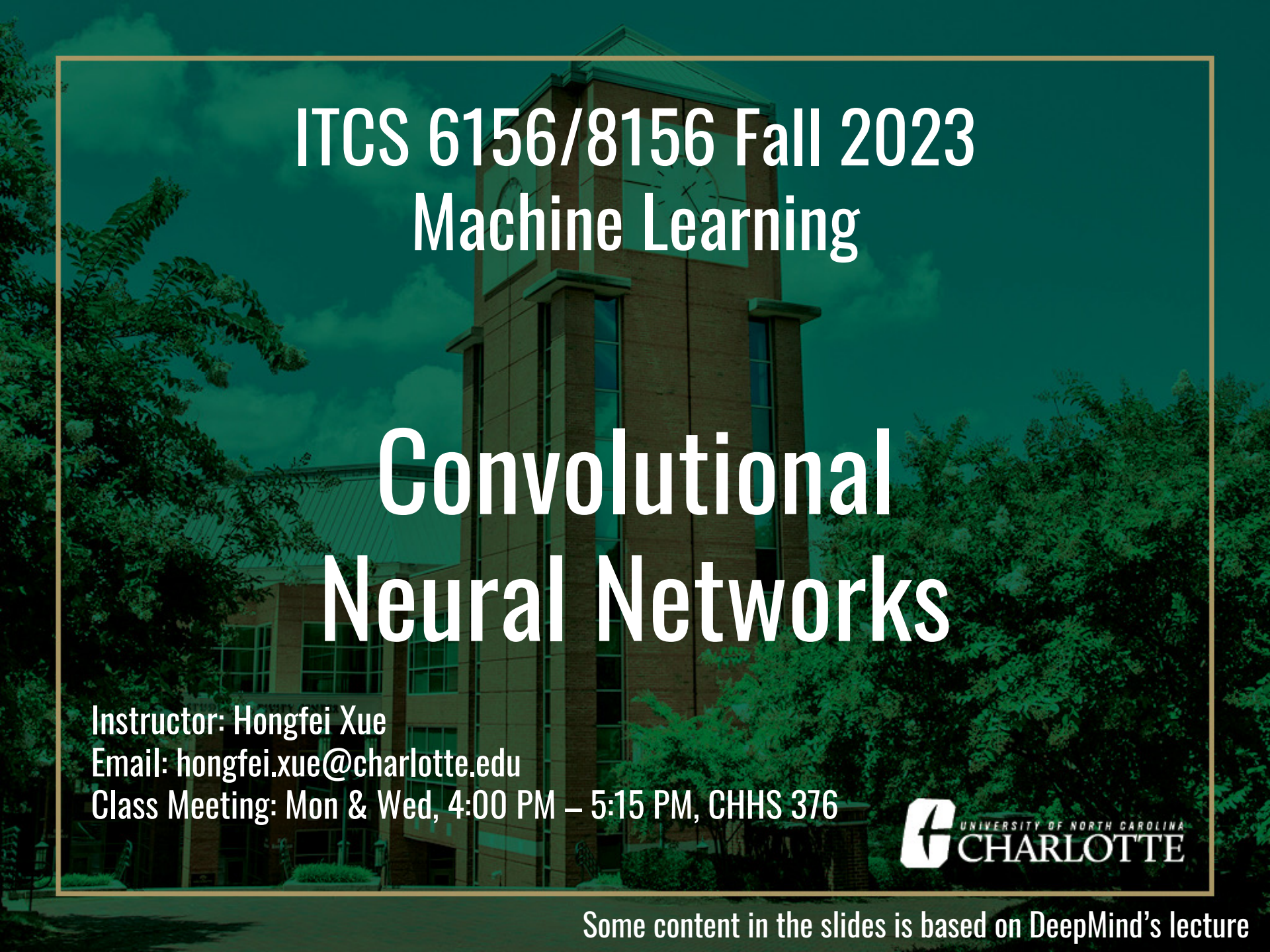


ITCS 6156/8156 Fall 2023
Machine Learning

Convolutional Neural Networks

Instructor: Hongfei Xue
Email: hongfei.xue@charlotte.edu
Class Meeting: Mon & Wed, 4:00 PM – 5:15 PM, CHHS 376

UNIVERSITY OF NORTH CAROLINA CHARLOTTE

Some content in the slides is based on DeepMind's lecture

Before Deep Learning

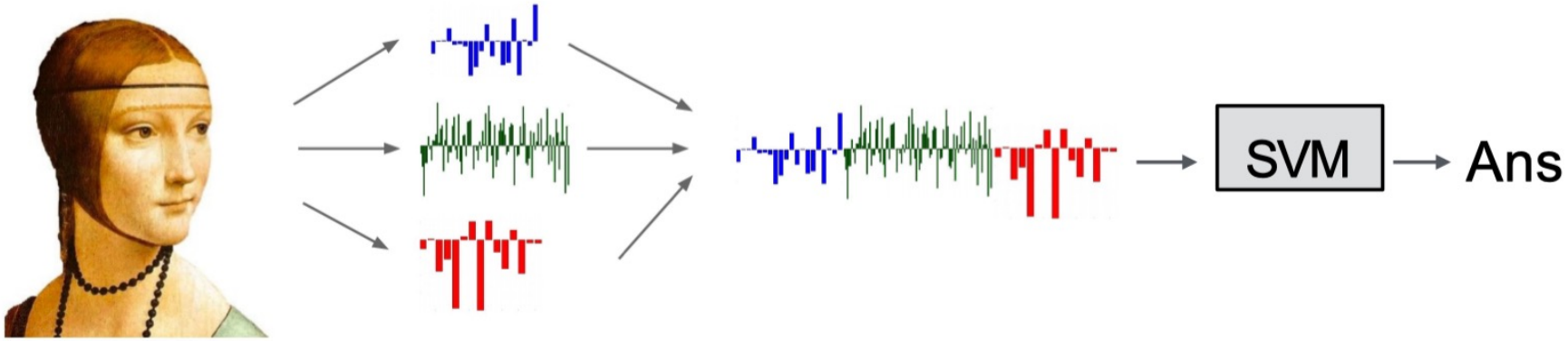


Figure: Karpathy 2016

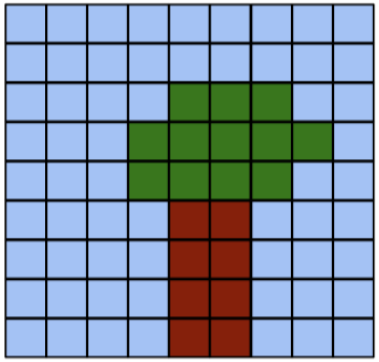
Using Deep Learning

Input Pixels

Perform everything with a big neural network, trained end-to-end

- Traditional machine learning models might struggle or require extensive **feature engineering** in these scenarios. Deep learning models can **automatically learn complex representations and feature hierarchies**, leading to superior performance on tasks like image recognition, natural language processing, and speech recognition.

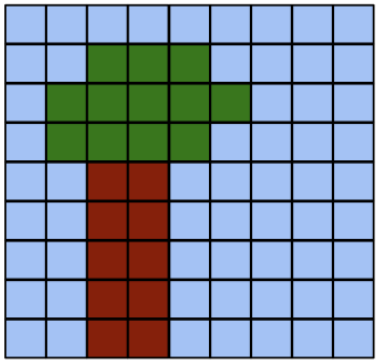
Neural Networks for Images



A digital image is a 2D **grid of pixels**.

A neural network expects a **vector of numbers** as input.

Neural Networks for Images



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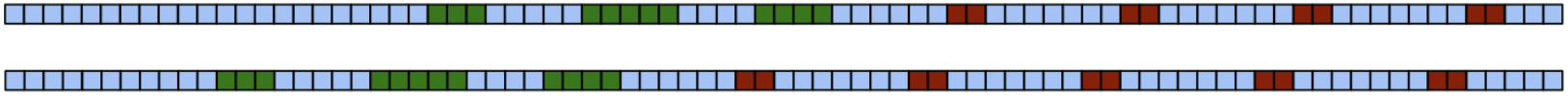
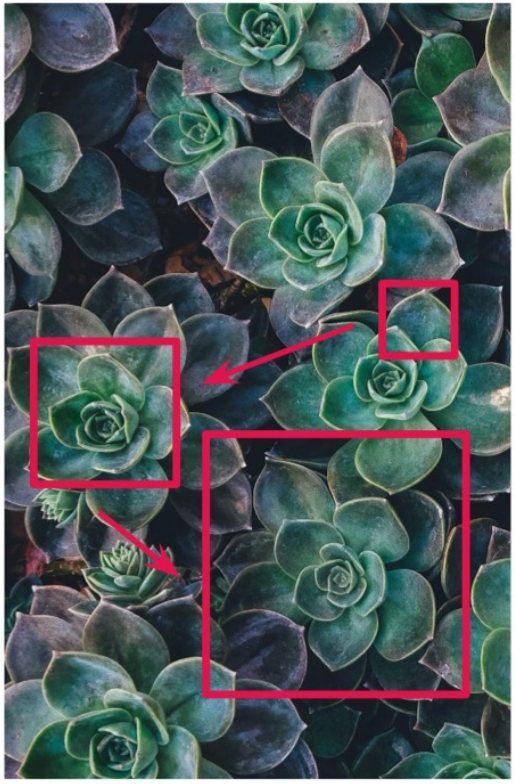


Locality and translation invariance

Locality: nearby pixels are more strongly correlated

Translation invariance: meaningful patterns can occur anywhere in the image

Taking advantage of topological structure

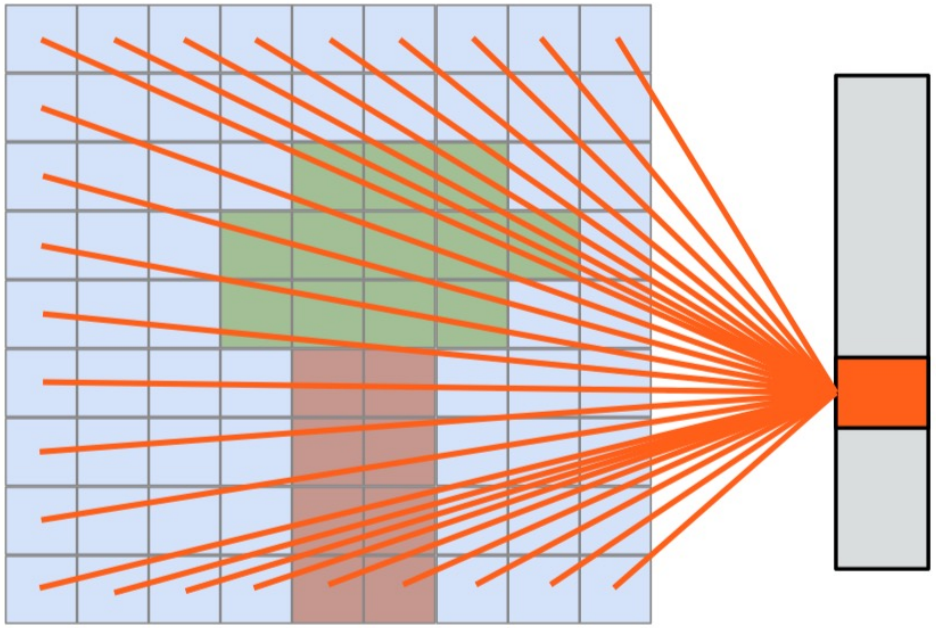


Weight sharing: use the same network parameters to detect local patterns at many locations in the image

Hierarchy: local low-level features are composed into larger, more abstract features

edges and textures → object parts → objects

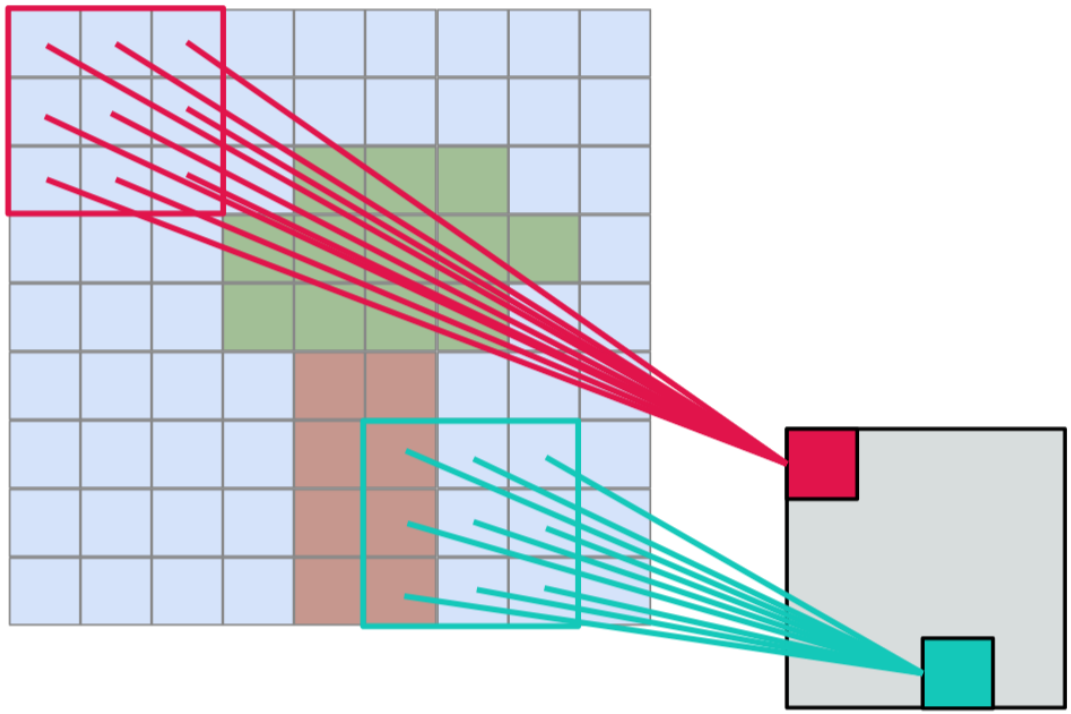
From fully connected to locally connected



fully-connected unit

$$y = \sum_{i \in \text{image}} \mathbf{w}_i \mathbf{x}_i + b$$

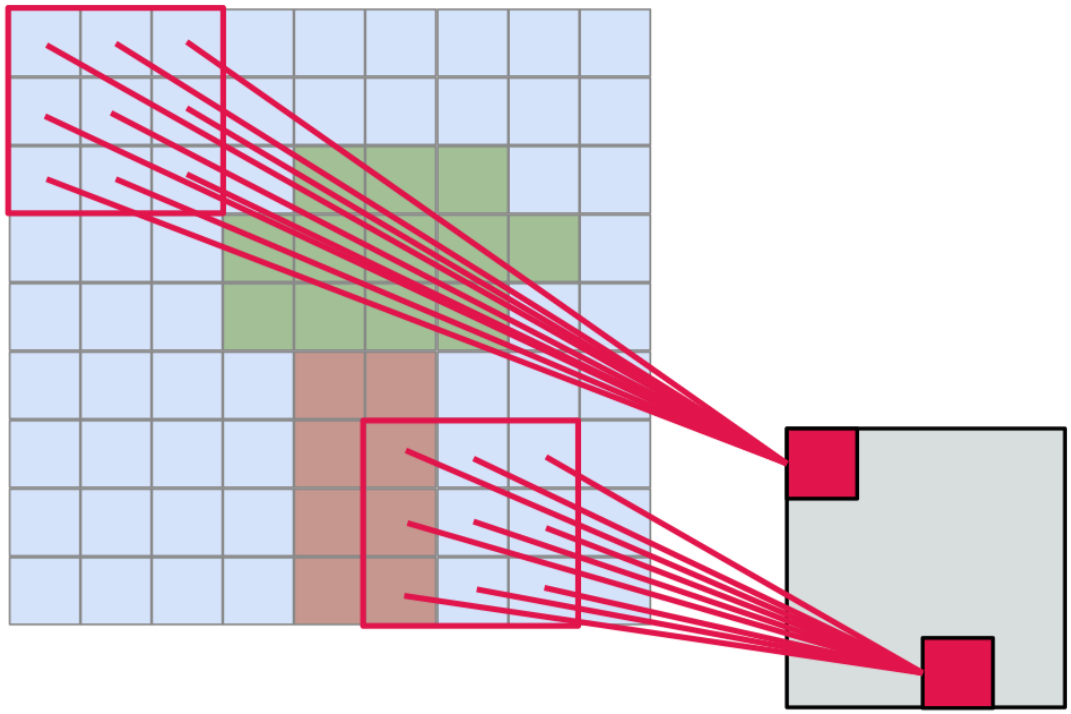
From fully connected to locally connected



$$y = \sum_{i \in 3 \times 3} \mathbf{w}_i \mathbf{x}_i + b$$

locally-connected units
3×3 receptive field

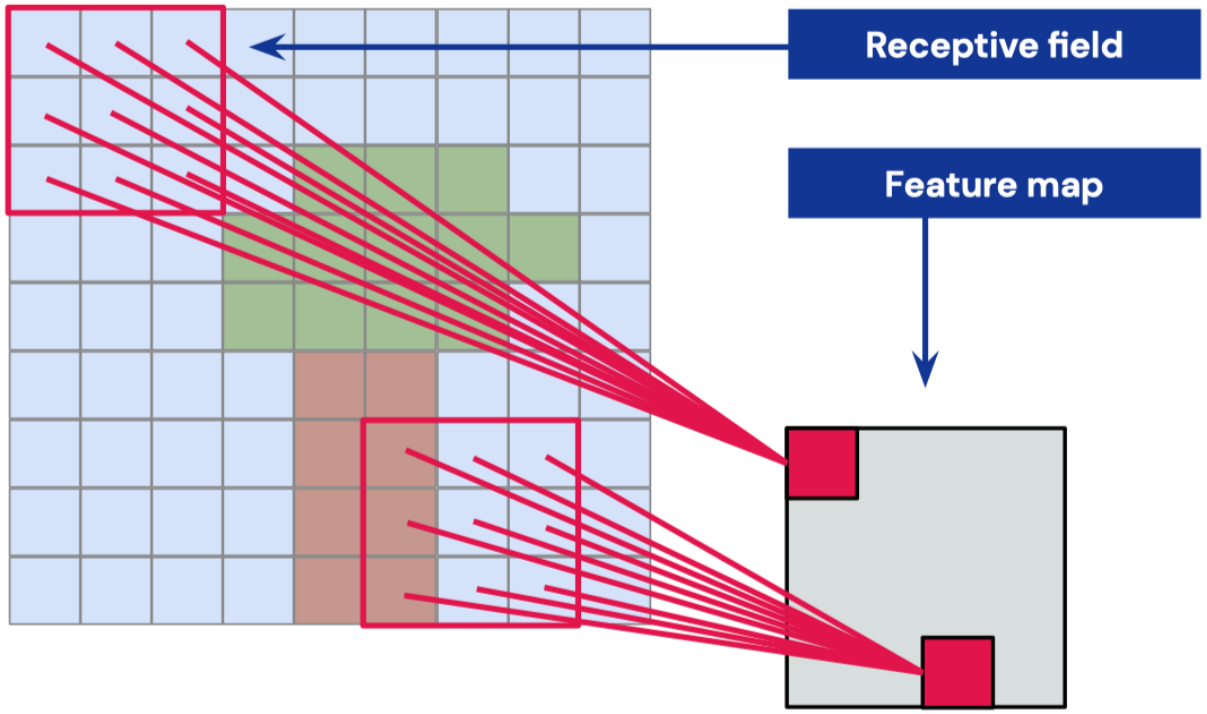
From fully connected to locally connected



$$y = \mathbf{w} * \mathbf{x} + b$$

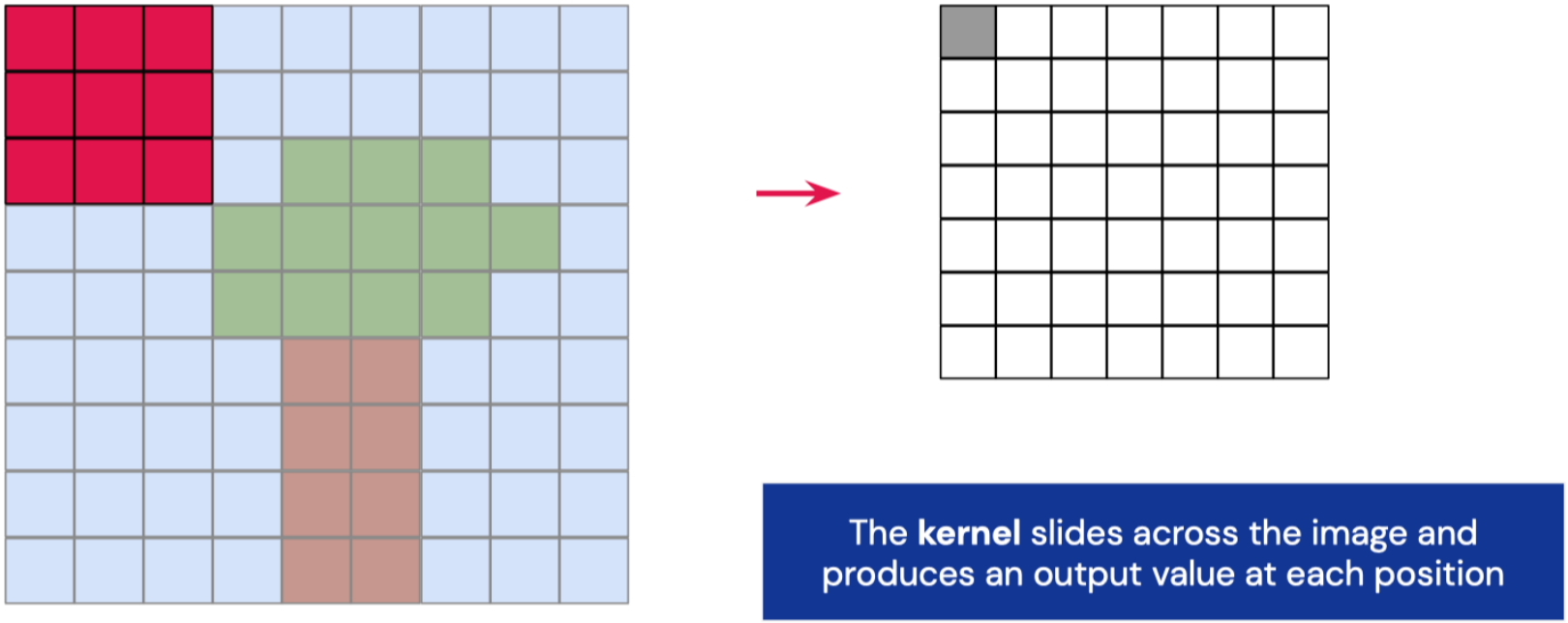
convolutional units
3×3 receptive field

From fully connected to locally connected



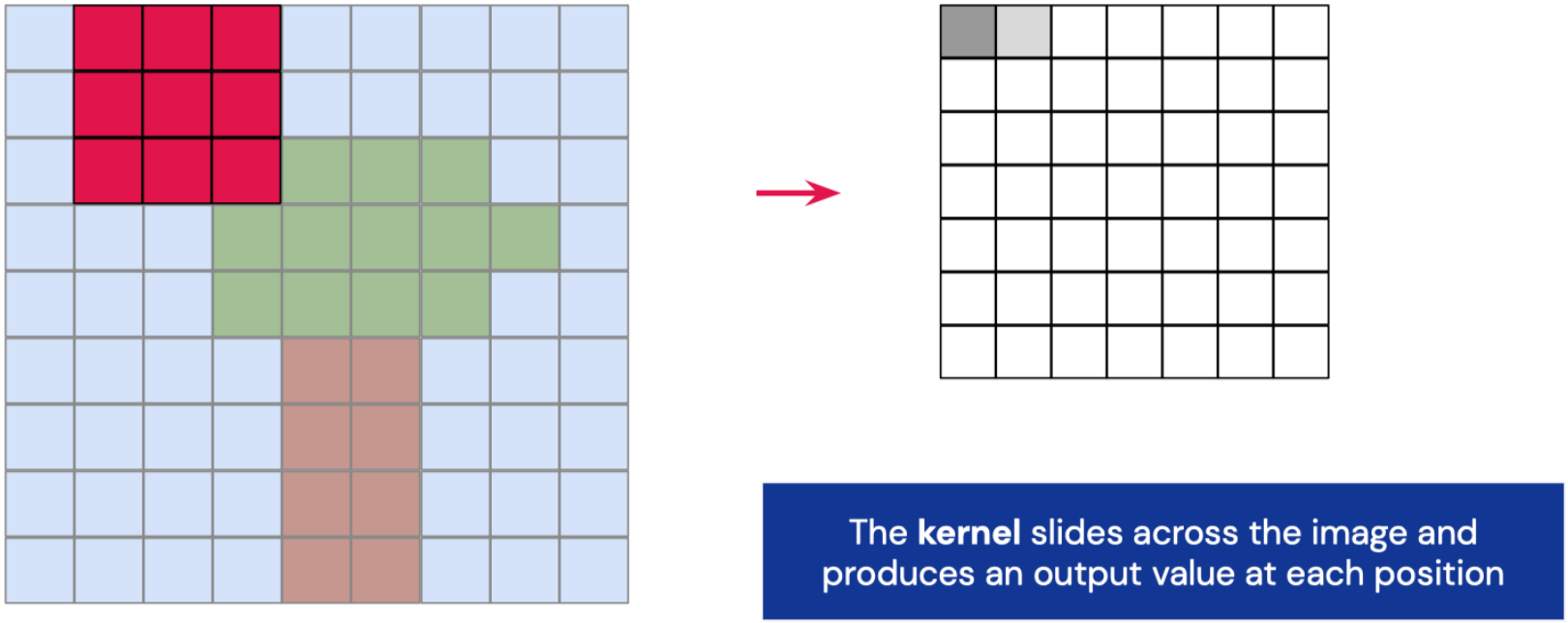
- **Receptive field**: the size of the region in the input that produces the feature. For a given layer in a CNN, the receptive field of a neuron is defined as the size of the region in the input space that affects the neuron's activation.
- **Feature map**: a feature map is a two-dimensional activation map that represents the response of a specific filter applied to the input data or to the output of a previous layer.

Implementation: the convolution operation



The **kernel** slides across the image and produces an output value at each position

Implementation: the convolution operation



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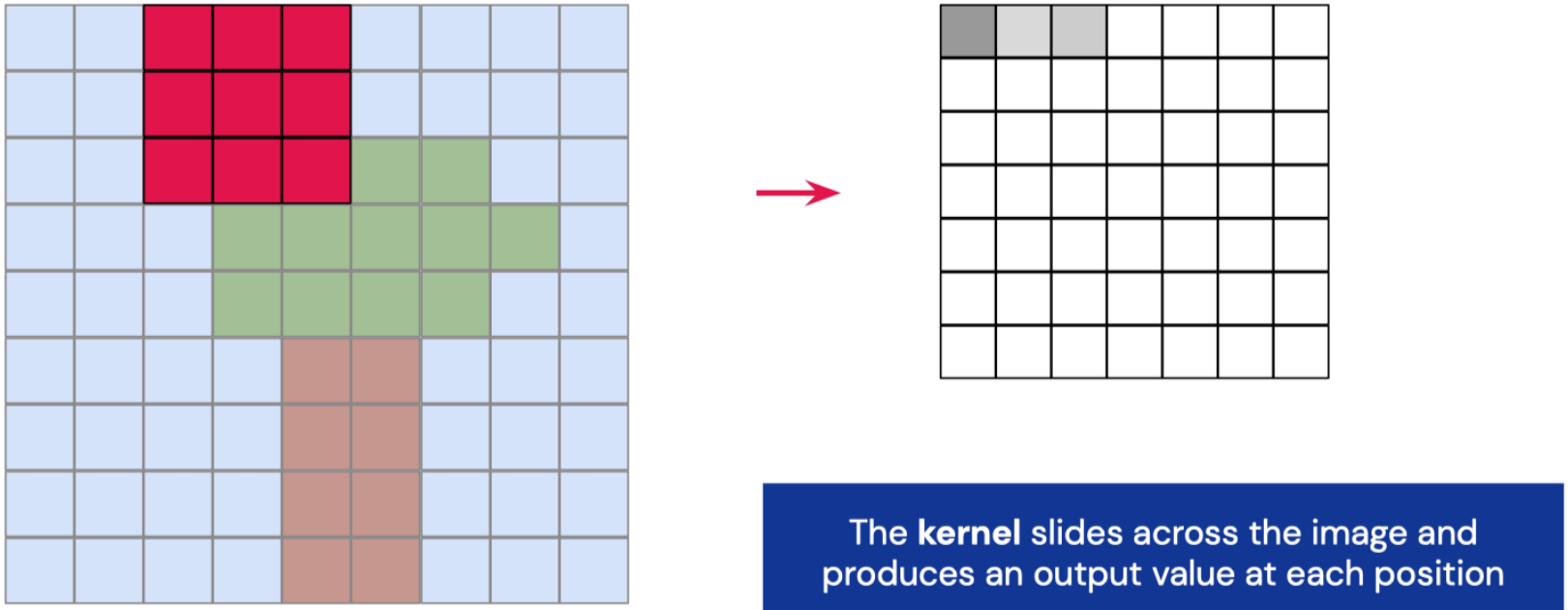

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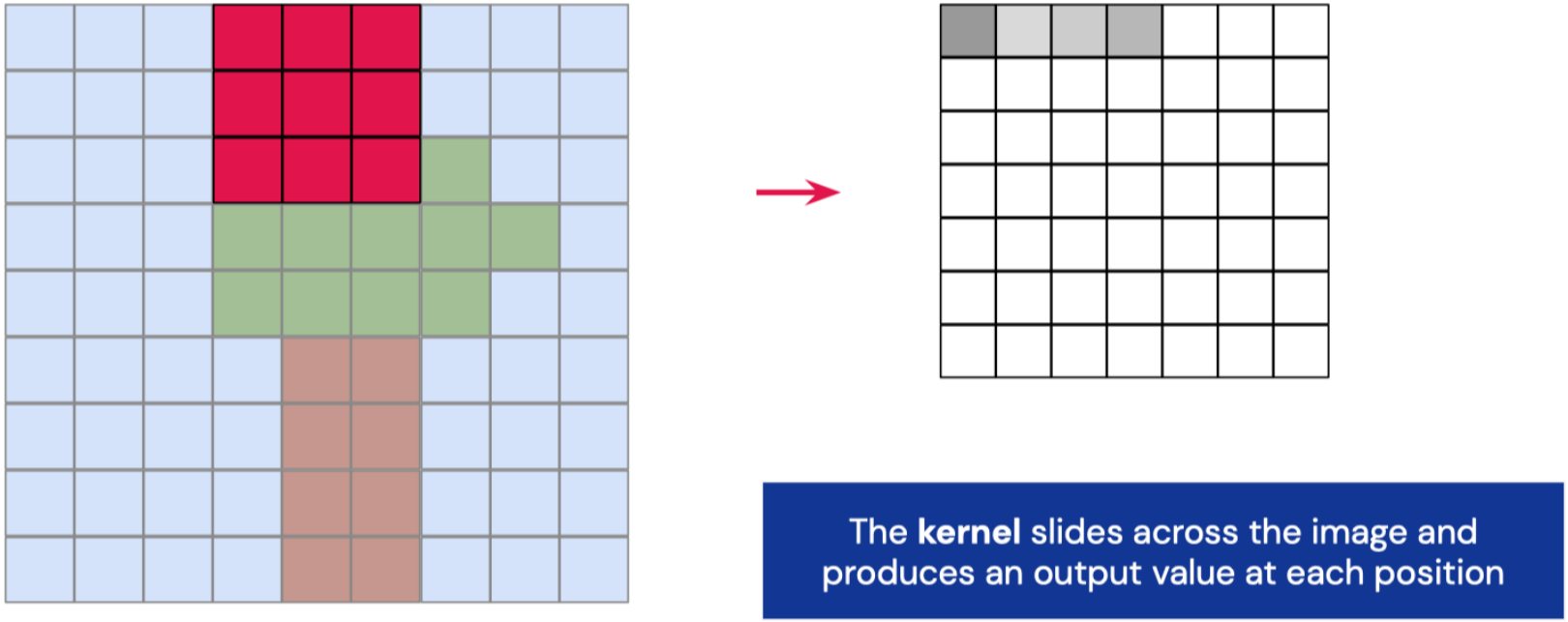

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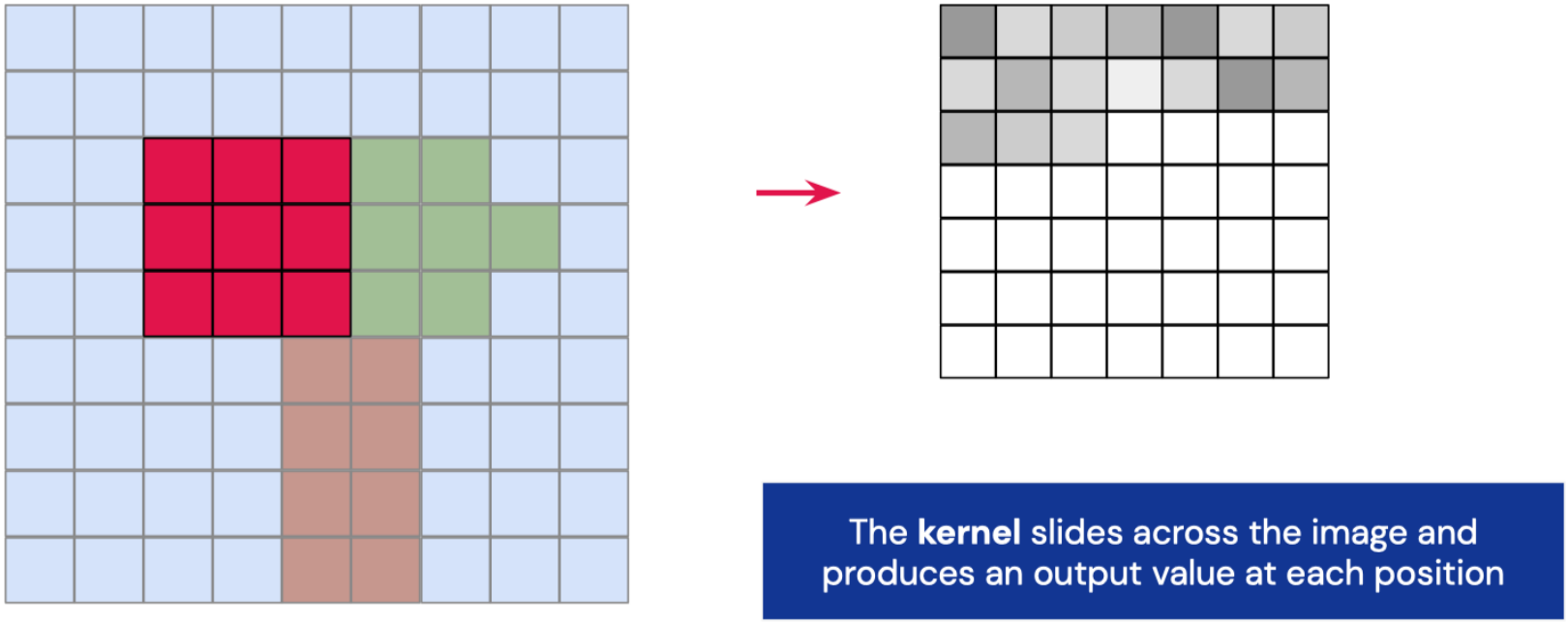
Implementation: the convolution operation



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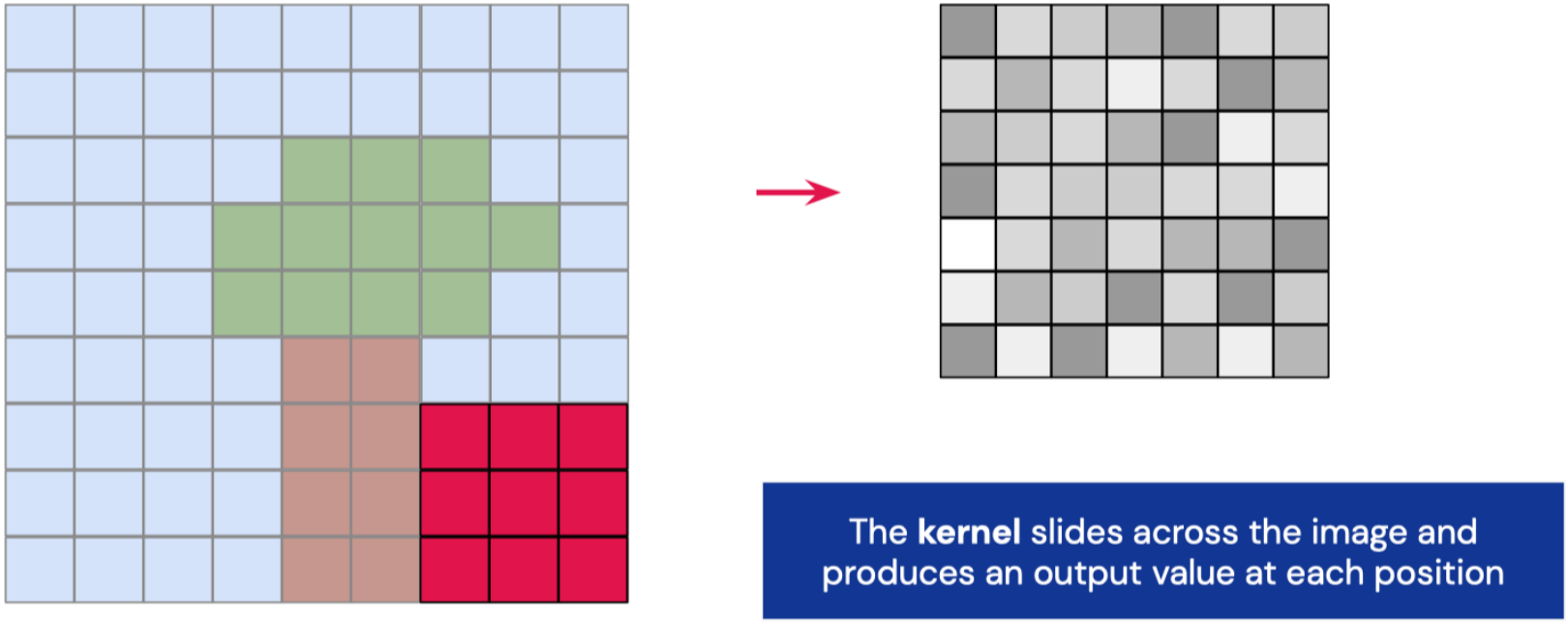
Implementation: the convolution operation



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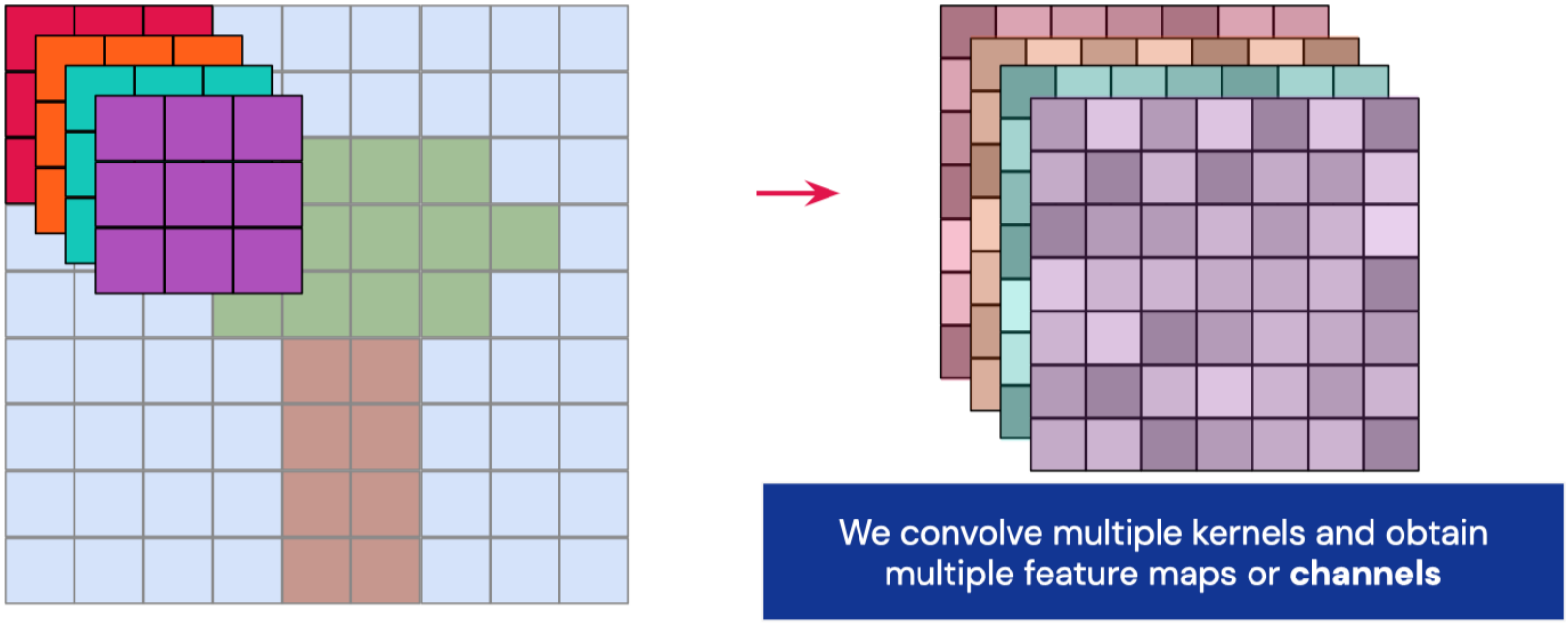
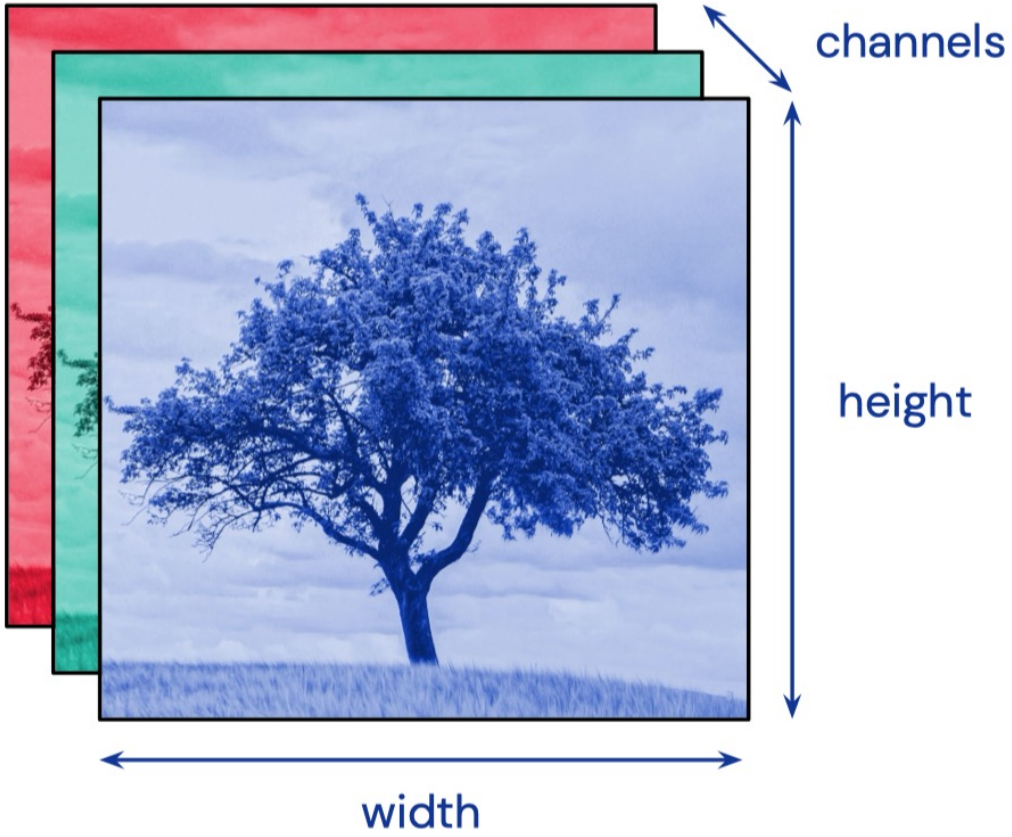
Implementation: the convolution operation



Inputs and outputs are tensors



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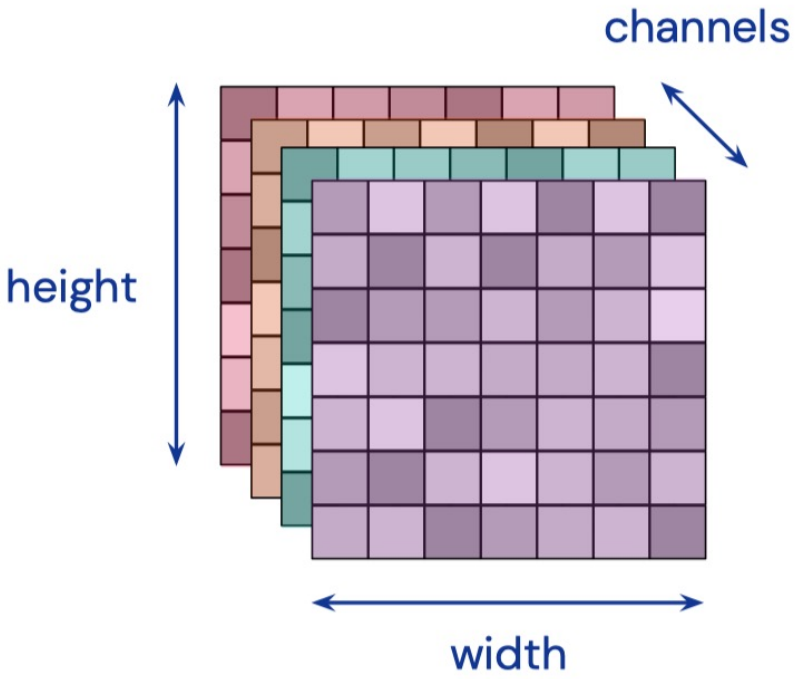
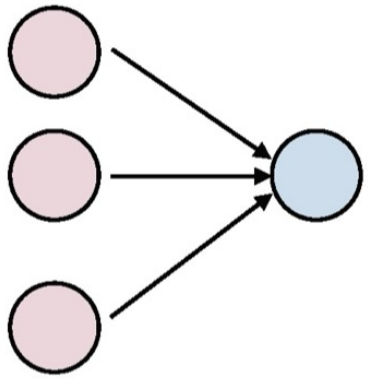
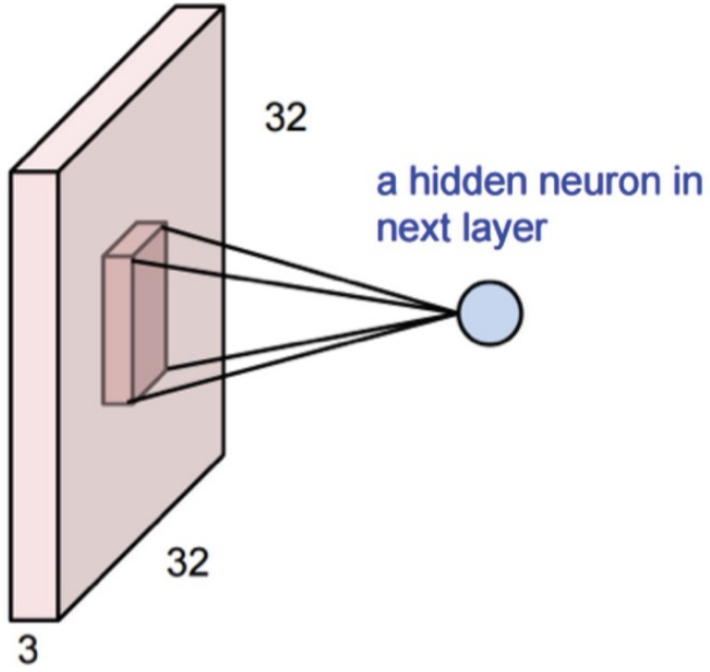


3D Activations

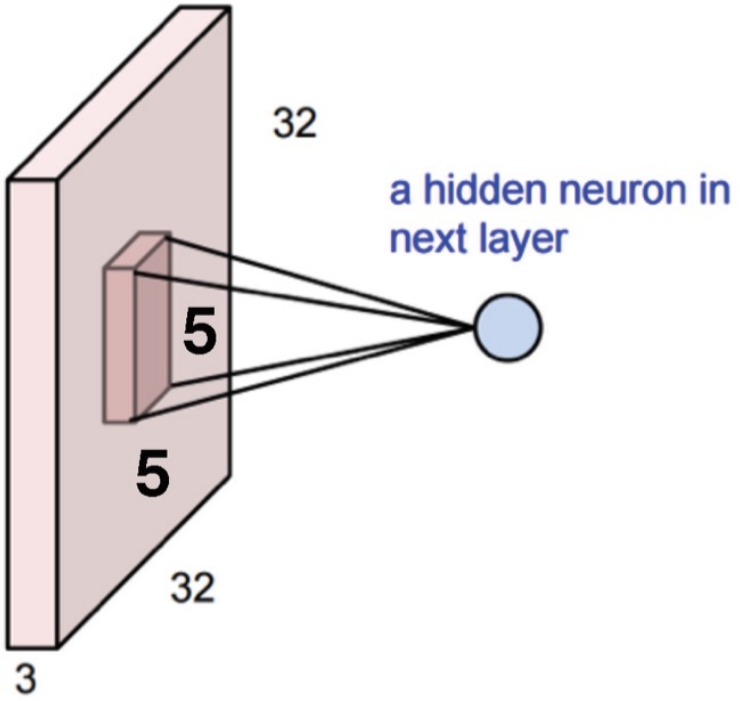
1D Activations:



3D Activations:

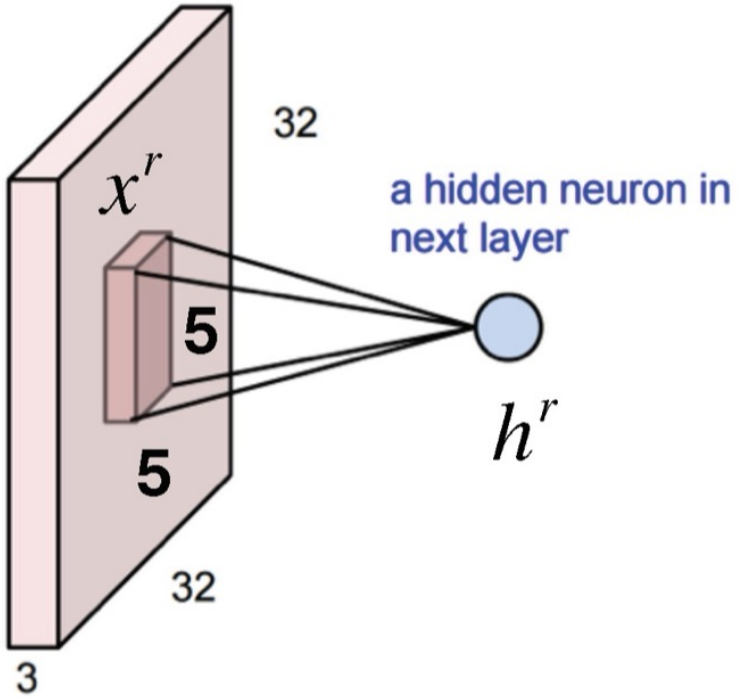


3D Activations



- The input is 3x32x32
- This neuron depends on a 3x5x5 chunk of the input
- The neuron also has a 3x5x5 set of weights and a bias (scalar)

3D Activations



Example: consider the region of the input "x^r"

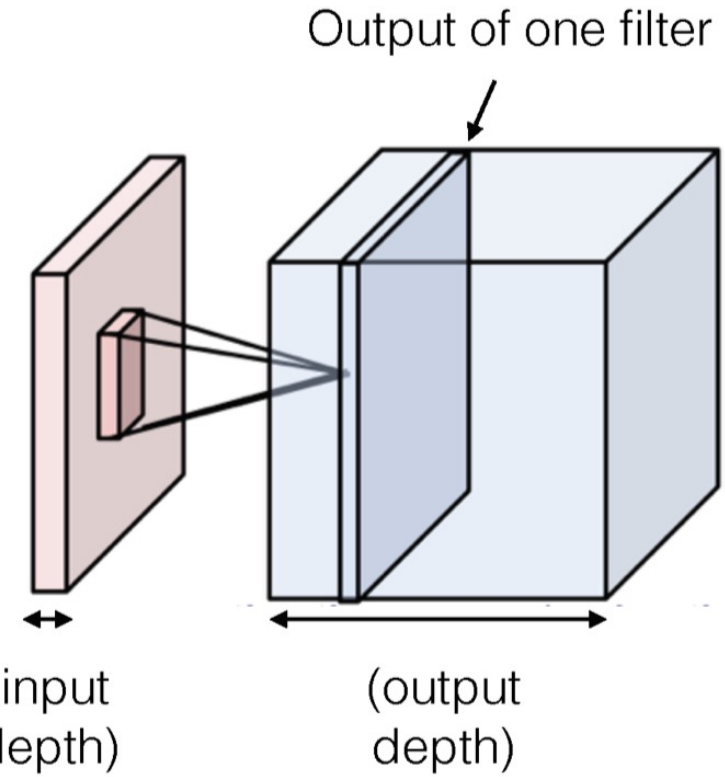
With output neuron h^r

Then the output is:

$$h^r = \sum_{ijk} x^r{}_{ijk} W_{ijk} + b$$

Sum over 3 axes

3D Activations



One set of weights gives one slice in the output

To get a 3D output of depth *D*, use *D* different filters

In practice, ConvNets use many filters (~64 to 1024)

Number of parameters of one convolutional layer without bias.

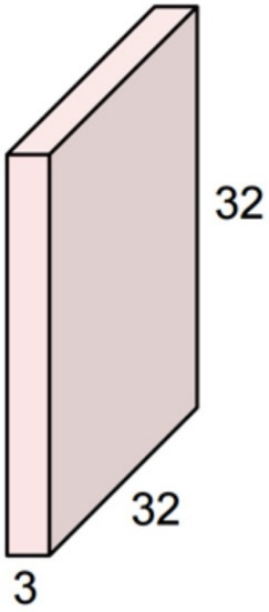
All together, the weights are **4** dimensional:
(output depth, input depth, kernel height, kernel width)

Recap

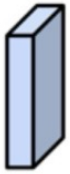
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image



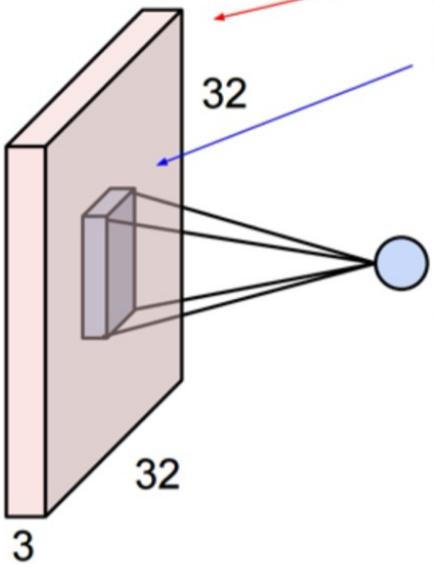
5x5x3 filter



Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

Recap

Convolution Layer



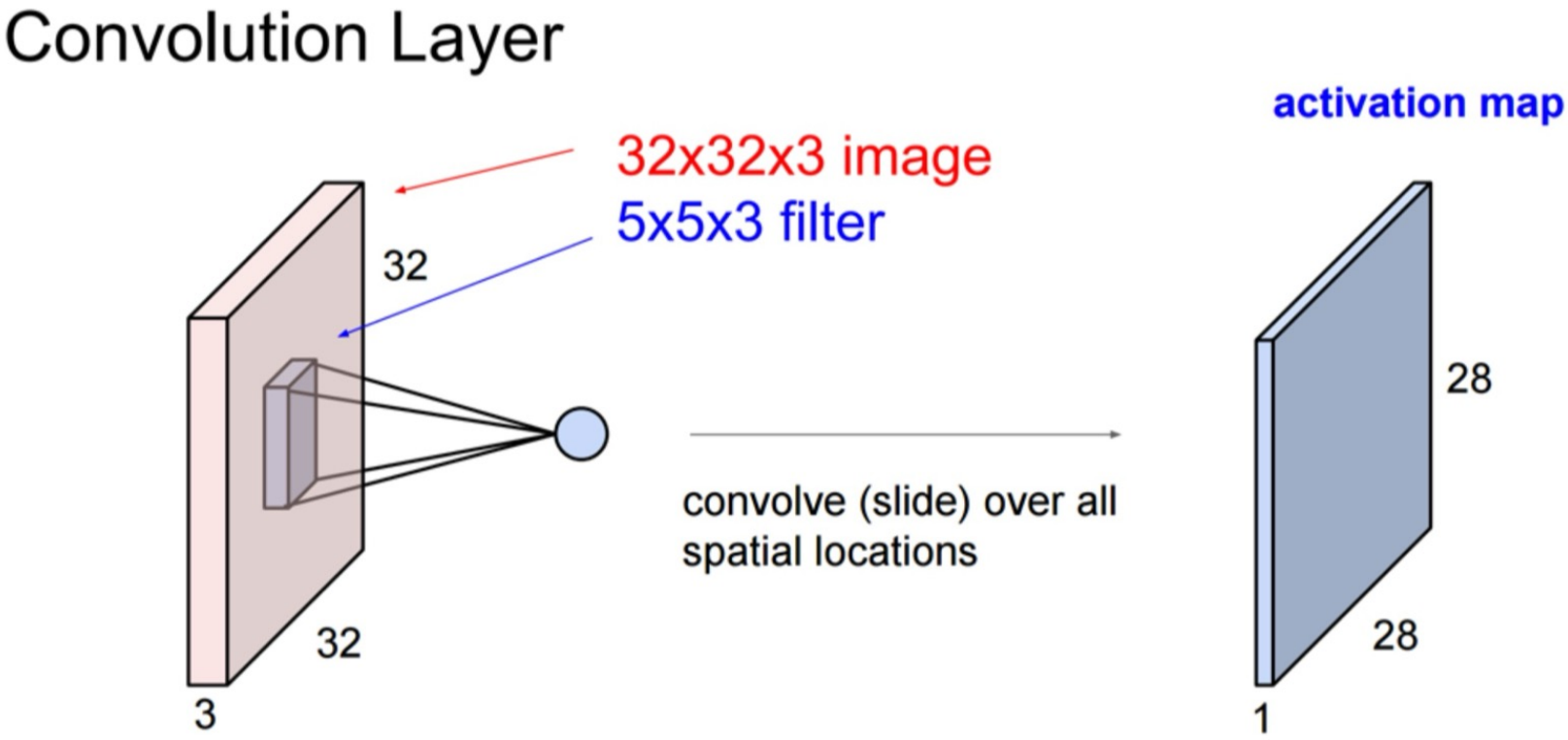
32x32x3 image

5x5x3 filter w

1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

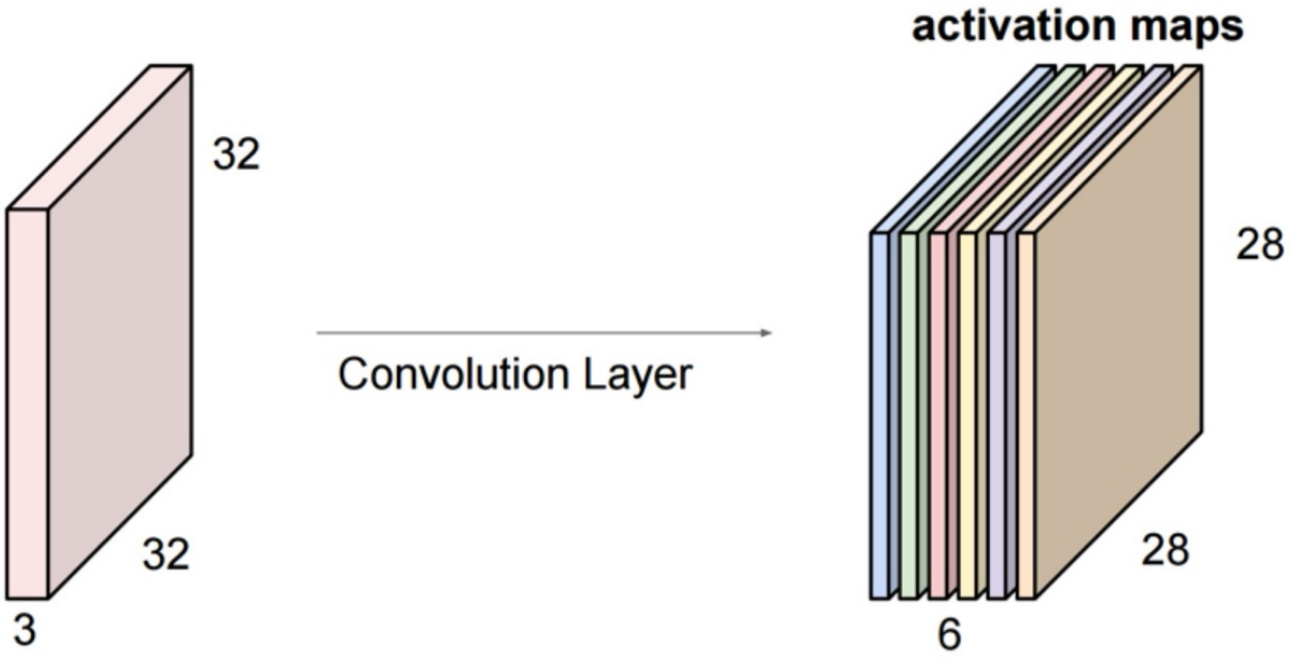
$$w^T x + b$$

Recap


Convolution Layer
activation map
32x32x3 image
5x5x3 filter
32
32
3
convolve (slide) over all
spatial locations
28
28
1

Recap

For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

- To measure the complexity of the network:
  - Number of parameters:

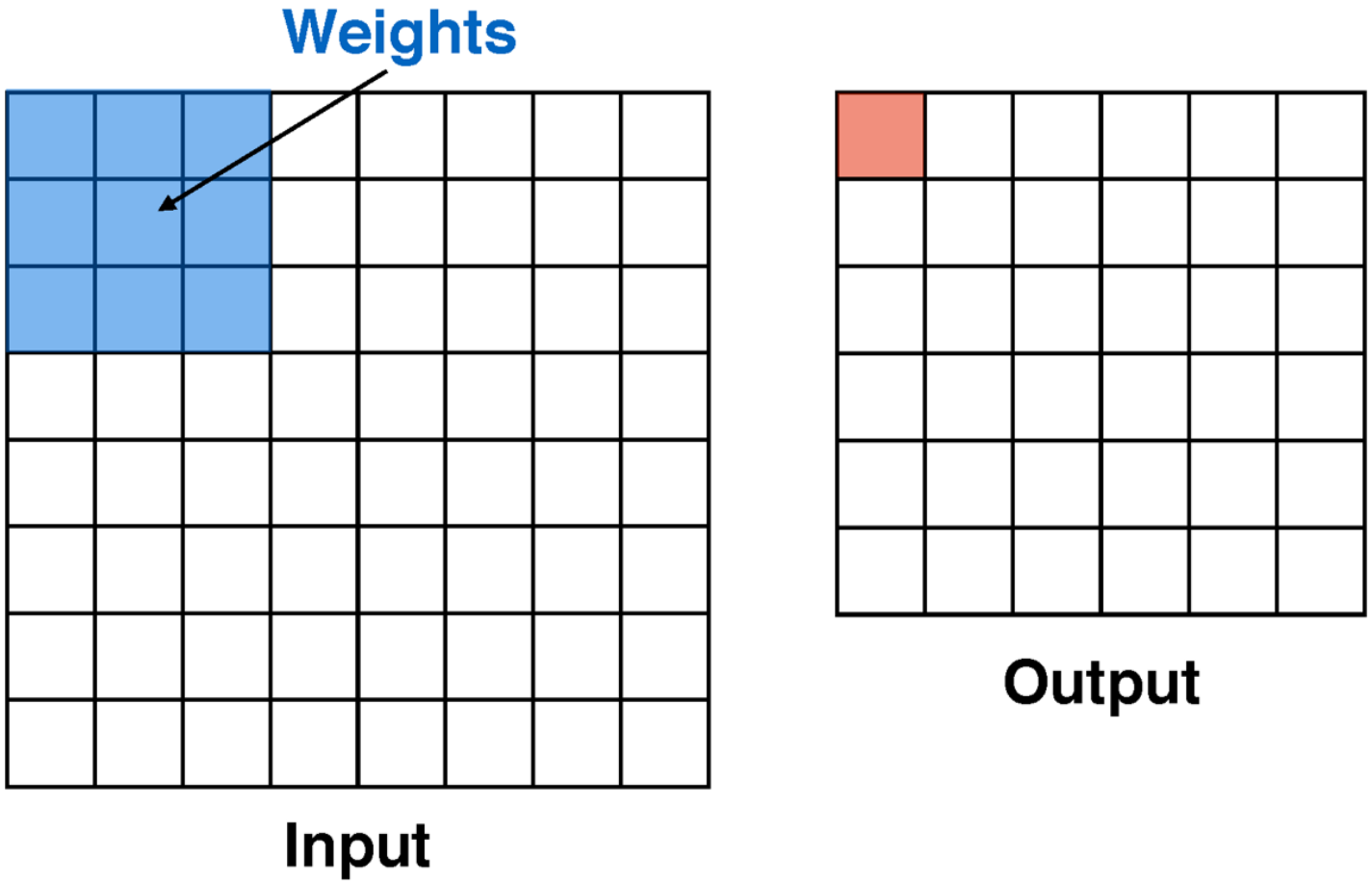
$$3 * 5 * 5 * 6 + 6 = 456$$

  - Number of multiplications:

$$3 * 5 * 5 * 6 * 28 * 28 = 352{,}800$$

Convolution operation: stride

During convolution, the weights "slide" along the input to generate each output



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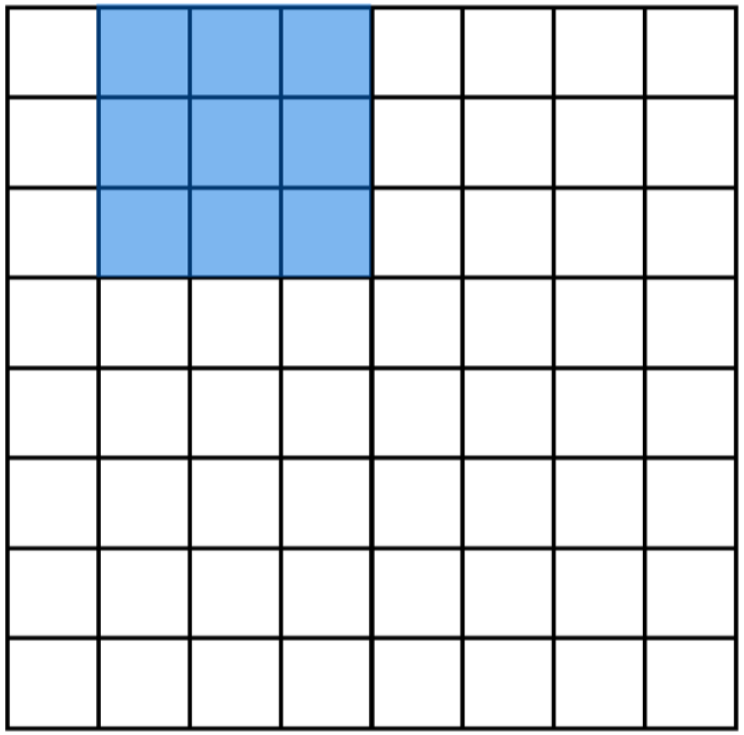
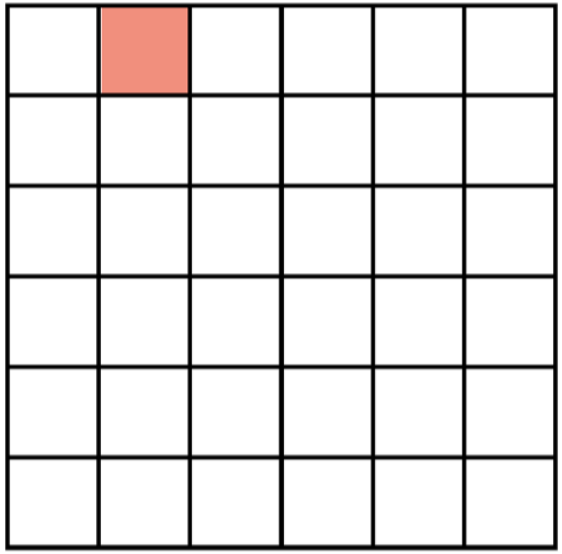


Input



Output

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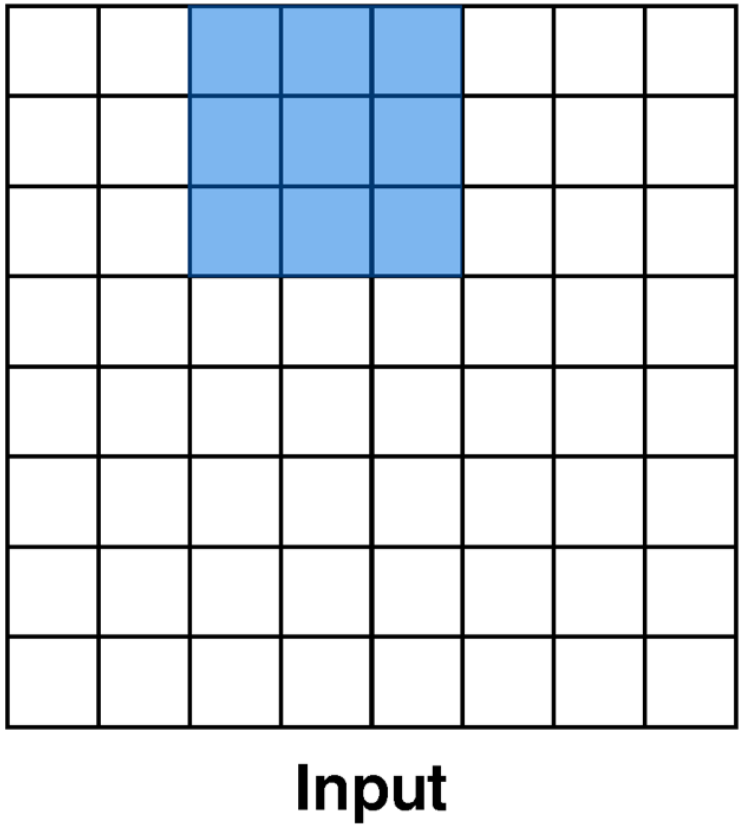
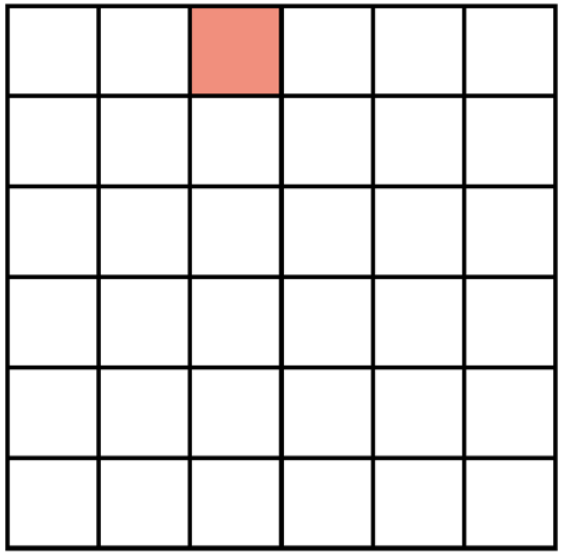


Input



Output

Convolution operation: stride

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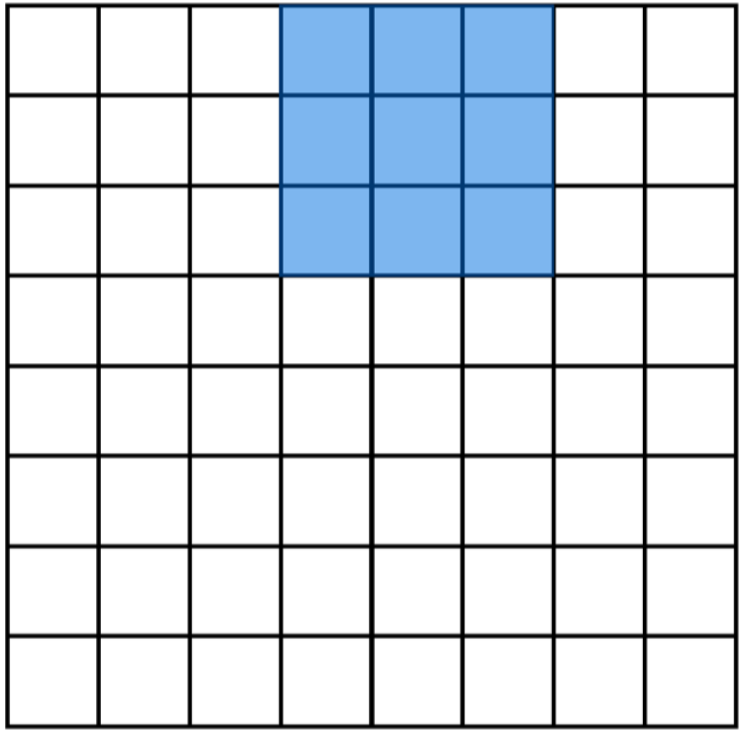
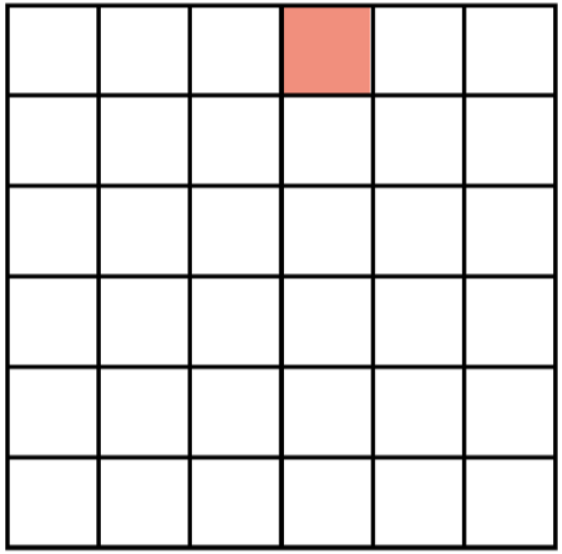


Input



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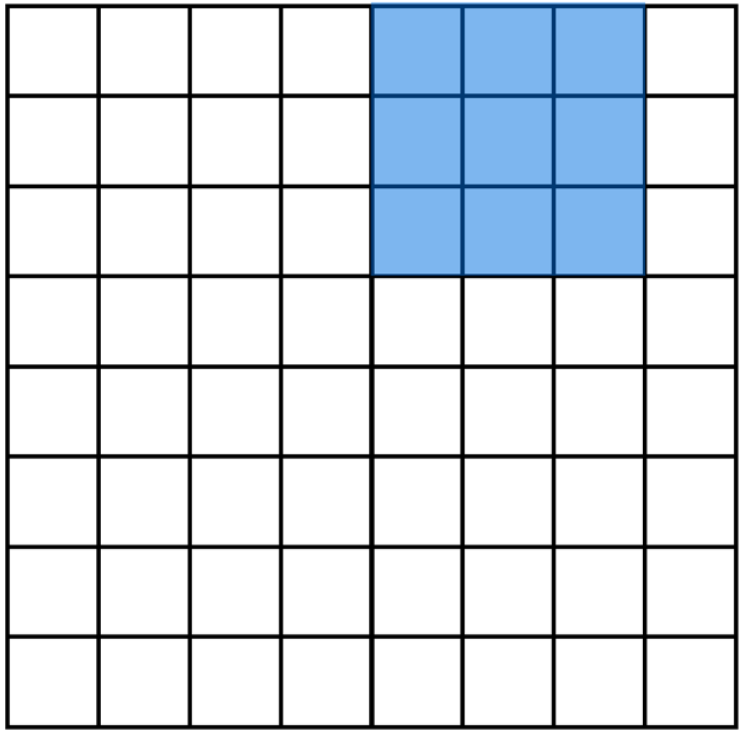
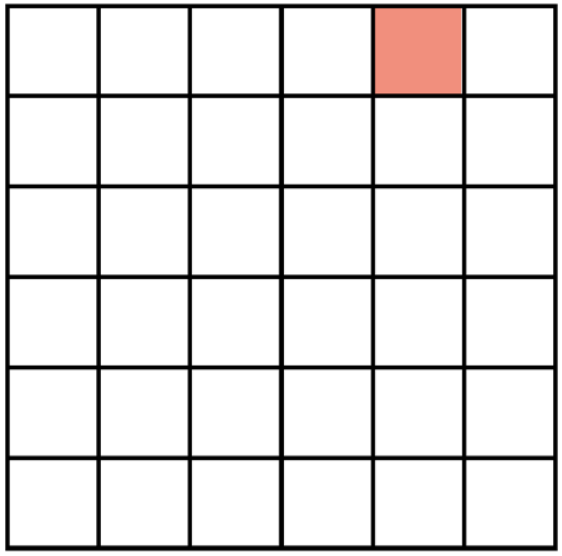


Input



Output

Convolution operation: stride

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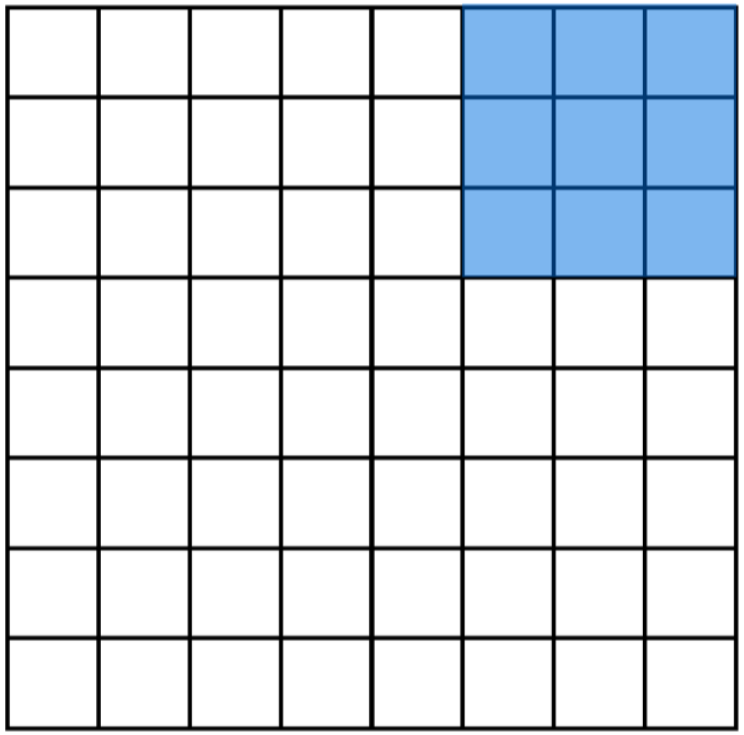
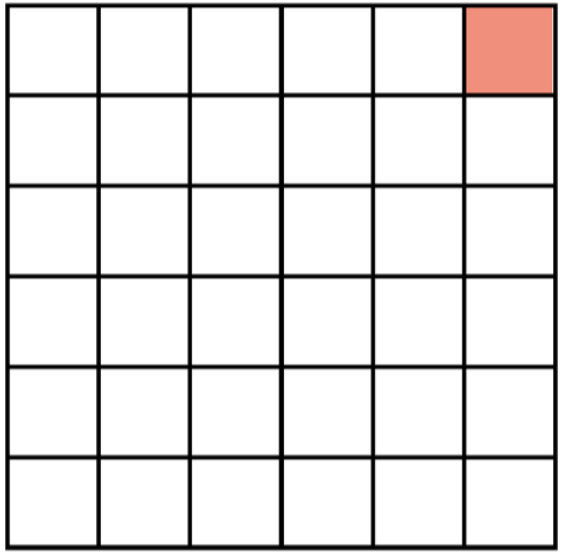


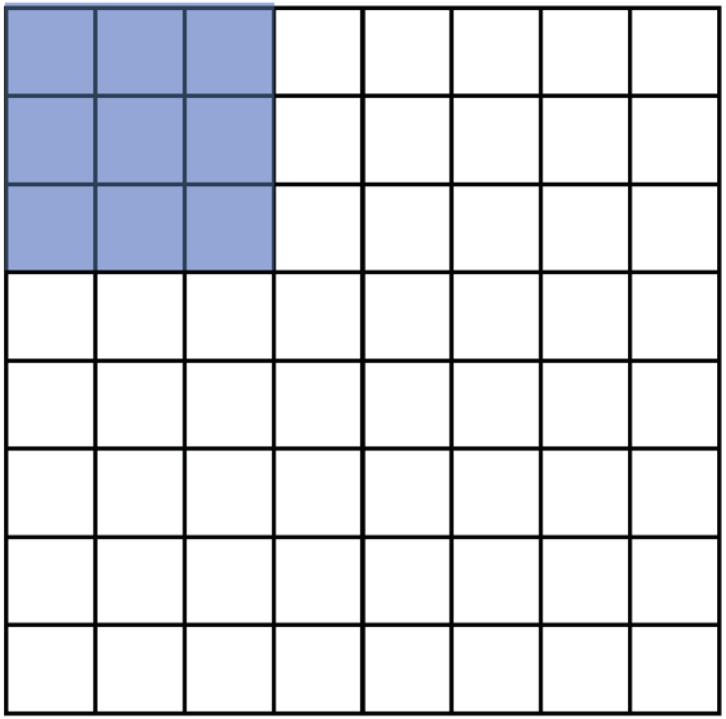
Input



Output

Convolution operation: stride

During convolution, the weights "slide" along the input to generate each output



Input

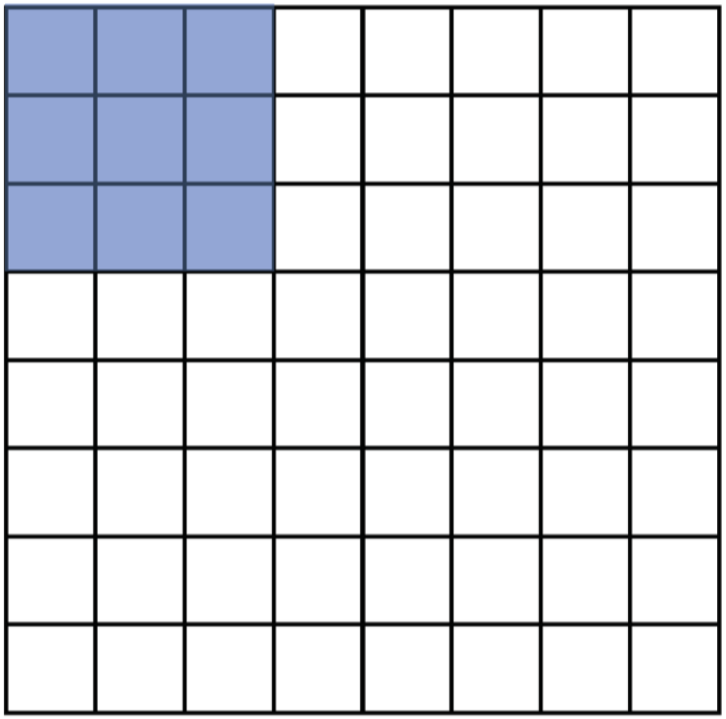
Recall that at each position, we are doing a **3D** sum:

$$h^r = \sum_{ijk} x^r{}_{ijk} W_{ijk} + b$$

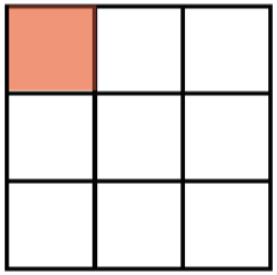
(channel, row, column)

Convolution operation: stride

But we can also convolve with a **stride**, e.g. stride = 2



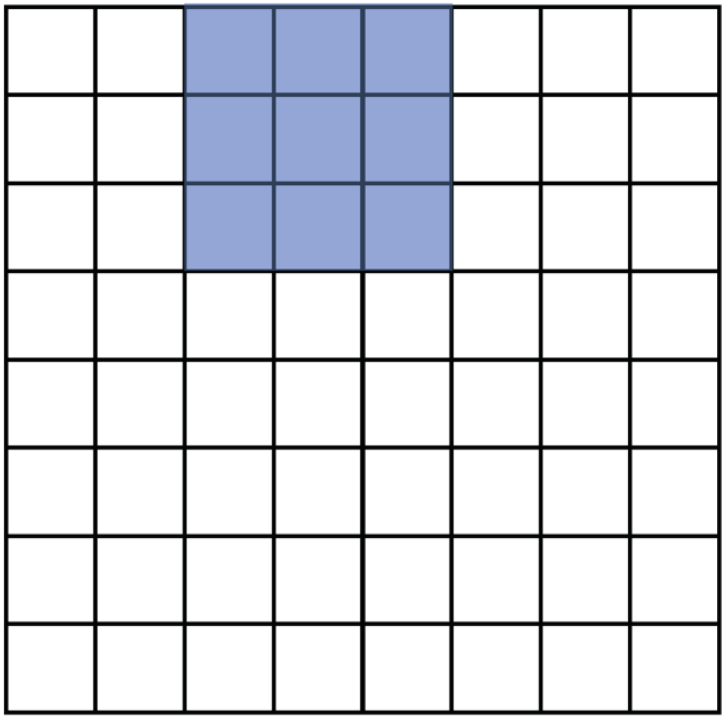
Input



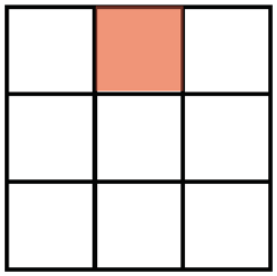
Output

Convolution operation: stride

But we can also convolve with a **stride**, e.g. stride = 2



Input



Output

Convolution operation: stride

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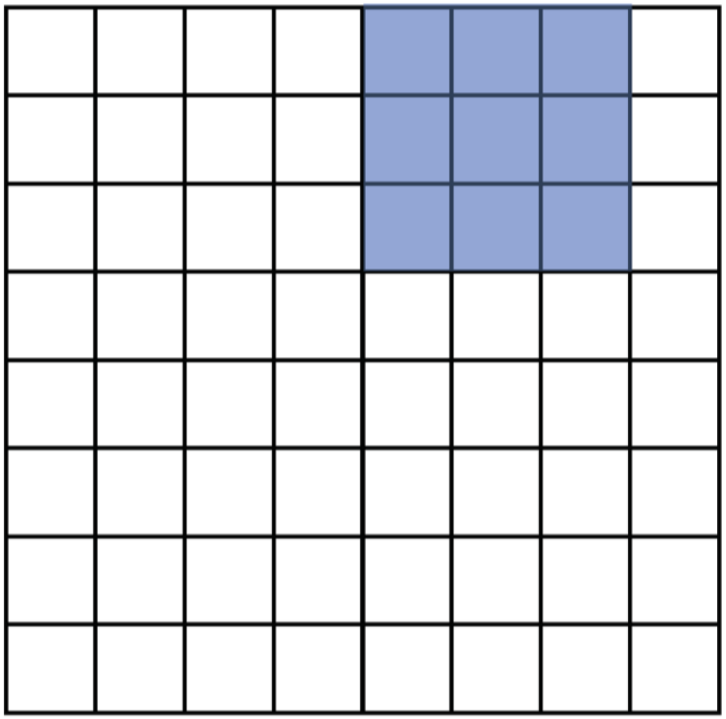
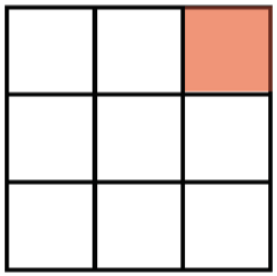


Input



Output

Convolution operation: stride

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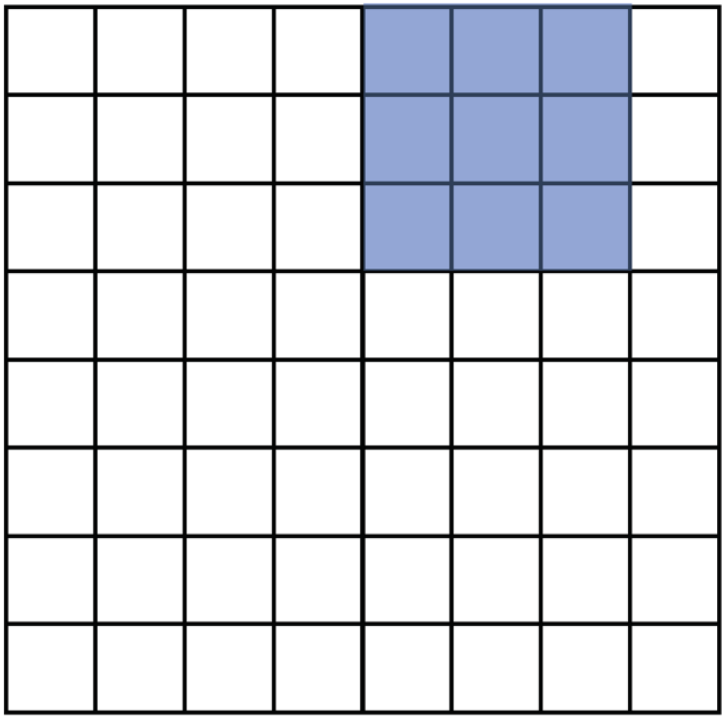
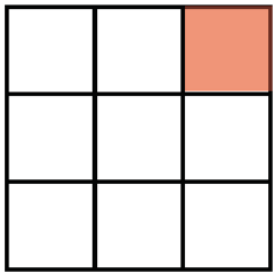


Input

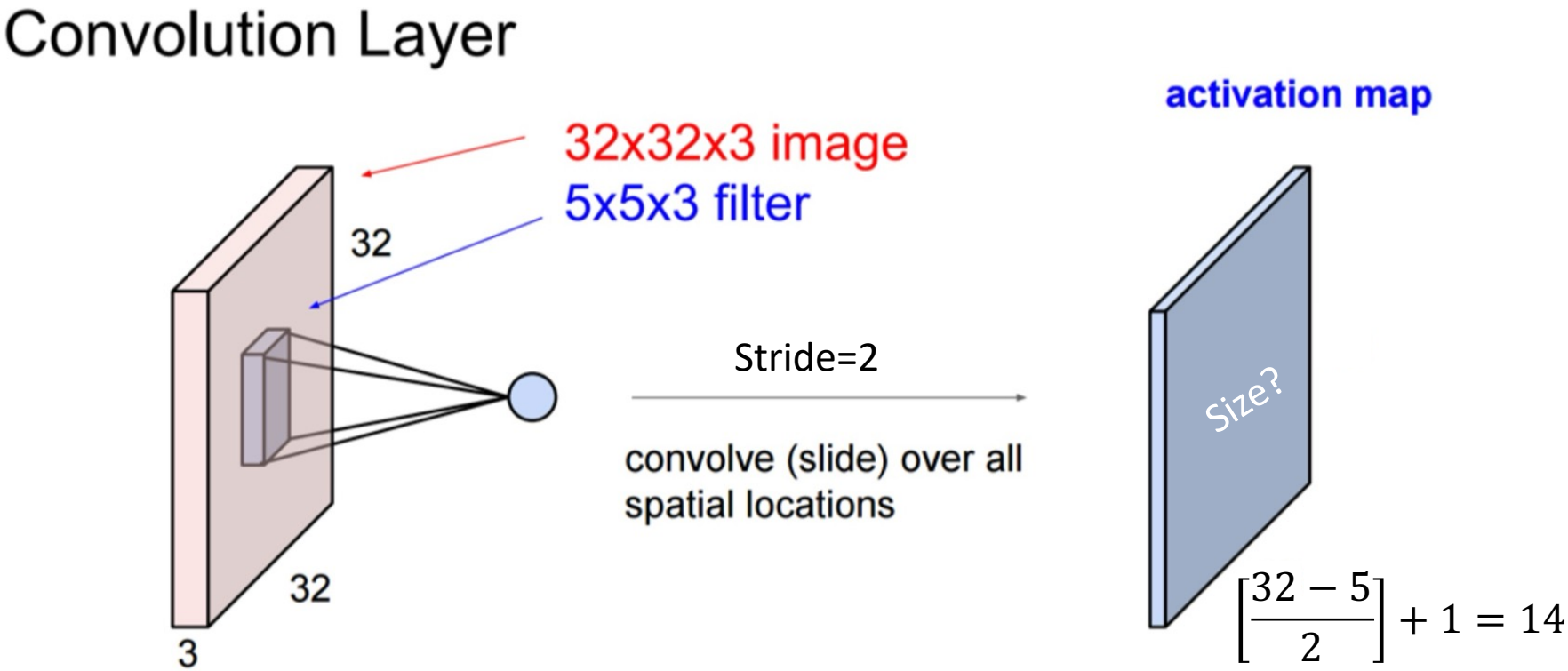


Output

- Notice that with certain strides, we may not be able to cover all of the input

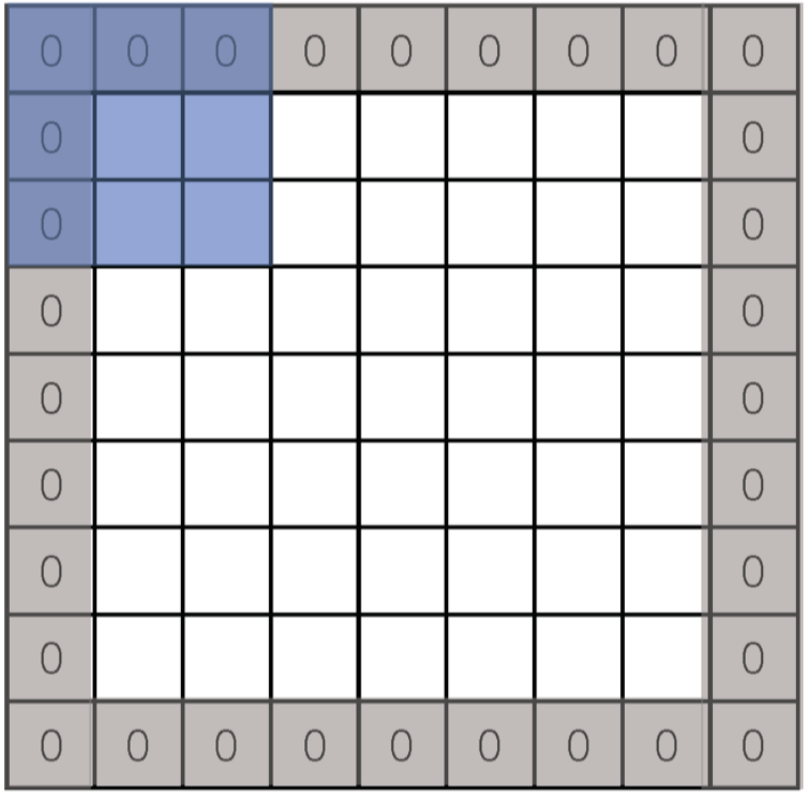
- The output is also half the size of the input

Convolution operation: stride

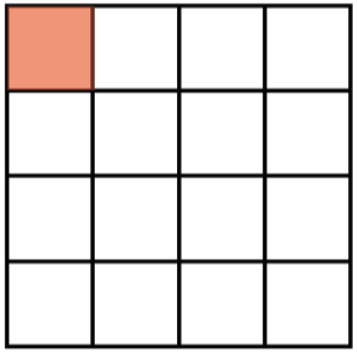


Convolution operation: padding

We can also pad the input with zeros.
Here, **pad = 1, stride = 2**



Input



Output

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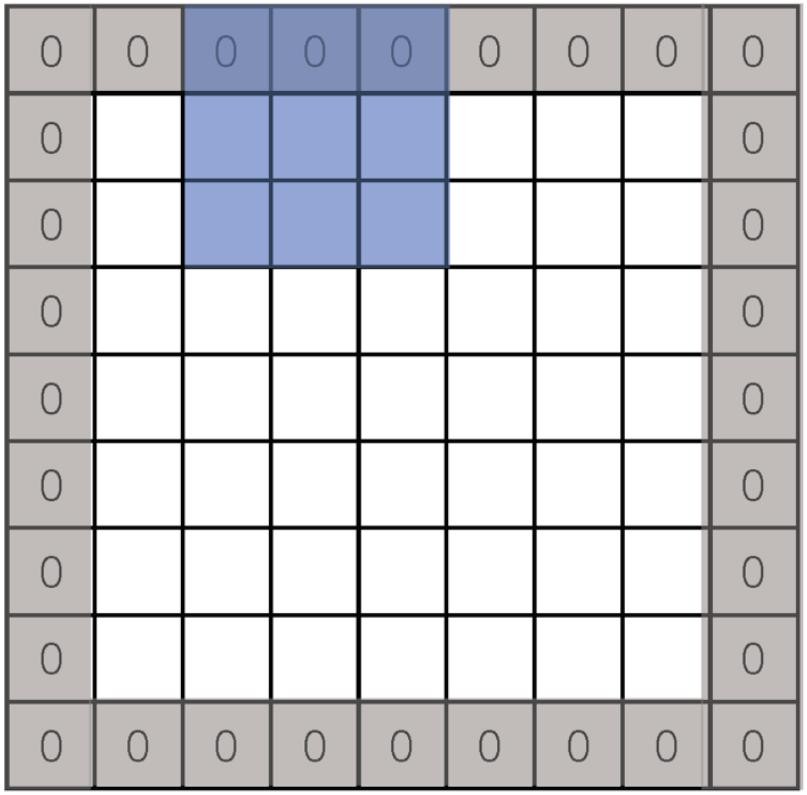
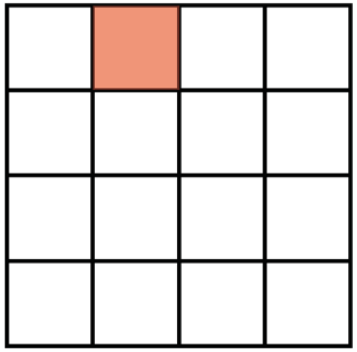


Input



Output

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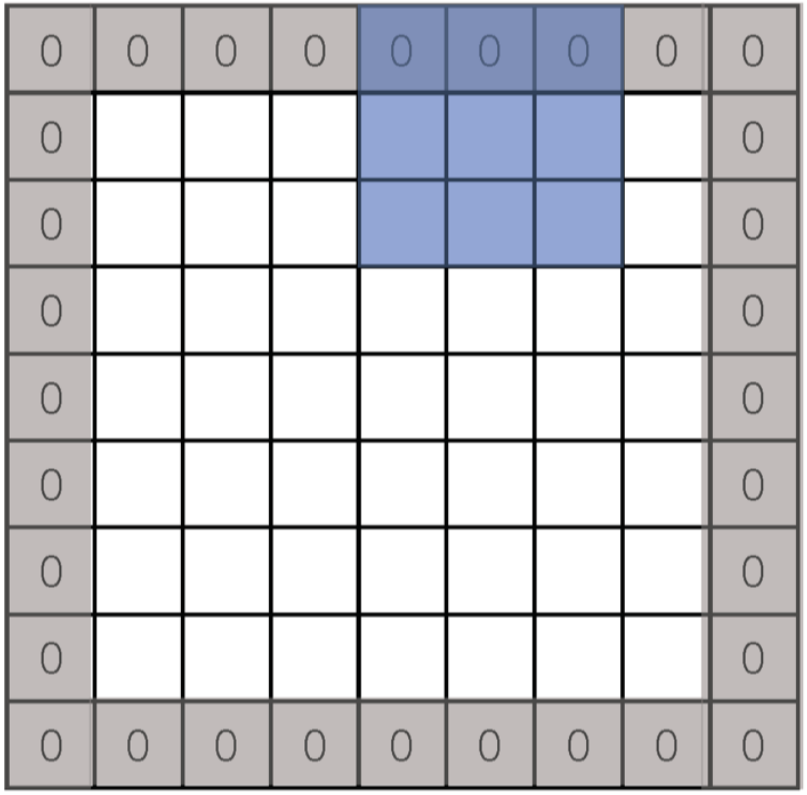
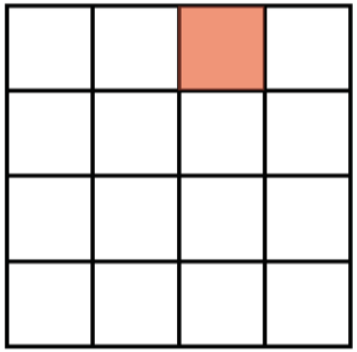


Input



Output

Convolution operation: padding

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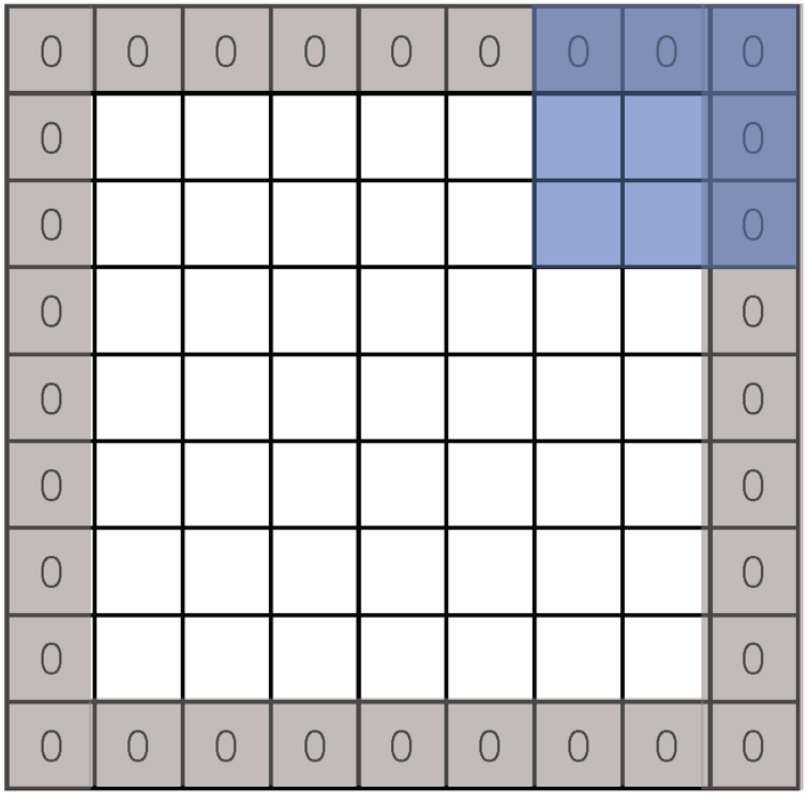
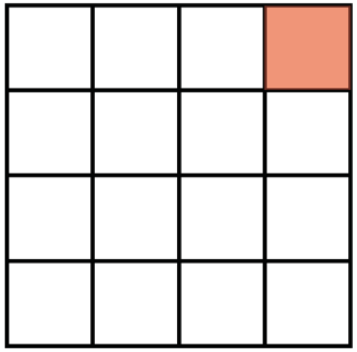
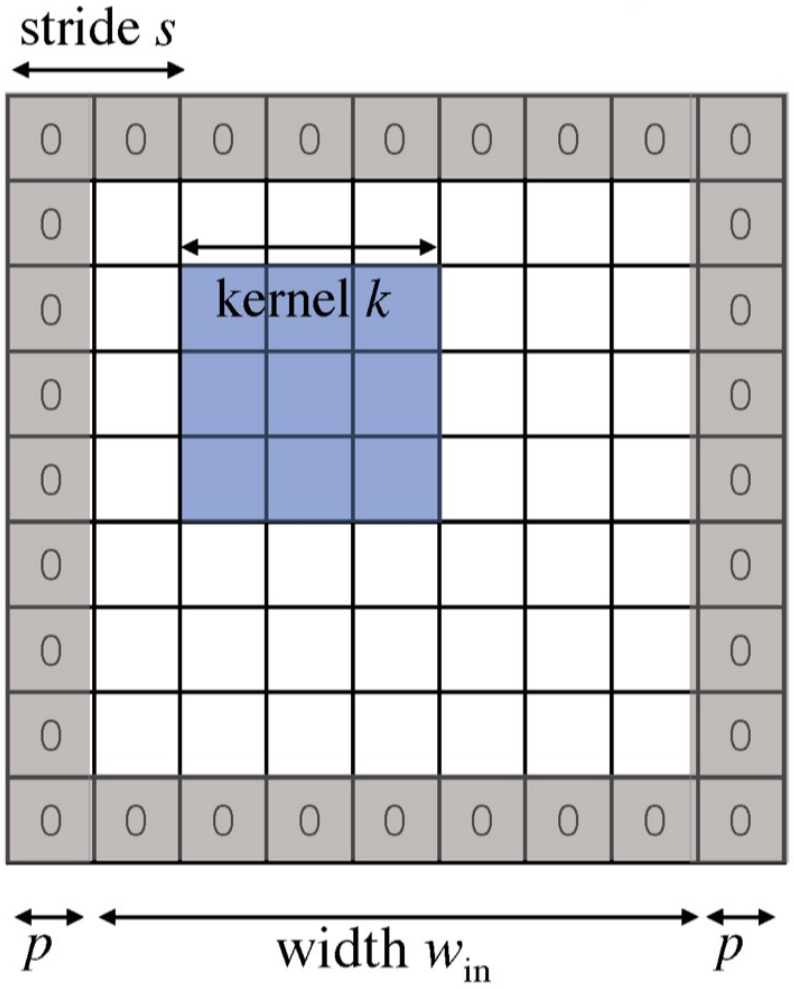


Input



Output

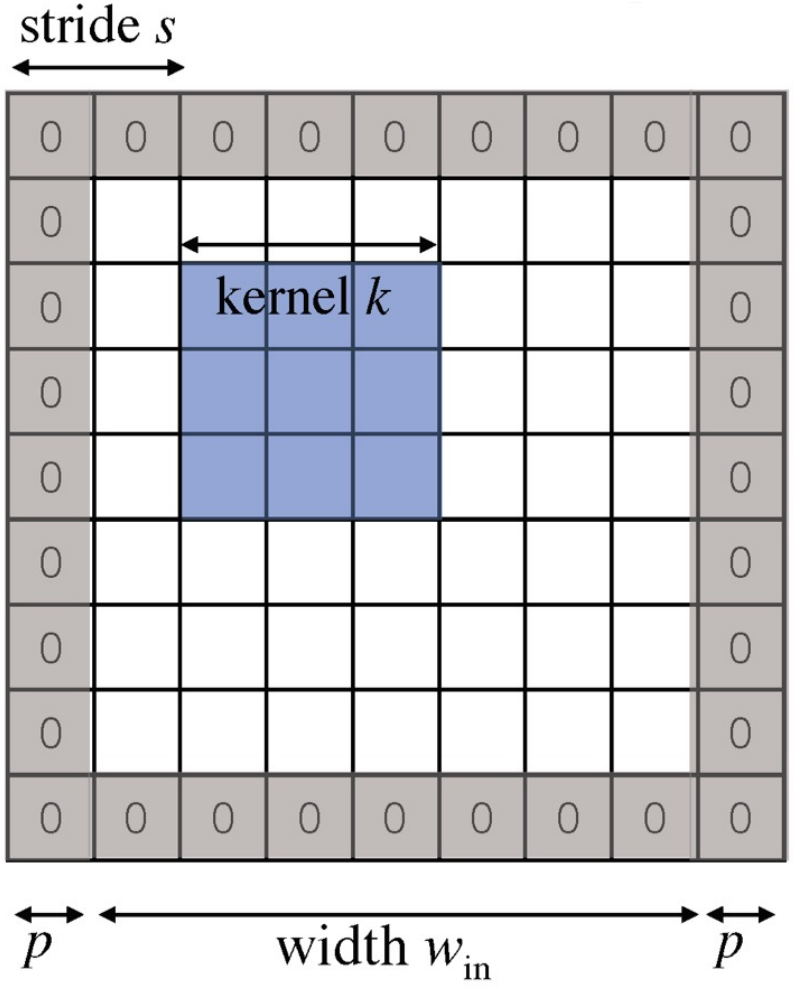
Convolution: output size



In general, the output has size:

$$w_{out} = \left\lfloor \frac{w_{in} + 2p - k}{s} \right\rfloor + 1$$

Convolution: output size



Example: k=3, s=1, p=1

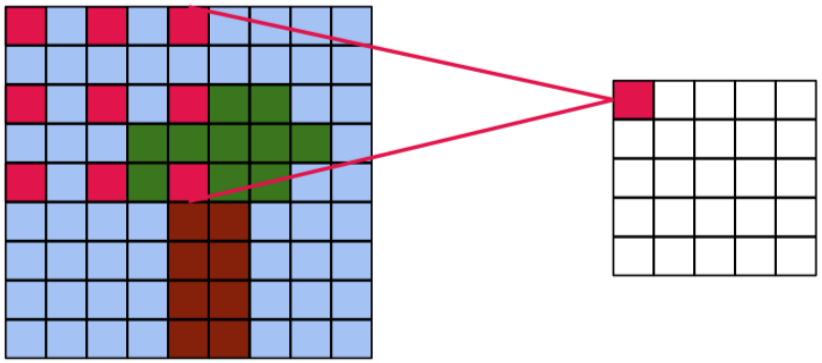
$$w_{out} = \left\lfloor \frac{w_{in} + 2p - k}{s} \right\rfloor + 1$$

$$= \left\lfloor \frac{w_{in} + 2 - 3}{1} \right\rfloor + 1$$

$$= w_{in}$$

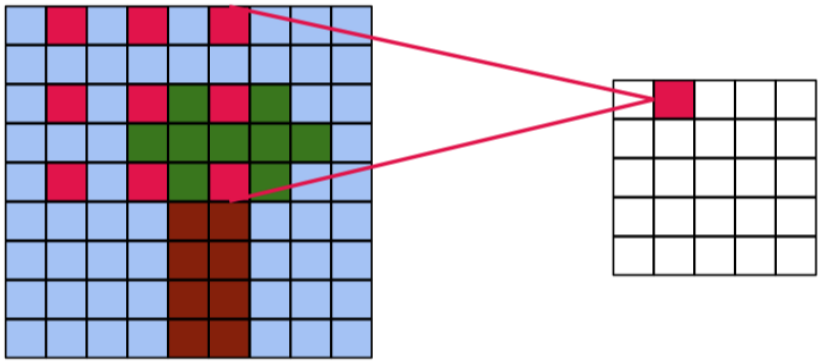
VGGNet [Simonyan 2014] uses filters of this shape

Convolution operation: dilation



Dilated convolution: kernel is spread out, step > 1 between kernel elements

Convolution operation: dilation

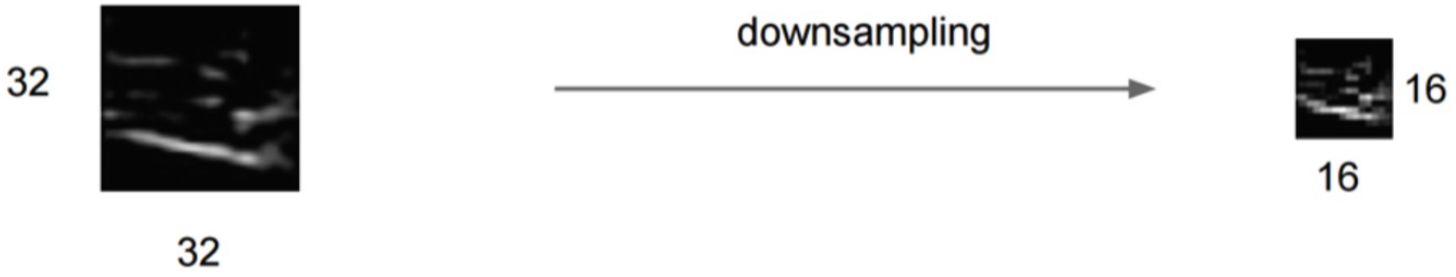


Dilated convolution: kernel is spread out, step > 1 between kernel elements

Pooling

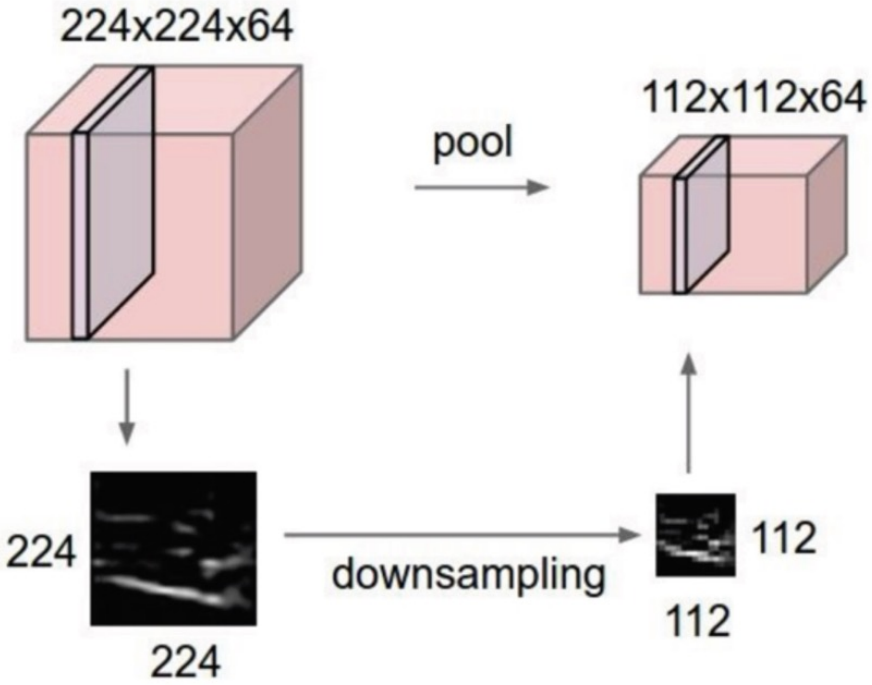
For most ConvNets, **convolution** is often followed by **pooling**:

- Creates a smaller representation while retaining the most important information
- The “max” operation is the most common
- Why might “avg” be a poor choice?

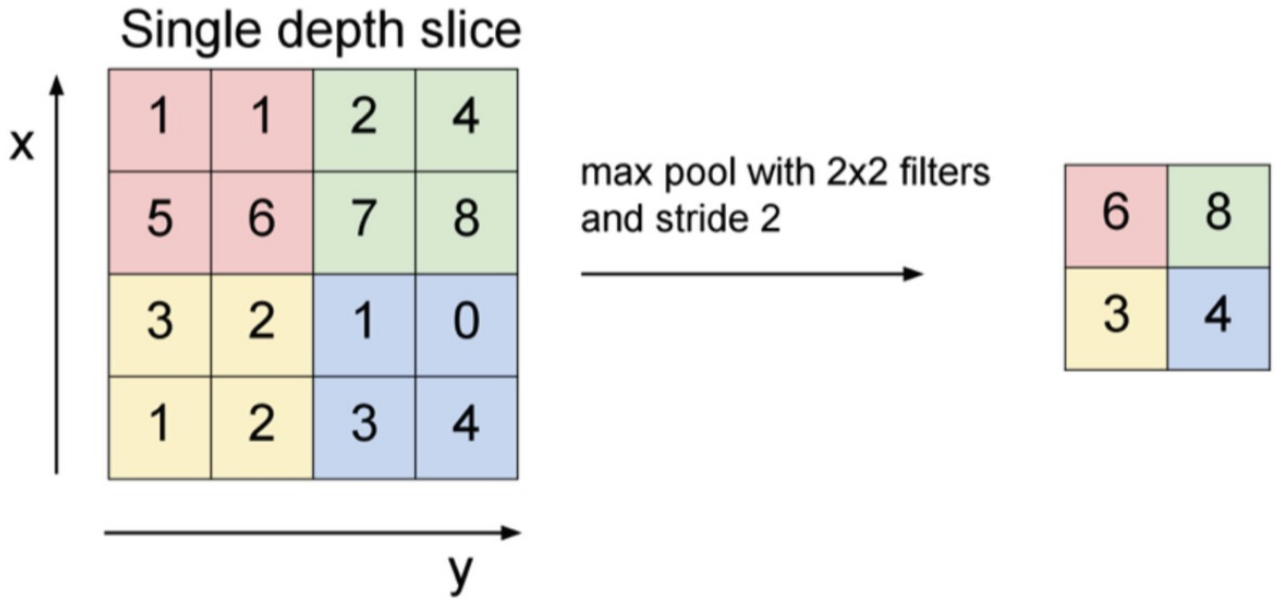


Pooling

- makes the representations smaller and more manageable
- operates over each activation map independently:



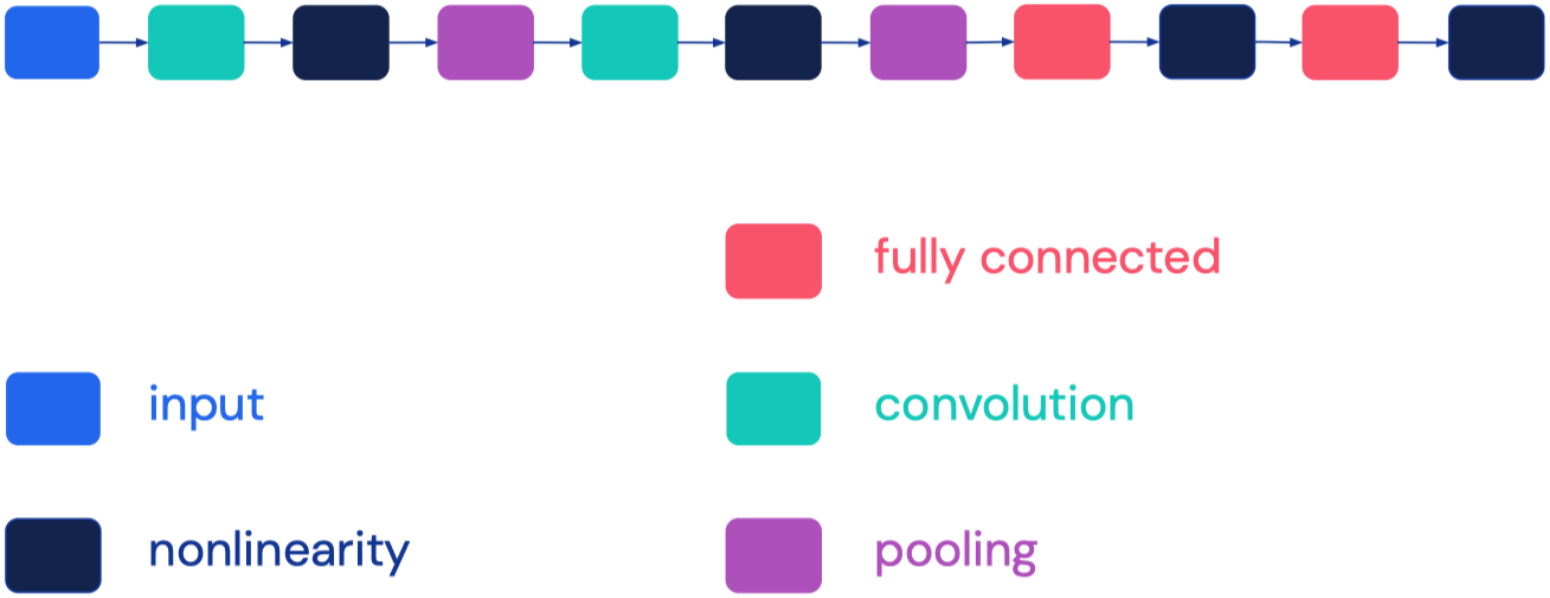
Max Pooling



What's the backprop rule for max pooling?

- In the forward pass, store the index that took the max
- The backprop gradient is the input gradient at that index

Computational building blocks of convnets



Inspirations from Neuroscience

A bit of history:

Hubel & Wiesel,

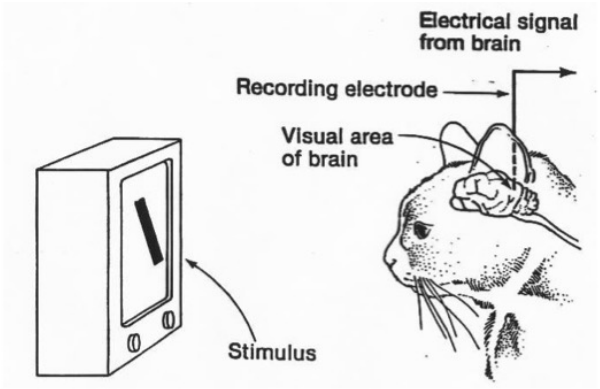
1959

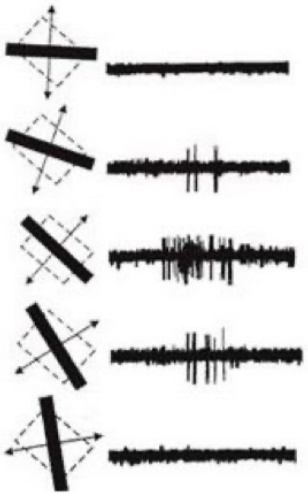
RECEPTIVE FIELDS OF SINGLE NEURONES IN
THE CAT'S STRIATE CORTEX

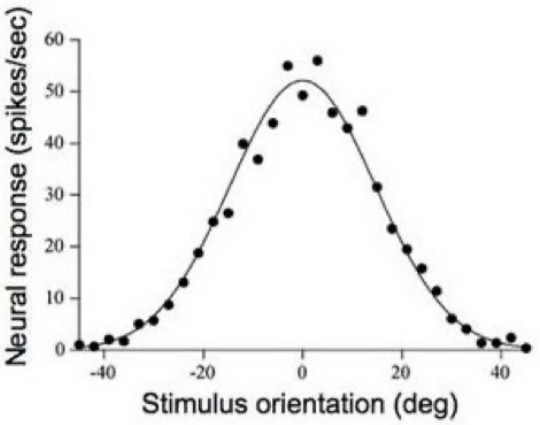
1962

RECEPTIVE FIELDS, BINOCULAR INTERACTION
AND FUNCTIONAL ARCHITECTURE IN
THE CAT'S VISUAL CORTEX

1968...

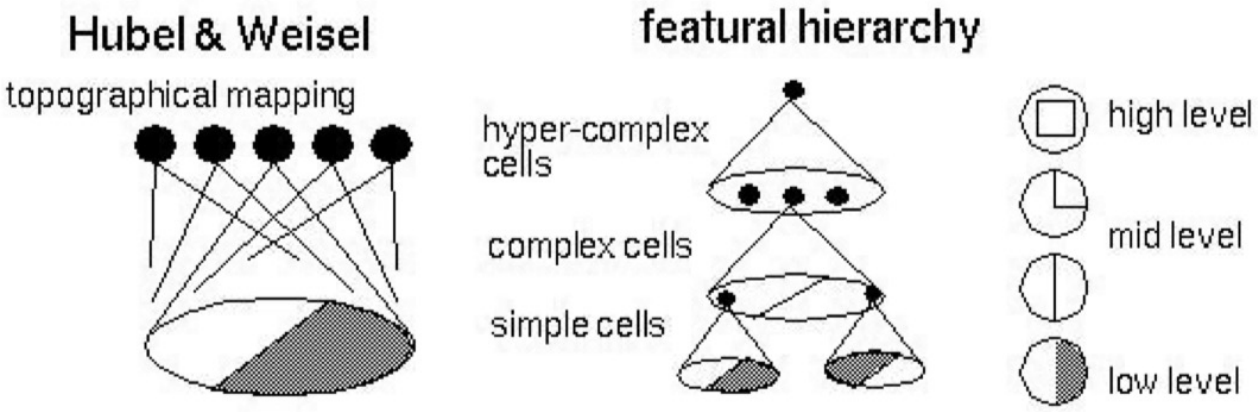






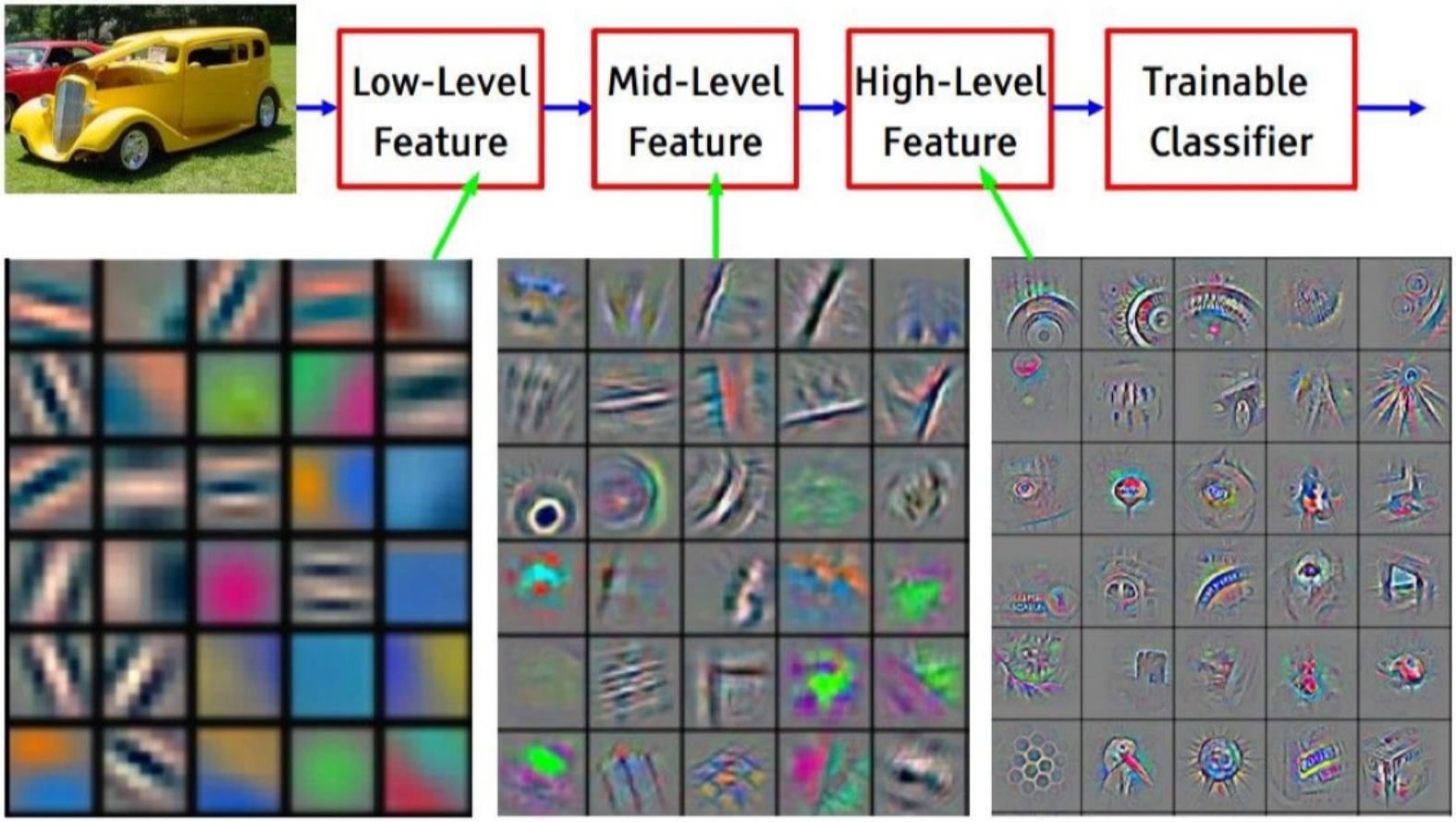
Inspirations from Neuroscience

Hierarchical organization



Inspirations from Neuroscience

- ConvNets:



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Questions?

UNIVERSITY OF NORTH CAROLINA CHARLOTTE