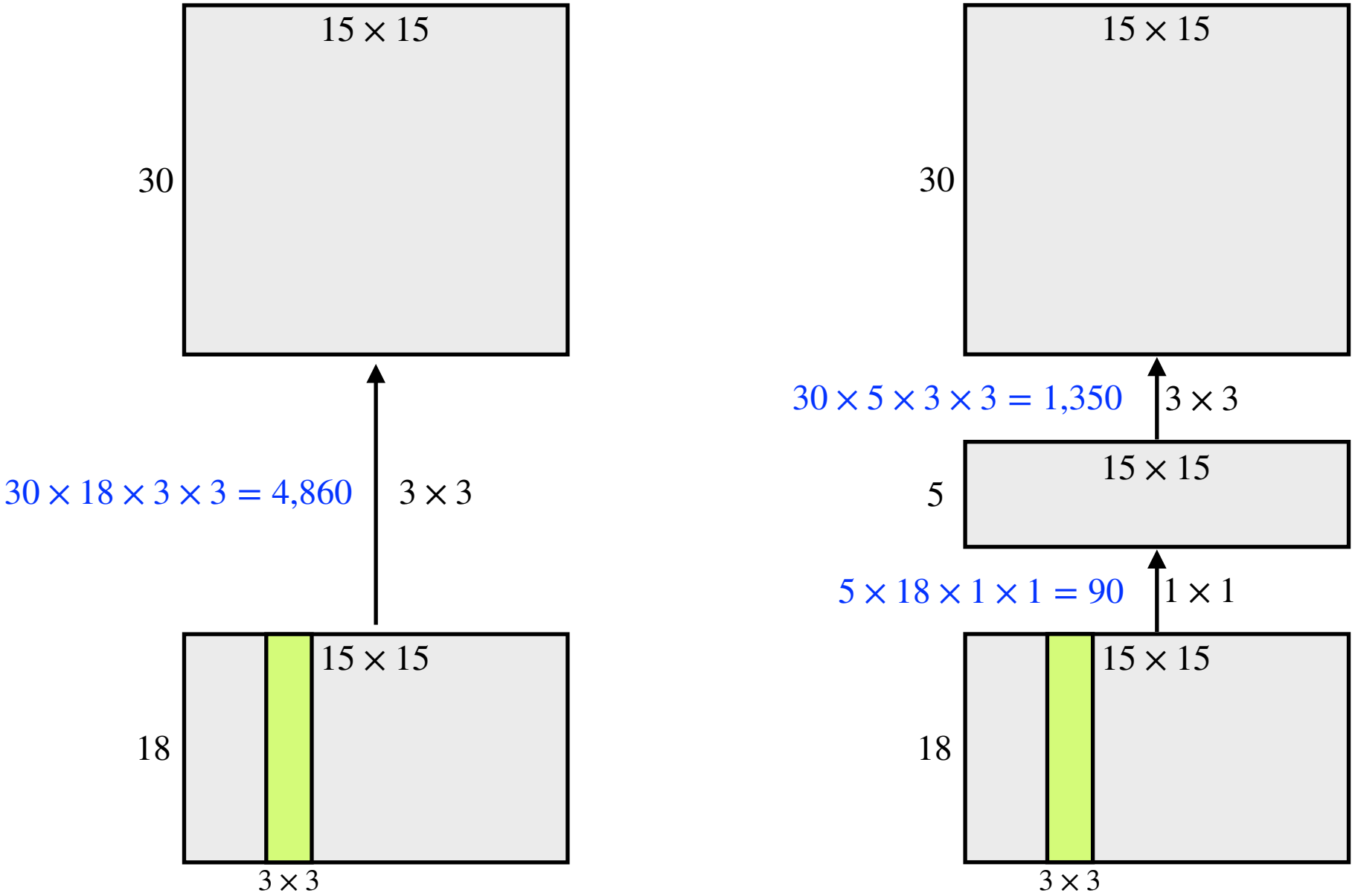
(b) Inception module with dimension reductions

Why adding 1x1 Convolution?

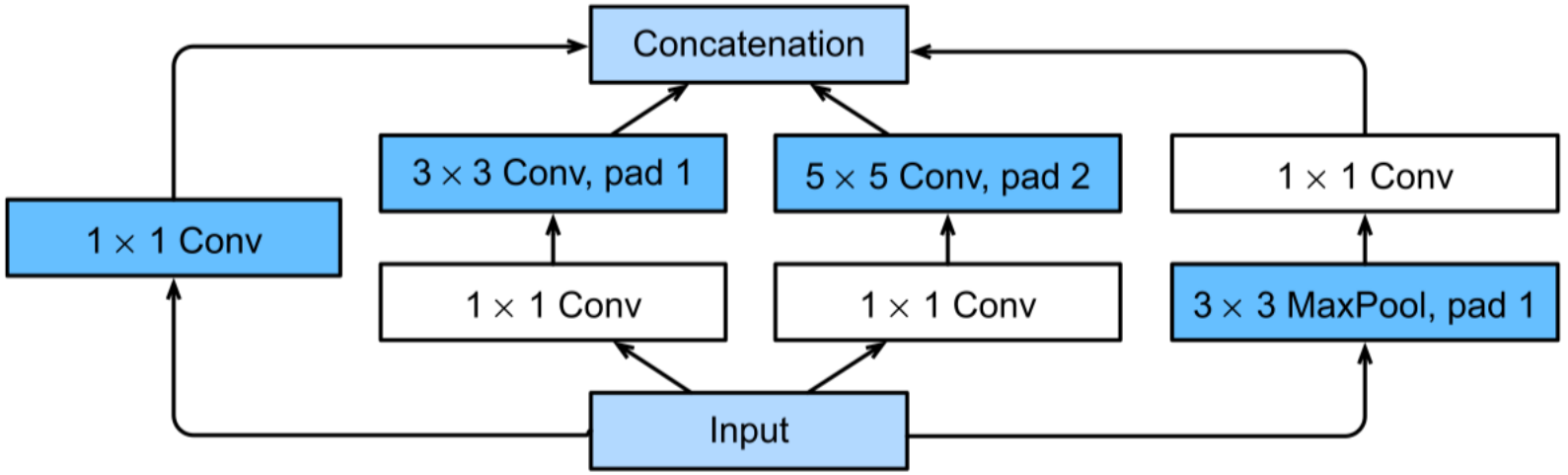




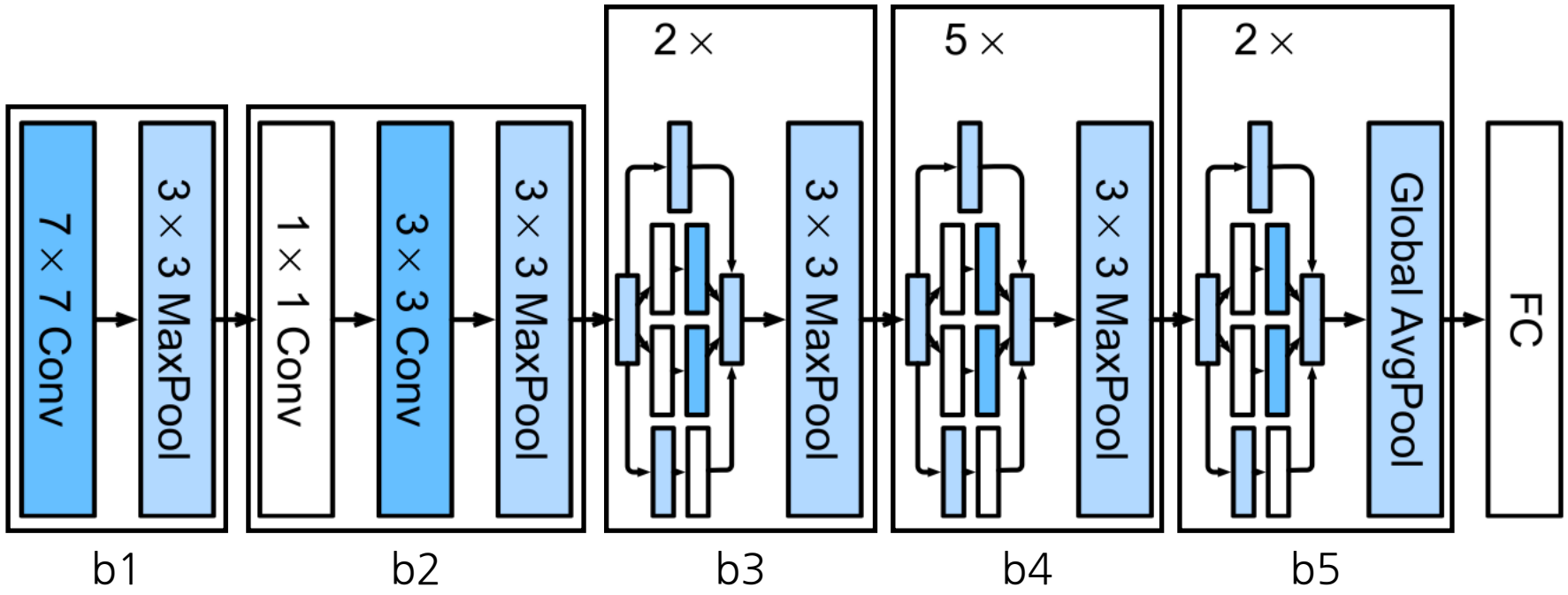
Why adding 1x1 Convolution?



Inception Blocks



Model


2 ×
5 ×
2 ×
7 × 7 Conv
3 × 3 MaxPool
1 × 1 Conv
3 × 3 Conv
3 × 3 MaxPool
3 × 3 MaxPool
3 × 3 MaxPool
Global AvgPool
FC
b1
b2
b3
b4
b5

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ResNet

"Deep Residual Learning for Image Recognition," 2016

A degradation problem

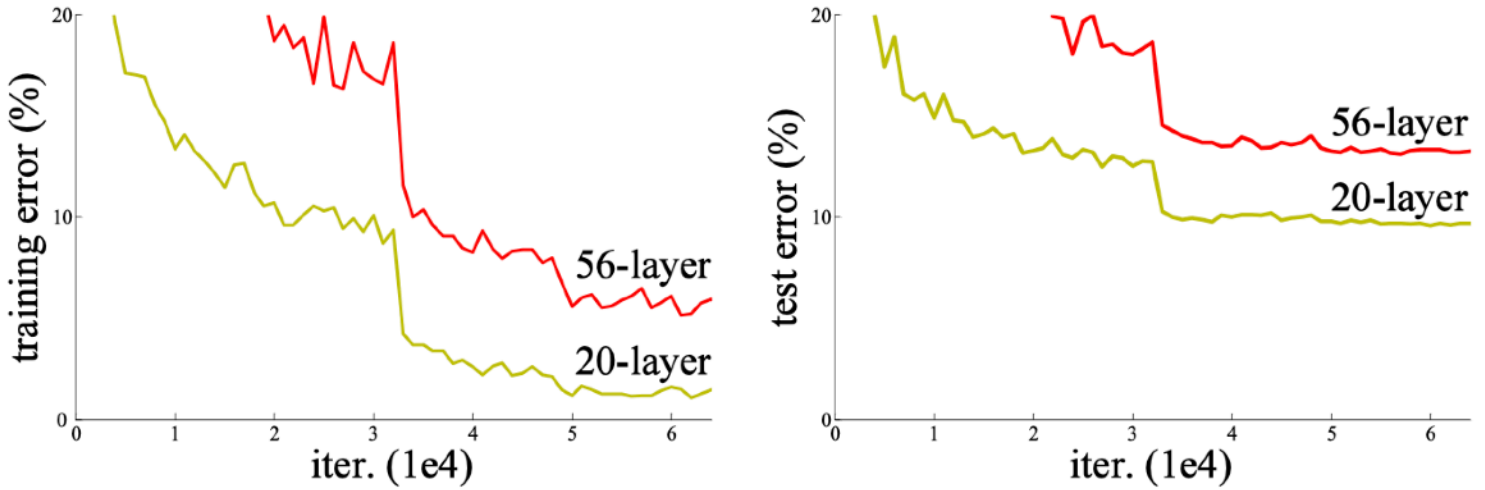

Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

- The **degradation** is not caused by overfitting, and adding more layers leads to higher training errors (and also higher test errors).

ResNet

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- ResNet won the ILSVRC in 2015.
- The key idea is that every additional layer should contain the identity function as one of its elements.

ResNet

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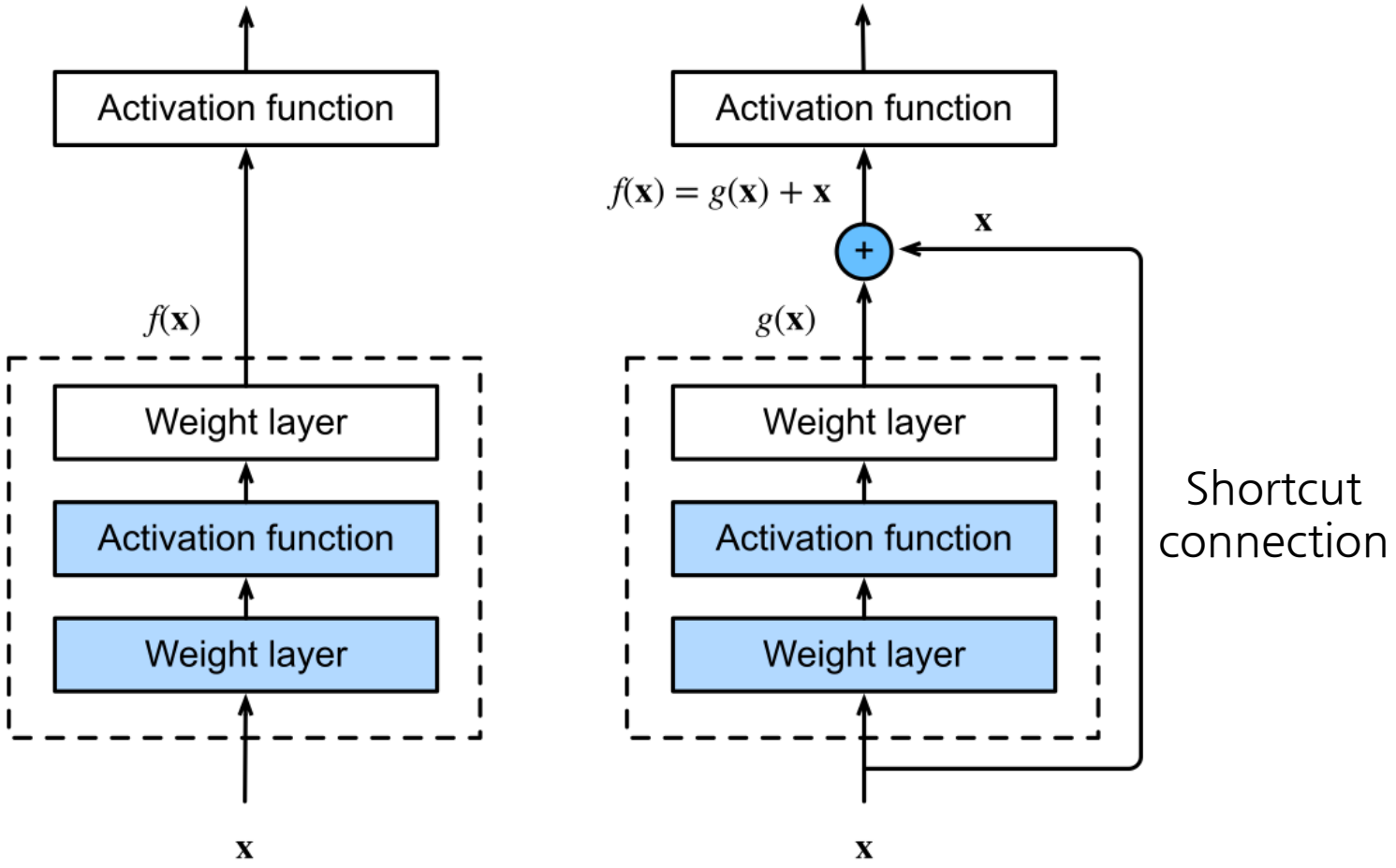
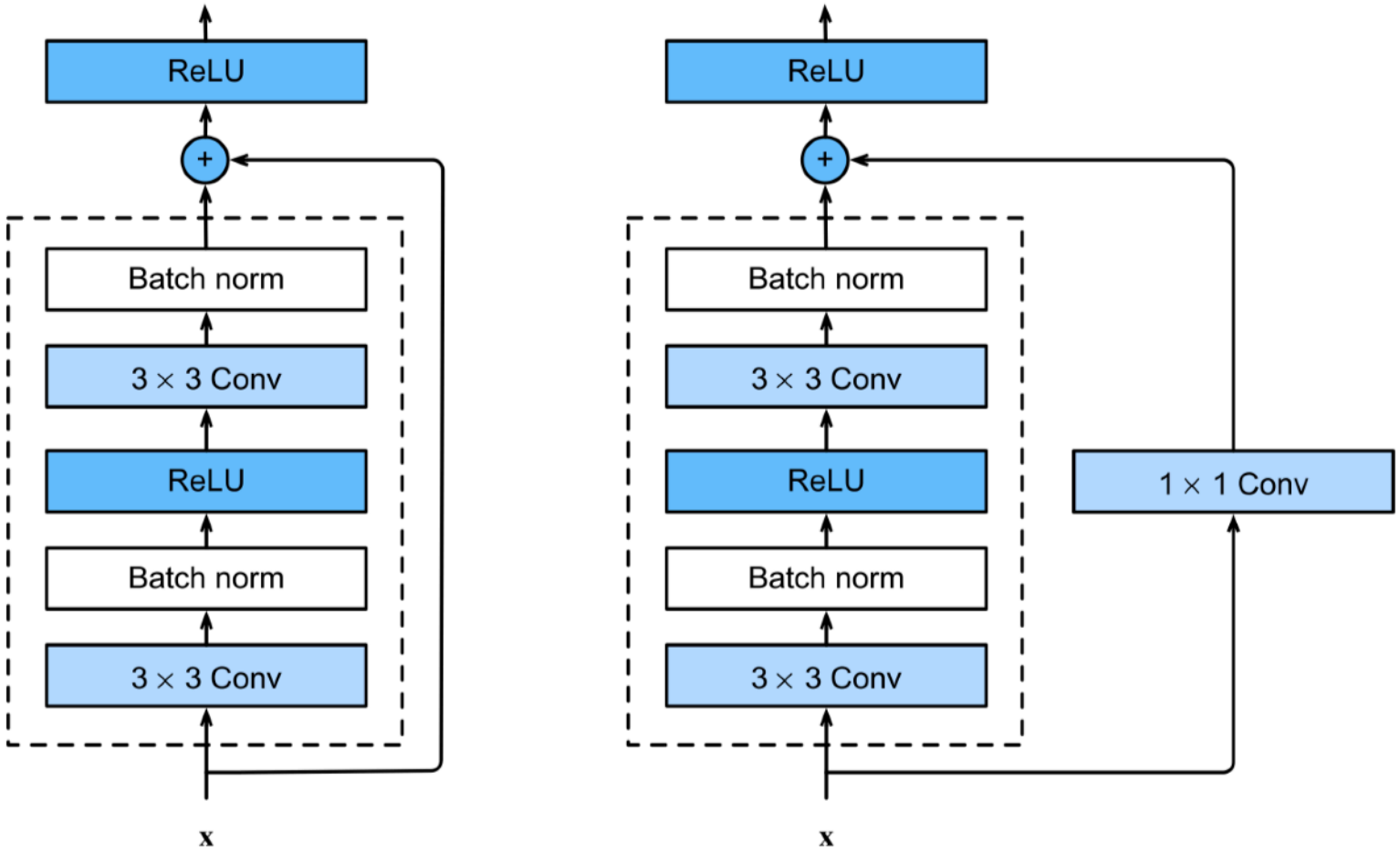
We hypothesize that it is easier to optimize the residual mapping than to optimize the original mapping.

Residual Blocks



Shortcut connection

Residual Blocks



- The order of operations matters.

Bottleneck Blocks

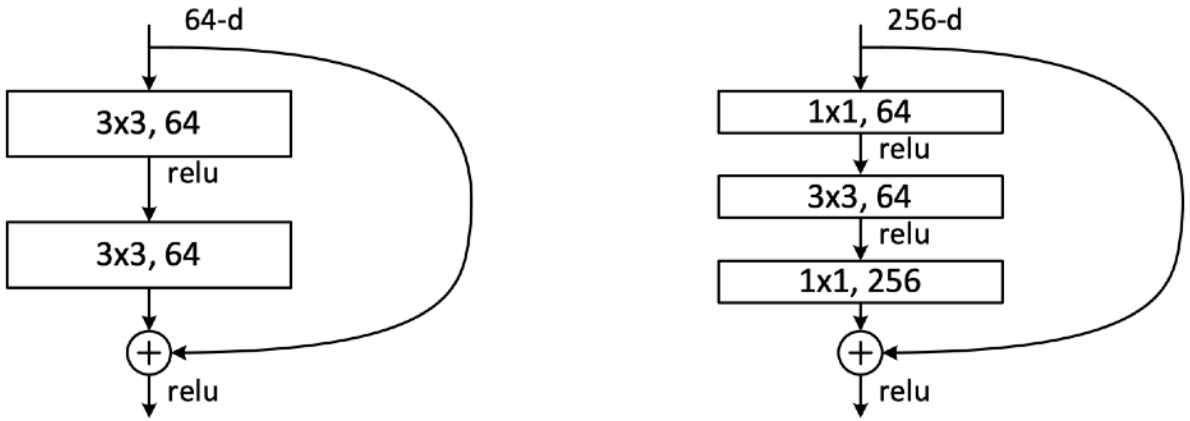
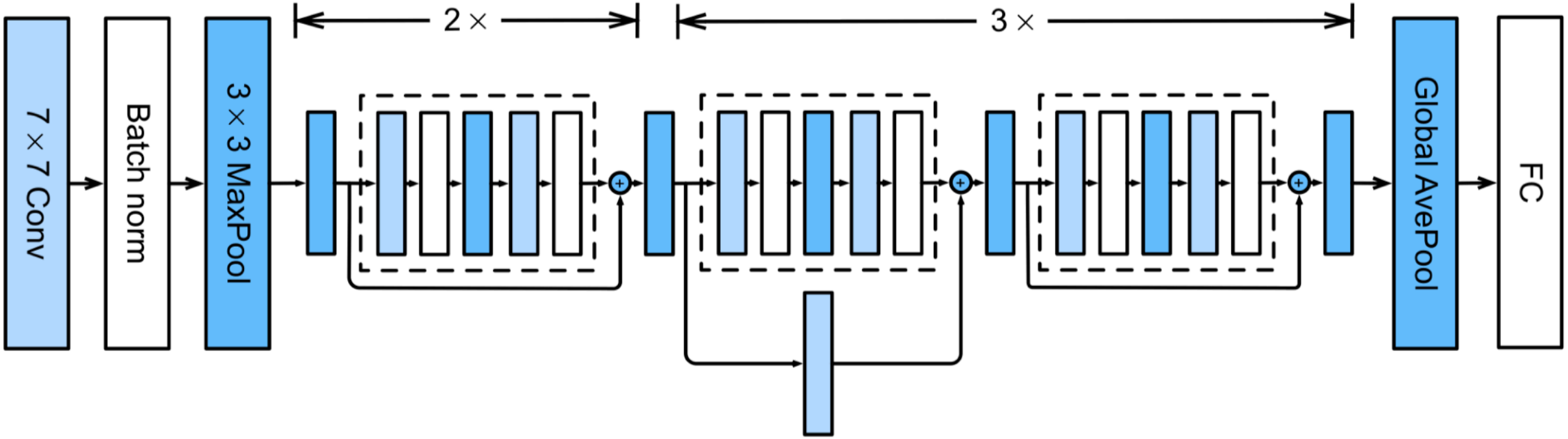


Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a "bottleneck" building block for ResNet-50/101/152.

ResNet-18



ImageNet Results

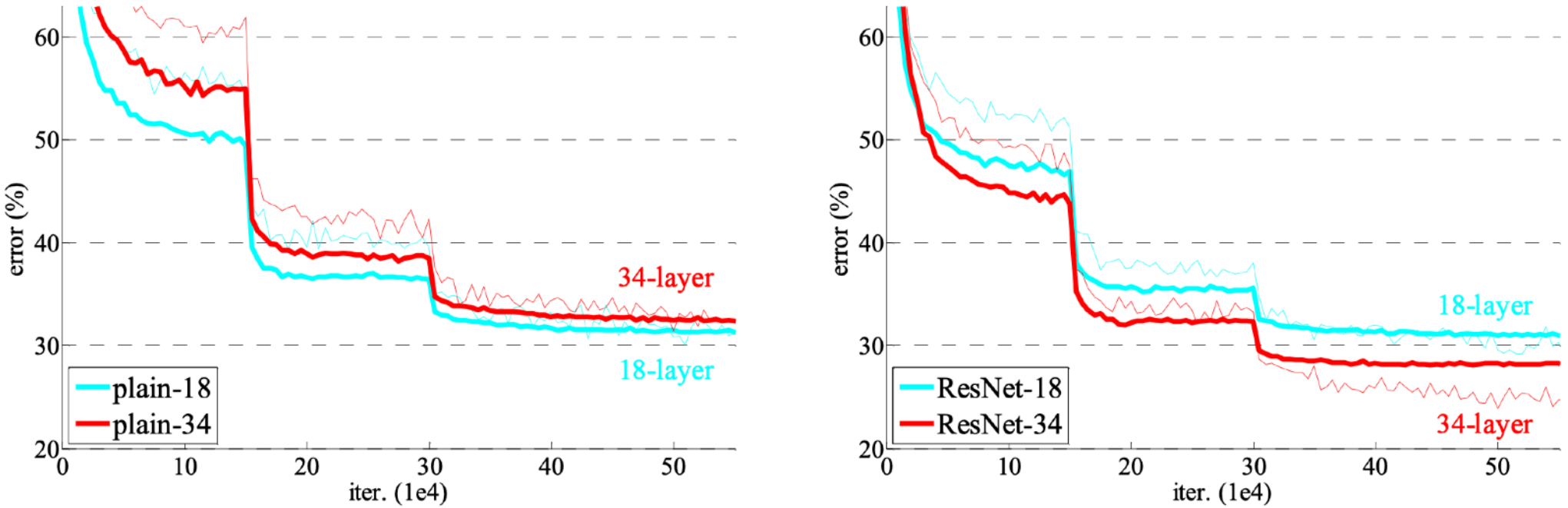


Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

CIFAR-10 Results

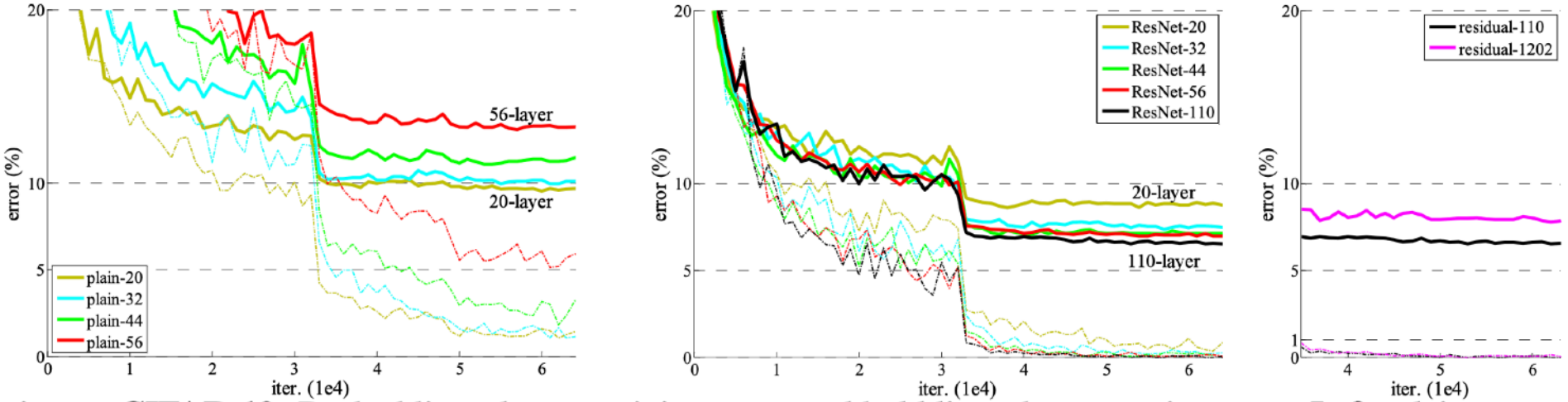


Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.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