CPEN 455: Deep Learning

Lecture 5: Convolutional Neural Networks II

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University of British Columbia

Winter, Term 2, 2024

Outline

- Invariance & Equivariance
- Convolution
  - 1D Convolution
  - Matrix Multiplication Views
  - Translation Equivariance
  - 2D Convolution
- Convolution Variants
  - **Transposed Convolution**
  - Dilated Convolution
  - Grouped Convolution
  - Separable Convolution
- Pooling
- Example Architectures

2D Transposed Convolution

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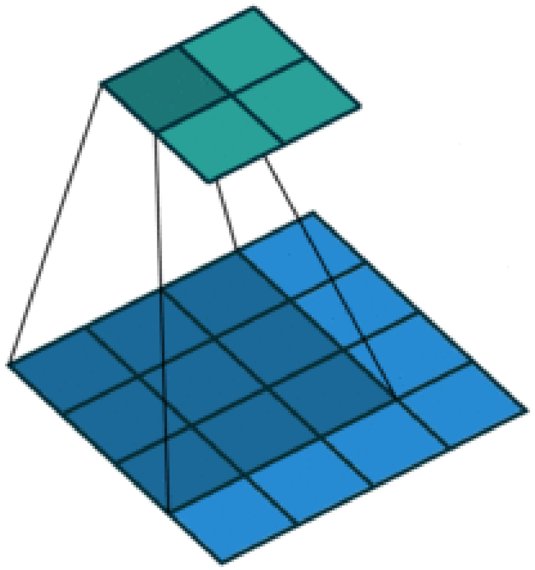
Shapes: 4x4 -> 2x2



2D Convolution
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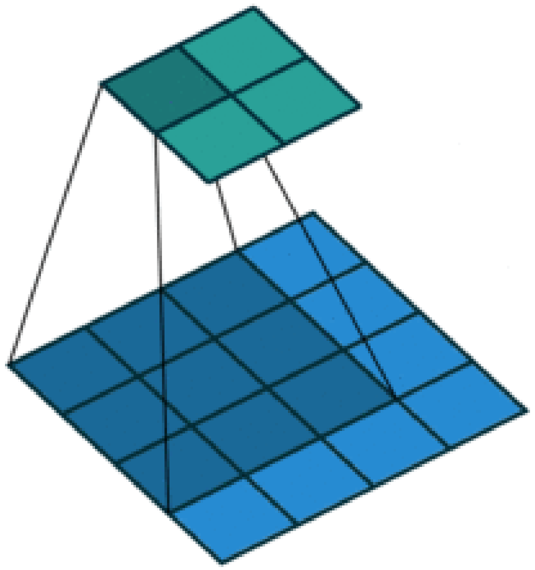

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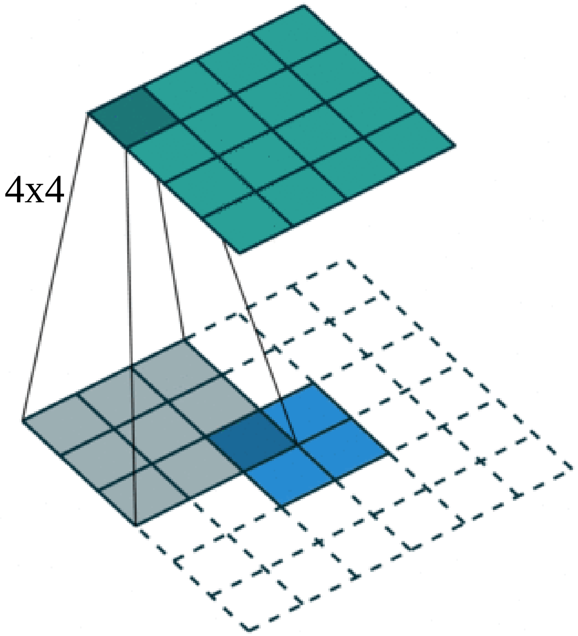
Shapes: 2x2 -> 4x4



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- Convolution and its transposed version are mutually inverse only w.r.t. shapes of input and output, but not w.r.t. values of input and output!

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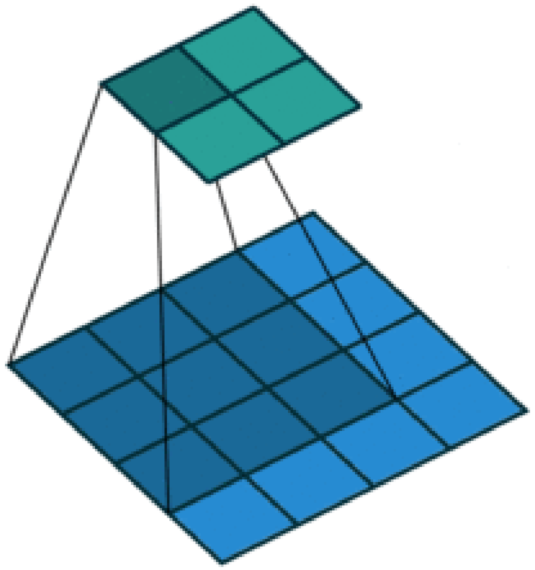

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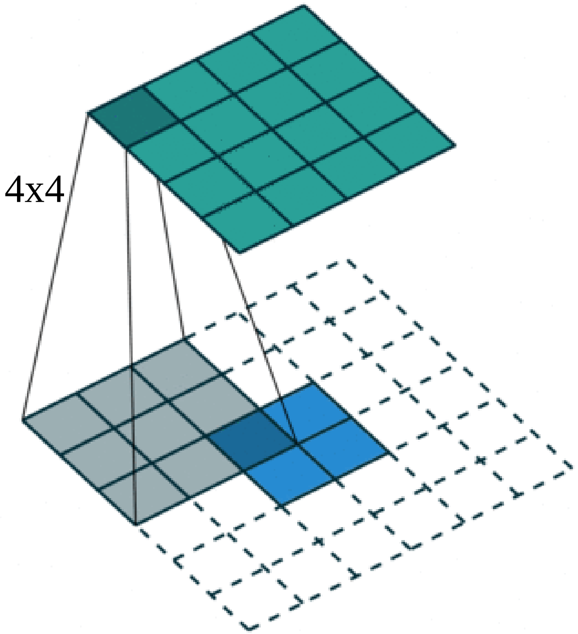

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- Convolution and deconvolution are mutually inverse w.r.t. values of input and output!

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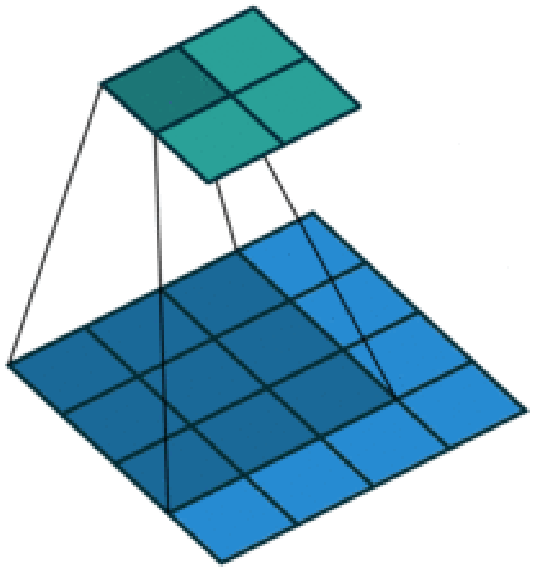

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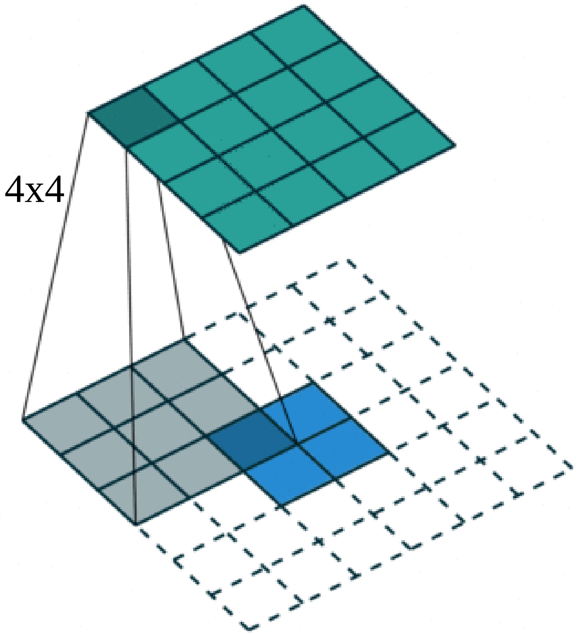

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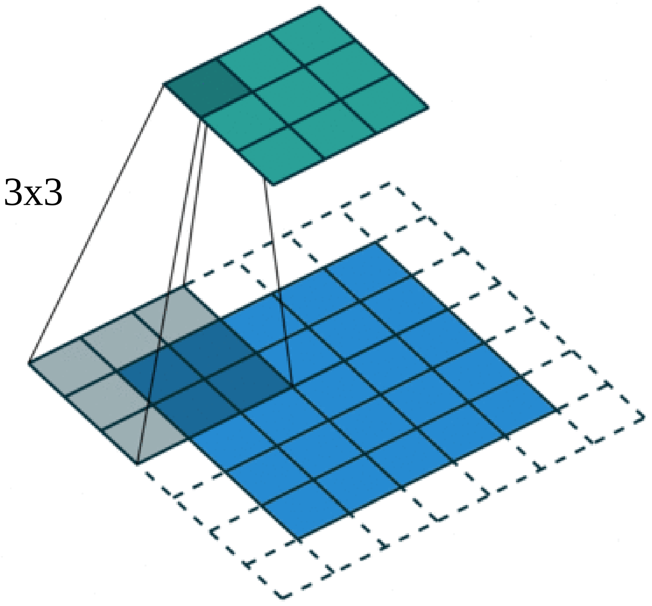
Try another example of 2D convolution (3x3 kernel):

Shapes: 5x5 -> 3x3



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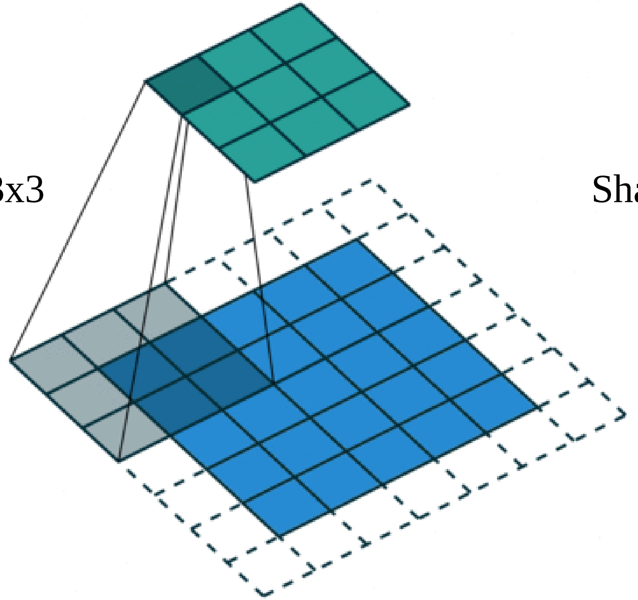

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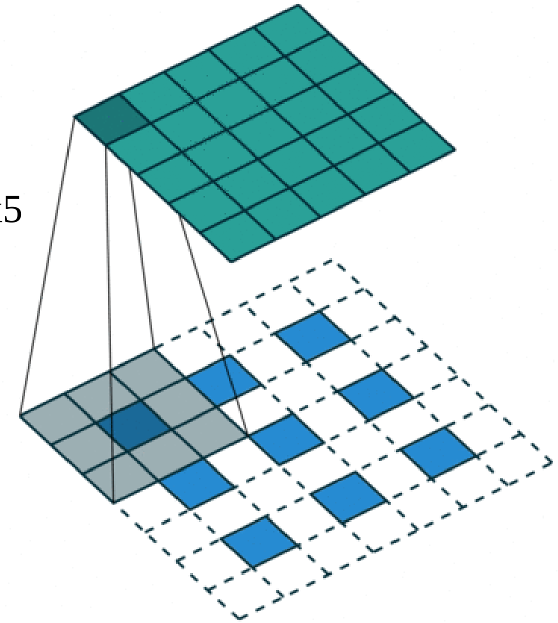
Shapes: 3x3 -> 5x5



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Transposed convolution is also known as fractionally strided convolution!

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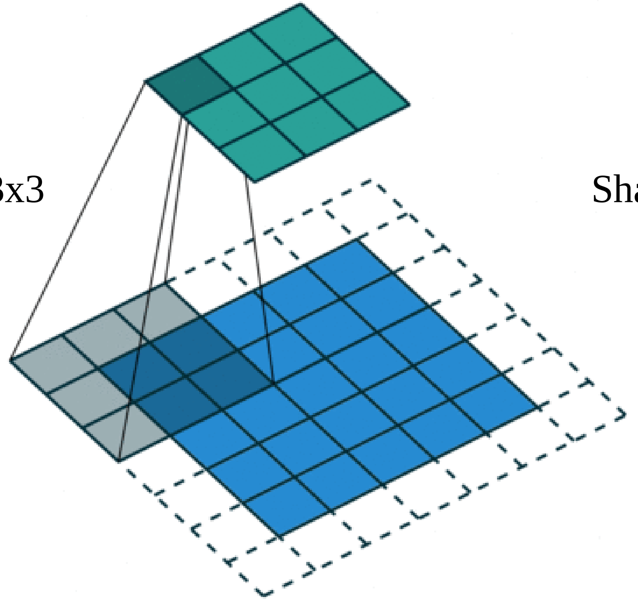

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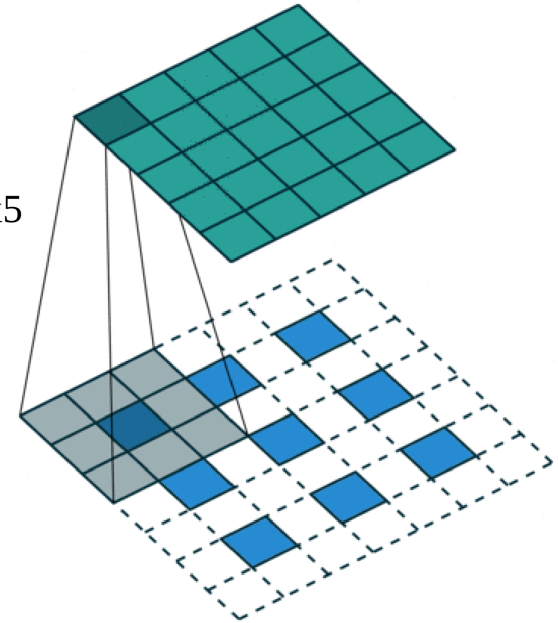

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In practice, we do not pad zeros in between and then perform convolution due to its high computational cost.

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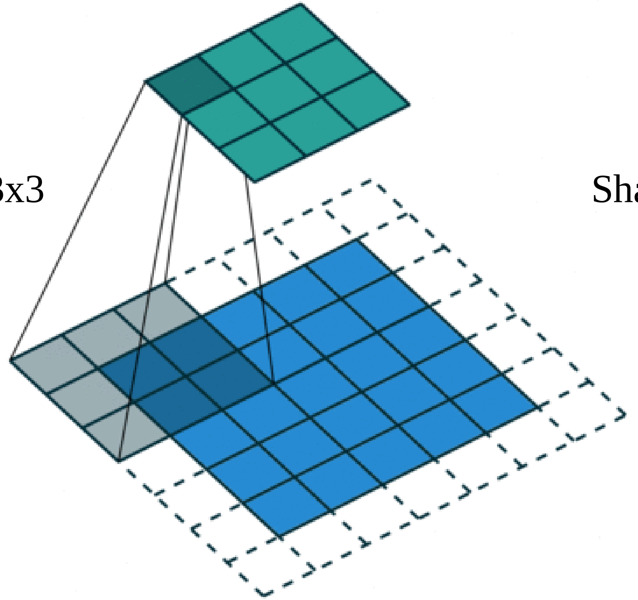

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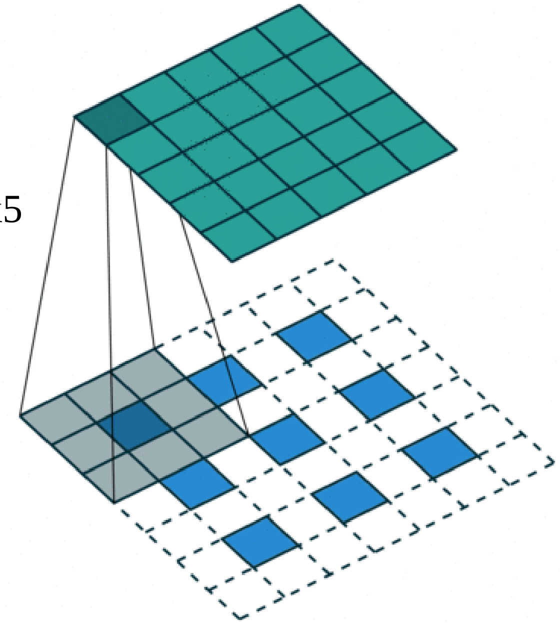

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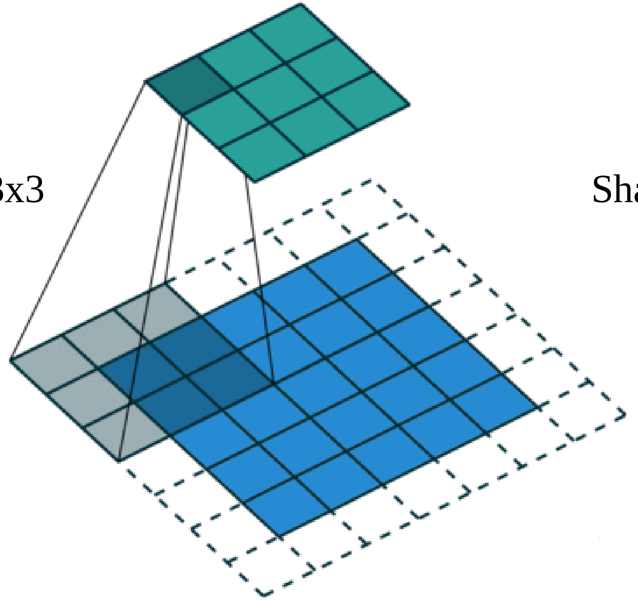
In practice, we do not pad zeros in between and then perform convolution due to its high computational cost. Instead, we leverage the gradient of convolution:

$$\mathbf{y} = W\mathbf{x} \qquad \text{Filter -> Matrix}$$

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = W$$

$$\hat{\mathbf{x}} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}}^{\top} y$$

Shapes: 5x5 -> 3x3



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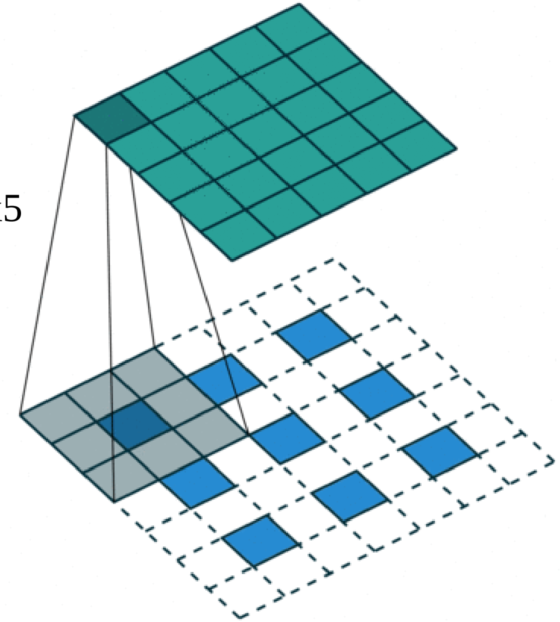

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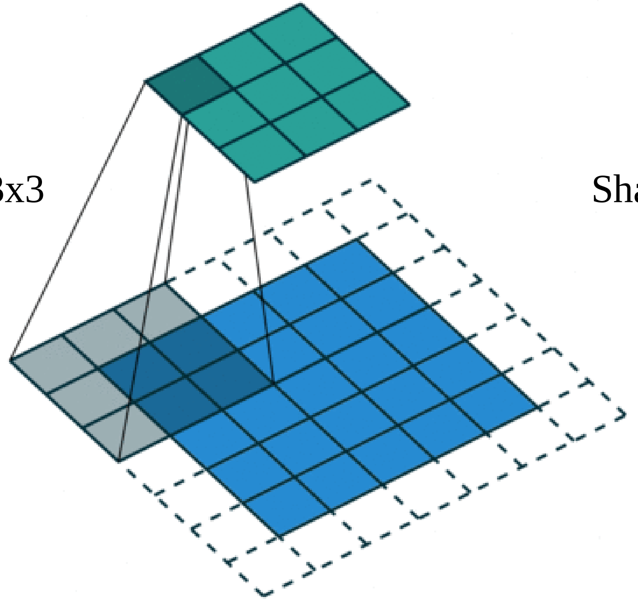

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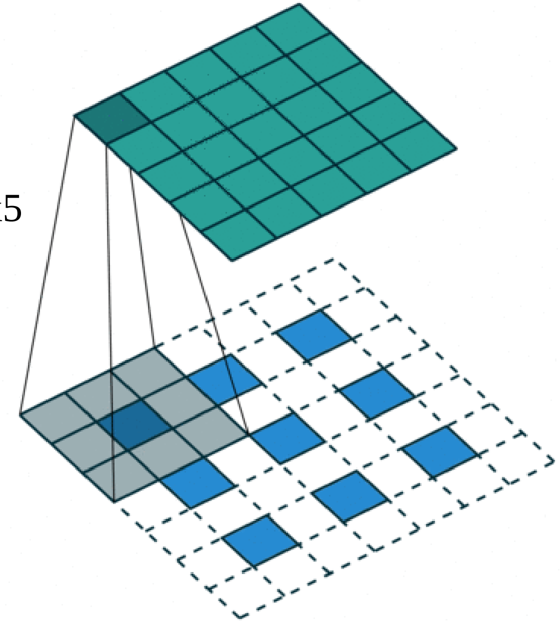

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This is why we need to specify the stride and padding of the corresponding convolution, e.g., in PyTorch.

For transposed convolution, stride is always 1 and we sometimes need (output) padding!

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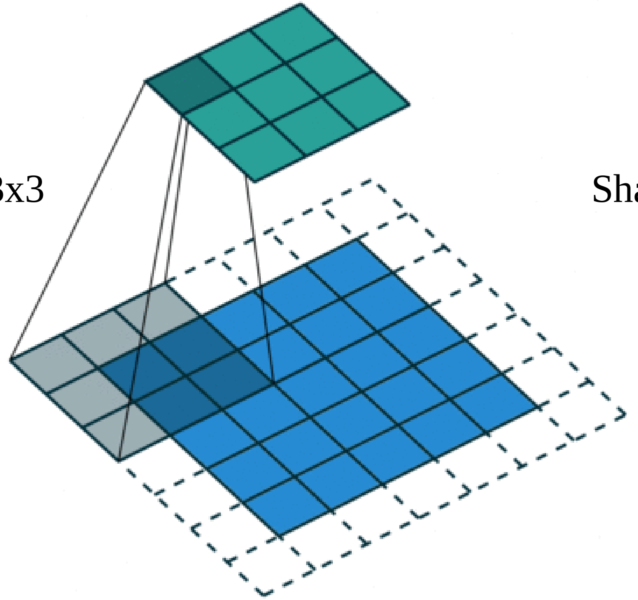

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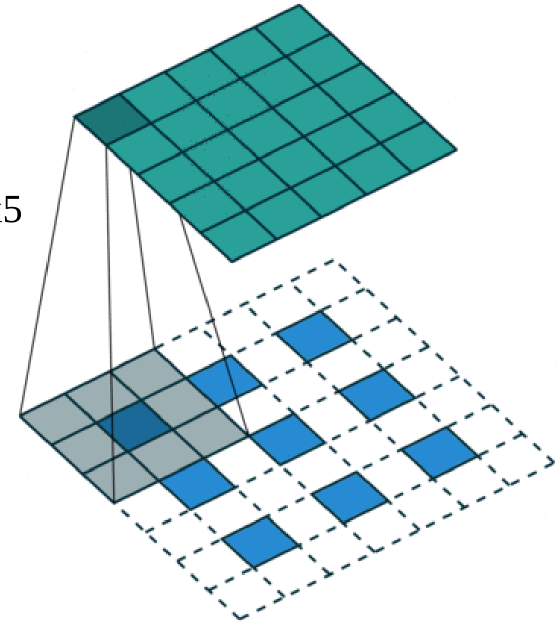

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The gradients of the following two convolutions have the same shape in im2patch (data-> toeplitz matrix) implementation.

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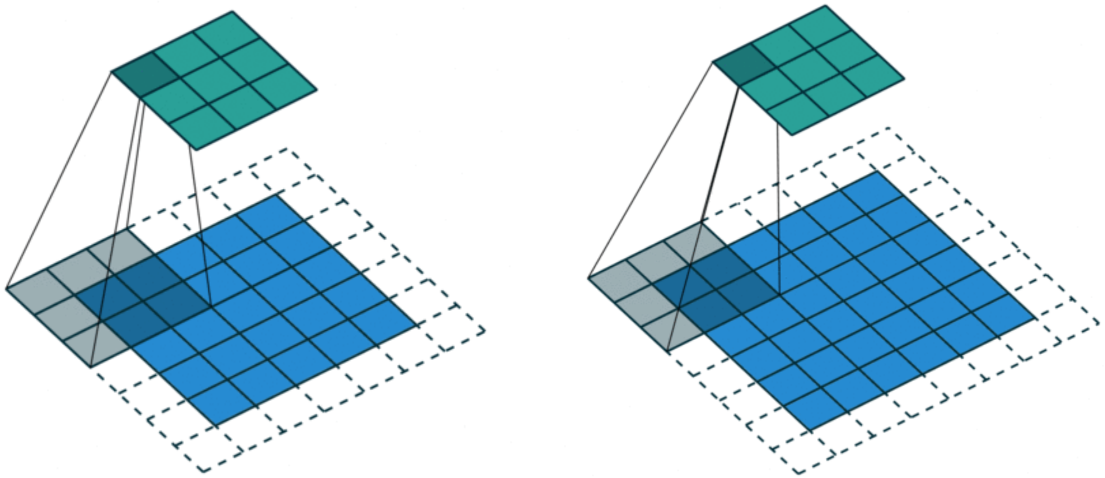

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To distinguish them and output correct shapes in their transposed convolutions, we add output padding on one side in the 2nd case.

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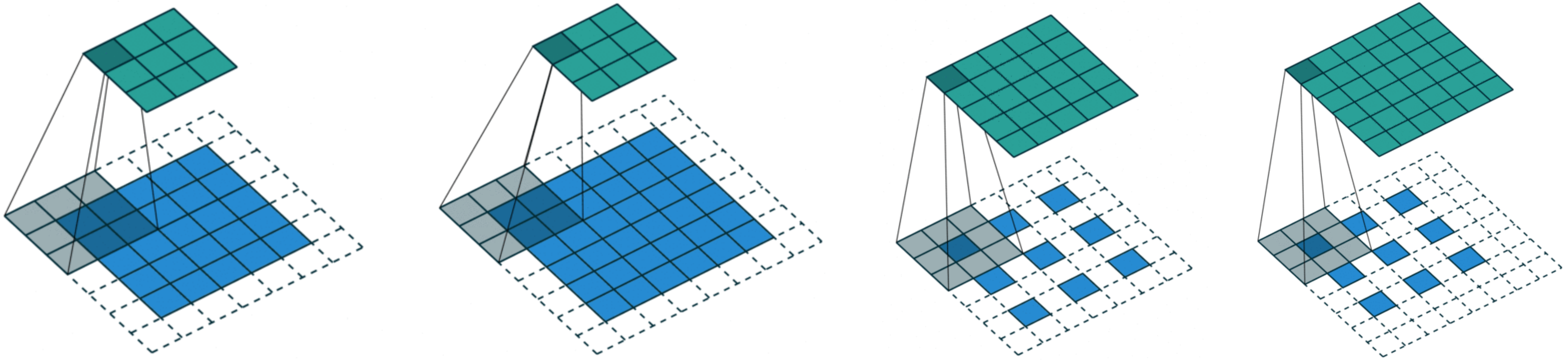

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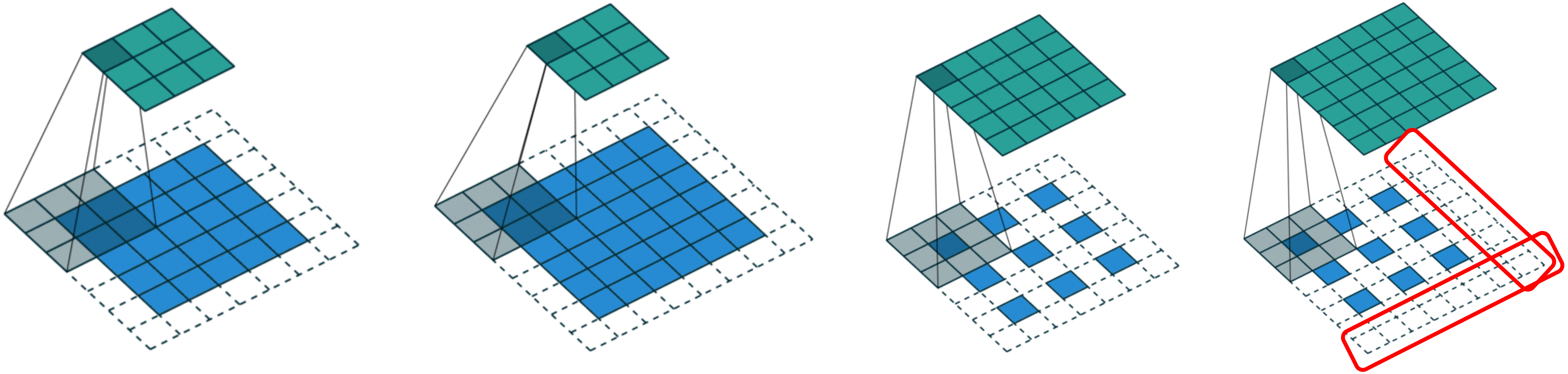

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2D Transposed Convolution

output padding=0 | output padding=1

Image Credit: [1]

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Take the API in PyTorch as an example

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Applies a 2D transposed convolution operator over an input image composed of several input planes.

This module can be seen as the gradient of Conv2d with respect to its input. It is also known as a fractionally-strided convolution or a deconvolution (although it is not an actual deconvolution operation as it does not compute a true inverse of convolution). For more information, see the visualizations here and the Deconvolutional Networks paper.

This module supports TensorFloat32.

On certain ROCm devices, when using float16 inputs this module will use different precision for backward.

- `stride` controls the stride for the cross-correlation.
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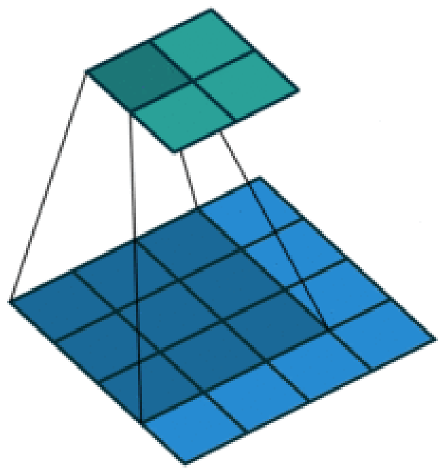

2D Convolution
(stride=1, padding=0)

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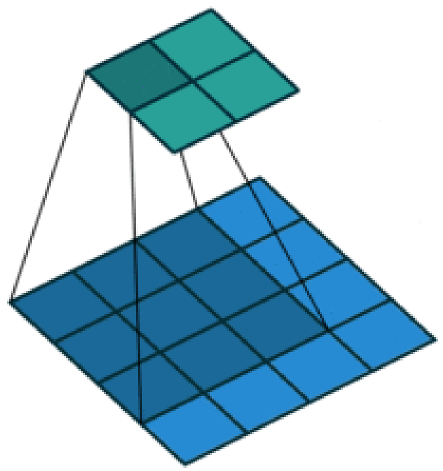

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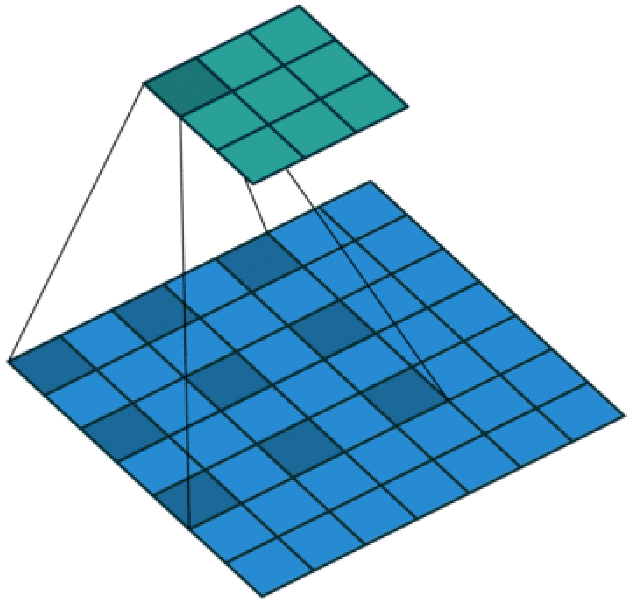

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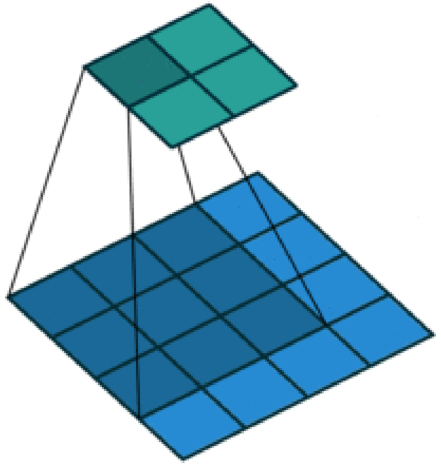
Suppose we have a 2D convolution:

By using dilated kernels, we effectively increase the receptive field (the region of input that affects the output)!



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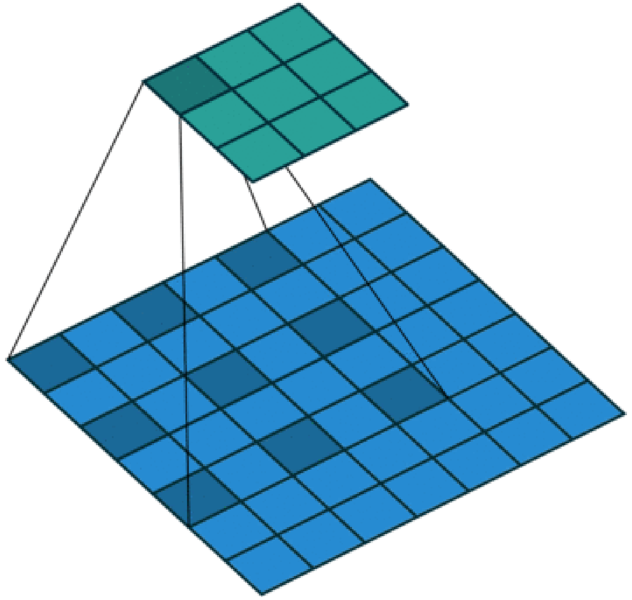

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It was first proposed in AlexNet [2]:

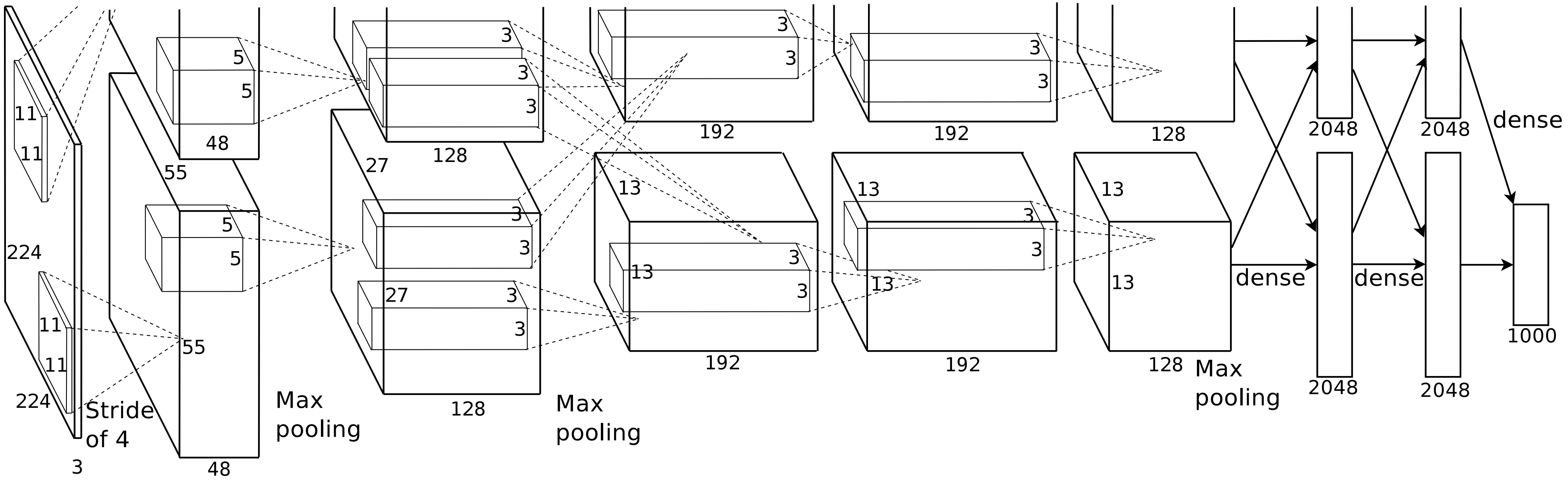

Image Credit: [2]

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Can we maintain the same shaped input and output in convolution with fewer number of parameters?

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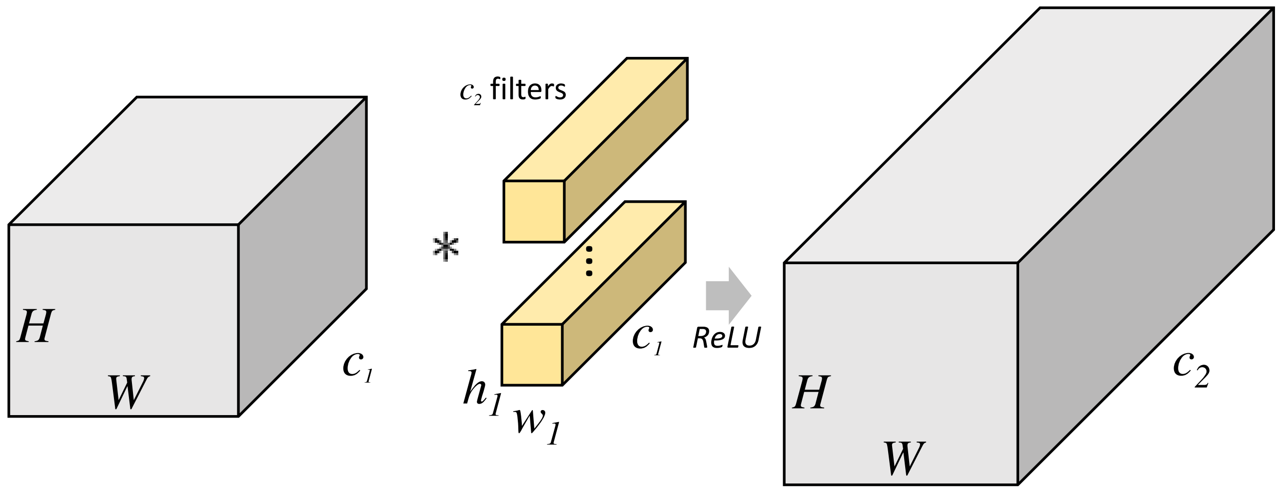
Suppose we have a convolution layer applied to input (shape $\mathrm{H} \times W \times c_1$):



We have c_2 filters with kernel size $h_1 \times w_1 \times c_1$

Image Credit: [3]

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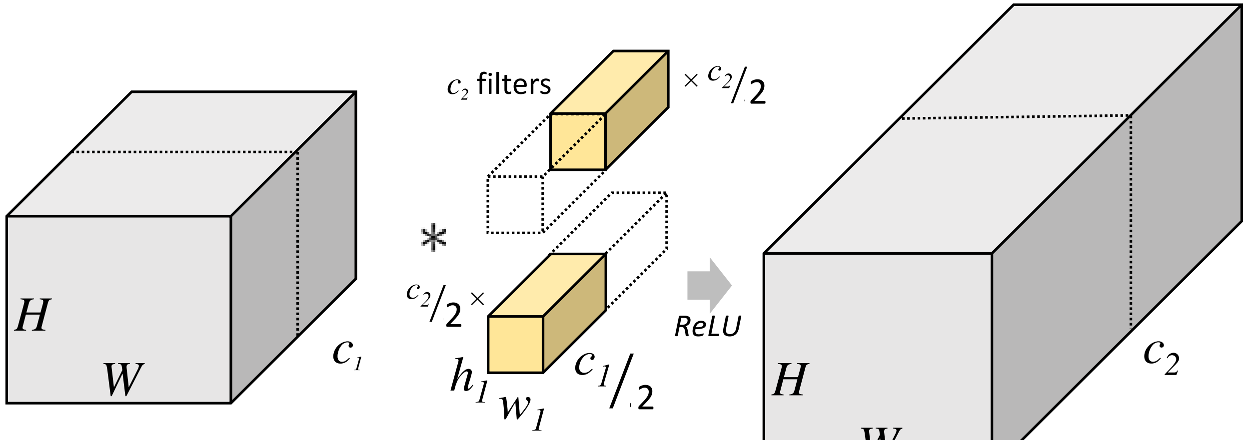
Now we switch to a grouped (# groups=2) convolution layer applied to the same input (shape $\mathrm{H} \times W \times c_1$):



We have 2 groups of filters, and the total number of parameters is the same as a single filter before!

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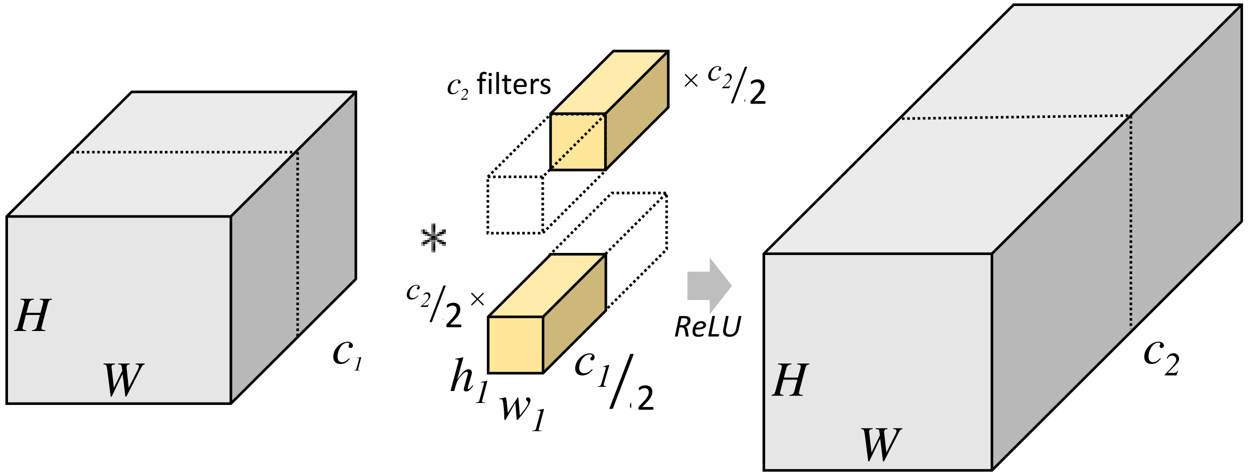

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Generalize it to multi-groups by yourself!

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Let us look at a 3x3 convolutional kernel:

$$\begin{bmatrix} 3 & 6 & 9 \\ 4 & 8 & 12 \\ 5 & 10 & 15 \end{bmatrix} = \begin{bmatrix} 3 \\ 4 \\ 5 \end{bmatrix} \times \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}$$

Image Credit: [4]

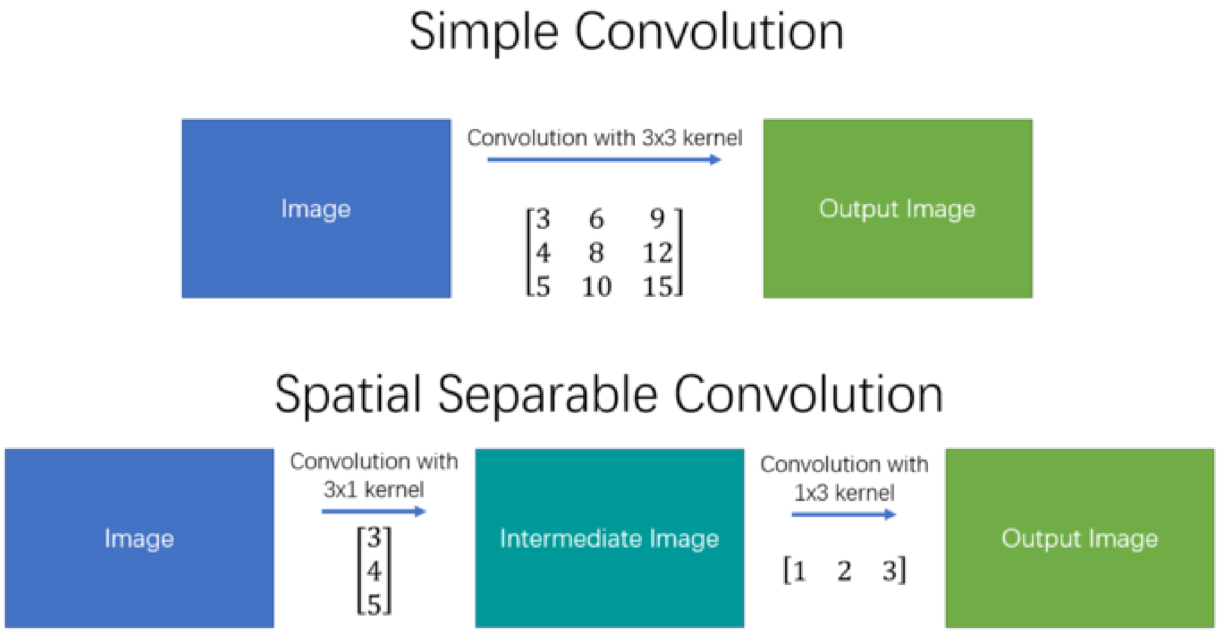
Separable Convolution

Can we maintain the same shaped input and output in convolution with fewer number of parameters?

Yes, grouped convolution & **separable convolution**!

Let us look at a 3x3 convolutional kernel:

$$\begin{bmatrix} 3 & 6 & 9 \\ 4 & 8 & 12 \\ 5 & 10 & 15 \end{bmatrix} = \begin{bmatrix} 3 \\ 4 \\ 5 \end{bmatrix} \times \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}$$



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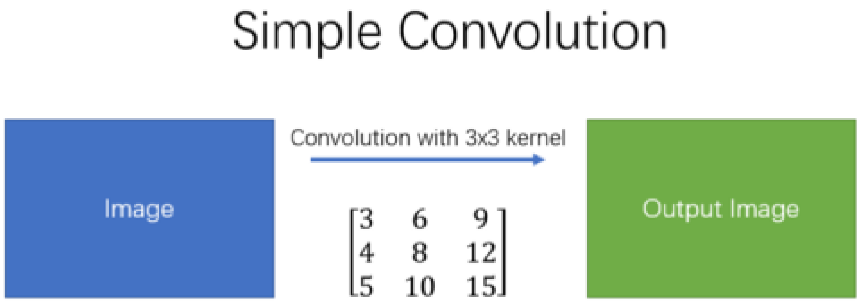
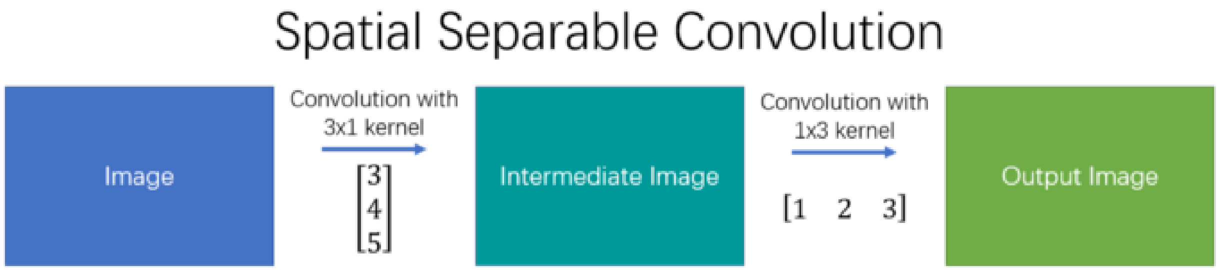
Spatial separable kernels are rank one and can not represent full-rank kernels, thus being limited in terms of expressiveness!





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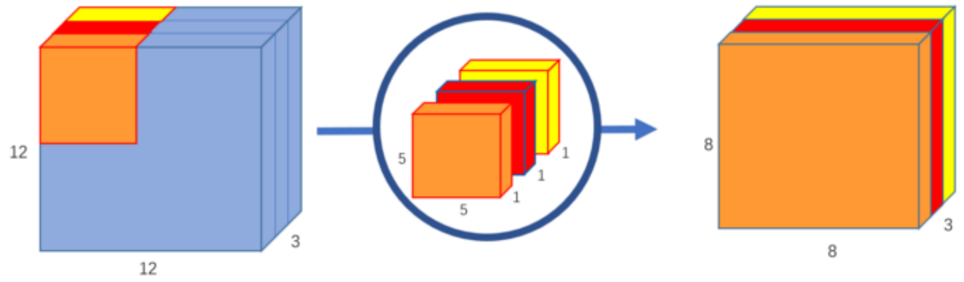

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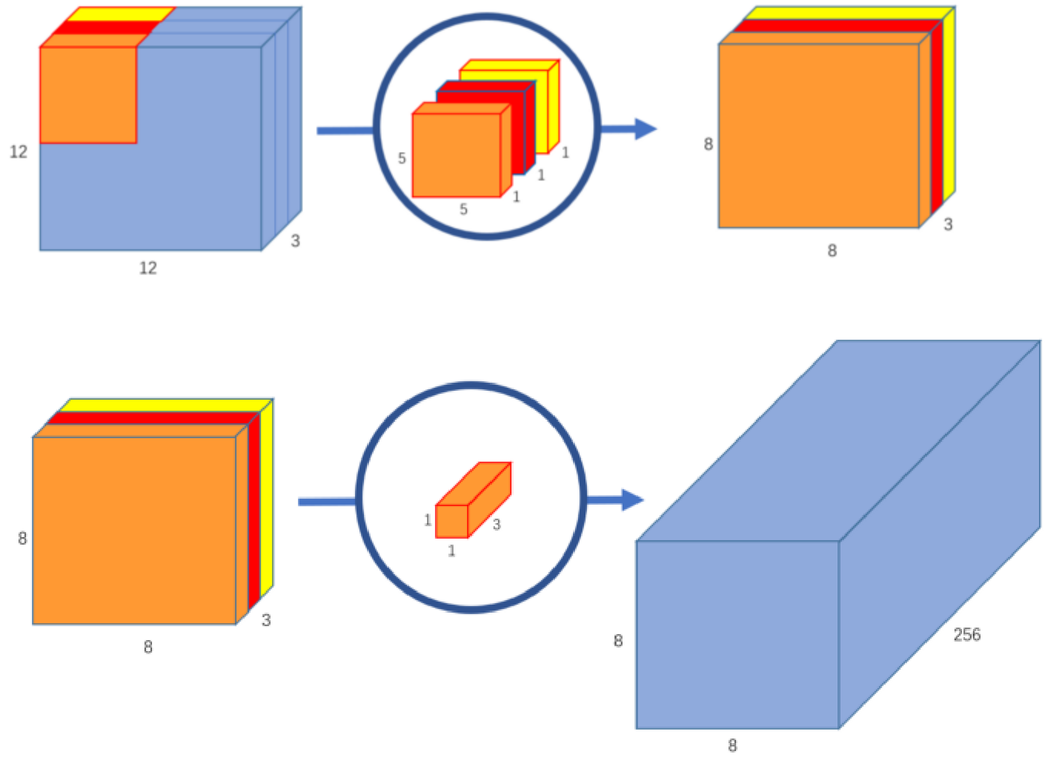

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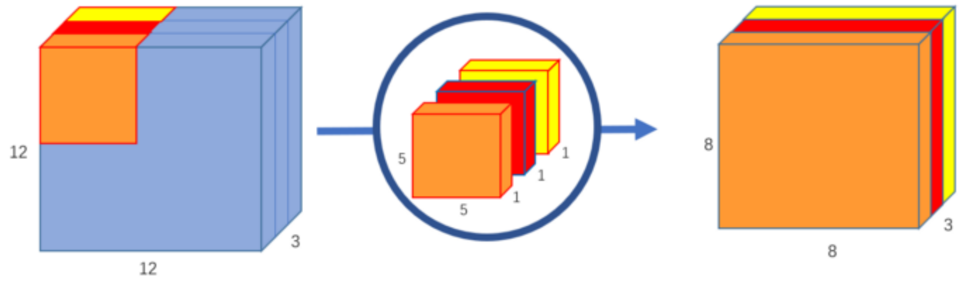
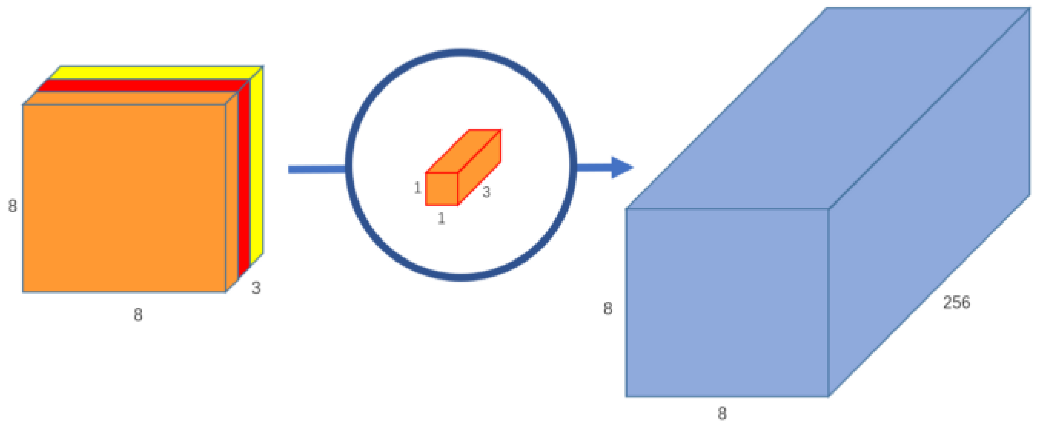


It is a separable convolution: spatial $\times$ depth (channel)!



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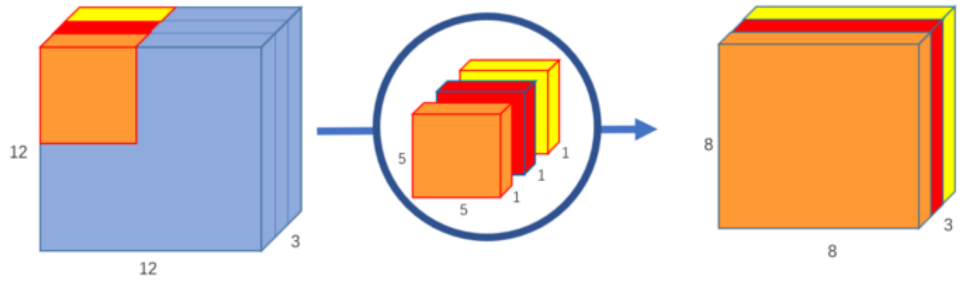
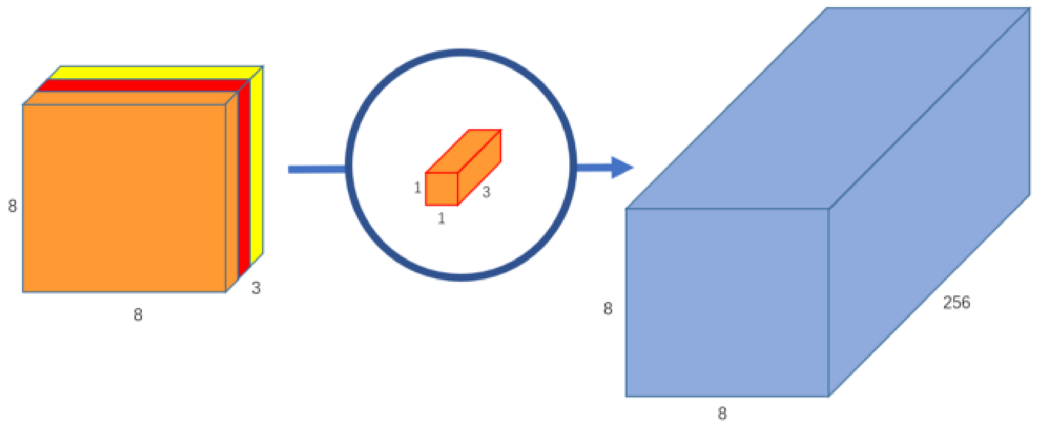


It is a separable convolution: spatial × depth (channel)!

Work out the numbers of parameters and operations, you will find it saves both!



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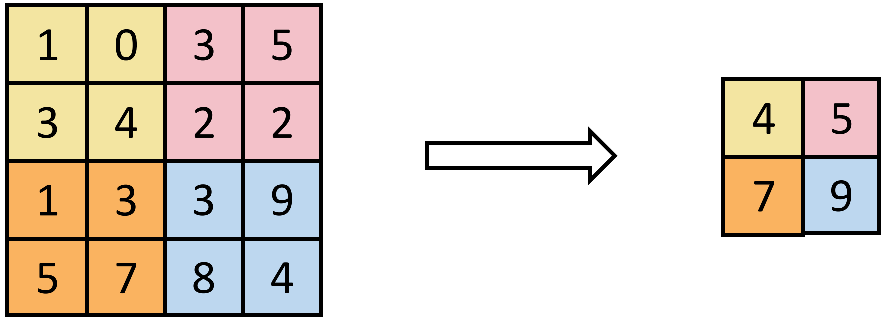
Outline

- Invariance & Equivariance
- Convolution
  - 1D Convolution
  - Matrix Multiplication Views
  - Translation Equivariance
  - 2D Convolution
- Convolution Variants
  - Transposed Convolution
  - Dilated Convolution
  - Grouped Convolution
  - Separable Convolution
- **Pooling**
- Example Architectures

Pooling

A similar idea as convolution except that you replace *weighted sum* operator with some pooling operator (e.g., *max*, mean)

2 X 2 Max Pooling with Stride 2



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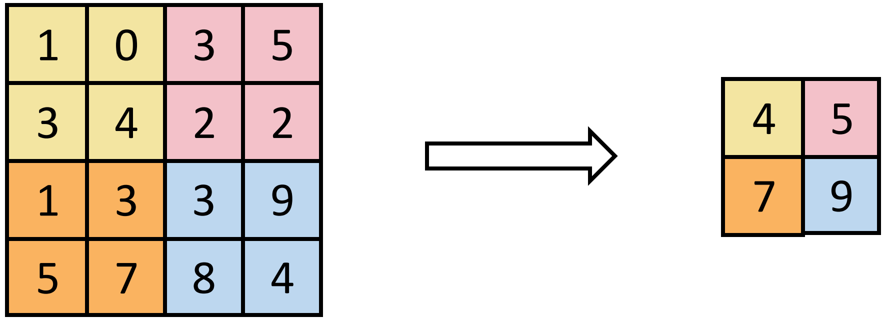

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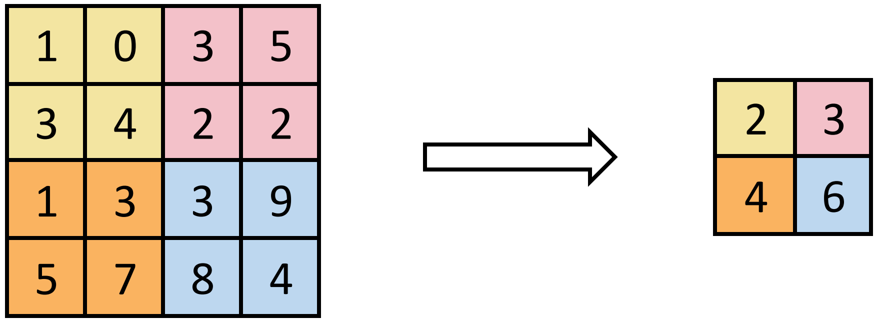

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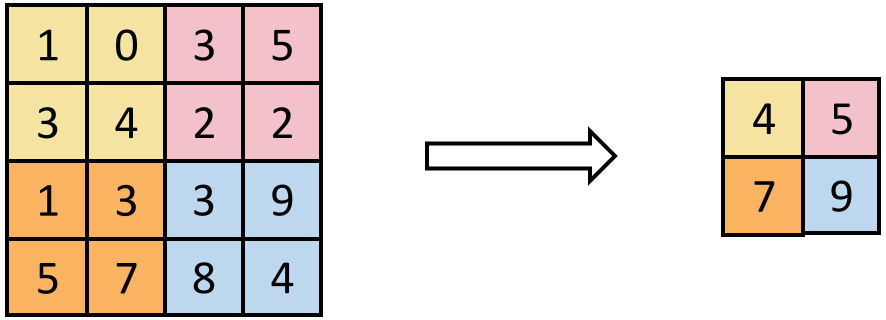

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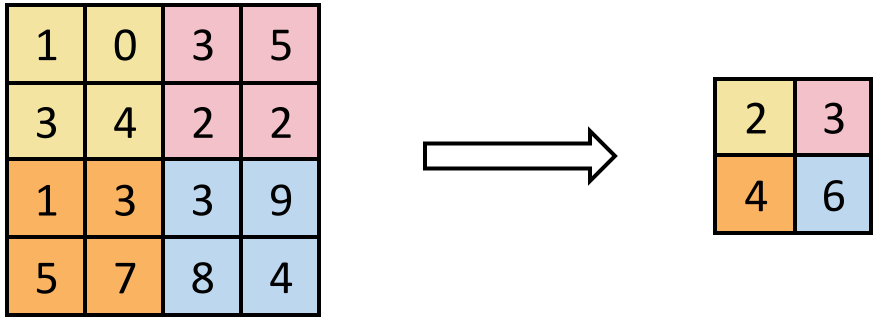

Pooling gives you permutation-invariance!

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Convolutional Neural Networks (CNNs)

Let us look at an example CNN:

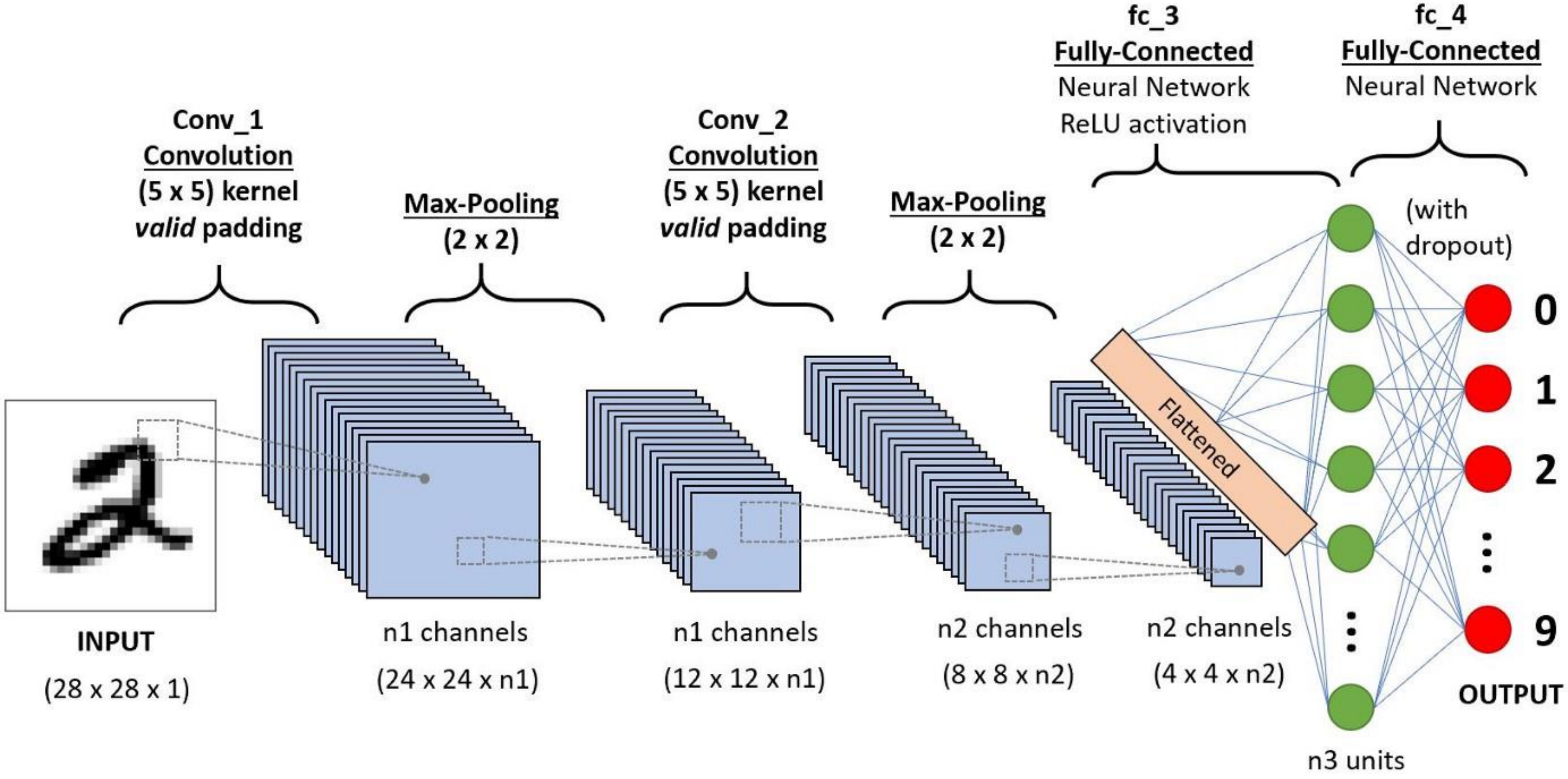


Image Credit: [5]

Translation/Shift Invariance

Suppose background does not change and one only shifts the foreground object, pooling gives you shift-invariance!

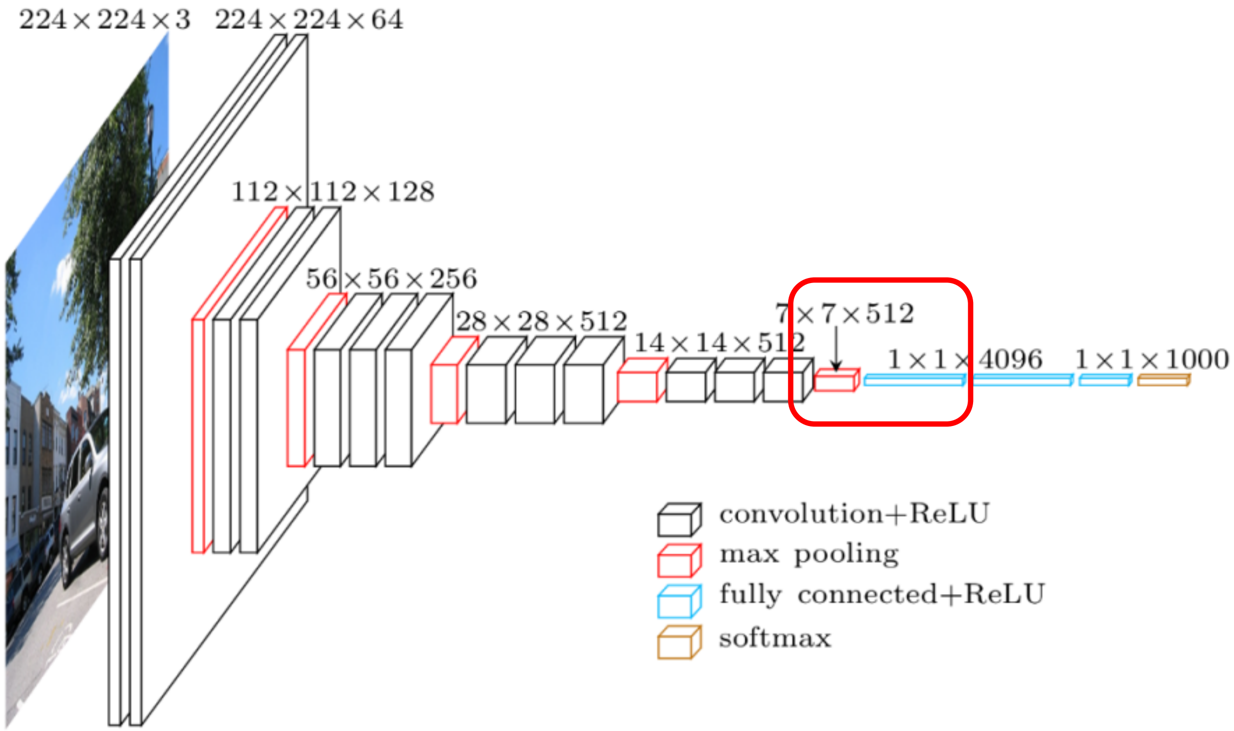
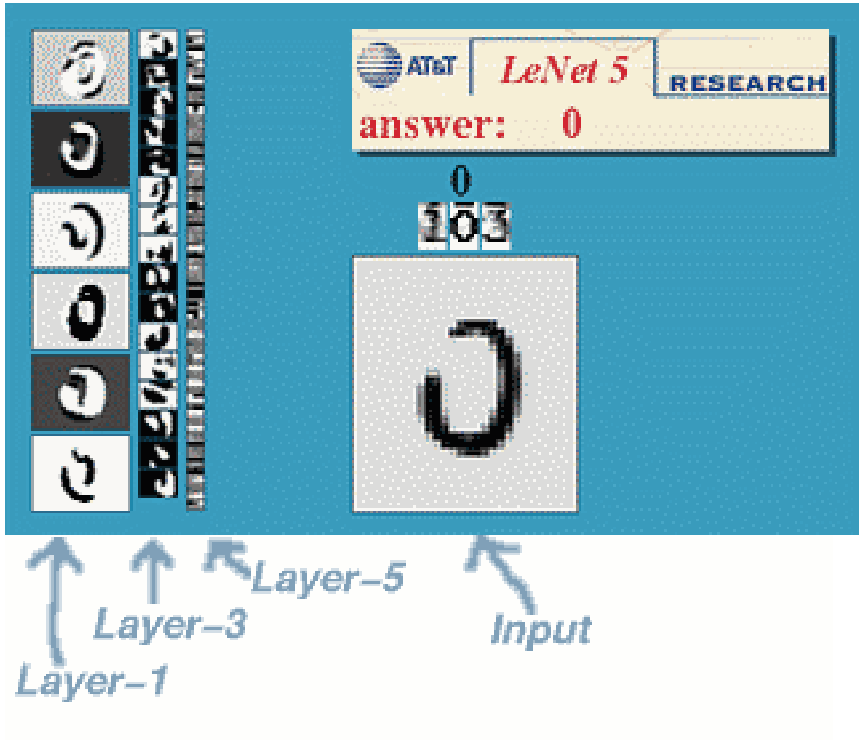


Image Credit: [6]

Translation/Shift Equivariance Invariance

Yann LeCun's LeNet Demo:



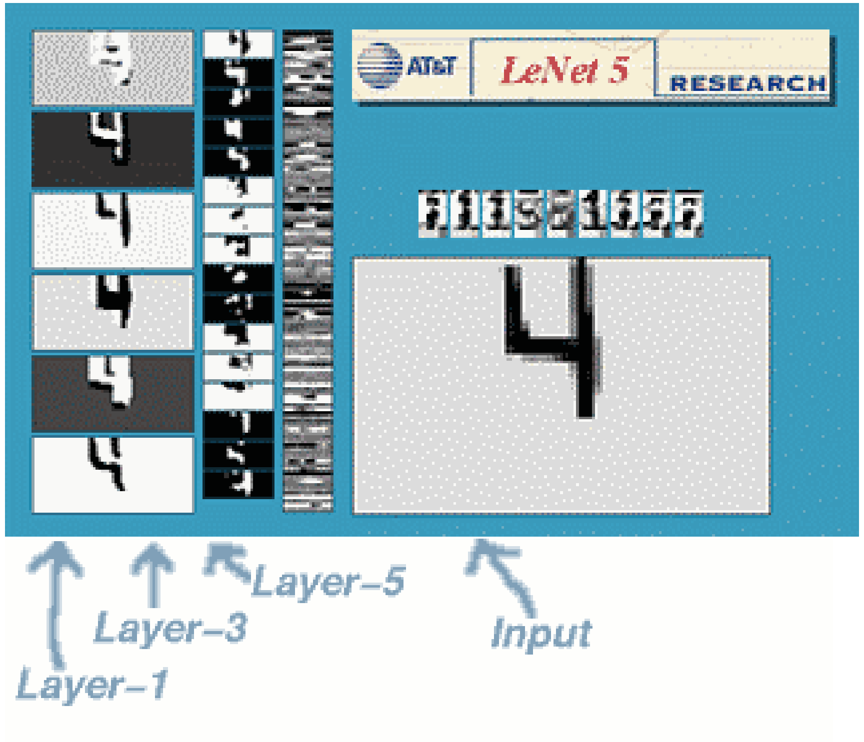


Image Credit: [7]

More on Invariance & Equivariance

What about other transformations, e.g., scaling, 2D/3D rotations?

Vanilla CNNs do not have such properties. One can add data augmentation to make the model approximately have them.

One can also design CNN architectures, e.g., spherical CNNs (rotation equivariant), that are guaranteed to have such properties [9].

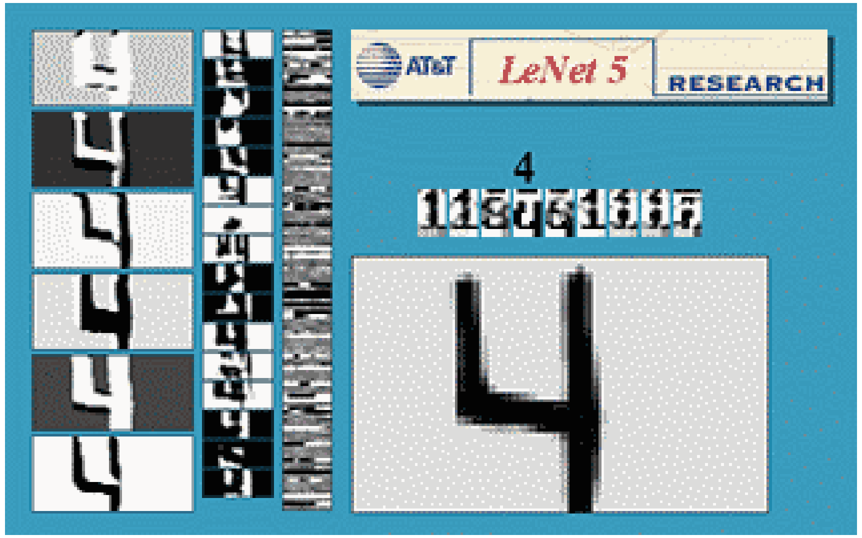
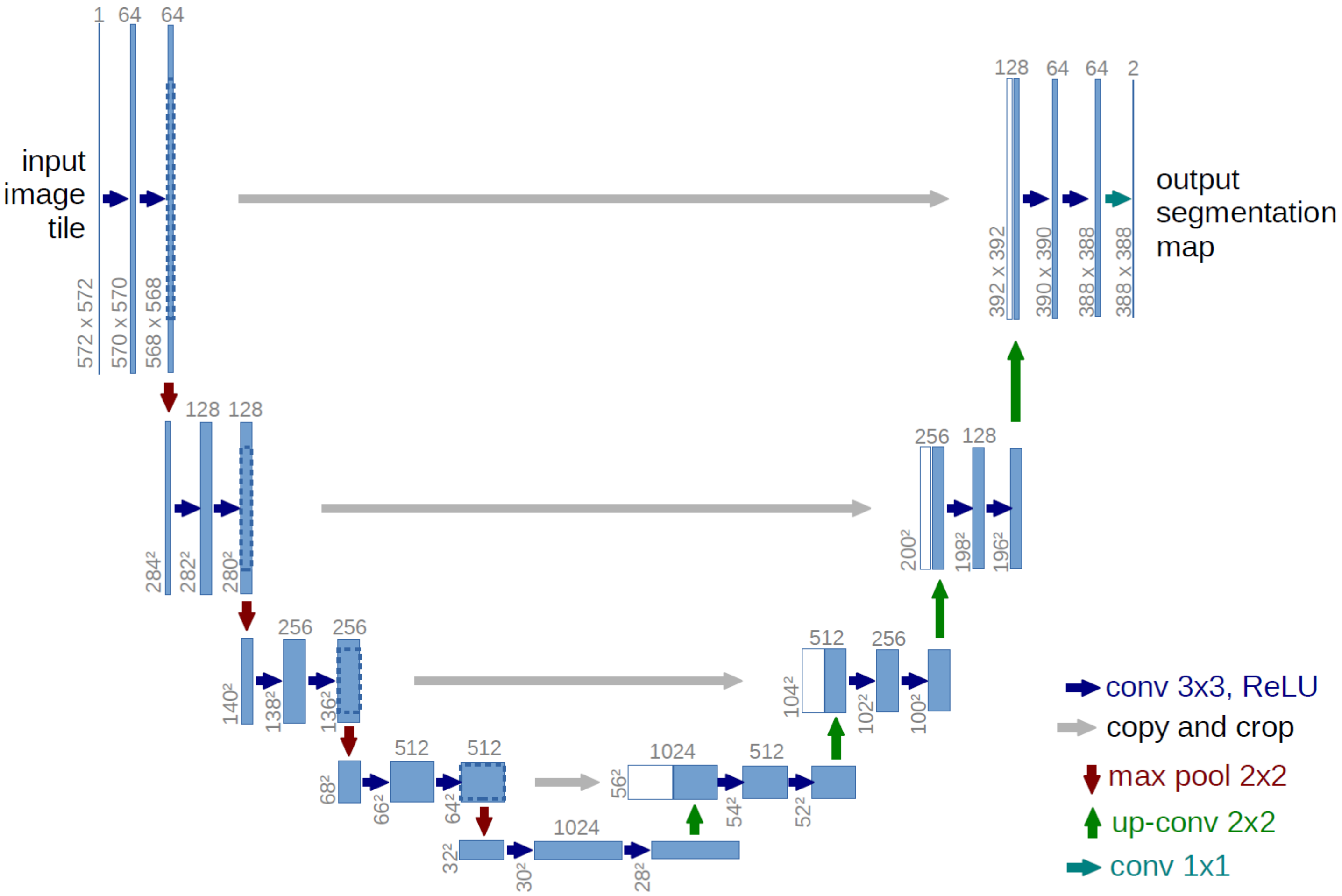


Image Credit: [8]

U-Net

U-Net [10] is a popular fully-convolutional CNN architecture for pixel-level tasks like image segmentation.



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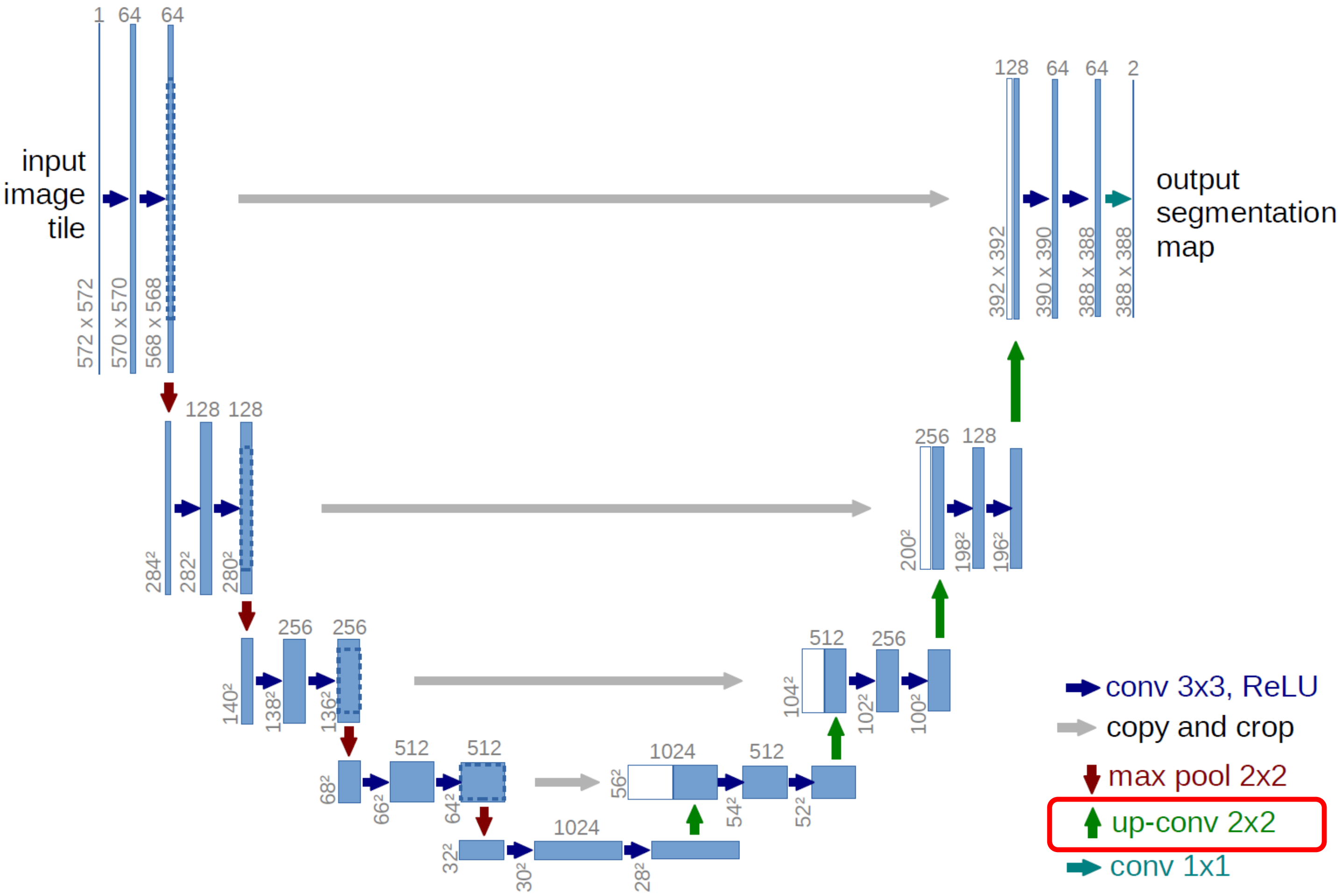

Transposed Convolution

Image Credit: [10]

ResNet

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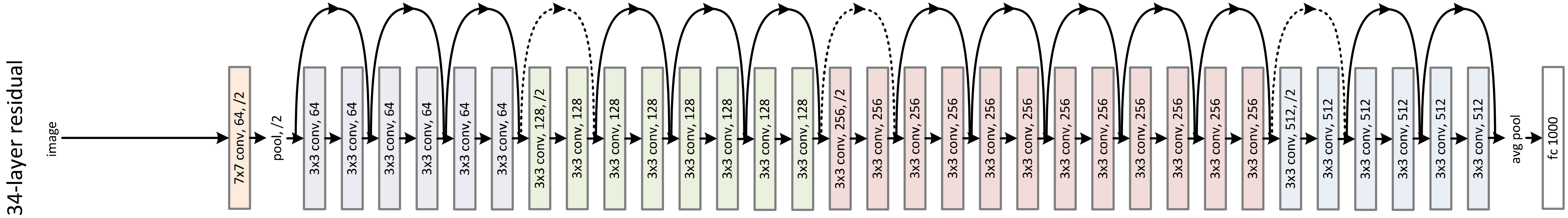

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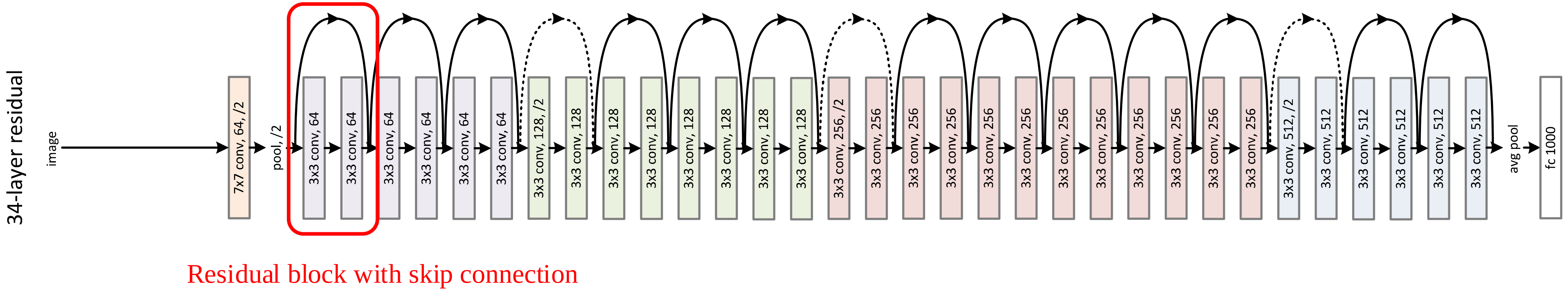

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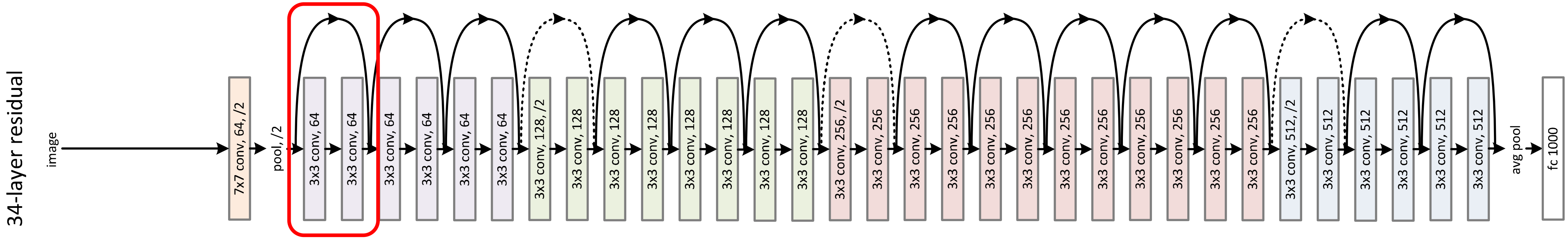
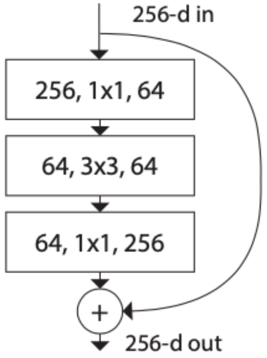


Residual block with skip connection

Build deeper ones (e.g., ResNet-50, ResNet-101)
by replacing it with the bottleneck structure!



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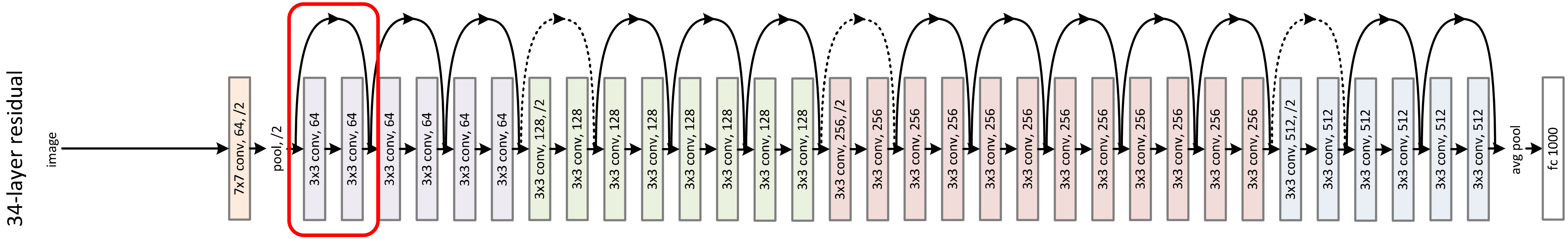

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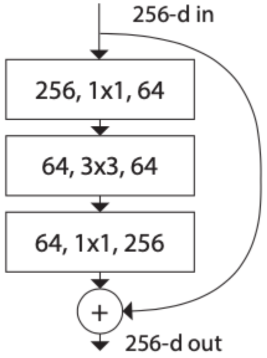


ResNeXt [12] replaces it with aggregated
transformations (similar to grouped convolution
but with shared input)!

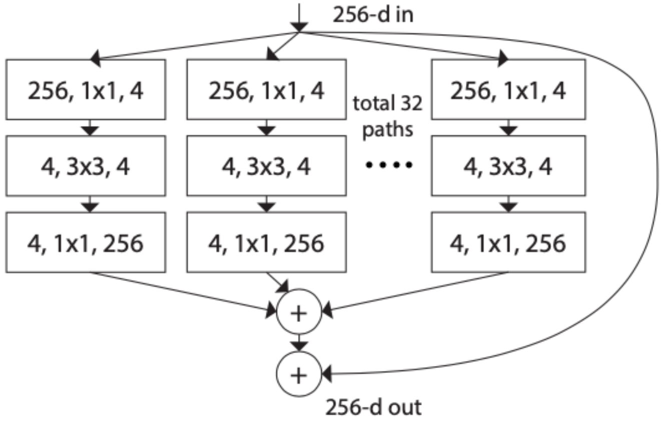
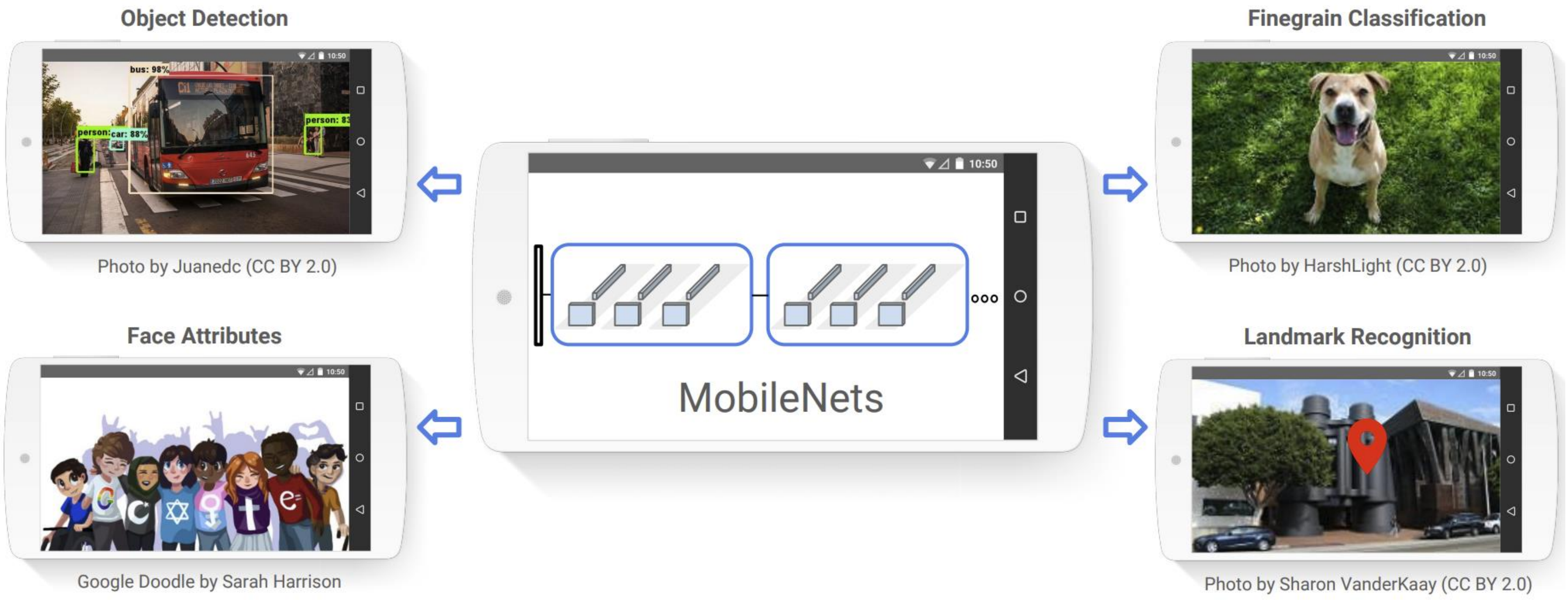


Image Credit: [11,12]

MobileNet

MobileNet [13] is designed to be used in mobile applications, achieving good performances with fewer computations.



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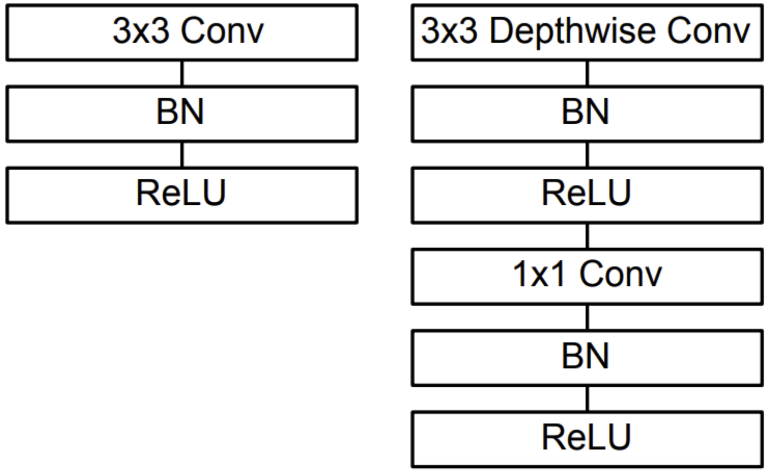

Replace the vanilla conv layer with depthwise separable convolutional layer

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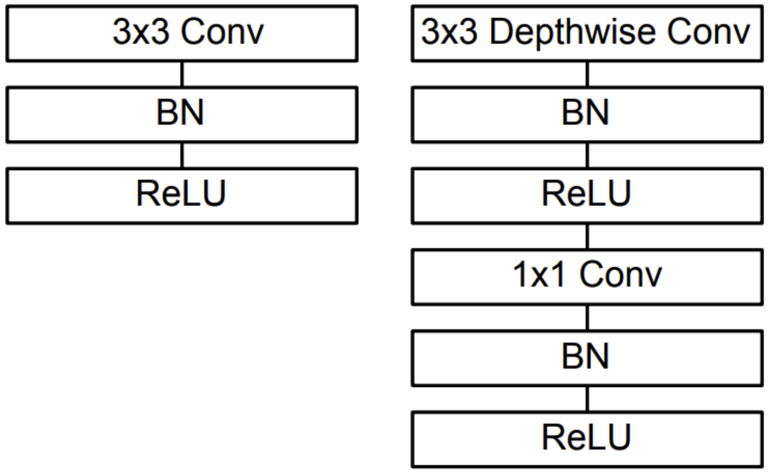

Replace the vanilla conv layer with depthwise separable convolutional layer

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1 Conv / s1	$3 \times 3 \times 512$ dw $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Image Credit: [13]

References

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[7] http://yann.lecun.com/exdb/lenet/translation.html

[8] http://yann.lecun.com/exdb/lenet/scale.html

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Questions?