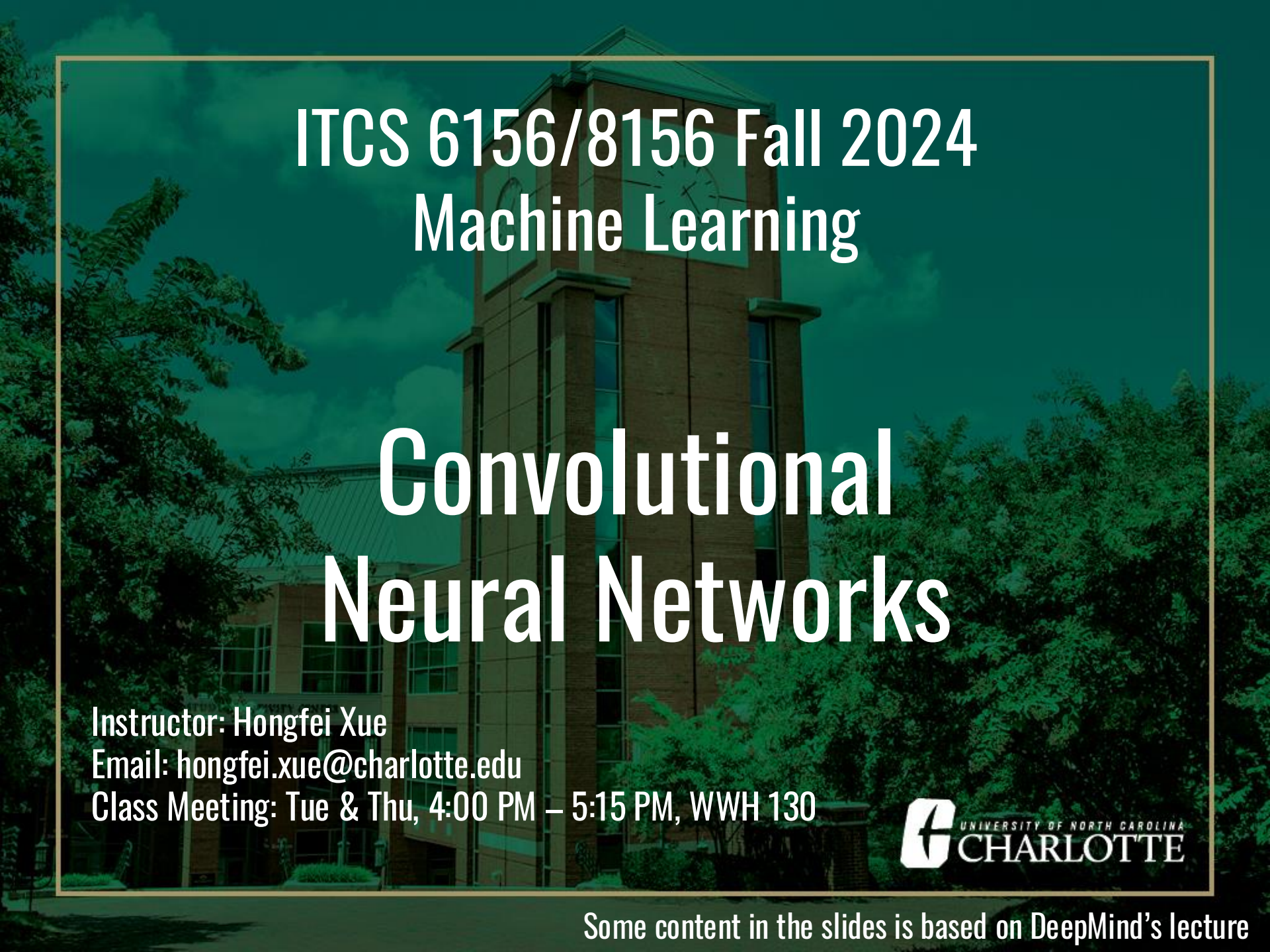


ITCS 6156/8156 Fall 2024
Machine Learning

Convolutional Neural Networks

Instructor: Hongfei Xue
Email: hongfei.xue@charlotte.edu
Class Meeting: Tue & Thu, 4:00 PM – 5:15 PM, WWH 130

UNIVERSITY OF NORTH CAROLINA CHARLOTTE

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

Before Deep Learning

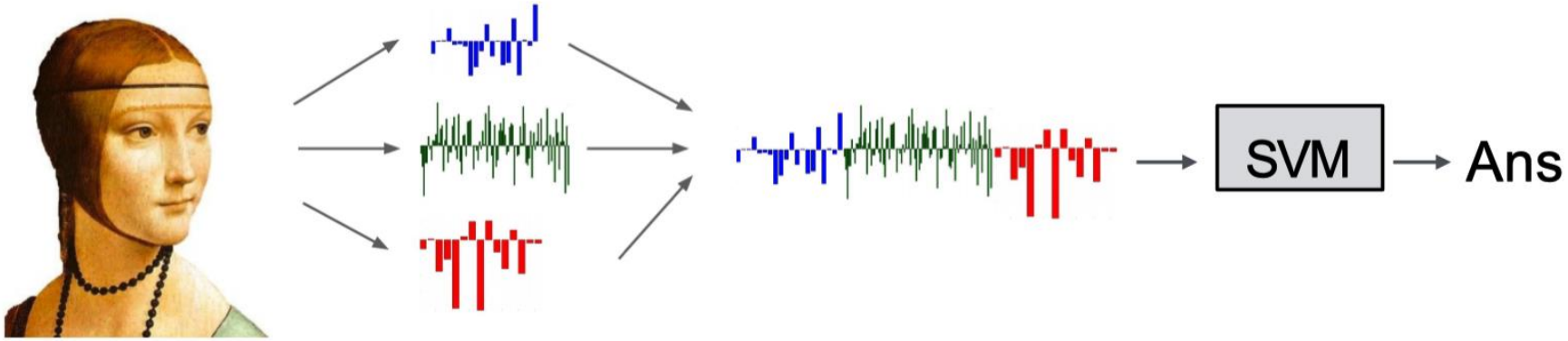


Figure: Karpathy 2016

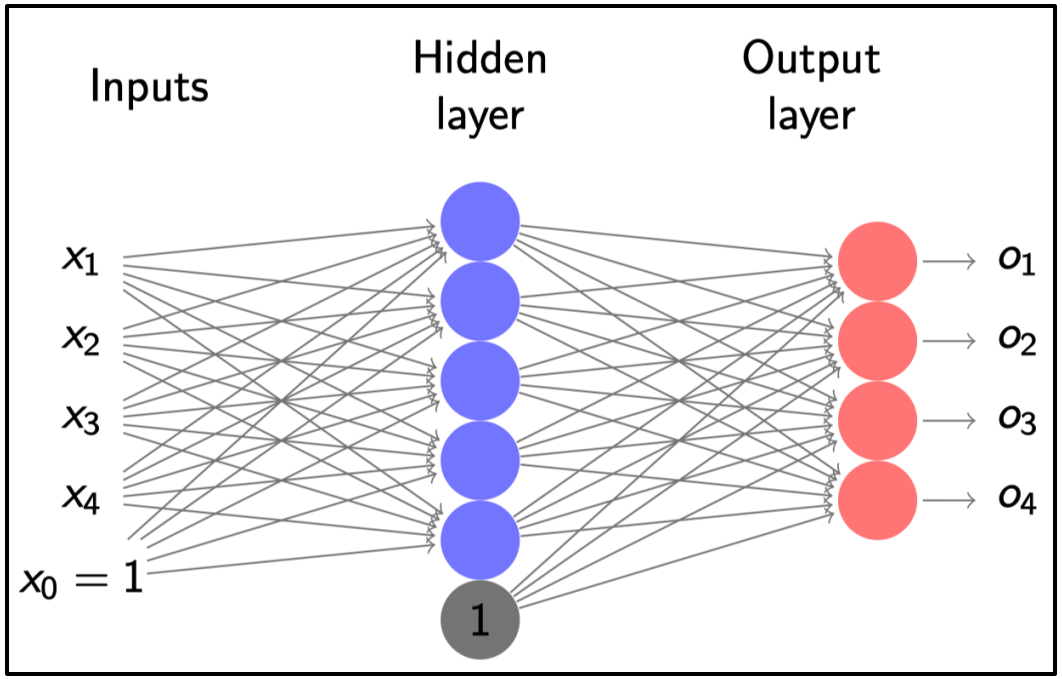
Using Deep Learning

Input Pixels

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

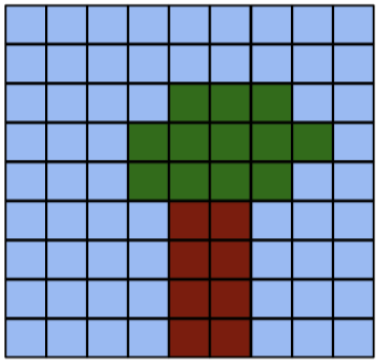
- Traditional machine learning models might struggle or require extensive **feature engineering** in these scenarios. Deep learning models can **automatically learn complex representations and feature hierarchies**, leading to superior performance on tasks like image recognition, natural language processing,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

Neural Networks



- D input nodes (excluding bias)
- M hidden nodes (excluding bias)
- K output nodes
- At hidden nodes: $\mathbf{w_j}, 1 \leq j \leq M$, $\mathbf{w_j} \in \mathbb{R}^{D+1}$
- At output nodes: $\mathbf{w_l}, 1 \leq l \leq K$, $\mathbf{w_l} \in \mathbb{R}^{M+1}$

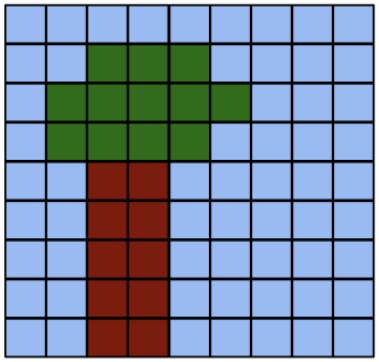
Neural Networks for Images



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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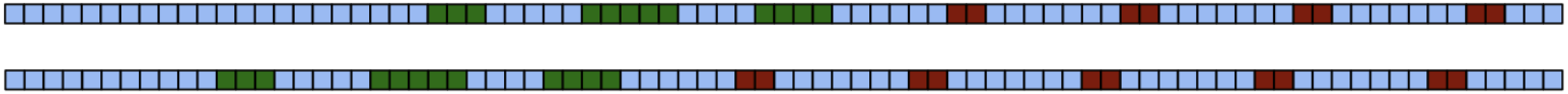
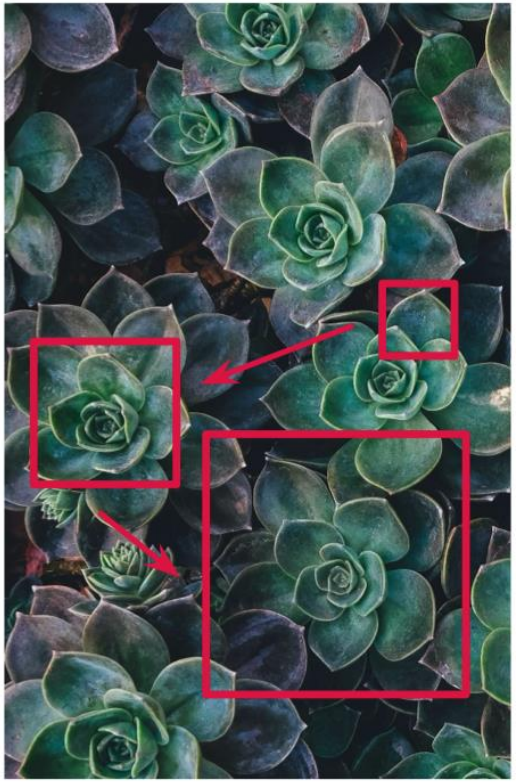


Locality and translation invariance

Locality: nearby pixels are more strongly correlated

Translation invariance: meaningful patterns can occur anywhere in the image

Taking advantage of topological structure

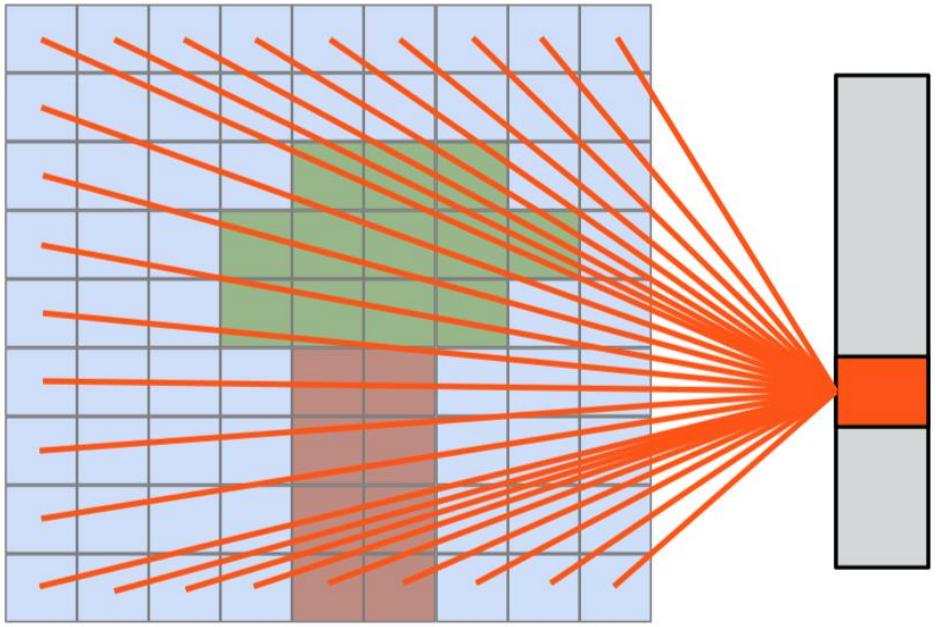


Weight sharing: use the same network parameters to detect local patterns at many locations in the image

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

edges and textures → object parts → objects

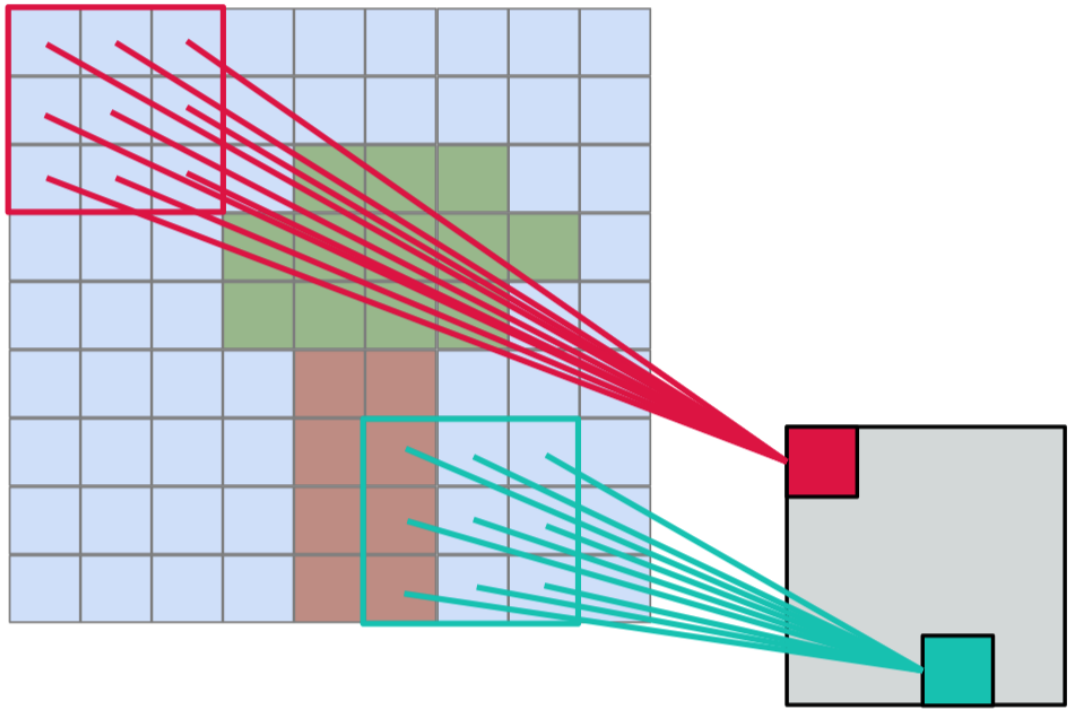
From fully connected to locally connected



fully-connected unit

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

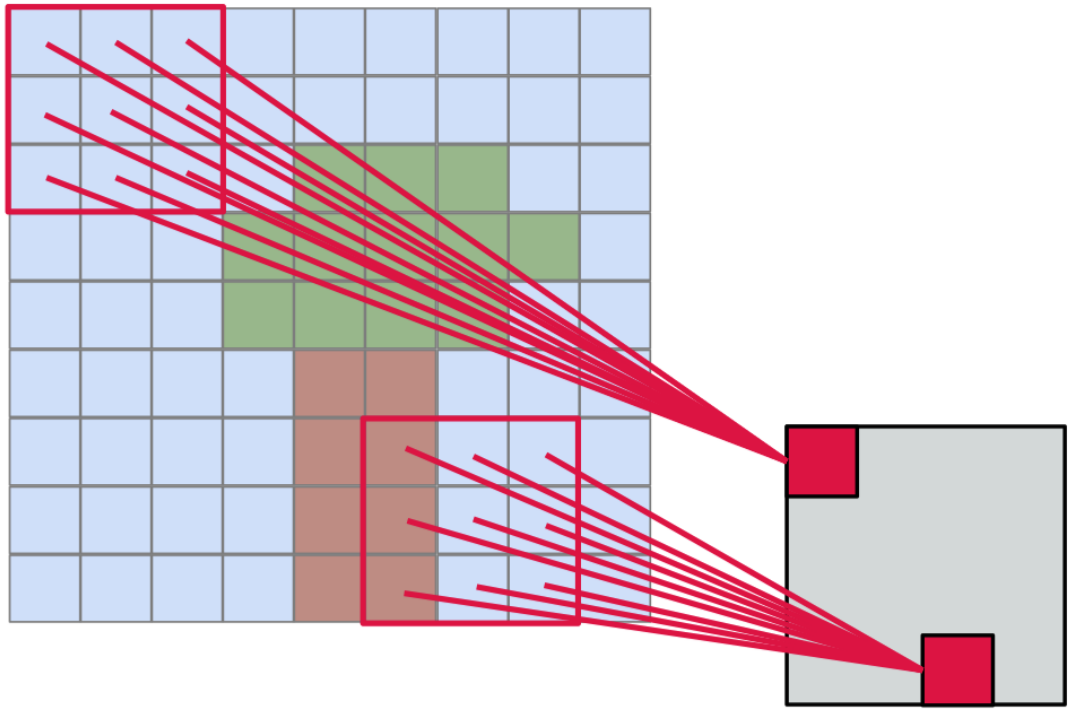
From fully connected to locally connected



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

locally-connected units
3×3 receptive field

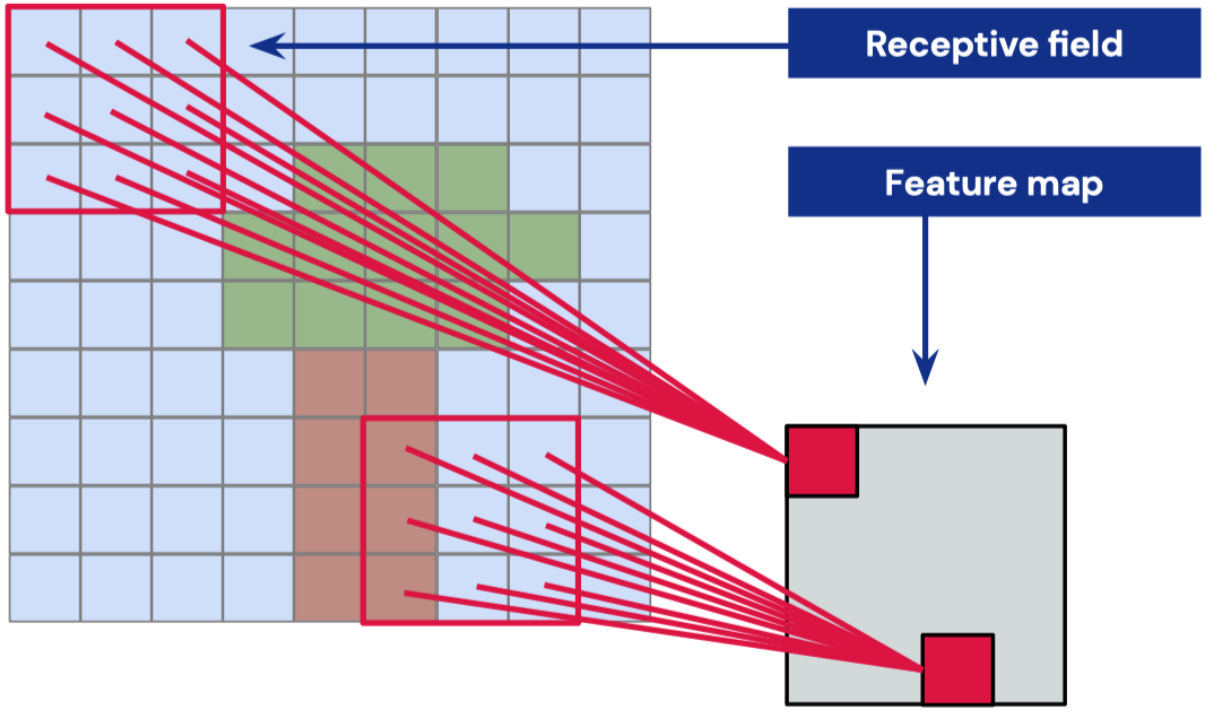
From fully connected to locally connected



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

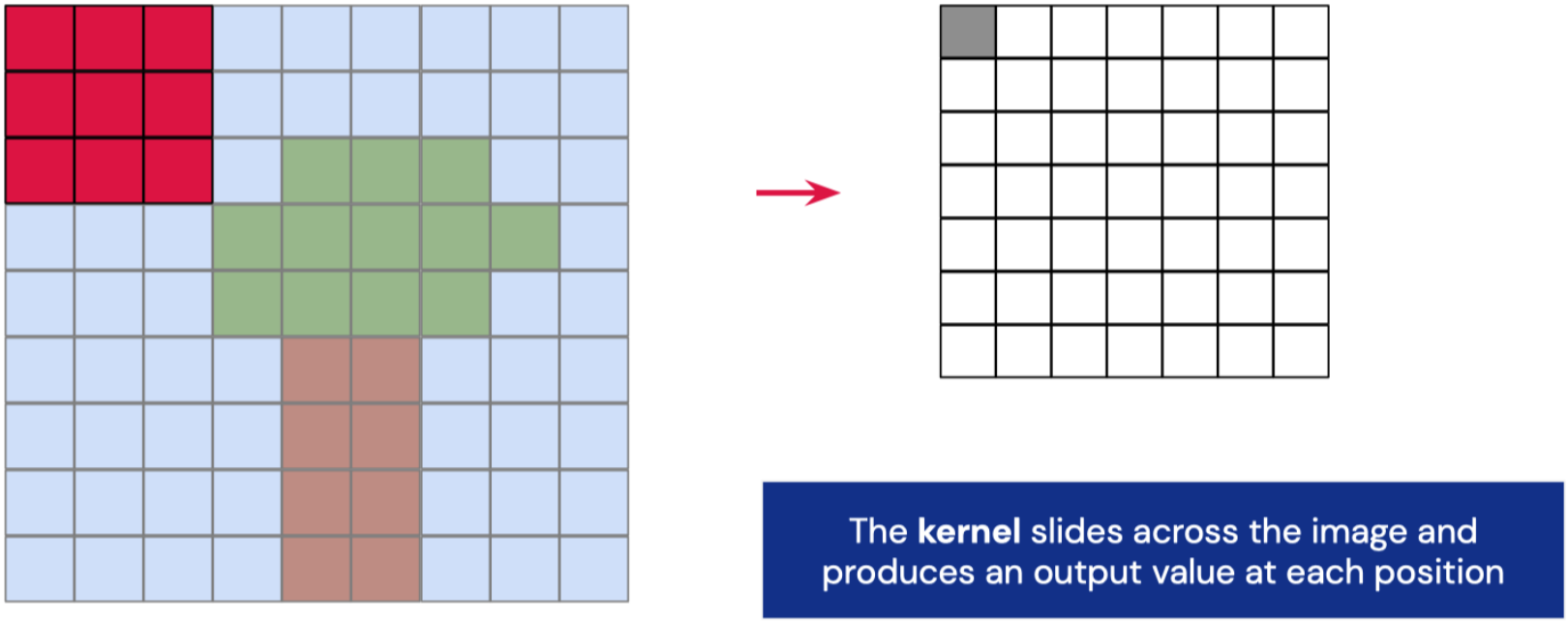
convolutional units
3×3 receptive field

From fully connected to locally connected



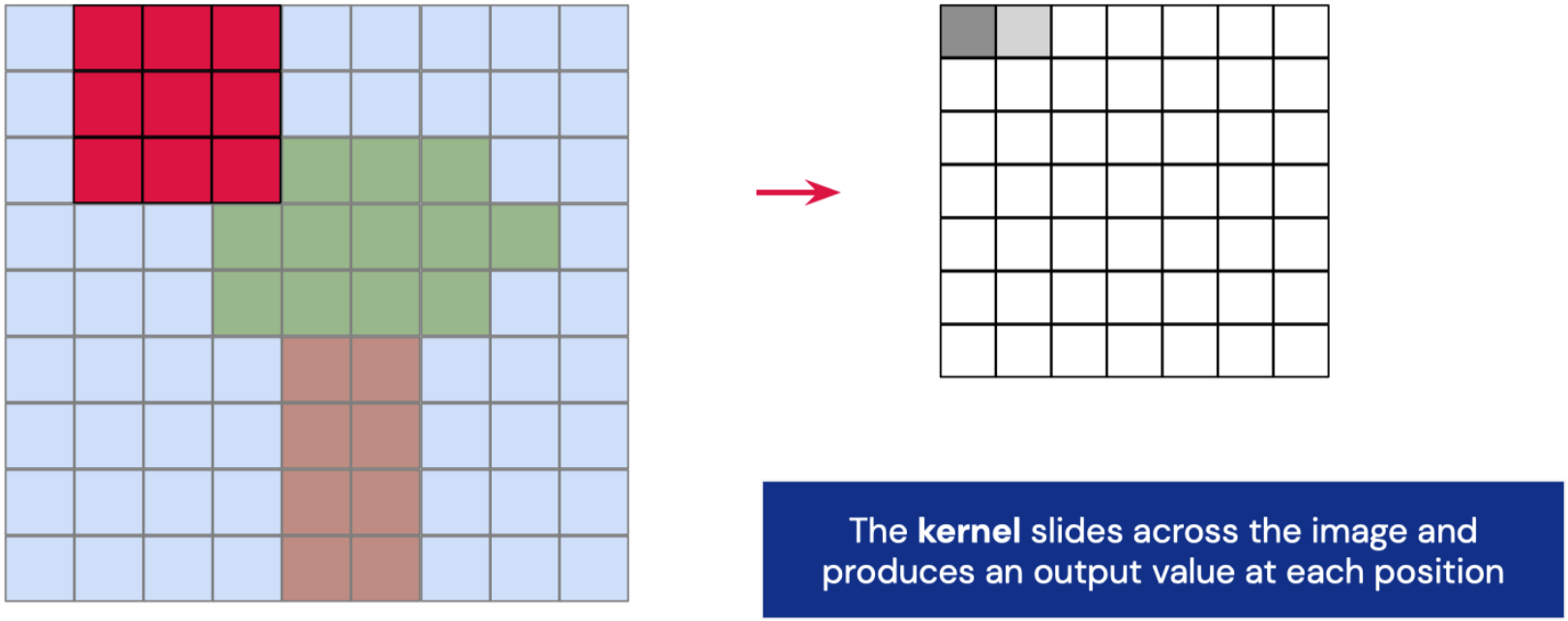
- **Receptive field**: the size of the region in the input that produces the feature. For a given layer in a CNN, the receptive field of a neuron is defined as the size of the region in the input space that affects the neuron's activation.
- **Feature map**: a feature map is a two-dimensional activation 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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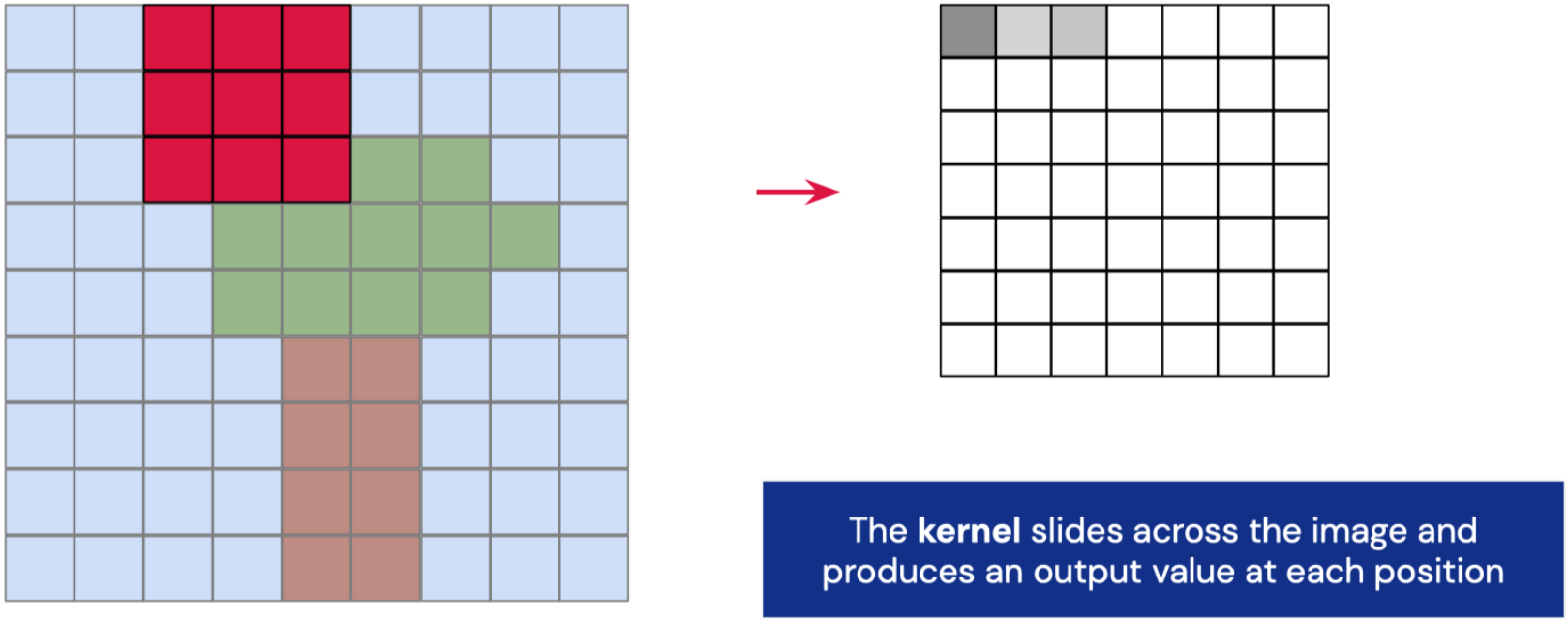

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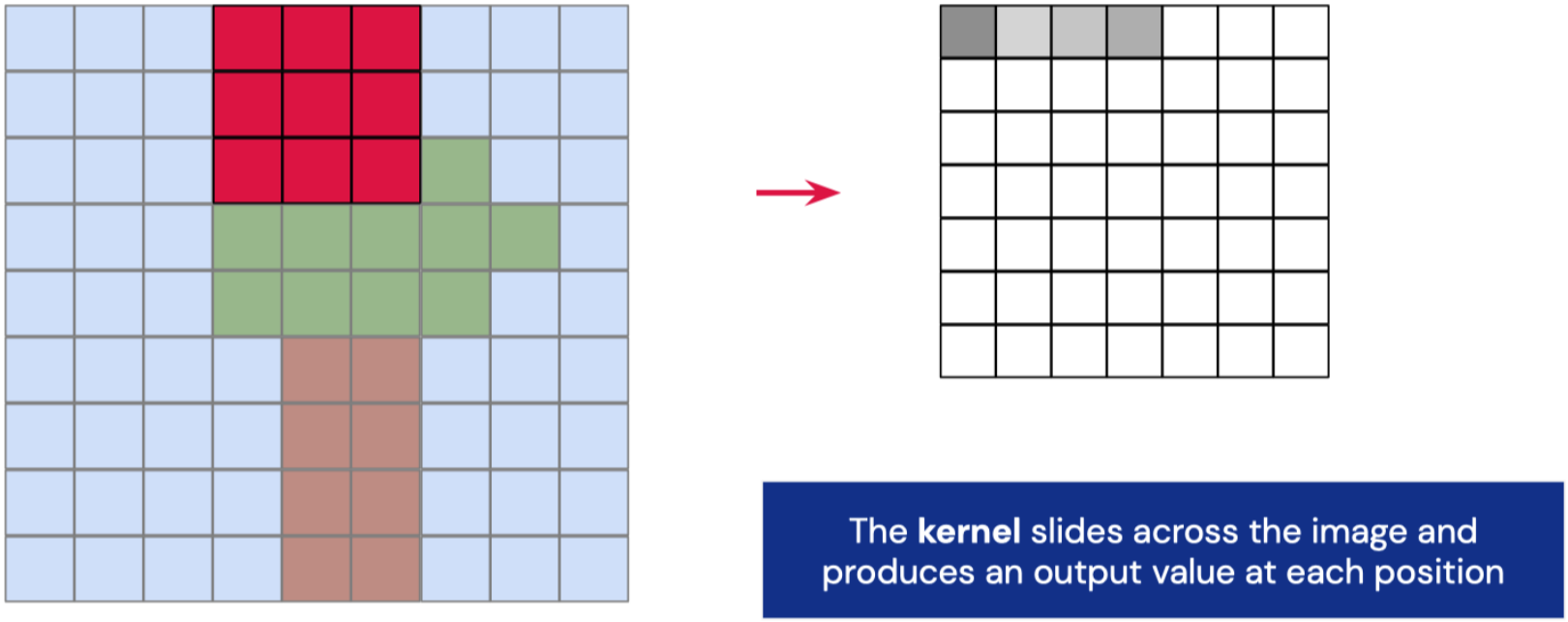

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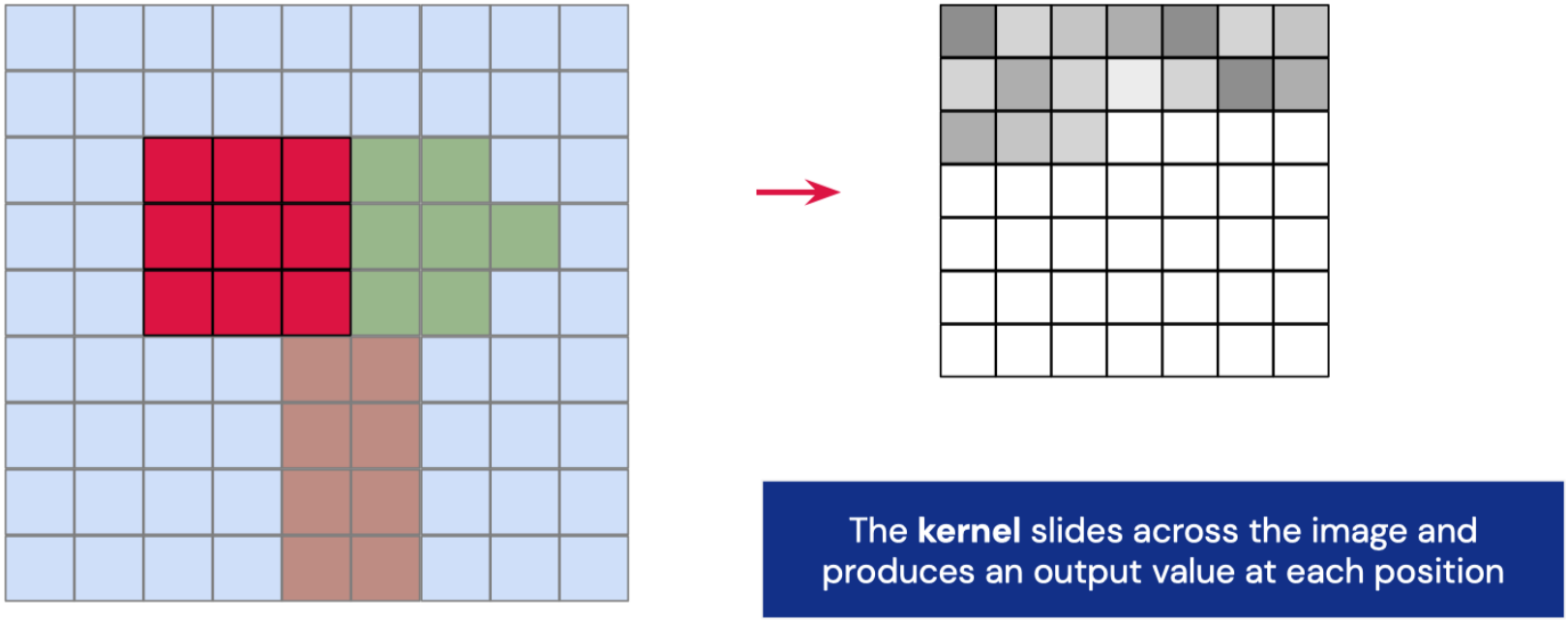

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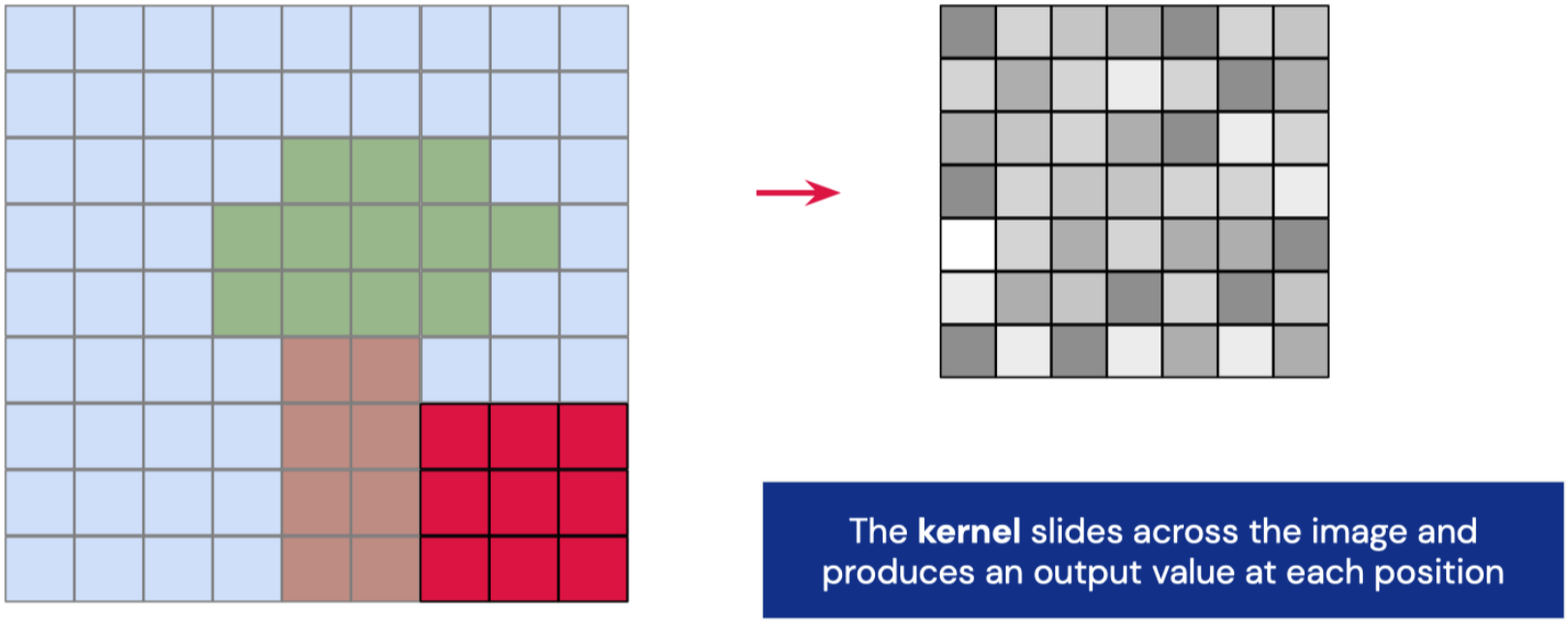
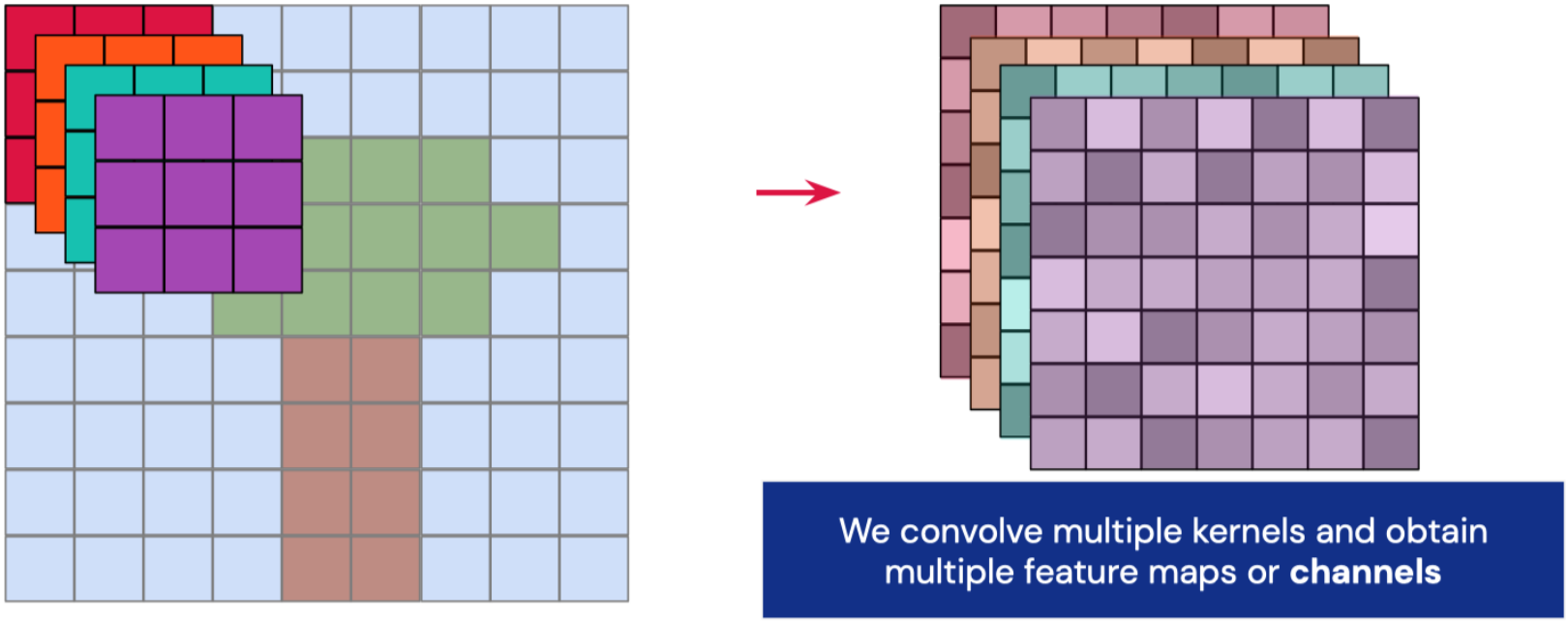
Implementation: the convolution operation



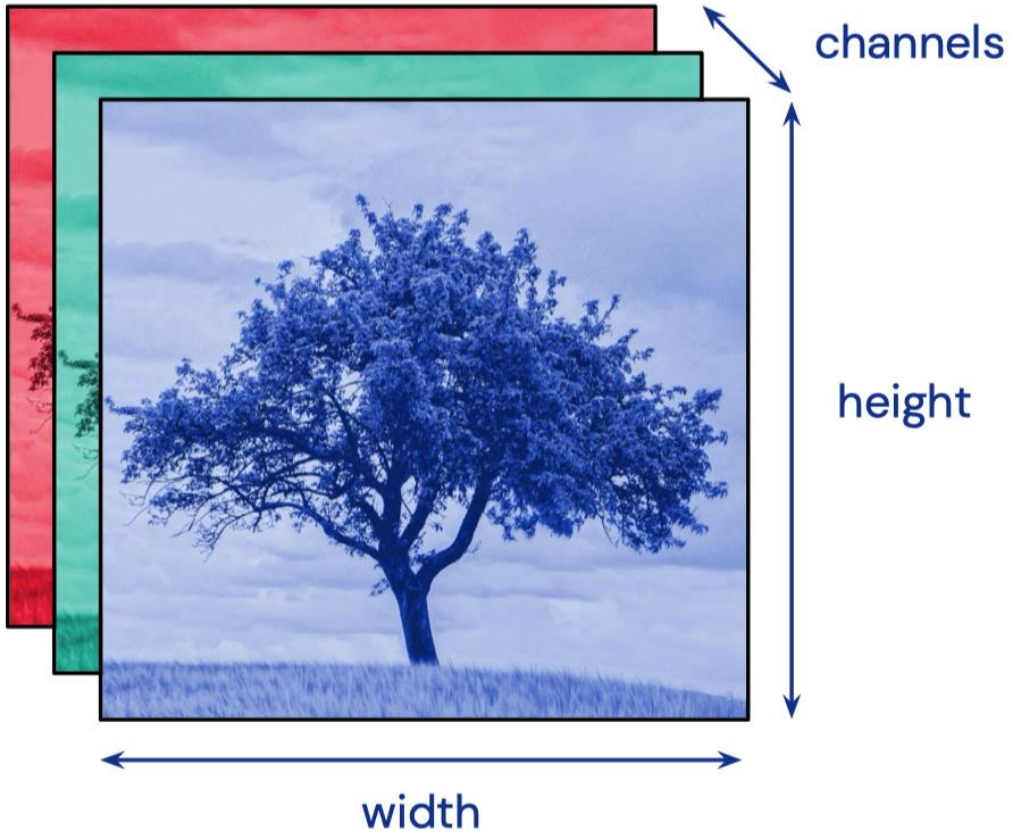
The **kernel** slides across the image and produces an output value at each position

Implementation: the convolution operation

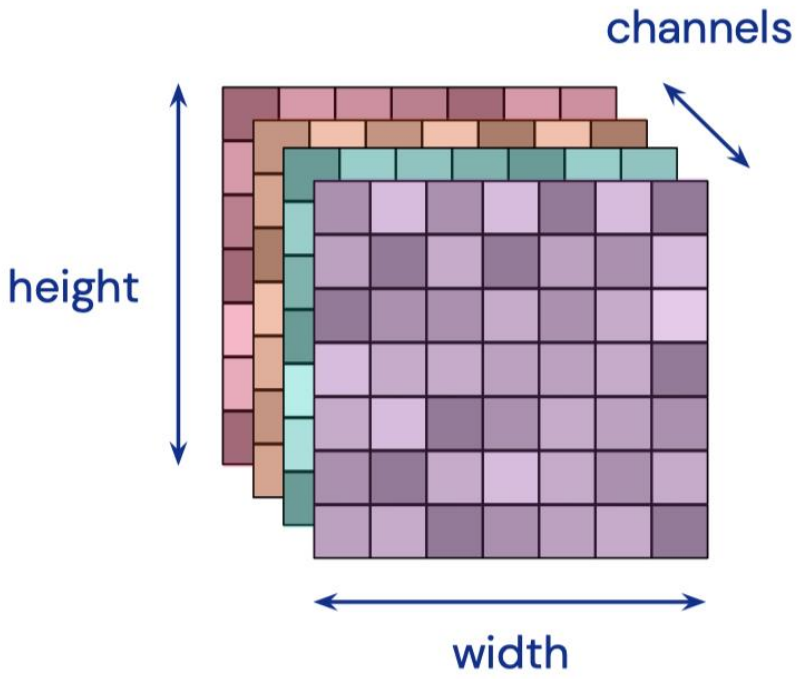


We convolve multiple kernels and obtain multiple feature maps or **channels**

Inputs and outputs are tensors

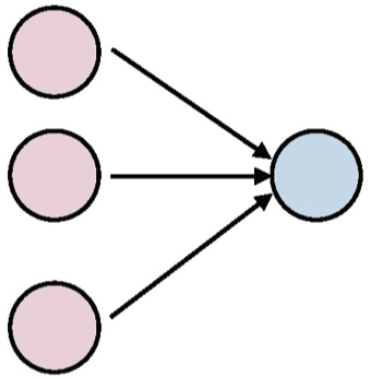


Inputs and outputs are tensors

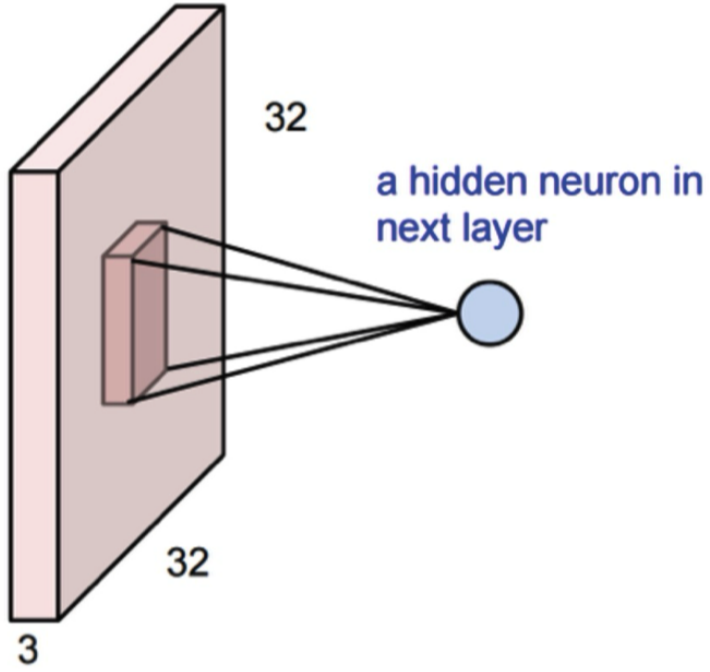


3D Activations

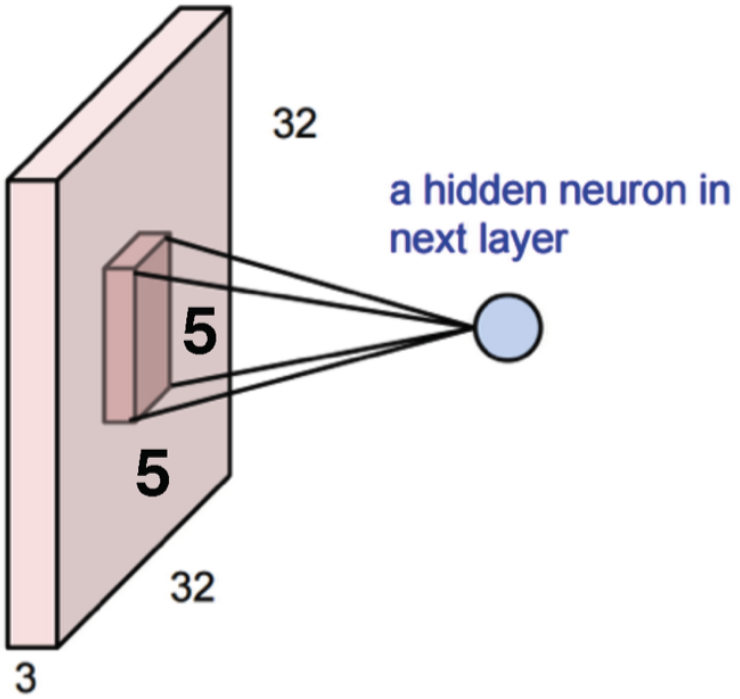
1D Activations:



3D Activations:

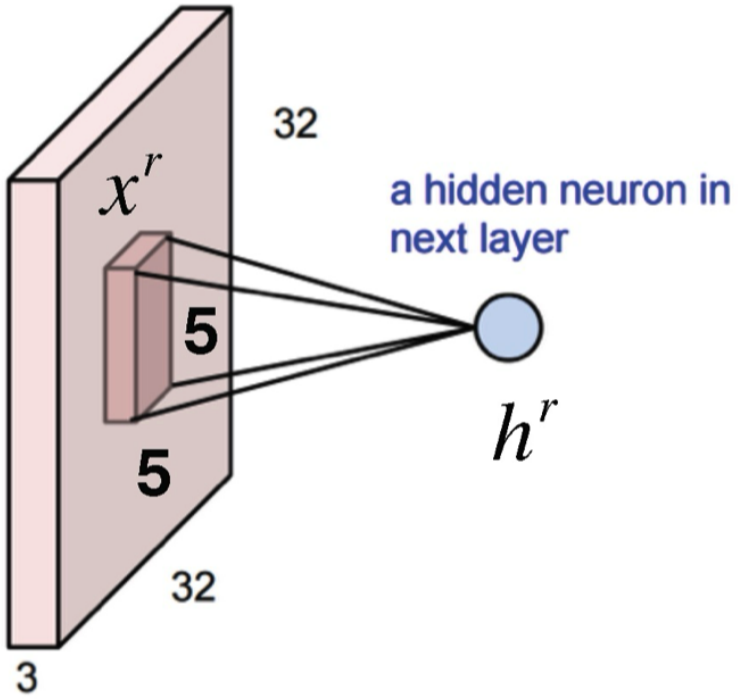


3D Activations



- 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"

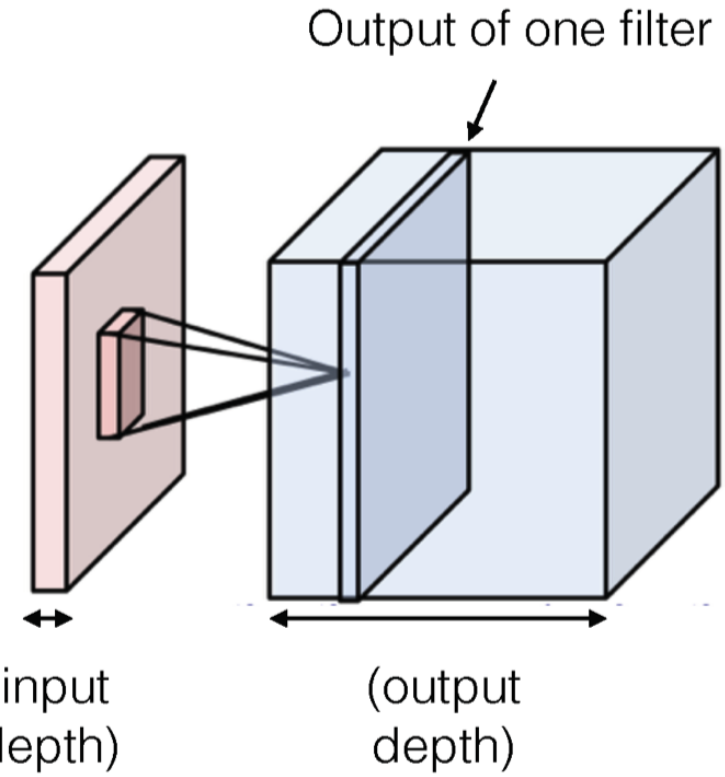
With output neuron h^r

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

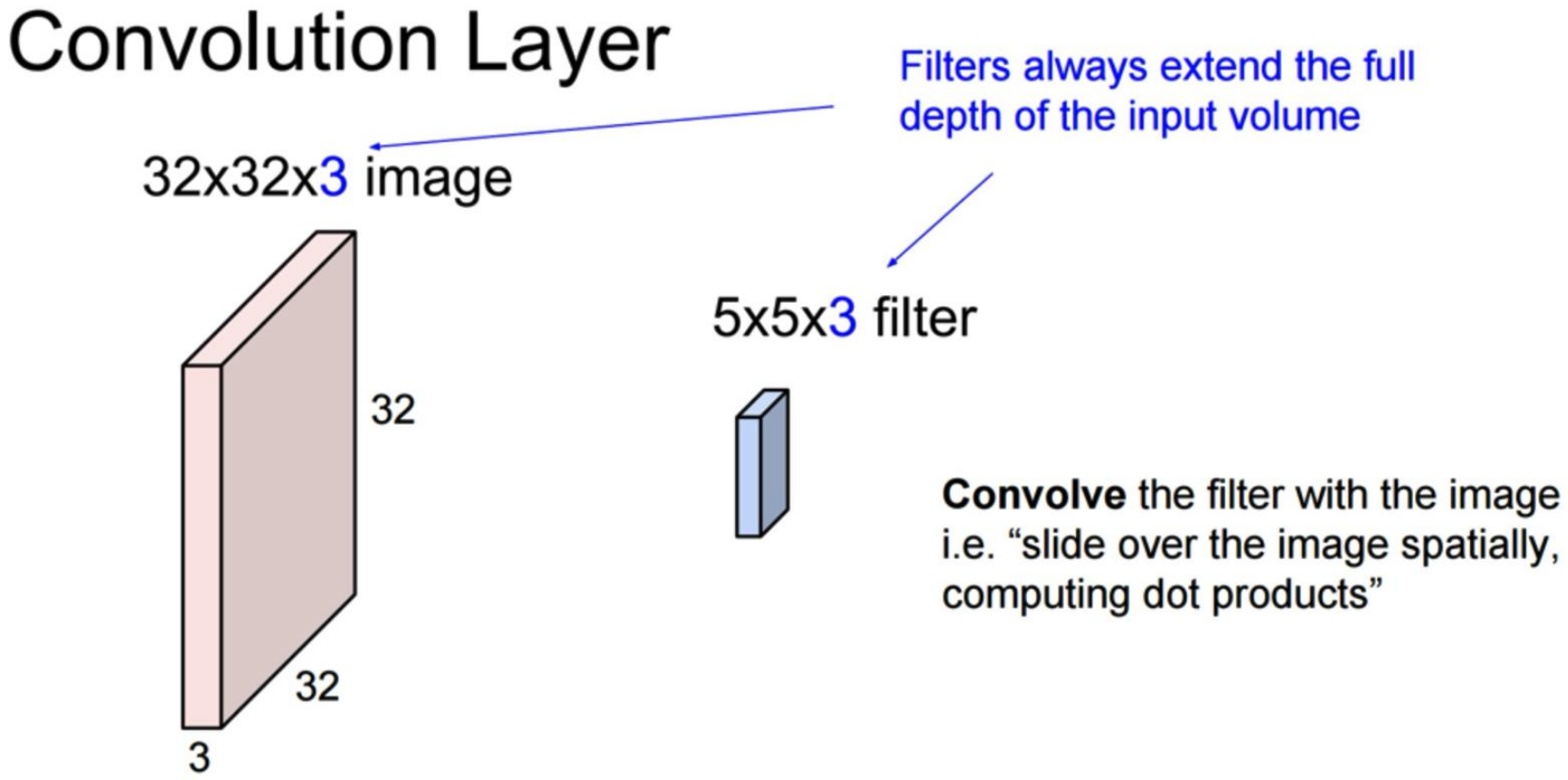
To get a 3D output of depth *D*, use *D* different filters

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

Number of parameters of one convolutional layer without bias.

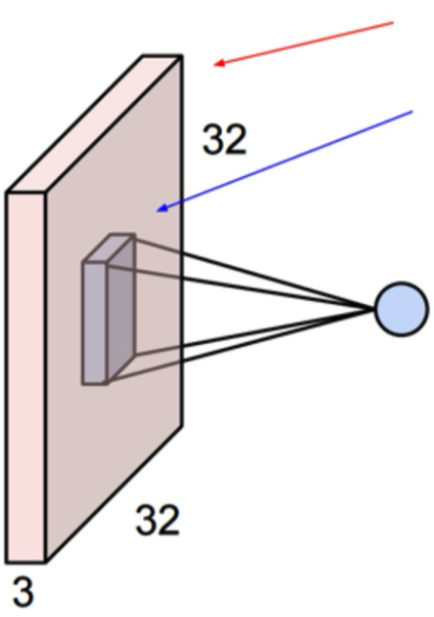
All together, the weights are **4** dimensional:
(output depth, input depth, kernel height, kernel width)

Recap


Convolution Layer
Filters always extend the full depth of the input volume
32x32x3 image
5x5x3 filter
32
32
3
Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

Recap

Convolution Layer



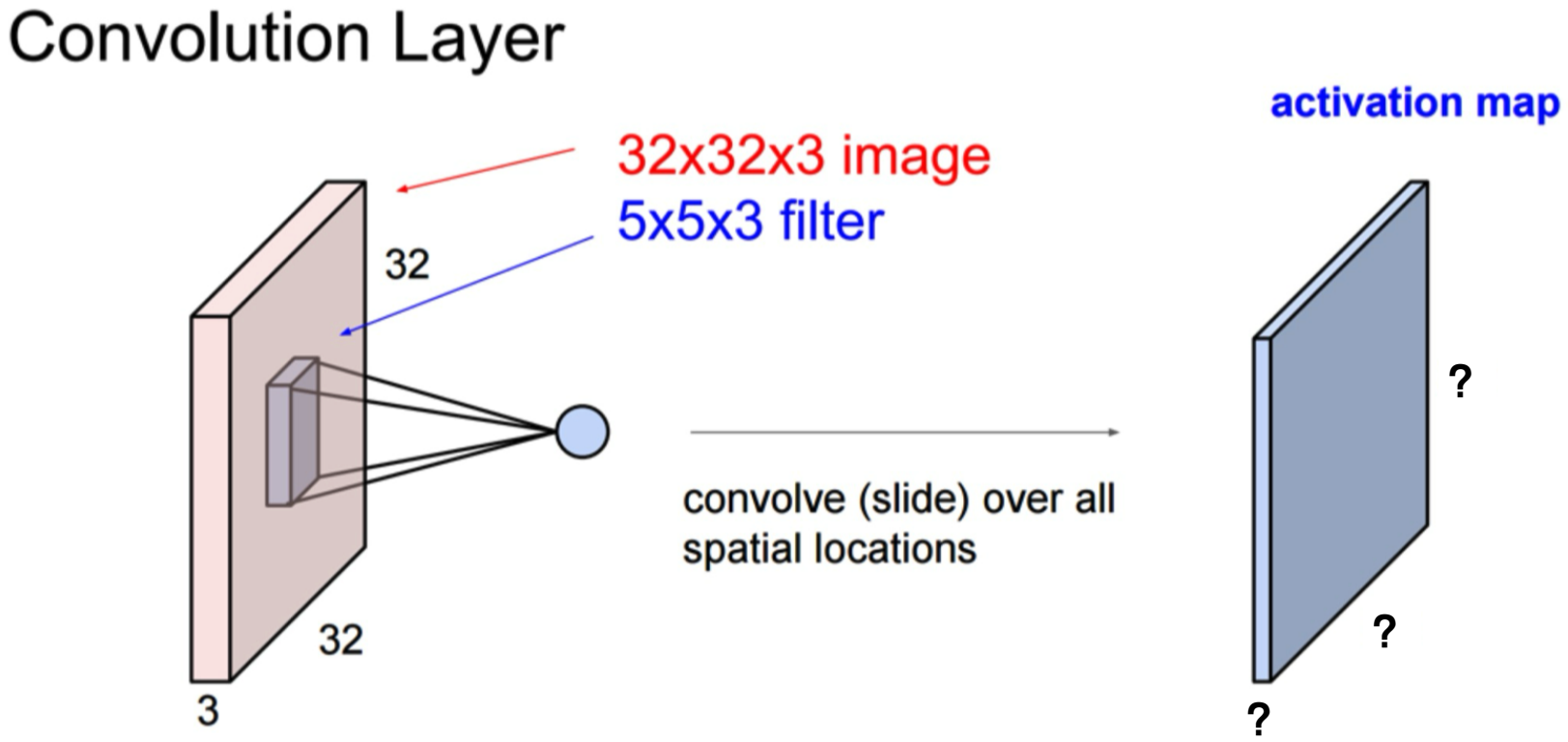
32x32x3 image

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)

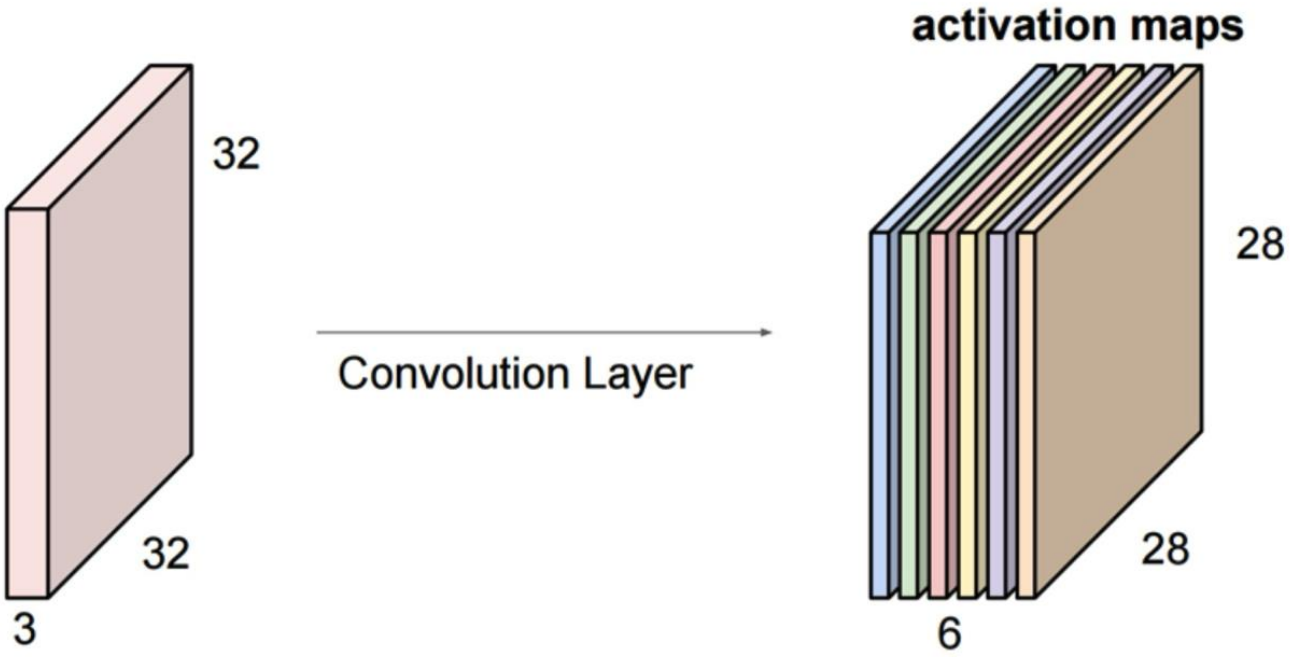
$$w^T x + b$$

Recap


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

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:

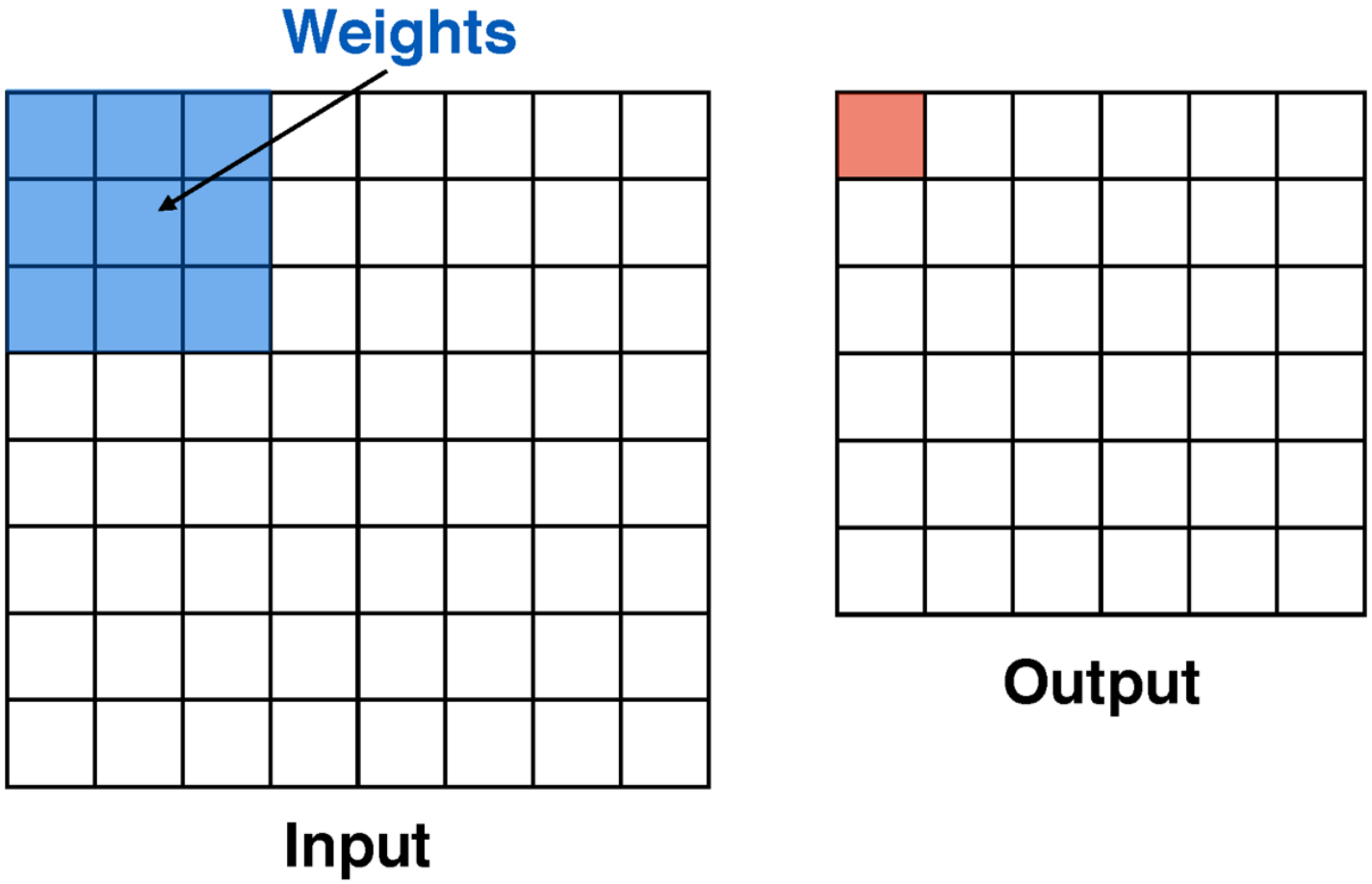
$$3 * 5 * 5 * 6 + 6 = 456$$

  - 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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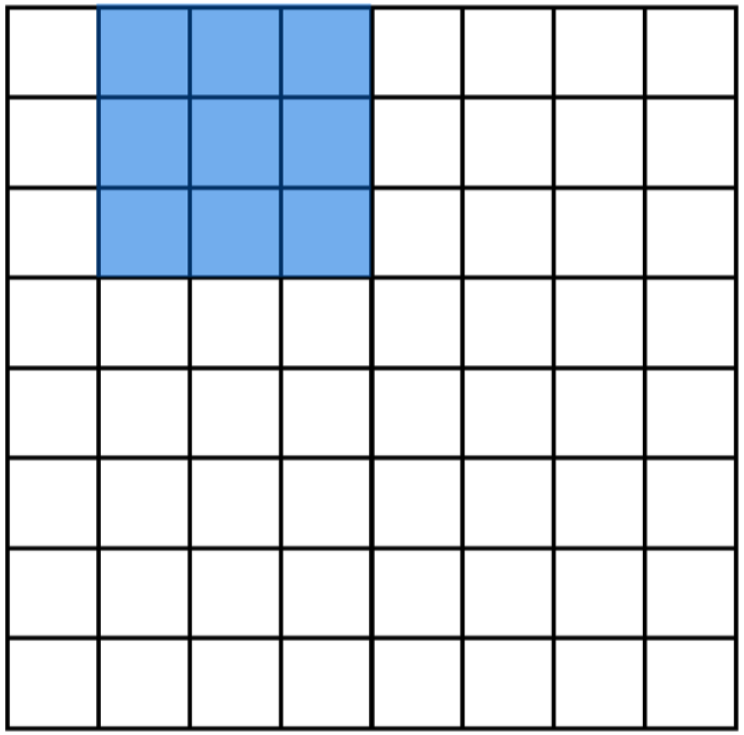
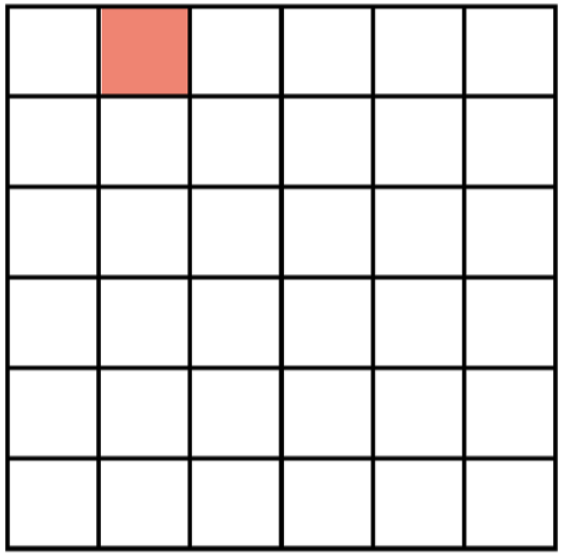


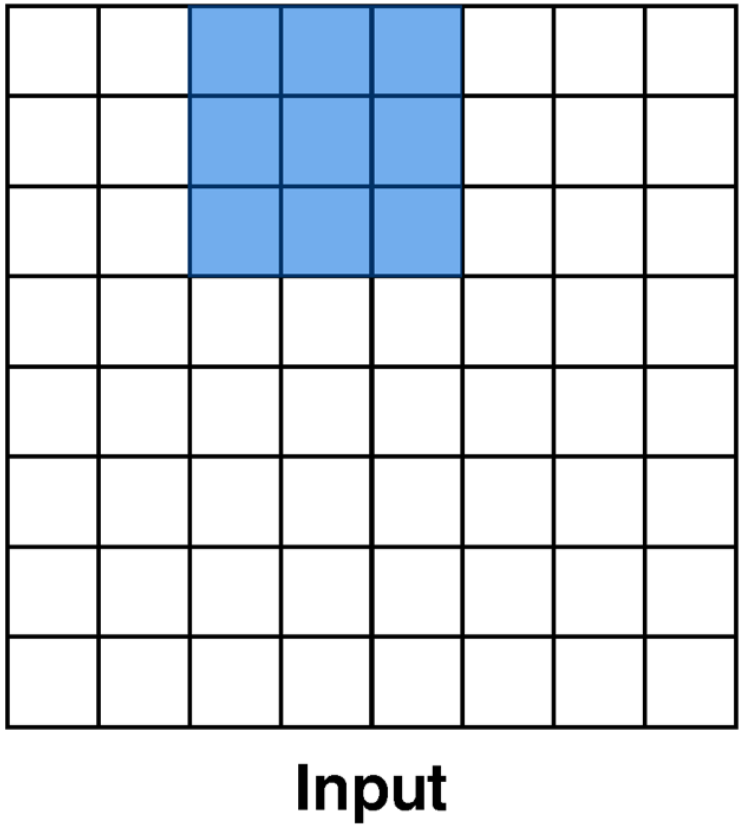
Input



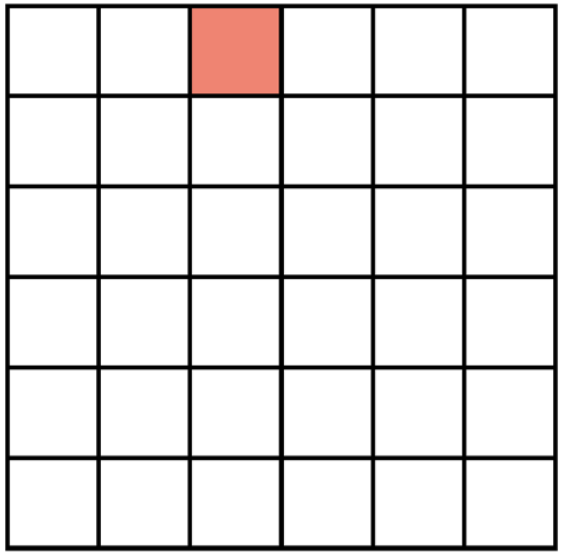
Output

Convolution operation: stride

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



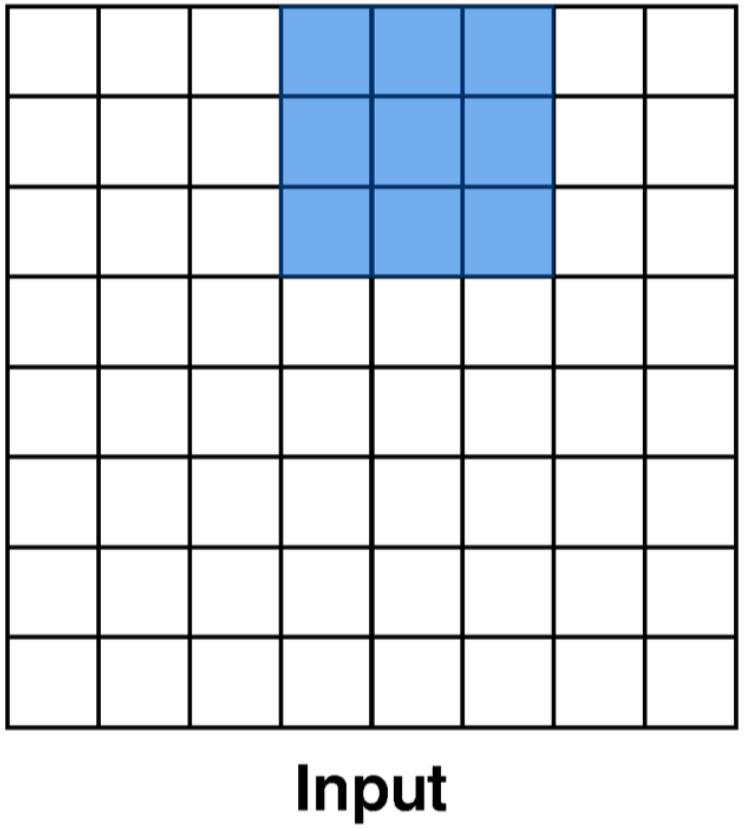
Input



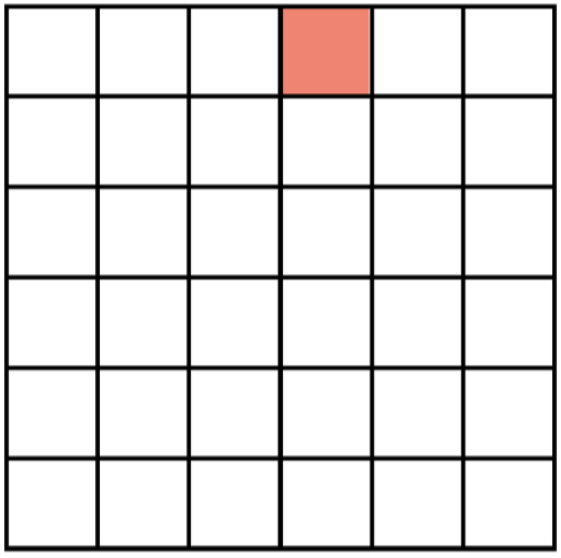
Output

Convolution operation: stride

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



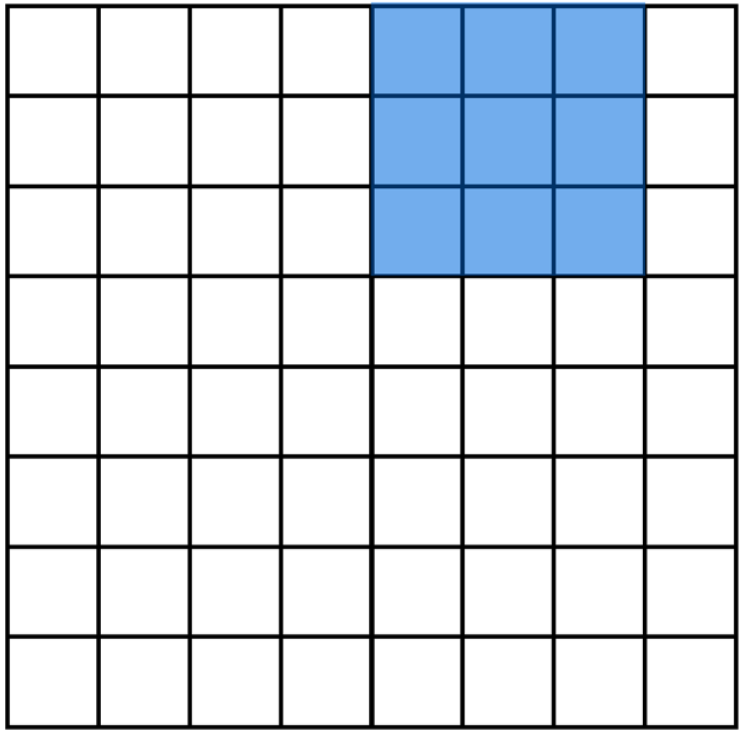
Input



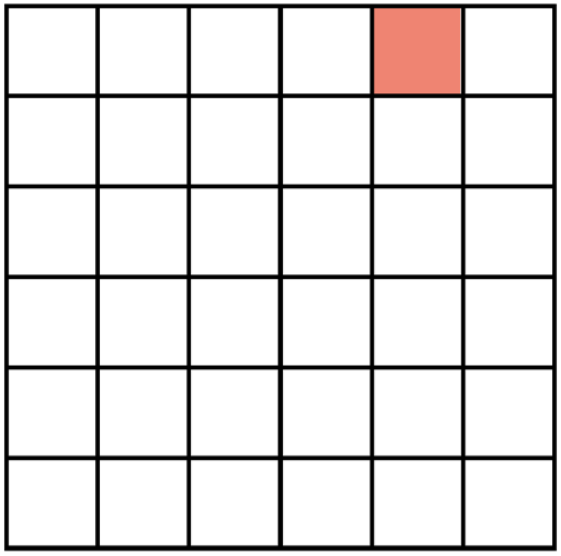
Output

Convolution operation: stride

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



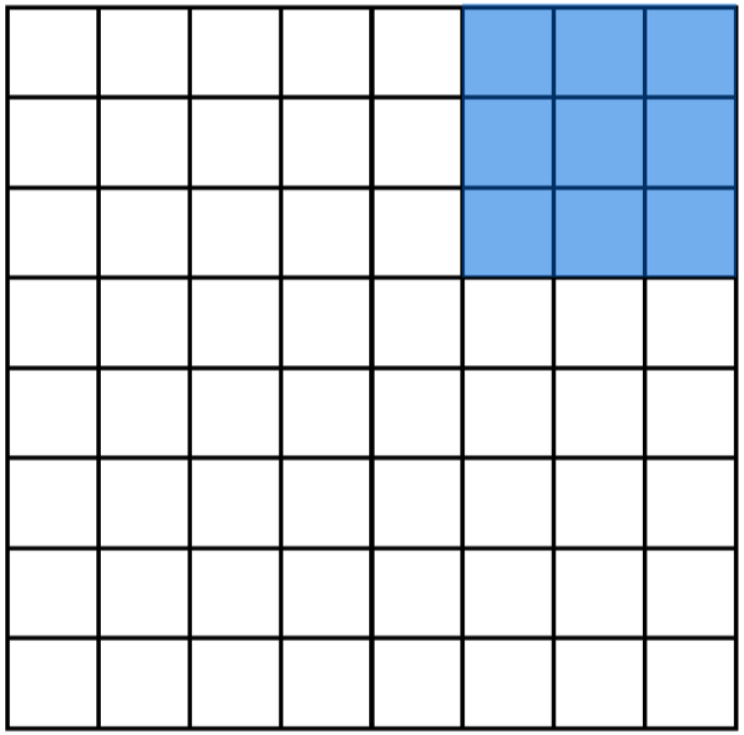
Input



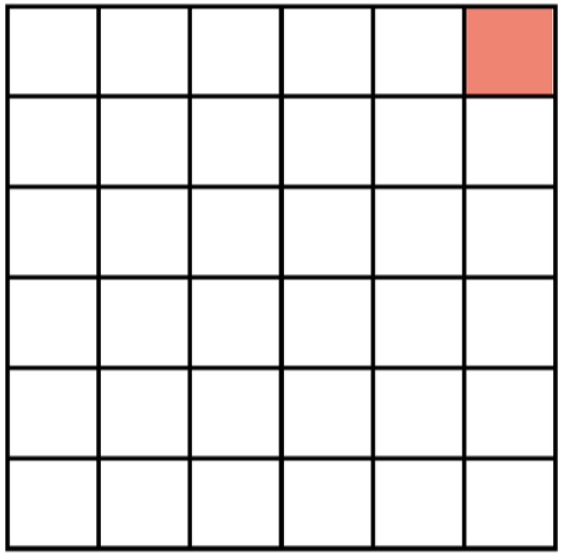
Output

Convolution operation: stride

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



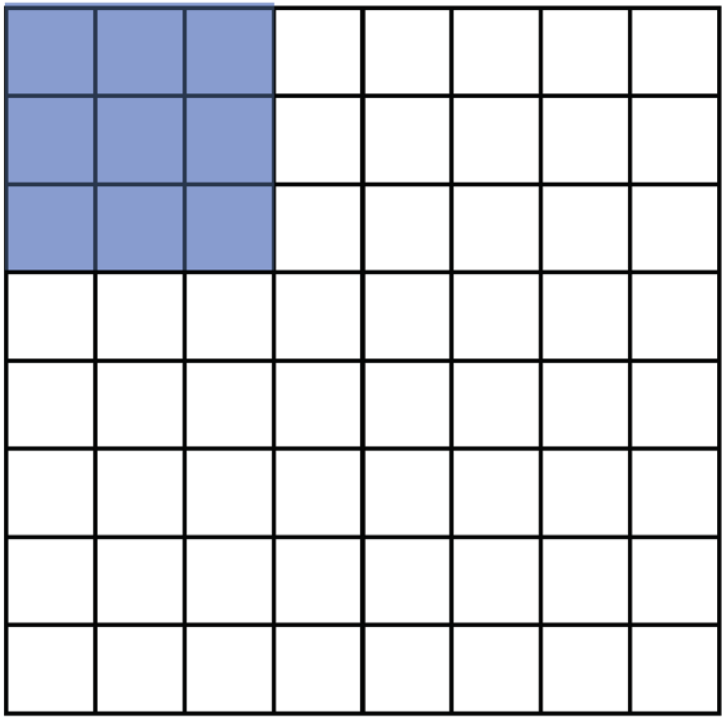
Input



Output

Convolution operation: stride

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



Input

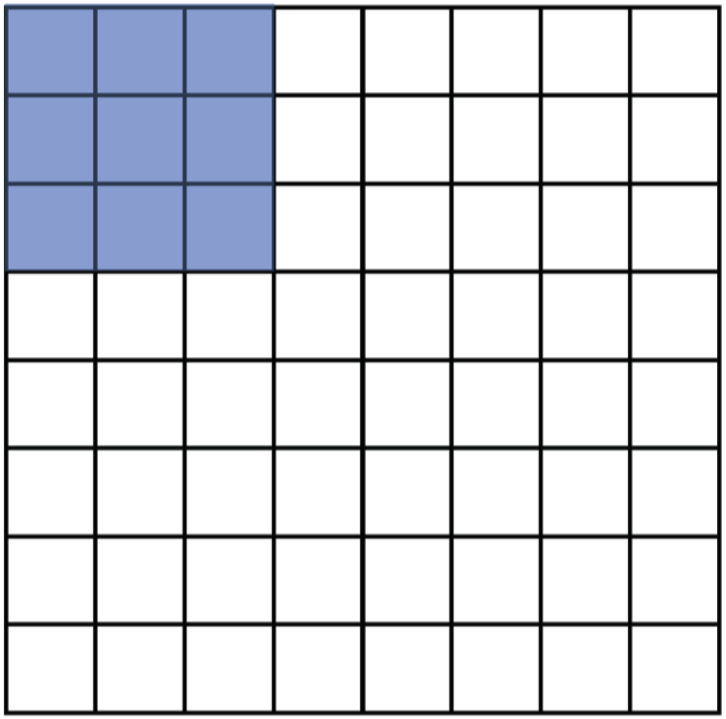
Recall that at each position, we are doing a **3D** sum:

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

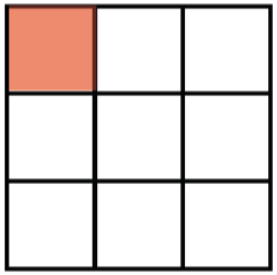
(channel, row, column)

Convolution operation: stride

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



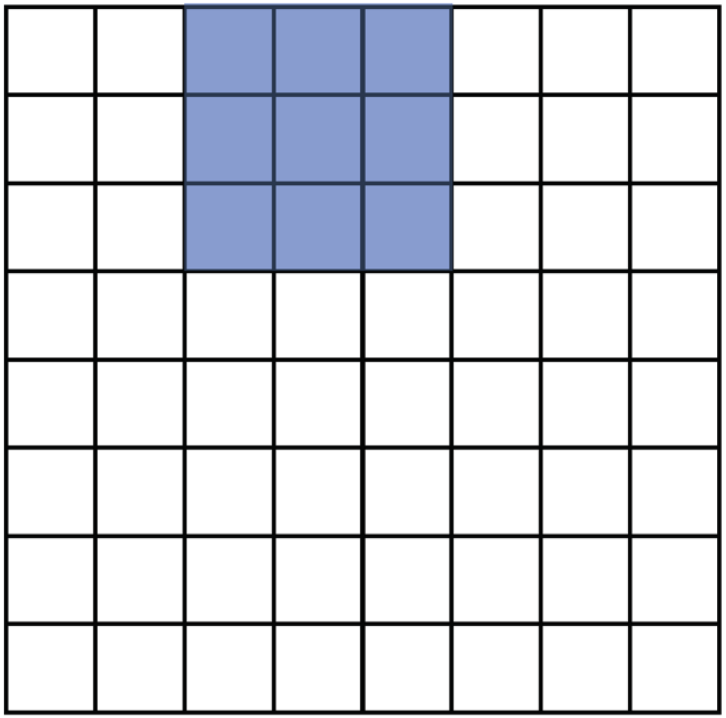
Input



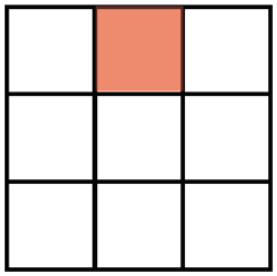
Output

Convolution operation: stride

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



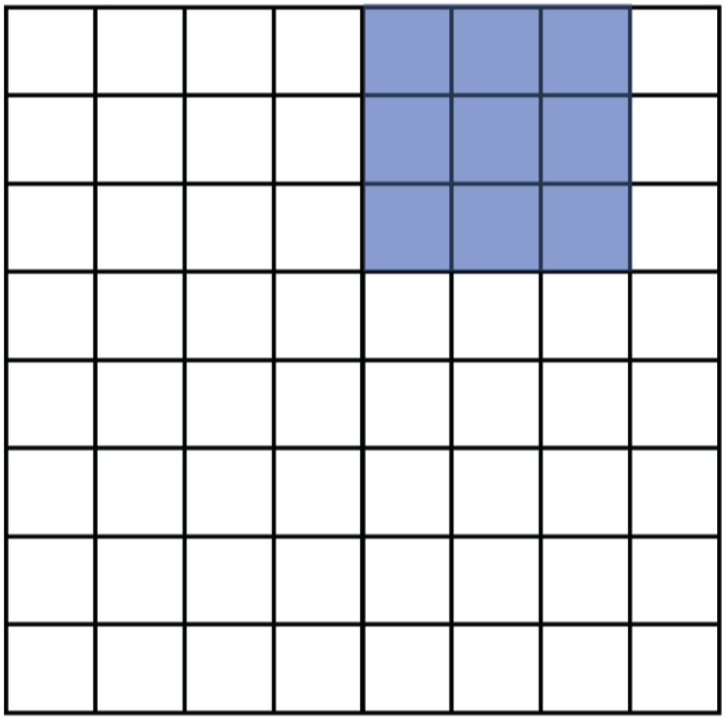
Input



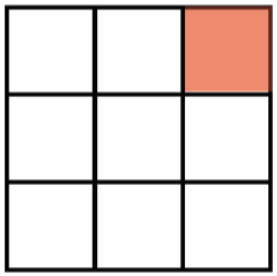
Output

Convolution operation: stride

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



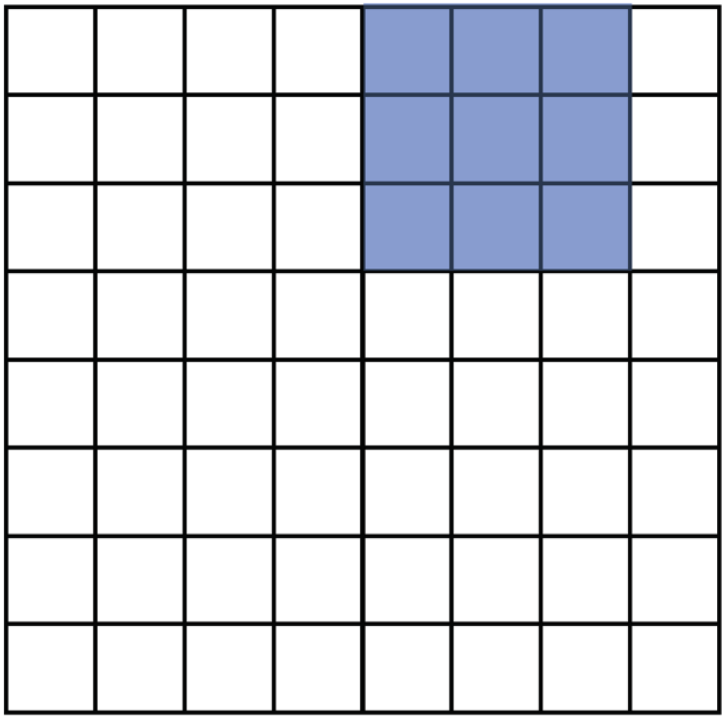
Input



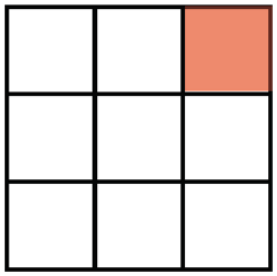
Output

Convolution operation: stride

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



Input

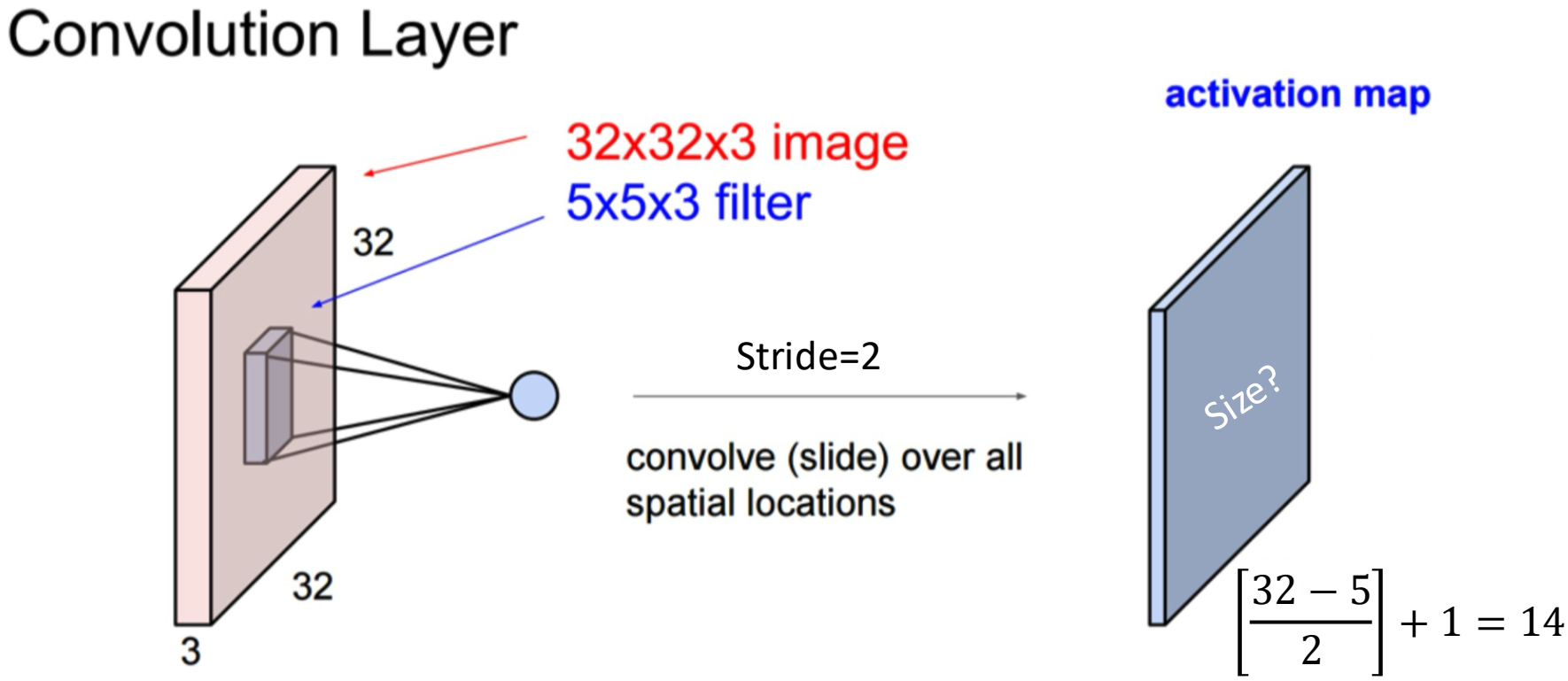


Output

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

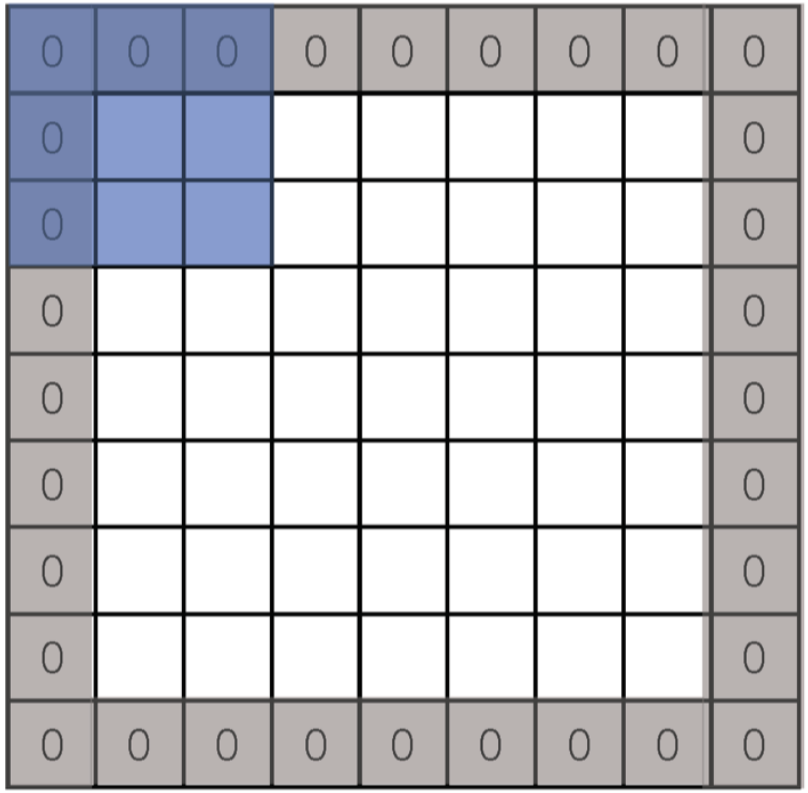
- The output is also half the size of the input

Convolution operation: stride

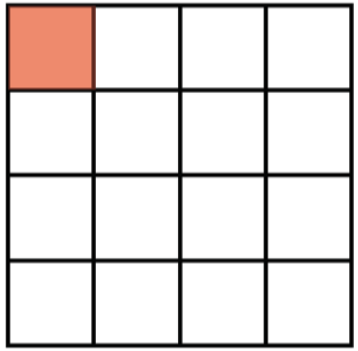


Convolution operation: padding

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



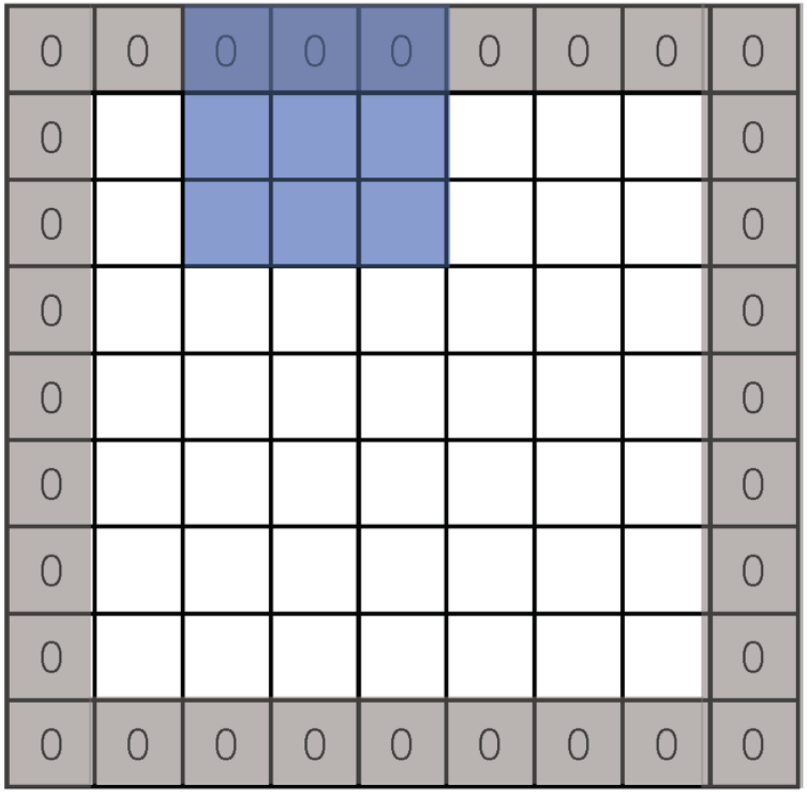
Input



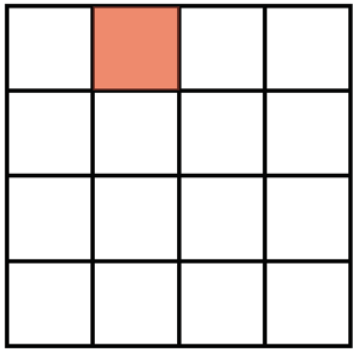
Output

Convolution operation: padding

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



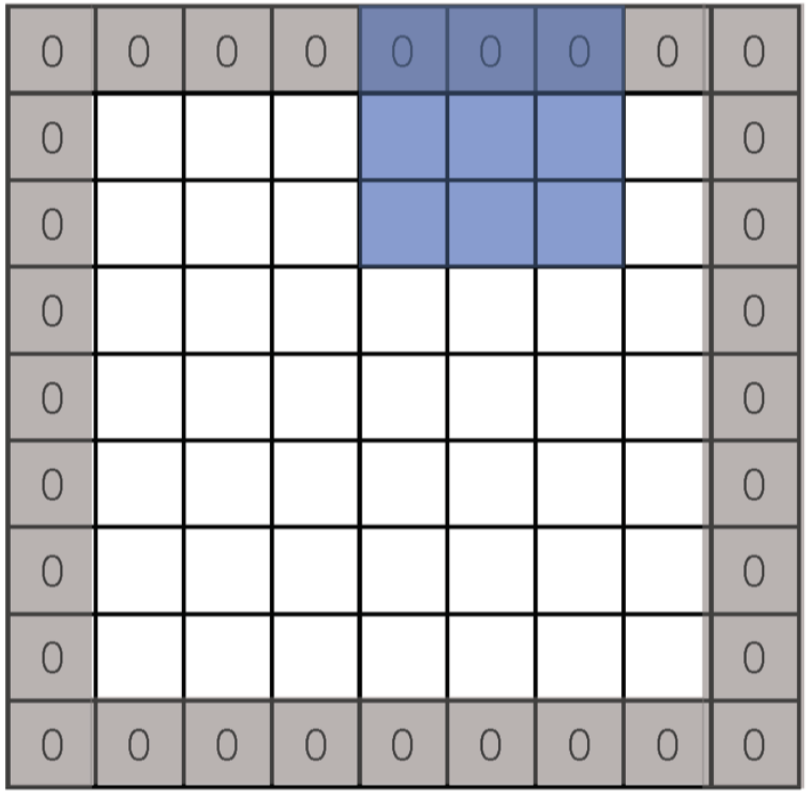
Input



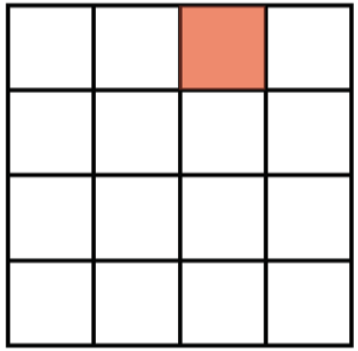
Output

Convolution operation: padding

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



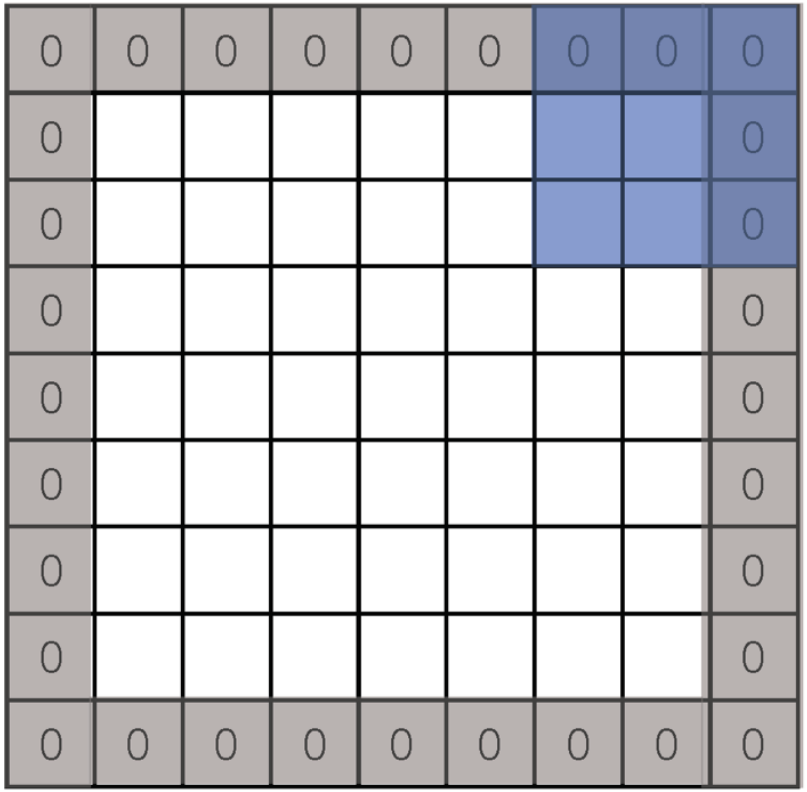
Input



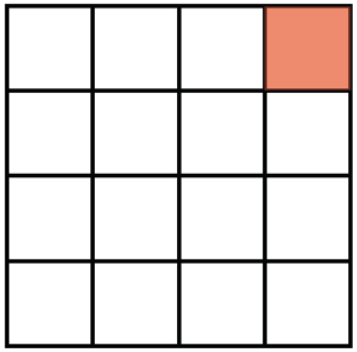
Output

Convolution operation: padding

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

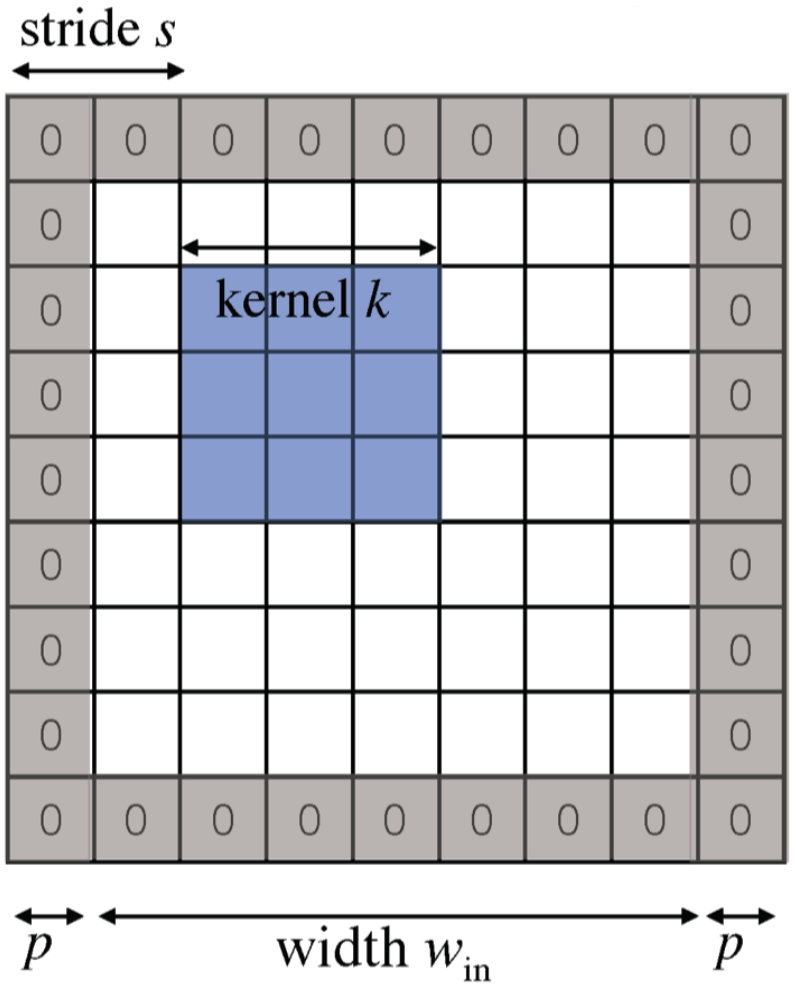


Input



Output

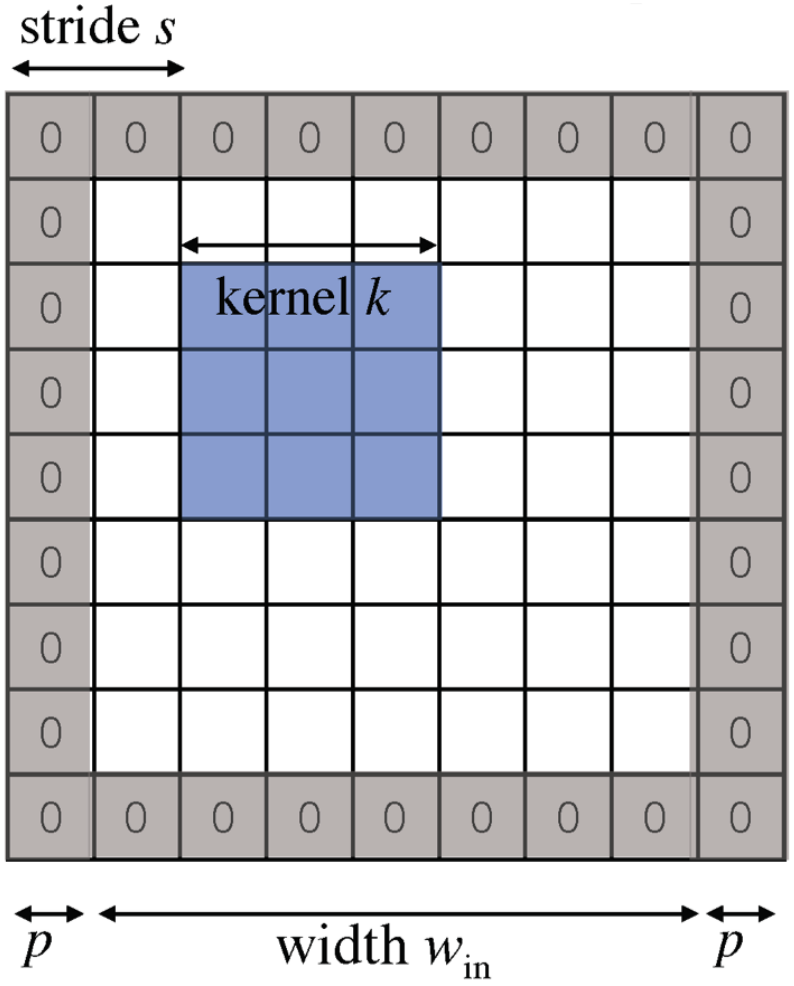
Convolution: output size



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

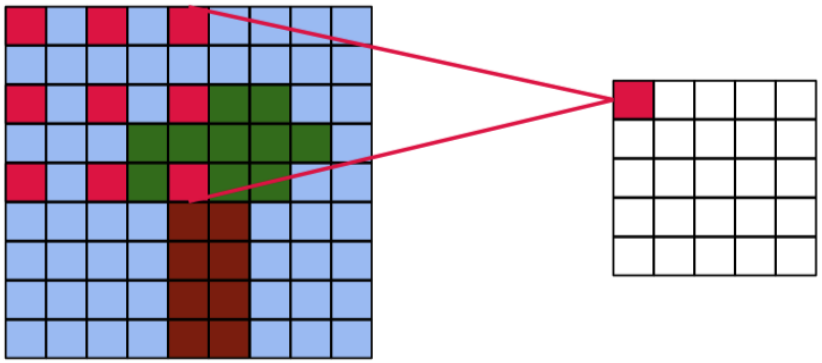
$$w_{out} = \left\lfloor \frac{w_{in} + 2p - k}{s} \right\rfloor + 1$$

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

$$= w_{in}$$

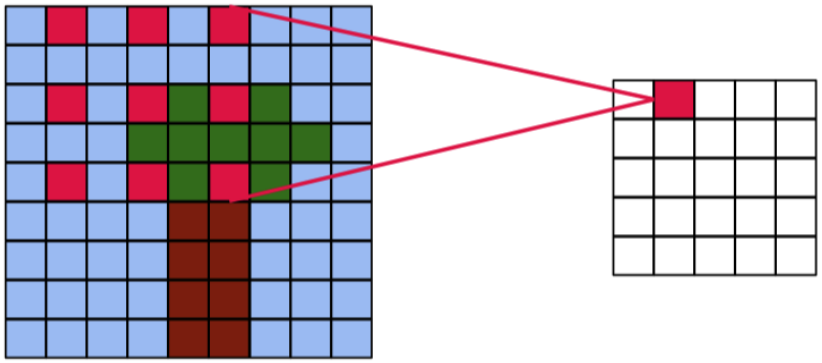
VGGNet [Simonyan 2014] uses filters of this shape

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

PyTorch – Conv2d

Conv2d

CLASS torch.nn.Conv2d(*in_channels*, *out_channels*, *kernel_size*, *stride=1*, *padding=0*, *dilation=1*, *groups=1*, *bias=True*, *padding_mode='zeros'*, *device=None*, *dtype=None*) [SOURCE]

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$ or (C_{in}, H_{in}, W_{in})
- Output: $(N, C_{out}, H_{out}, W_{out})$ or $(C_{out}, H_{out}, W_{out})$, where

$$H_{out} = \left\lfloor \frac{H_{in} + 2 \times \text{padding}[0] - \text{dilation}[0] \times (\text{kernel\_size}[0] - 1) - 1}{\text{stride}[0]} + 1 \right\rfloor$$

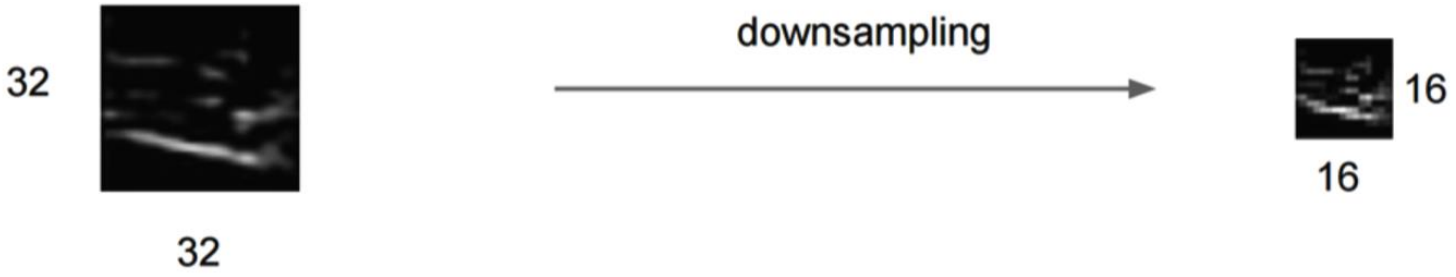
$$W_{out} = \left\lfloor \frac{W_{in} + 2 \times \text{padding}[1] - \text{dilation}[1] \times (\text{kernel\_size}[1] - 1) - 1}{\text{stride}[1]} + 1 \right\rfloor$$

Source: https://pytorch.org/docs/stable/generated/torch.nn.Conv2d.html

Pooling

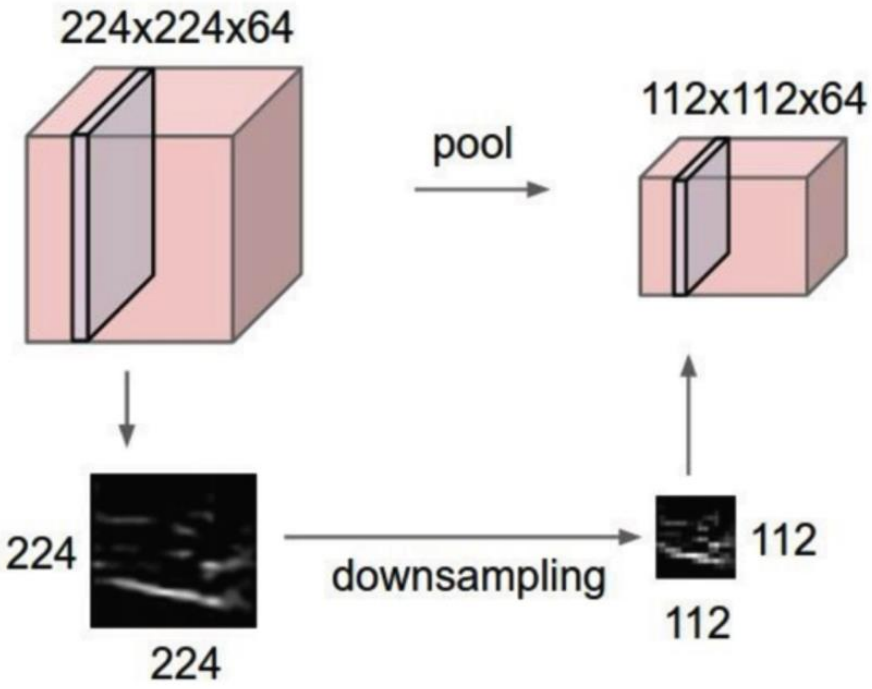
For most ConvNets, **convolution** is often followed by **pooling**:

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

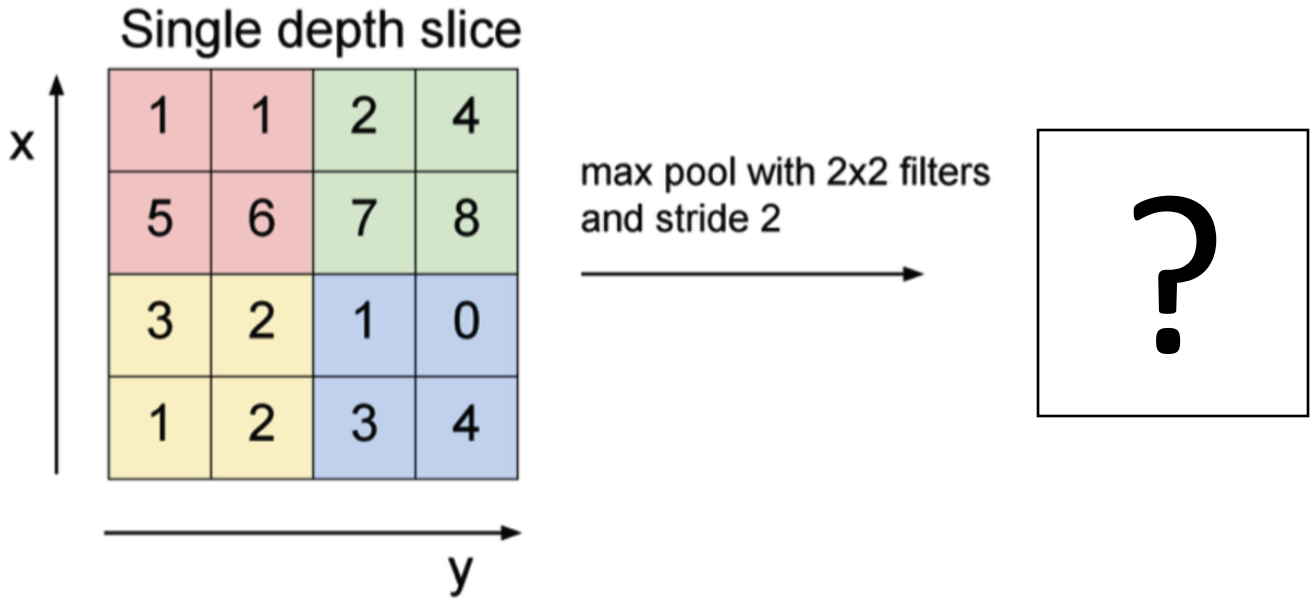


Pooling

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



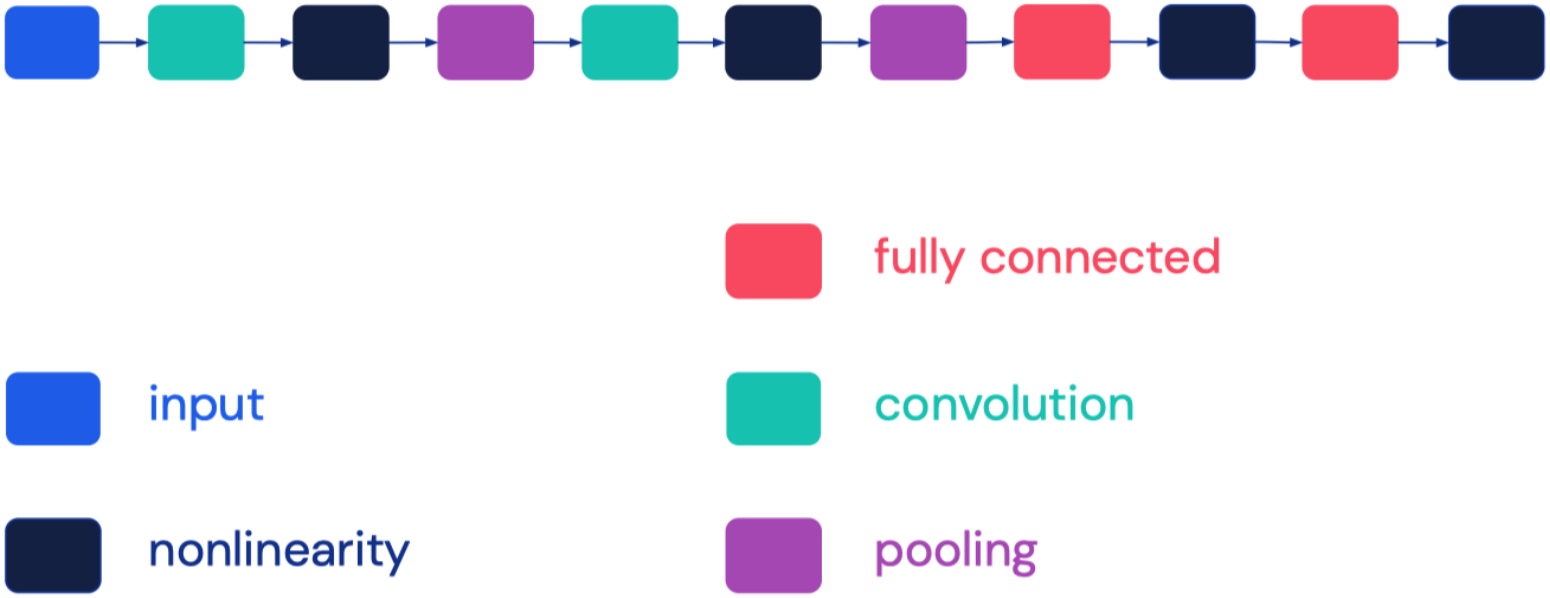
Max Pooling



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,

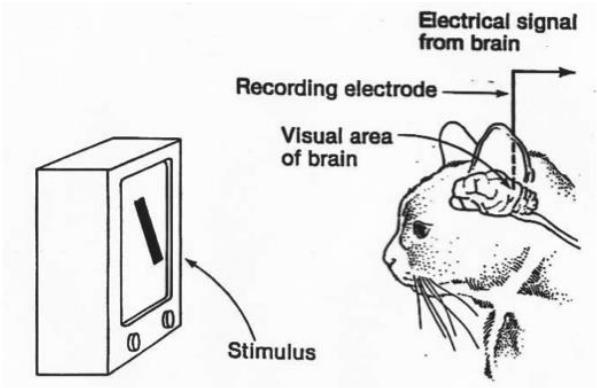
1959

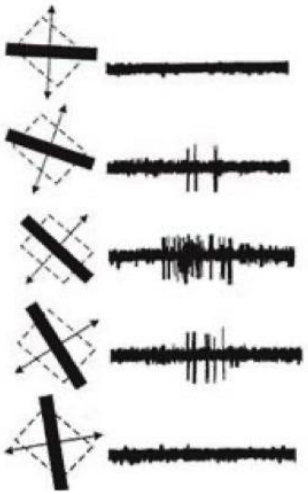
RECEPTIVE FIELDS OF SINGLE NEURONES IN
THE CAT'S STRIATE CORTEX

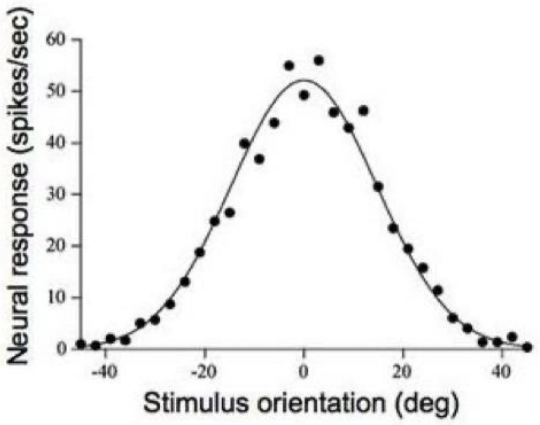
1962

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

1968...

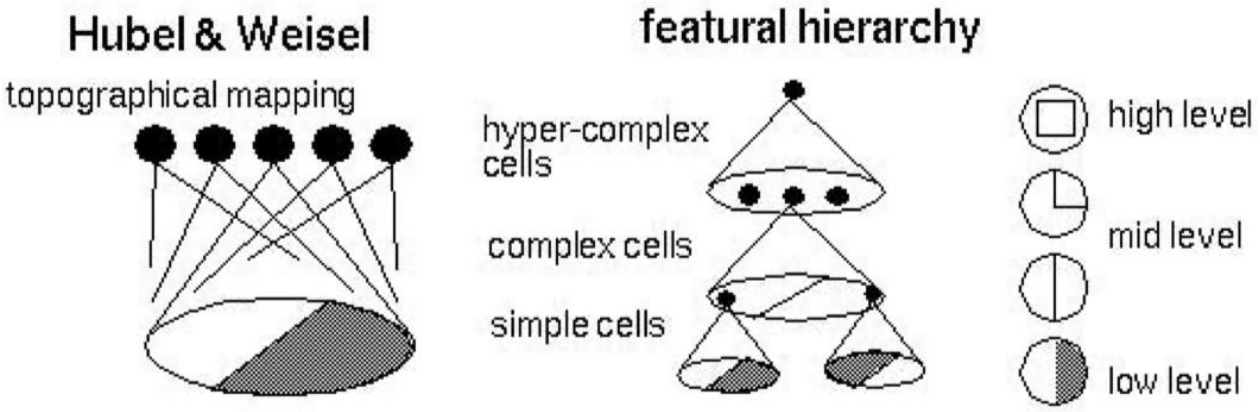






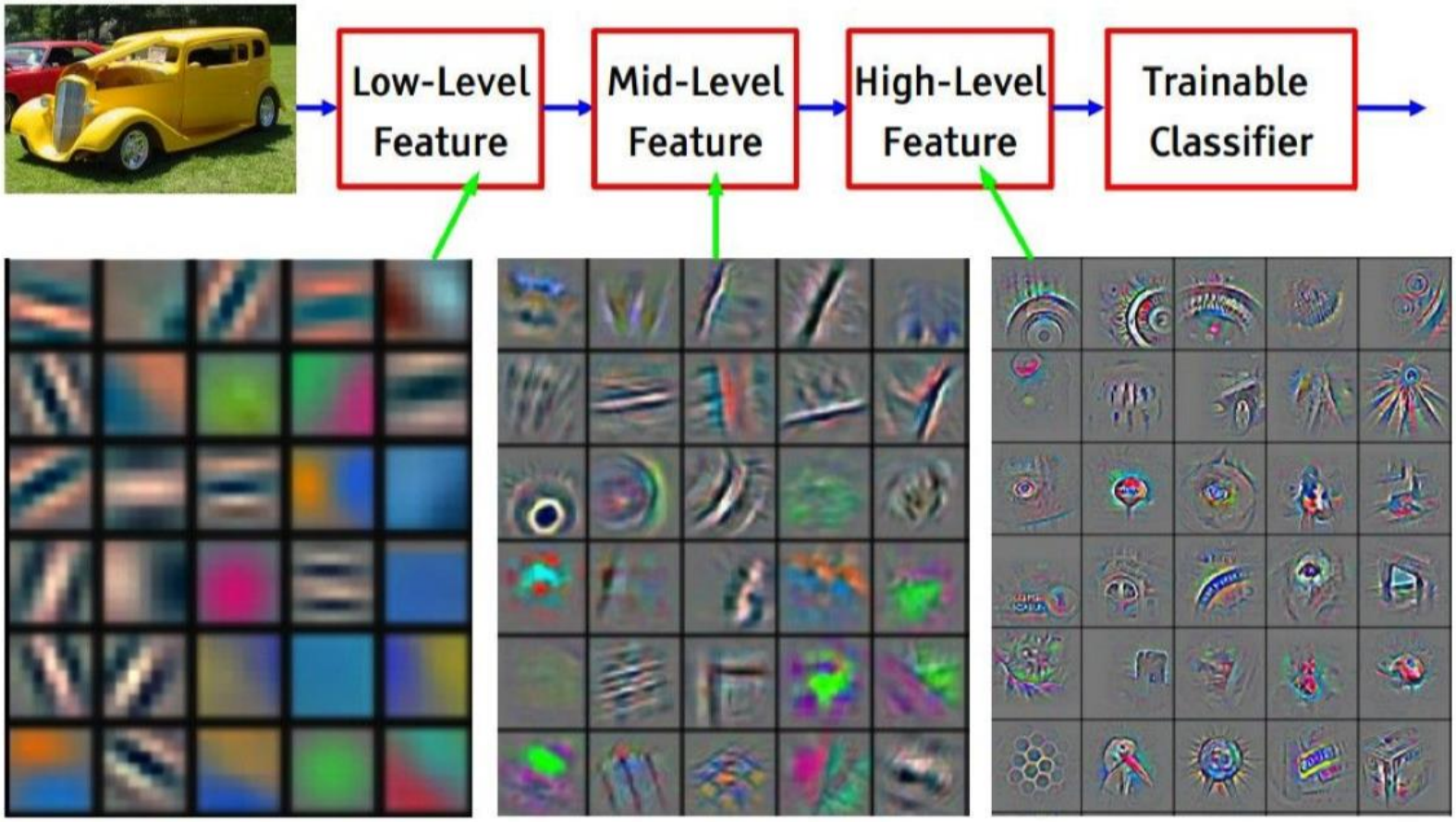
Inspirations from Neuroscience

Hierarchical organization



Inspirations from Neuroscience

- ConvNets:



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

Feature Visualization

Feature Visualization

How neural networks build up their understanding of images

Edges (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a) **Parts** (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)

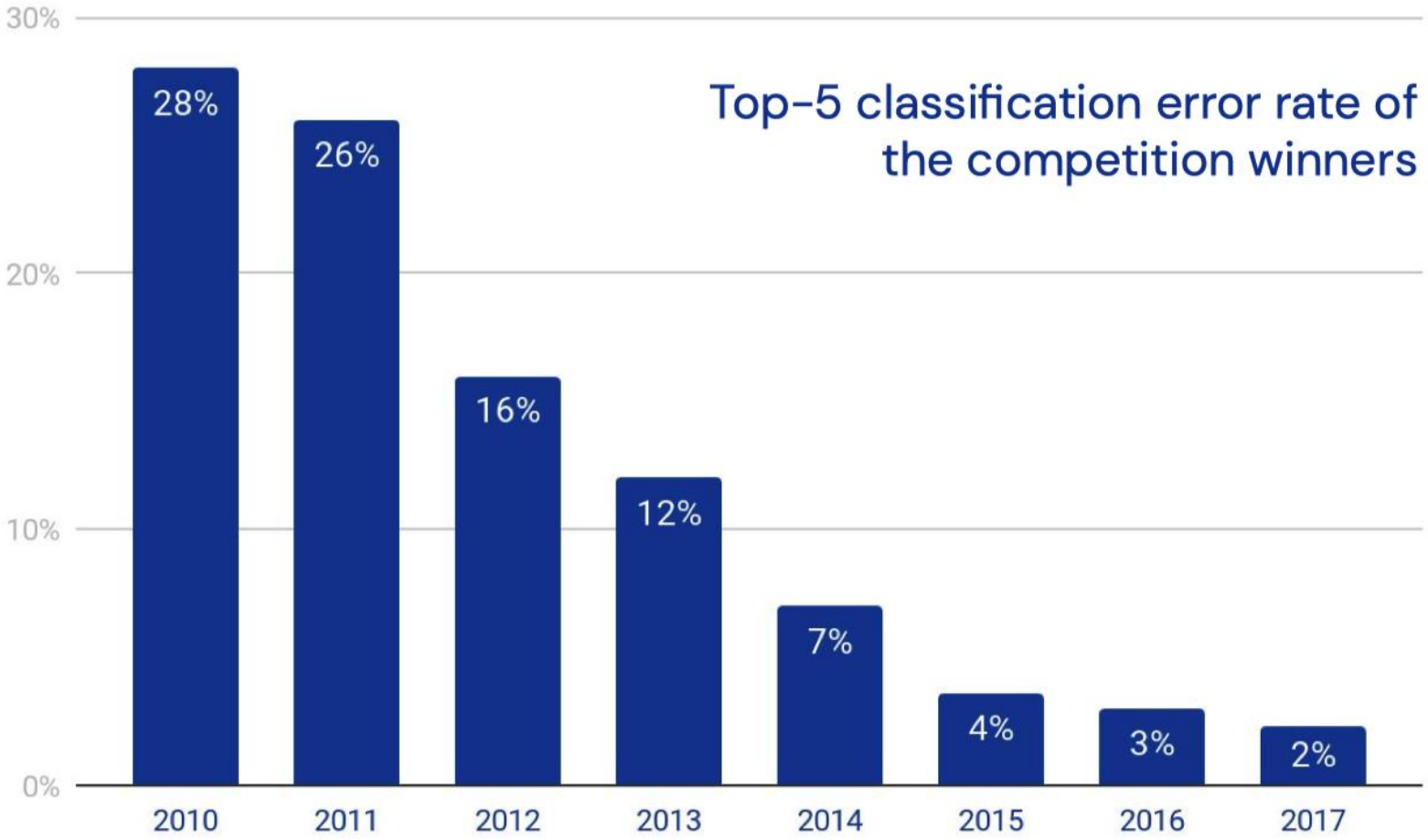
Feature visualization allows us to see how GoogLeNet [1], trained on the ImageNet [2] dataset, builds up its understanding of images over many layers. Visualizations of all channels are available in the appendix.

AUTHORS	AFFILIATIONS	PUBLISHED	DOI
Chris Olah	Google Brain Team	Nov. 7, 2017	10.23915/distill.00007
Alexander Mordvintsev	Google Research		
Ludwig Schubert	Google Brain Team		

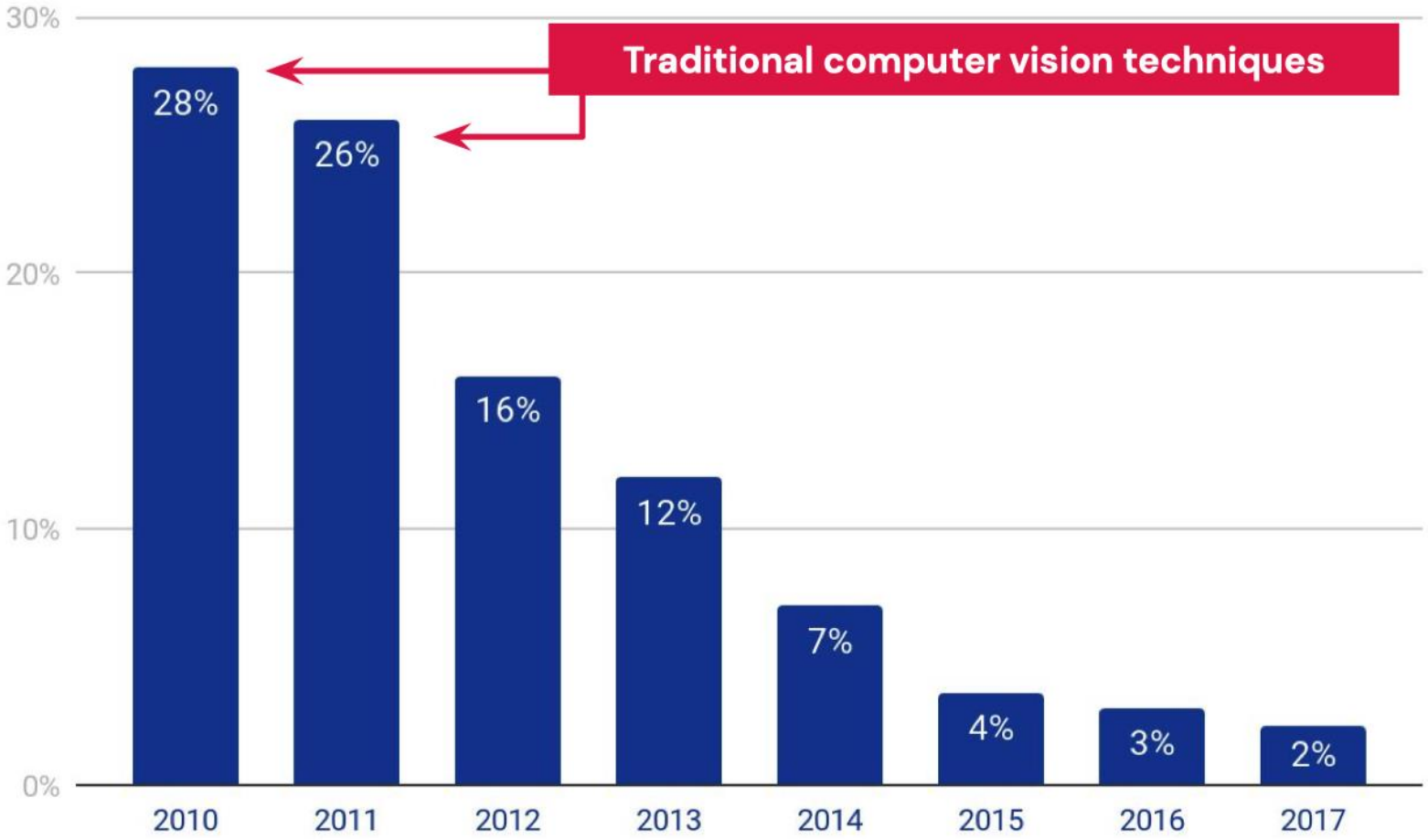
The ImageNet Challenge

- Major computer vision benchmark
- Ran from 2010 to 2017
- 1.4M images, 1000 classes
- Image classification

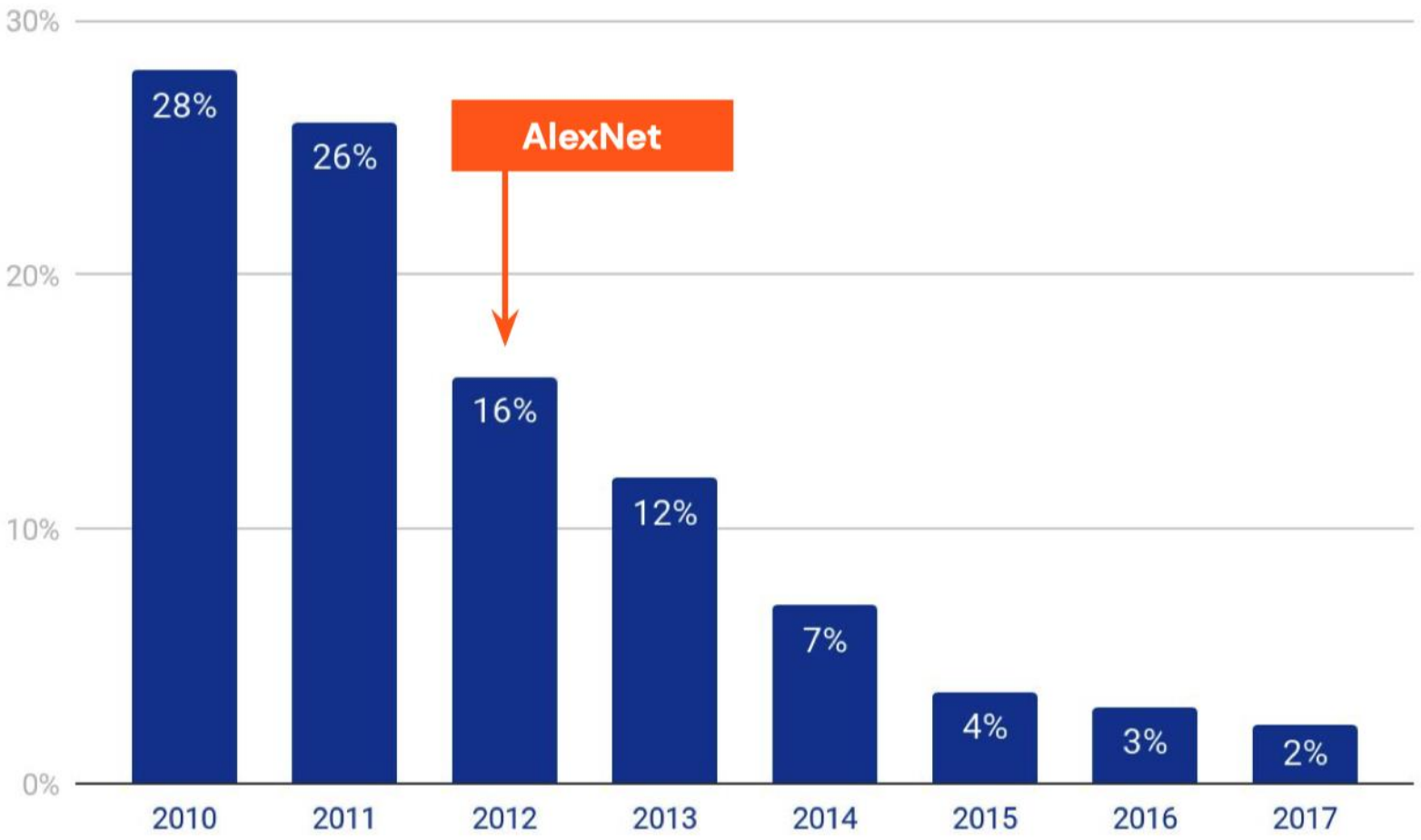
The ImageNet Challenge



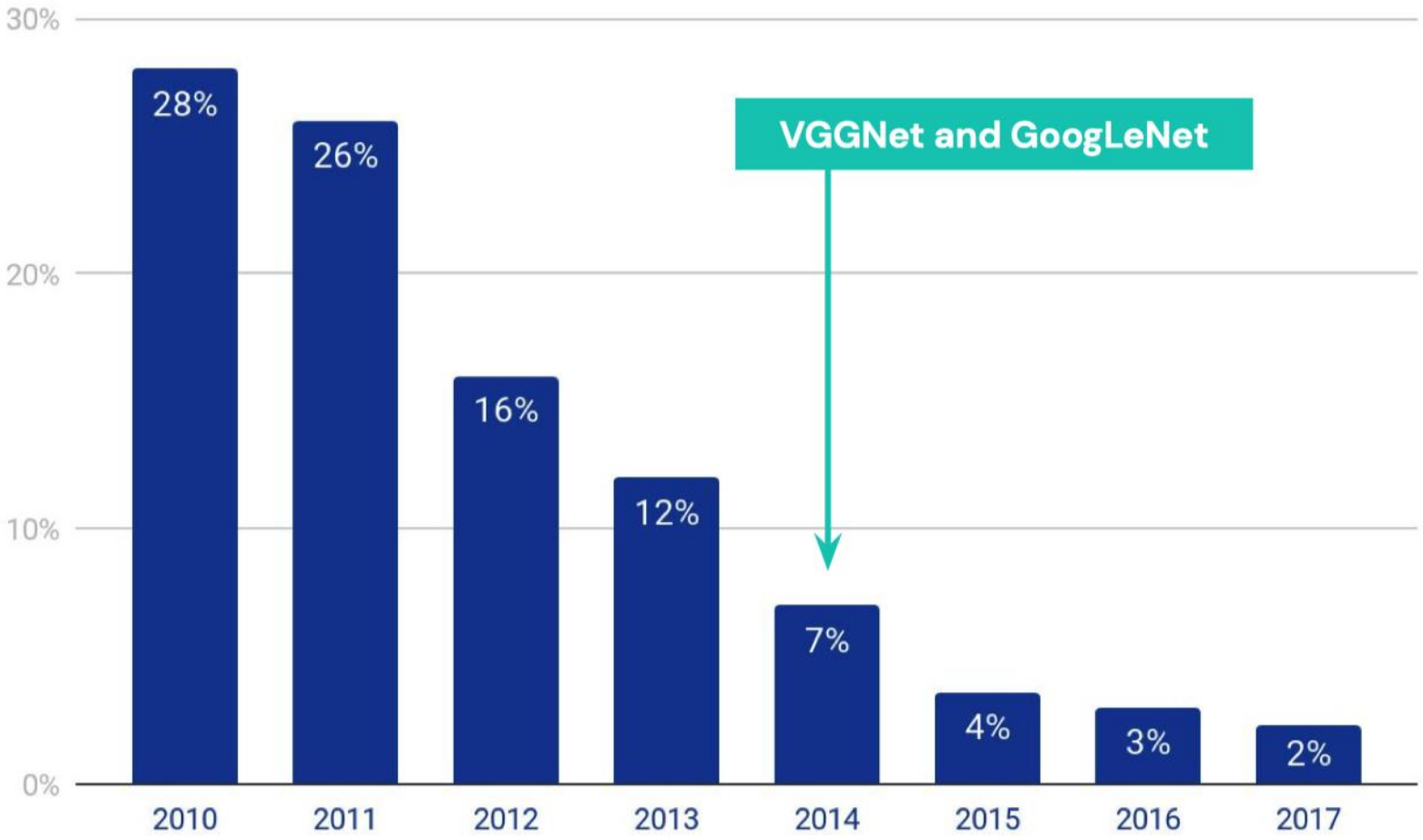
The ImageNet Challenge



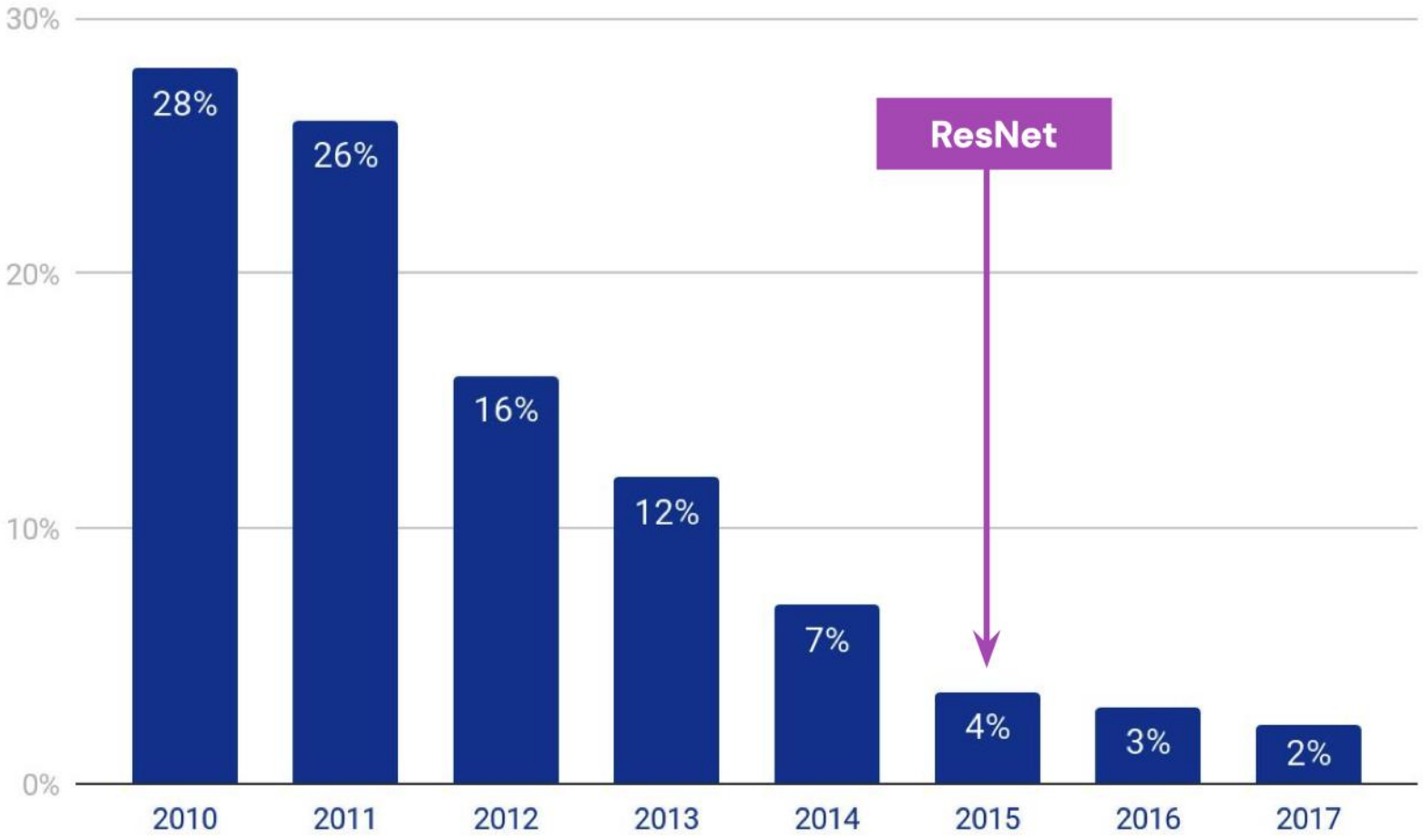
The ImageNet Challenge



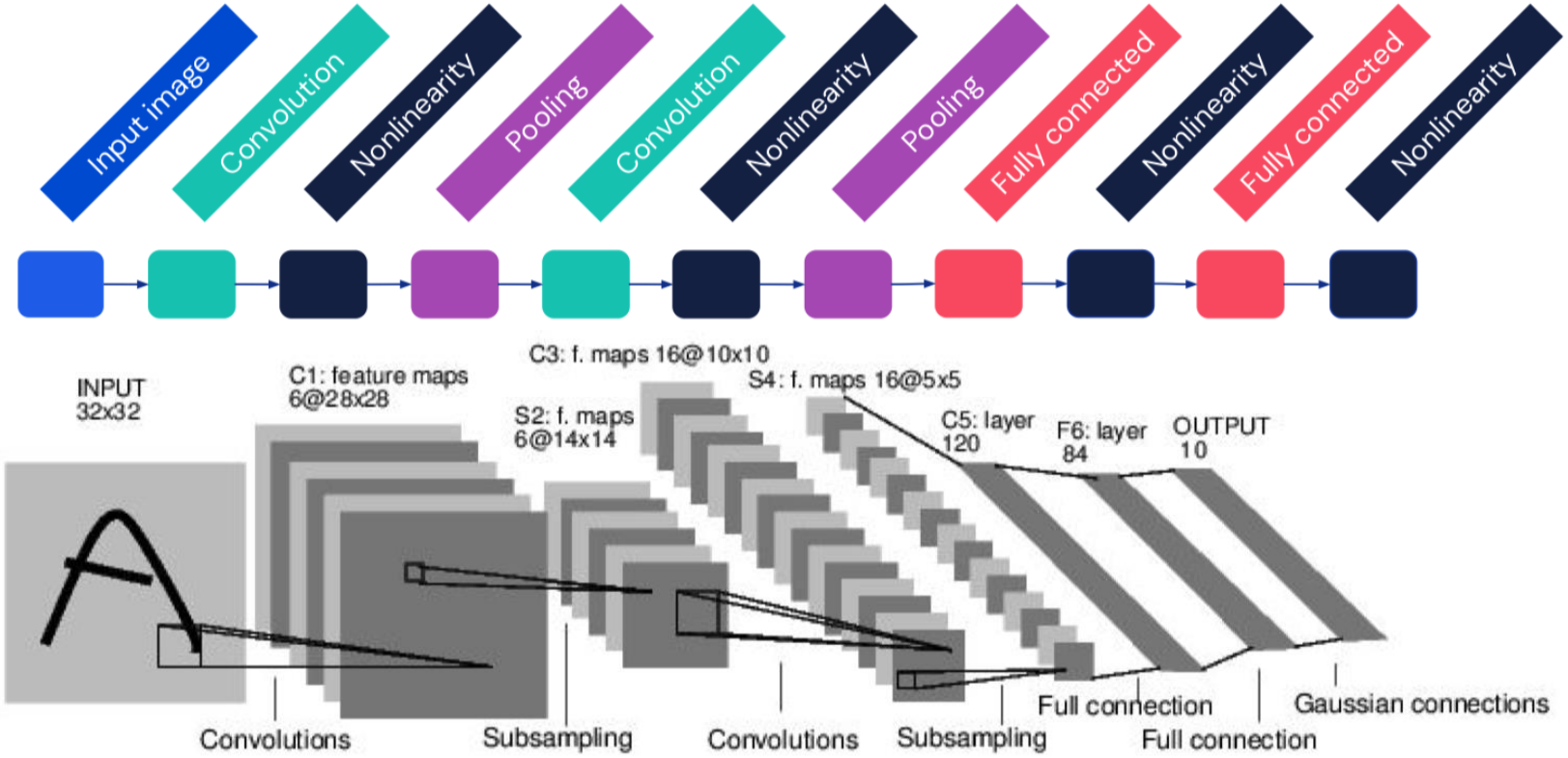
The ImageNet Challenge



The ImageNet Challenge



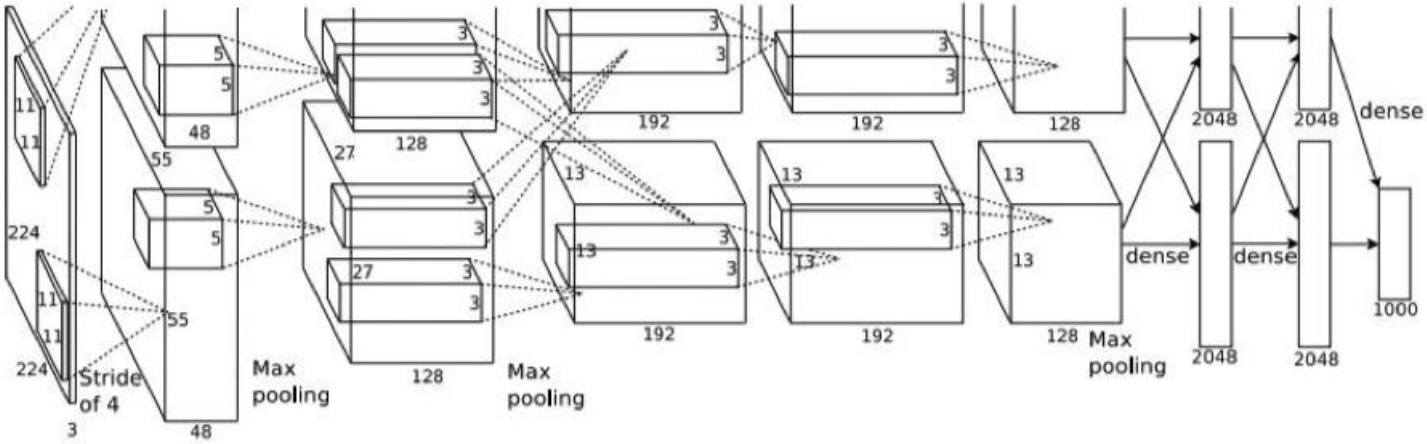
Case Study: LeNet-5 (1998)



Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

Architecture of **LeNet-5**, a convnet for handwritten digit recognition

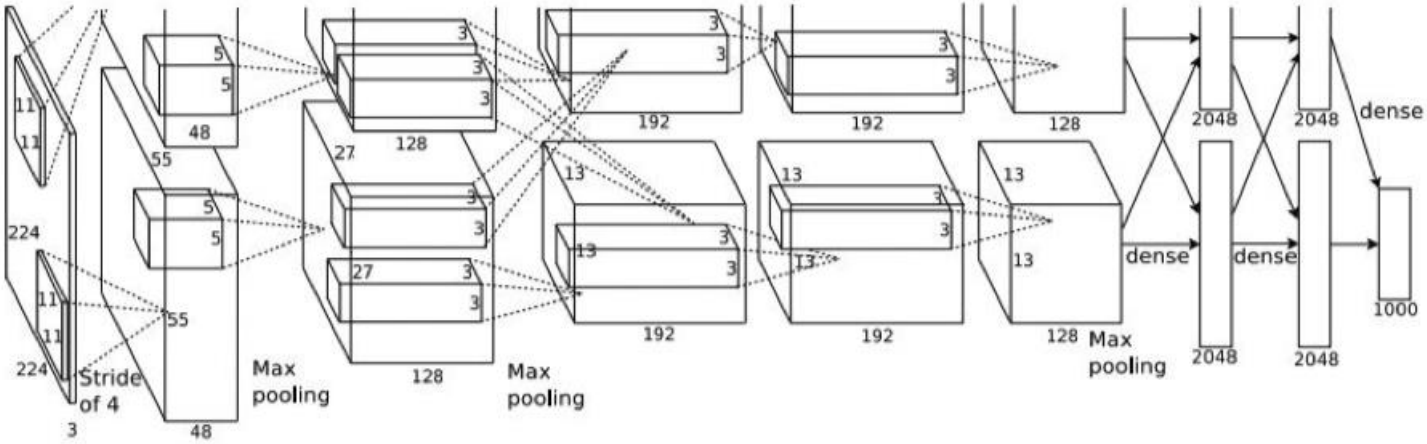
Case Study: AlexNet (2012)



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Q: what is the output volume size? Hint: (227-11)/4+1 = 55

Case Study: AlexNet (2012)

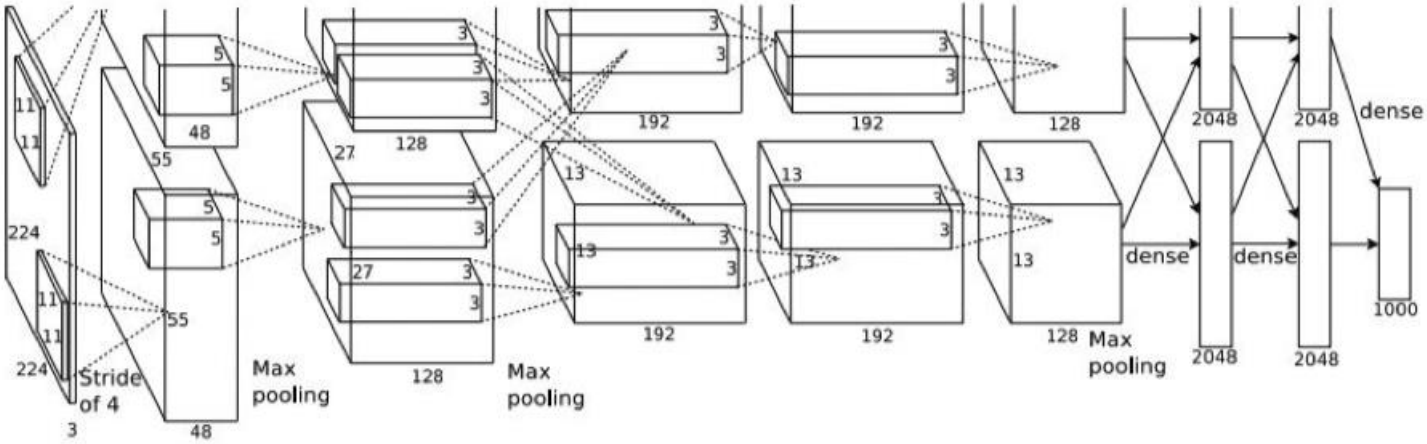


Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?

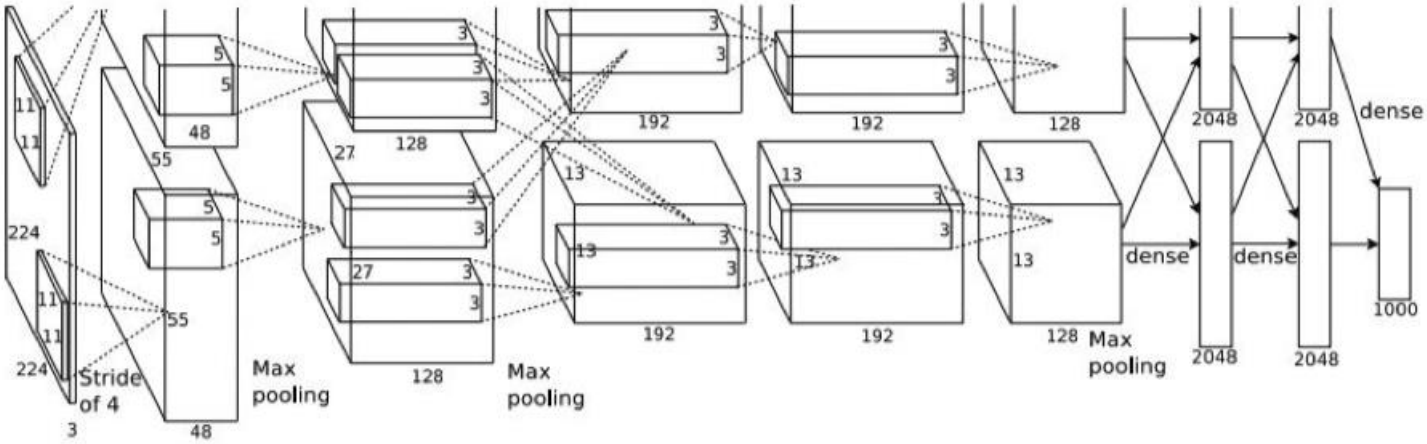
Case Study: AlexNet (2012)



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Parameters: (11*11*3)*96 = **35K**

Case Study: AlexNet (2012)

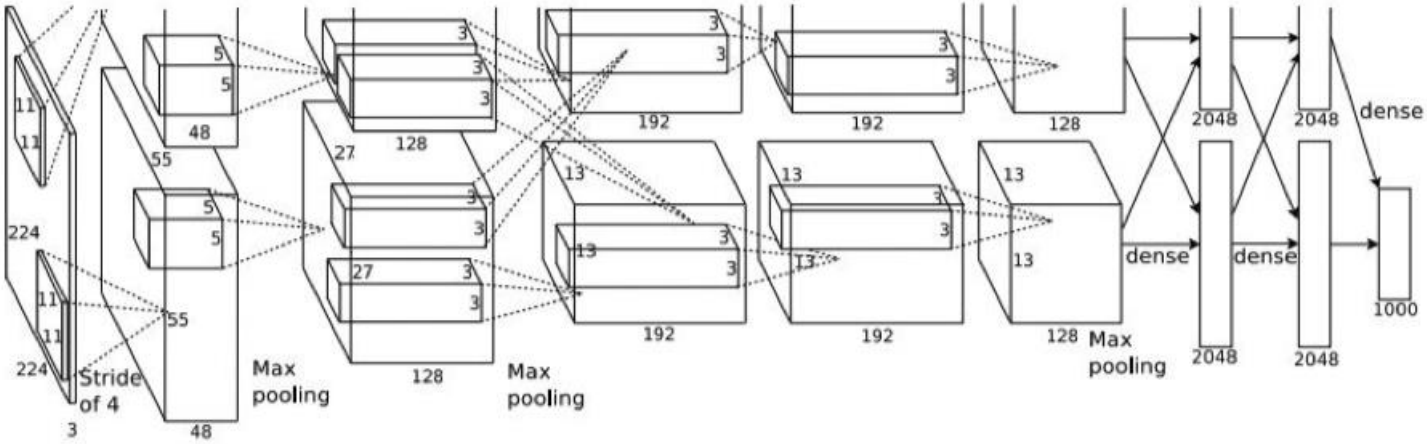


Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2

Q: what is the output volume size? Hint: (55-3)/2+1 = 27

Case Study: AlexNet (2012)

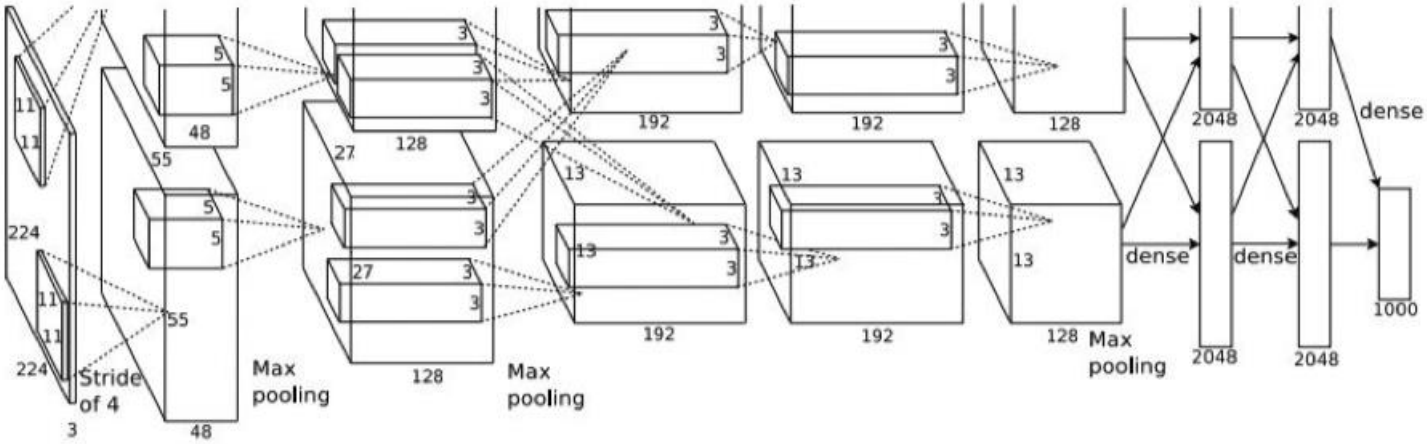


Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

Q: what is the number of parameters in this layer?

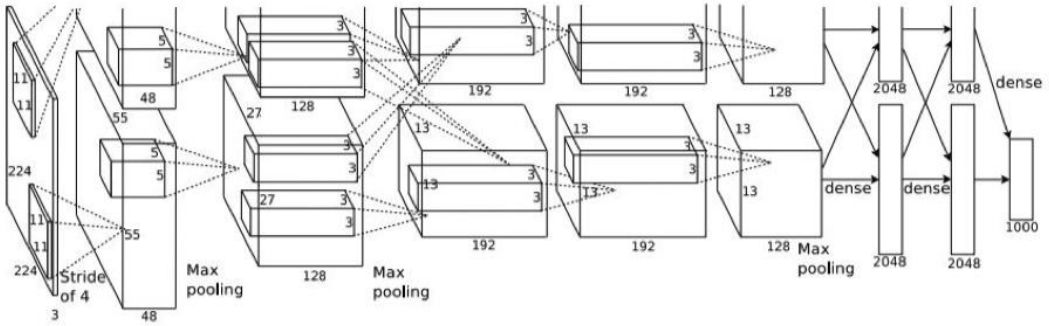
Case Study: AlexNet (2012)



Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

Case Study: AlexNet (2012)



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4

Case Study: VGGNet (2014)

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

best model

11.2% top 5 error in ILSVRC 2013
->
7.3% top 5 error

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					

Table 2: **Number of parameters** (in millions).

Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

Case Study: VGGNet (2014)

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = **102,760,448**
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

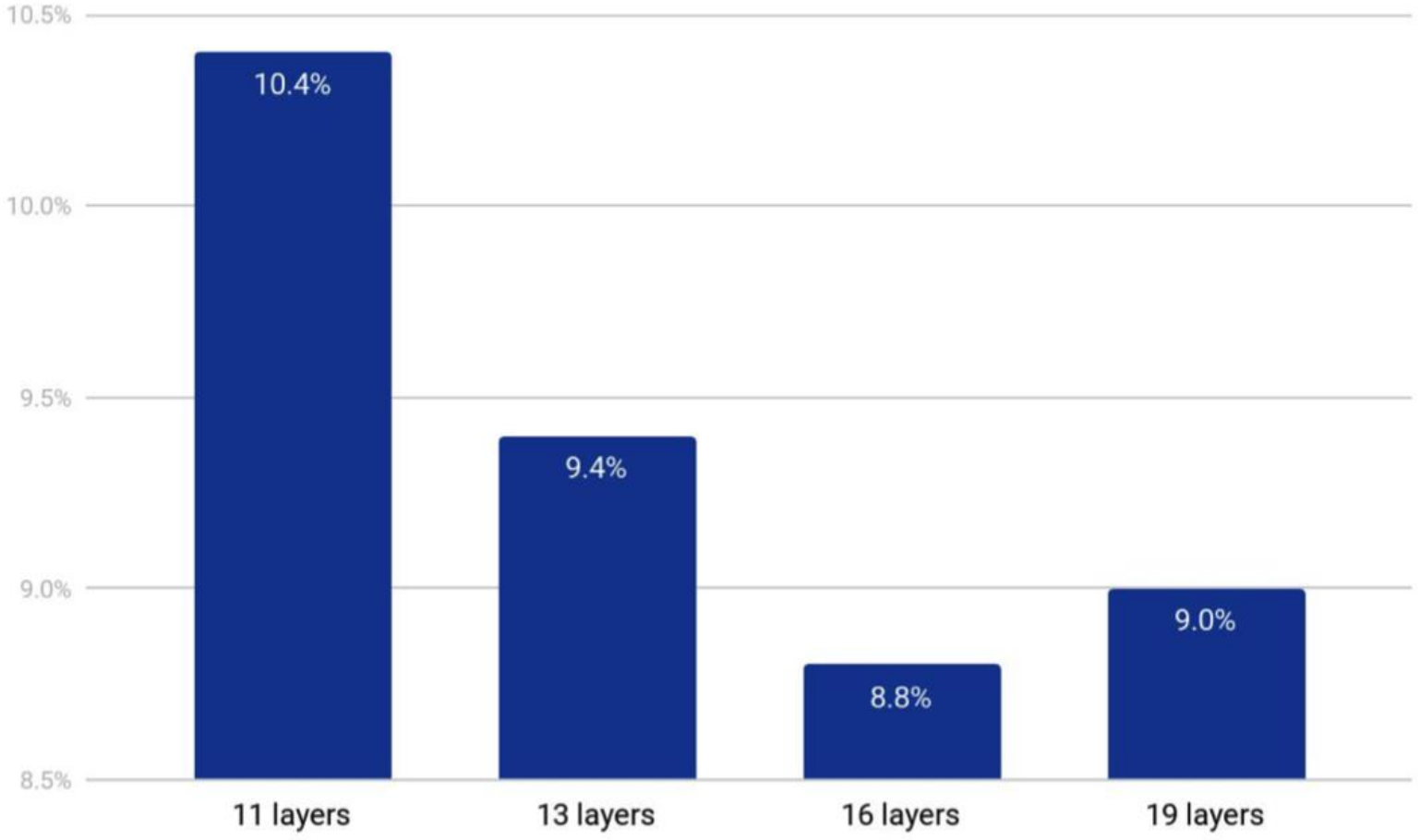
Note:

Most memory is in early CONV

Most params are in late FC

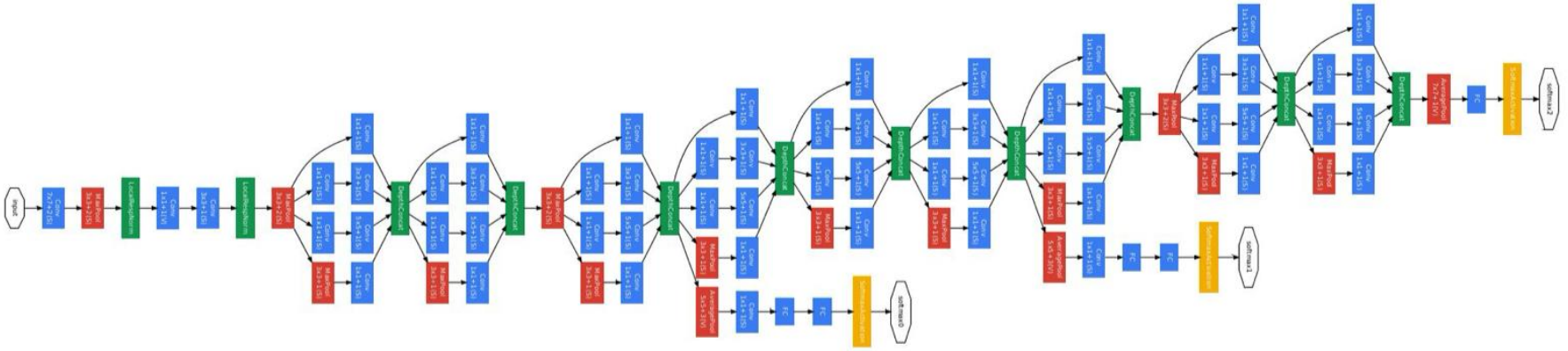
Case Study: VGGNet (2014)

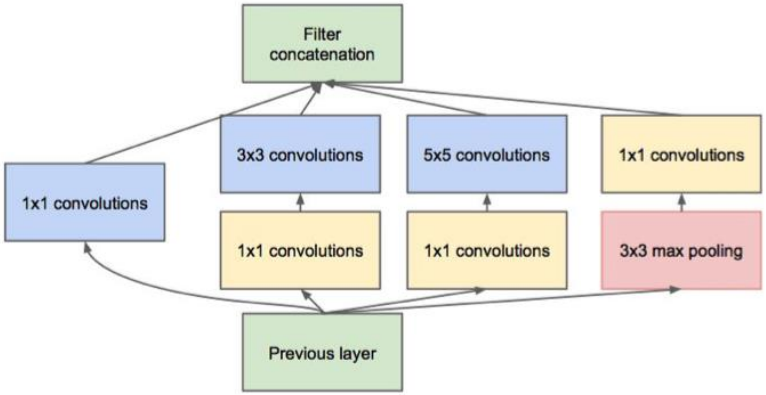
- Deeper is better?



- Challenge of Depth:
  - Computational complexity
  - Optimization difficulties

Case Study: GoogLeNet (2014)





Inception module

ILSVRC 2014 winner (6.7% top 5 error)

Case Study: GoogLeNet (2014)

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Fun features:

- Only 5 million params! (Removes FC layers completely)

Compared to AlexNet:
- 12X less params
- 2x more compute
- 6.67% (vs. 16.4%)

Case Study: GoogLeNet (2014)

- Batch Normalization:

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Figure from Ioffe et al. (2015)

Reduces sensitivity to **initialisation**

Introduces stochasticity and acts as a **regulariser**

Case Study: GoogLeNet (2014)

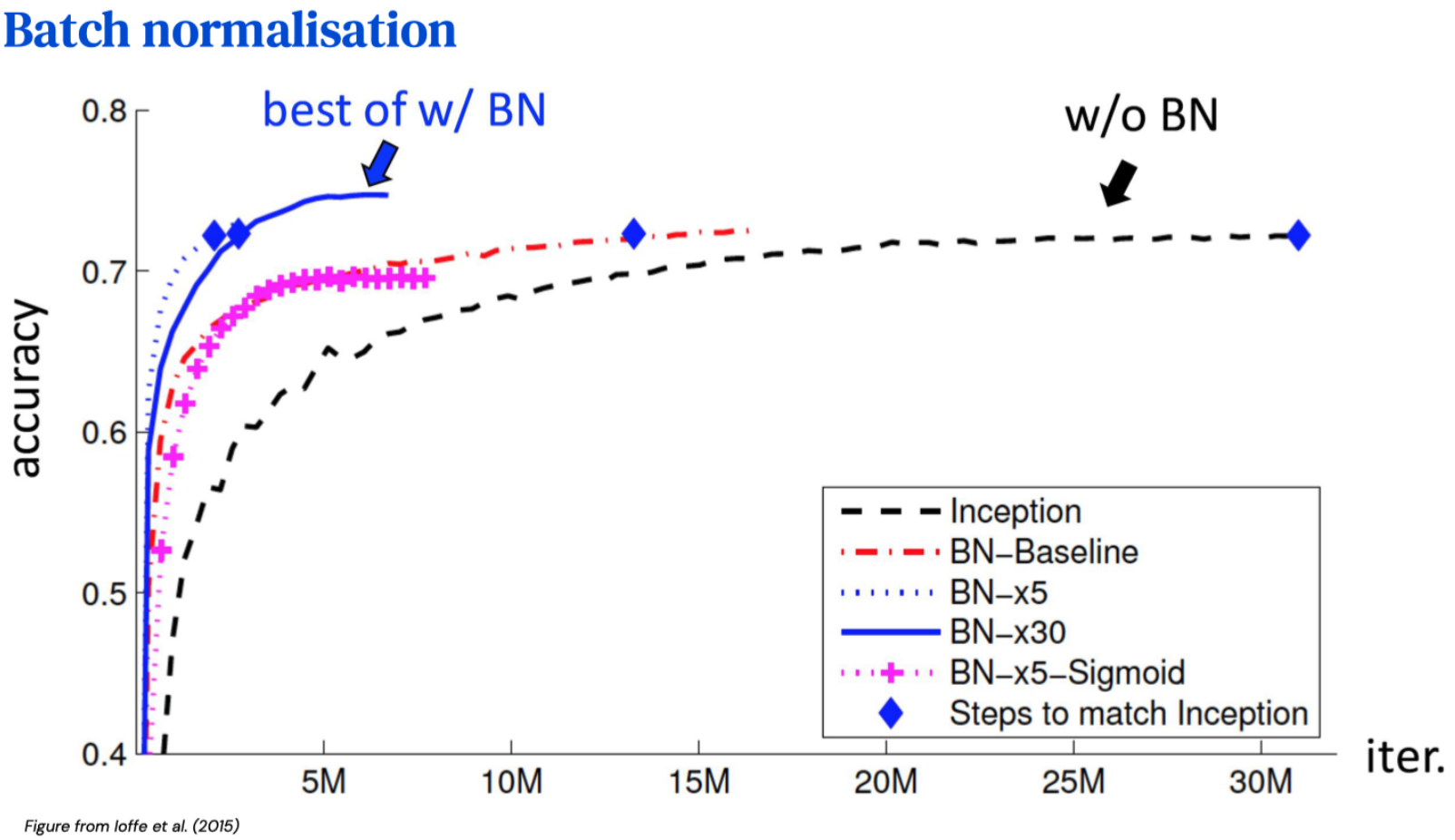
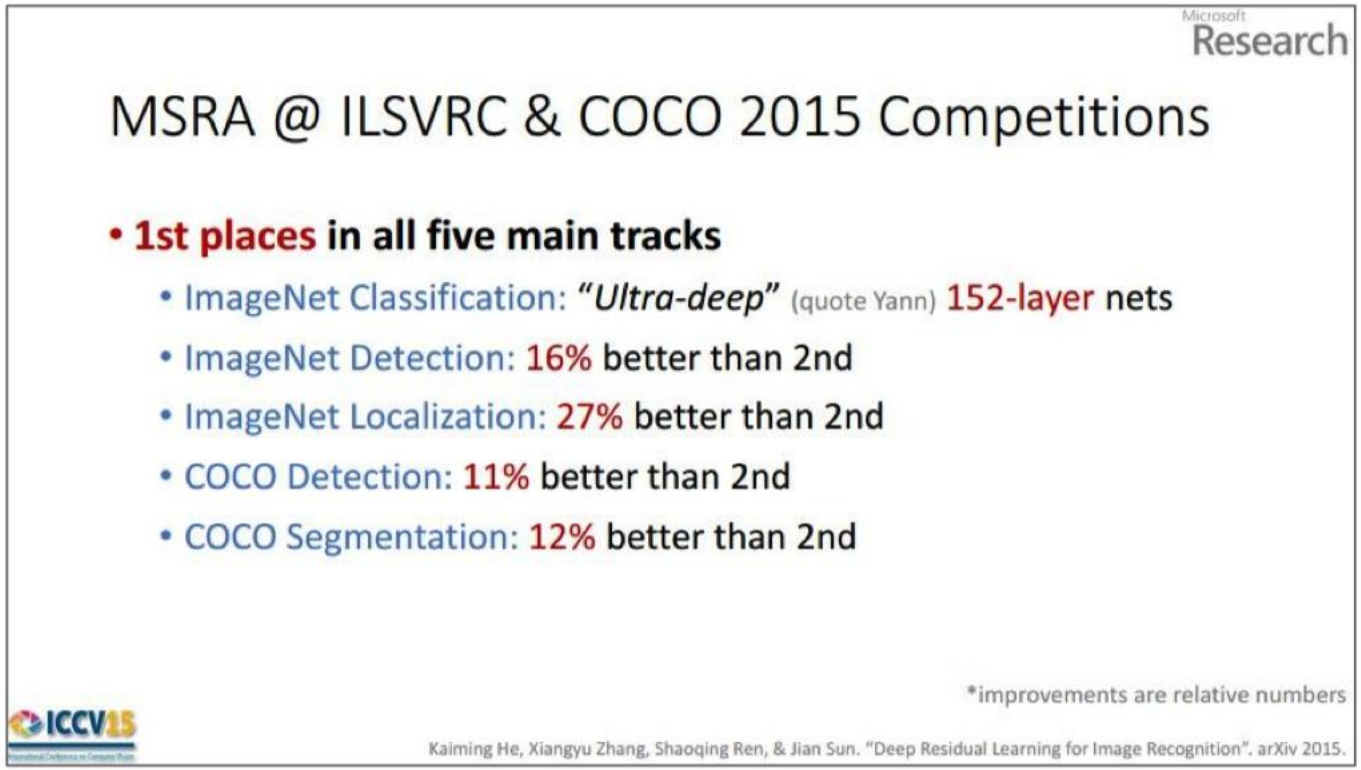


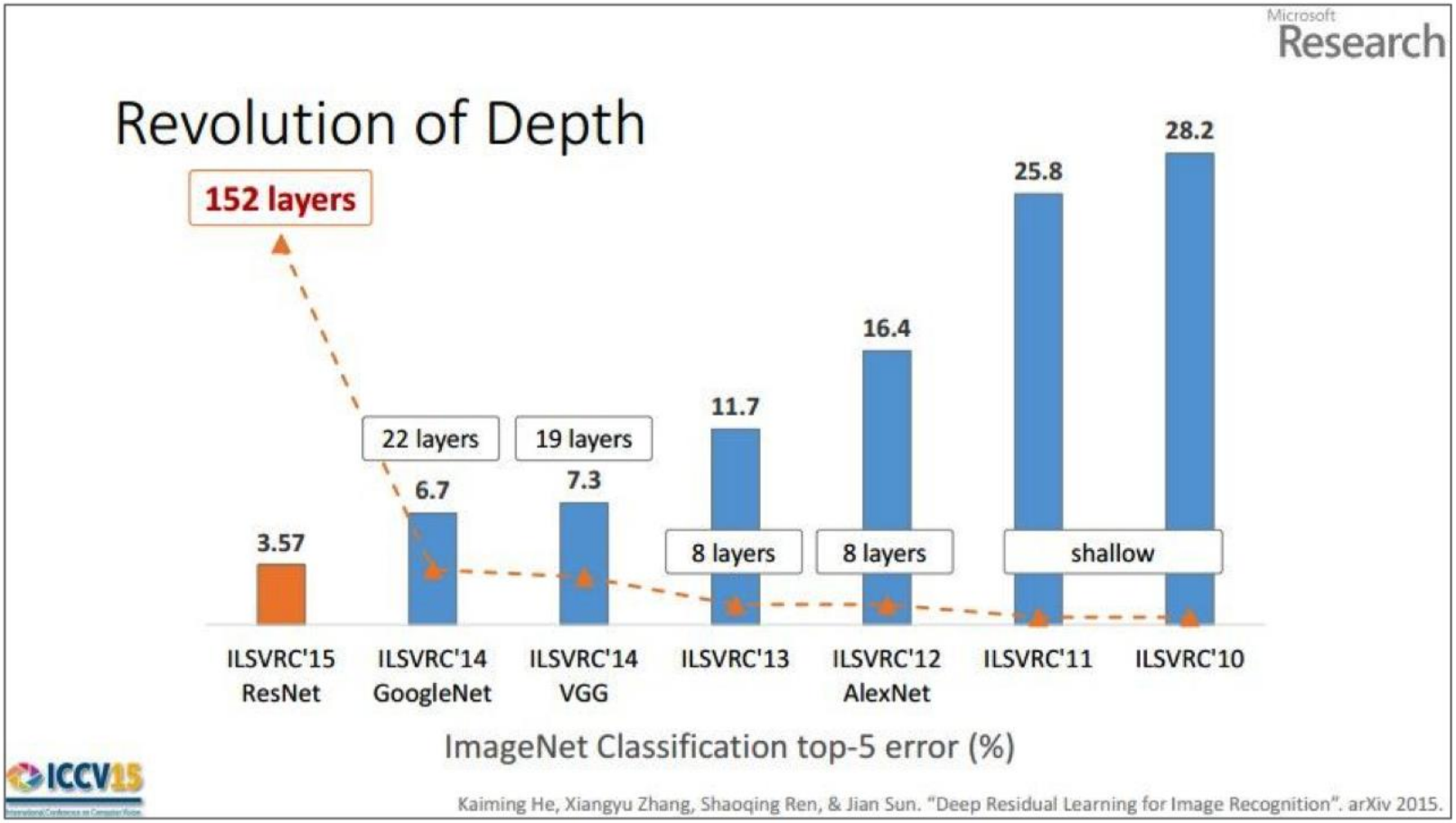
Figure from Ioffe et al. (2015)

Case Study: ResNet (2015)



Slide from Kaiming He's recent presentation https://www.youtube.com/watch?v=1PGLj-uKT1w

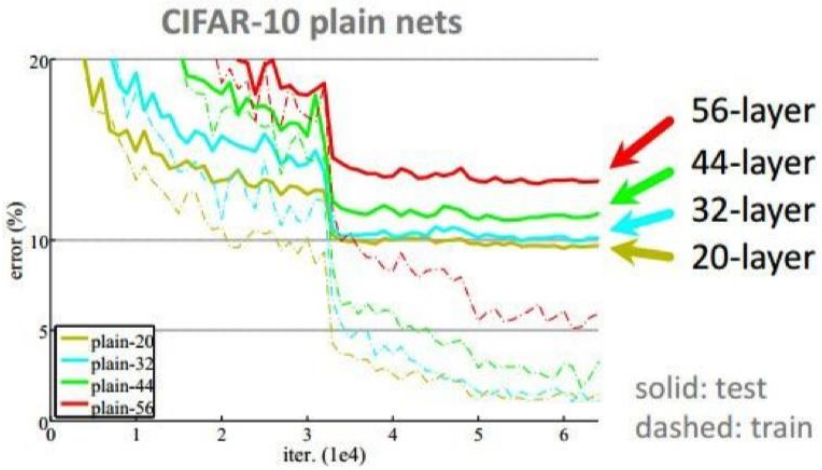
Case Study: ResNet (2015)

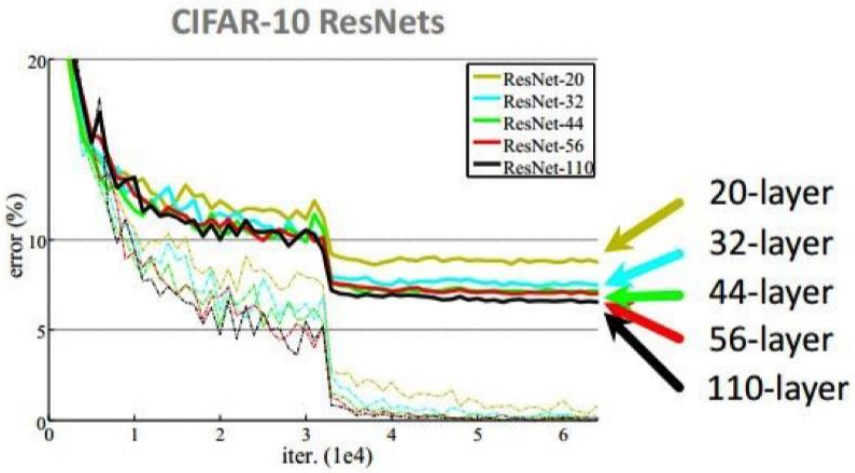


(slide from Kaiming He's recent presentation)

Case Study: ResNet (2015)

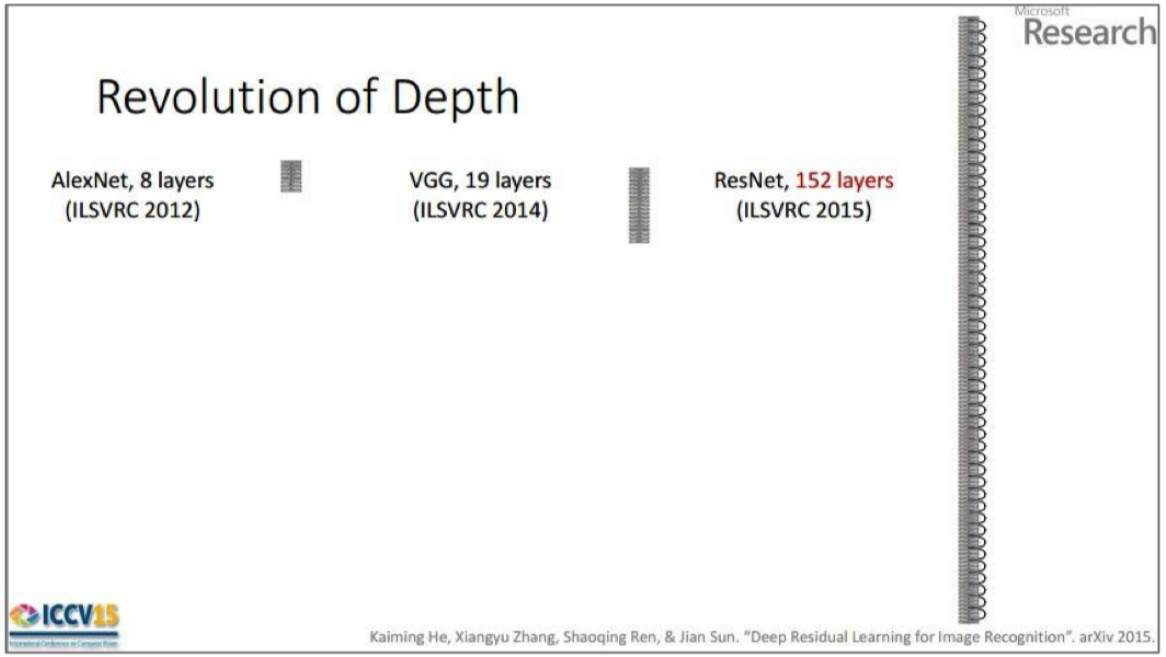
CIFAR-10 experiments





Case Study: ResNet (2015)

ILSVRC 2015 winner (3.6% top 5 error)

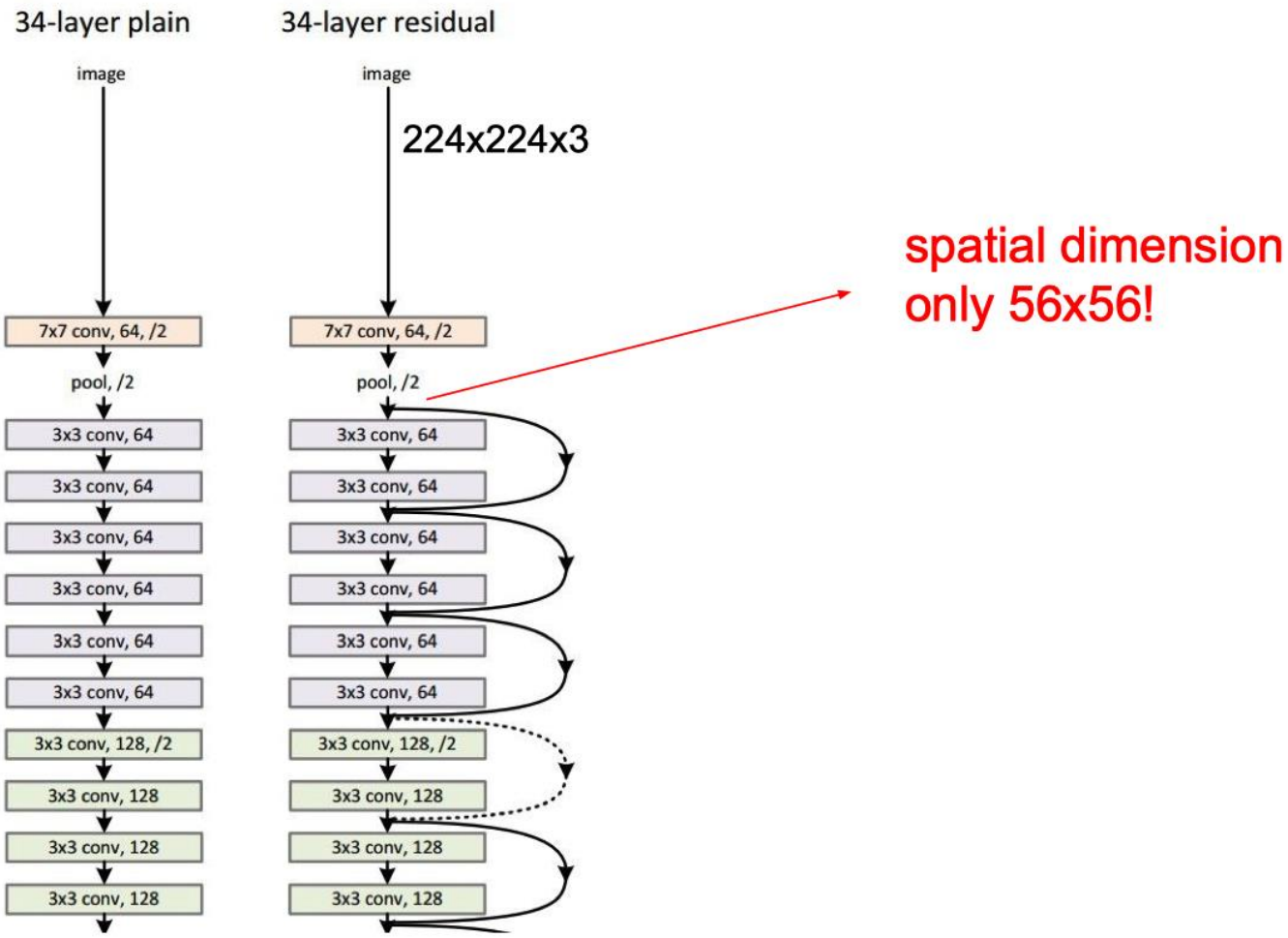


2-3 weeks of training on 8 GPU machine

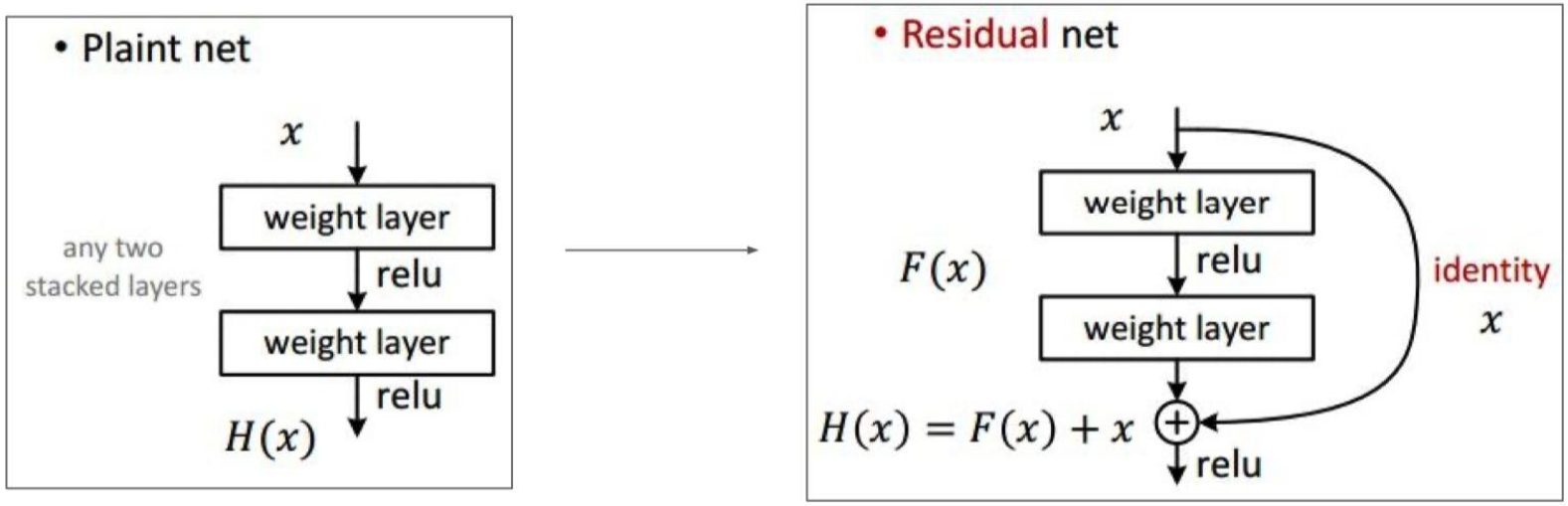
at runtime: faster than a VGGNet! (even though it has 8x more layers)

(slide from Kaiming He's recent presentation)

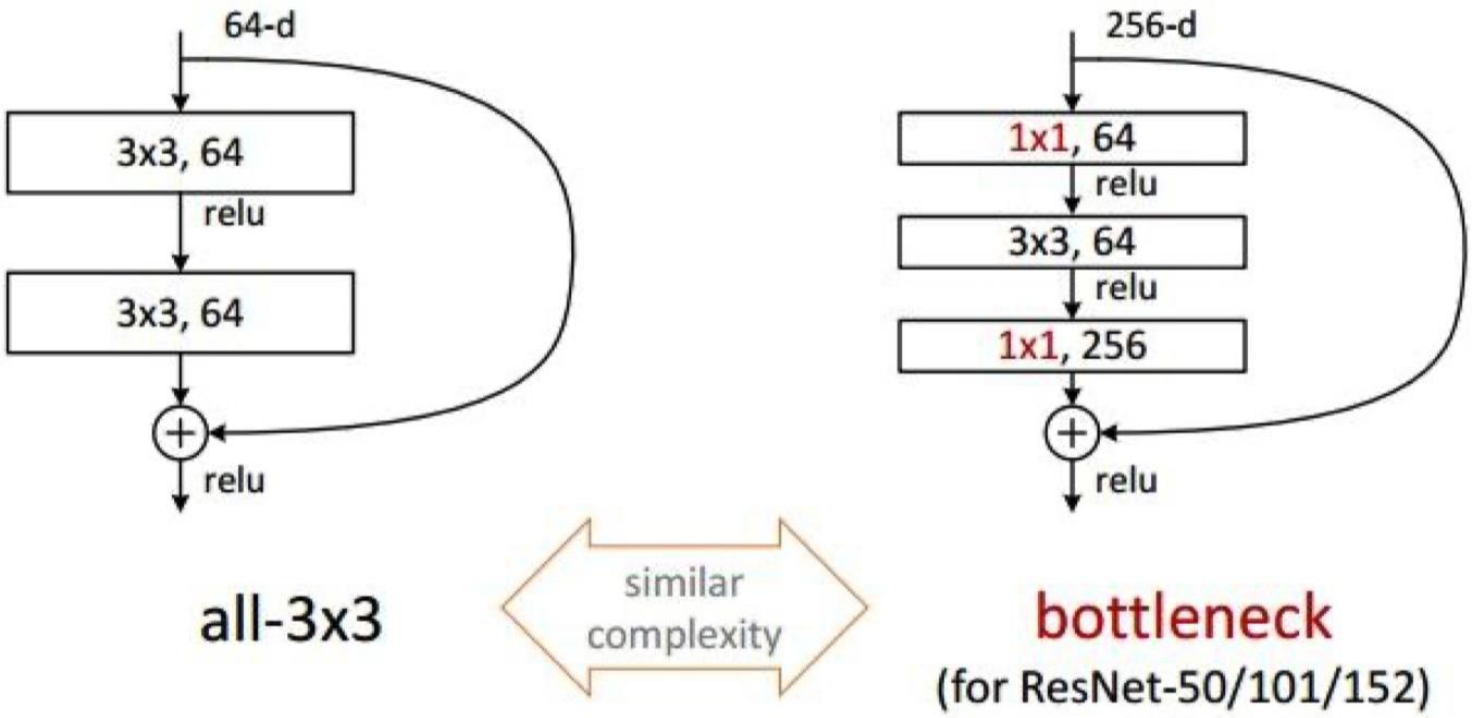
Case Study: ResNet (2015)



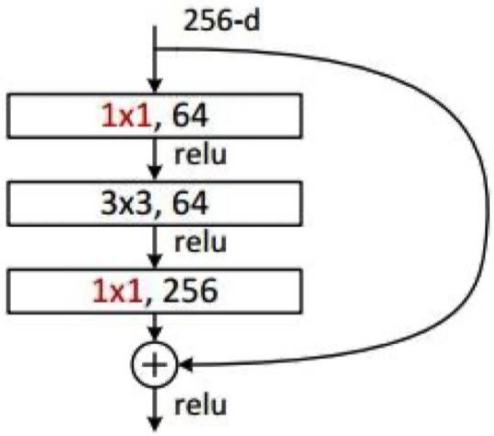
Case Study: ResNet (2015)

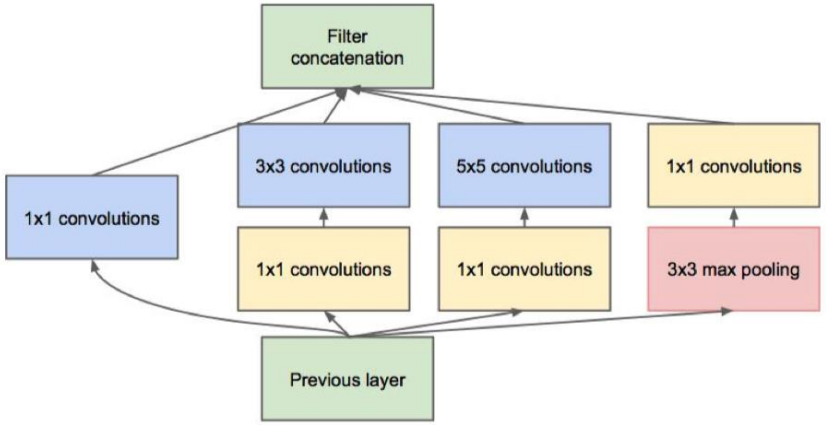


Case Study: ResNet (2015)



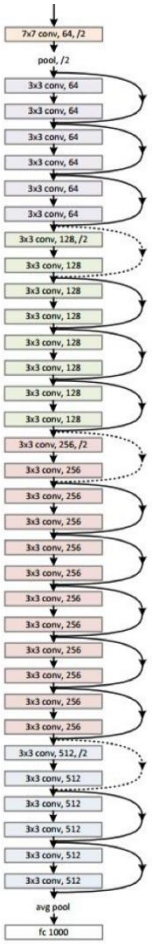
Case Study: ResNet (2015)





(this trick is also used in GoogLeNet)

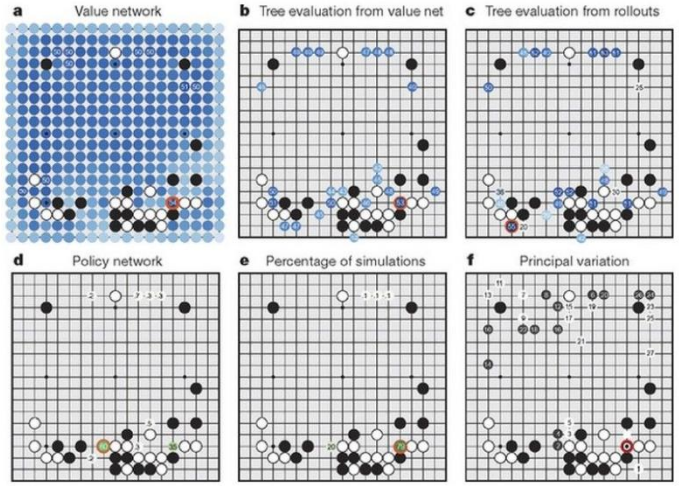
Case Study: ResNet (2015)



Case Study: ResNet *[He et al., 2015]*

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Case Study Bonus: DeepMind's AlphaGo



How will you design the networks?

- What's the input?
- What's the output? (Hint: classification or regression?)
- Is the ConvNet appliable to the problem?

Case Study Bonus: DeepMind's AlphaGo

> The input to the policy network is a 19 × 19 × 48 image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a 23 × 23 image, then convolves *k* filters of kernel size 5 × 5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21 × 21 image, then convolves *k* filters of kernel size 3 × 3 with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size 1 × 1 with stride 1, with a different bias for each position, and applies a softmax function. The match version of AlphaGo used *k* = 192 filters; Fig. 2b and Extended Data Table 3 additionally show the results of training with *k* = 128, 256 and 384 filters.

policy network:
[19x19x48] Input
CONV1: 192 5x5 filters , stride 1, pad 2 => [19x19x192]
CONV2..12: 192 3x3 filters, stride 1, pad 1 => [19x19x192]
CONV: 1 1x1 filter, stride 1, pad 0 => [19x19] *(probability map of promising moves)*

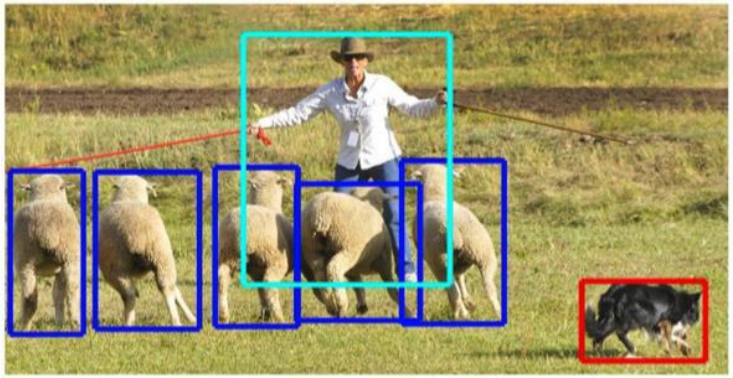
Summary of ConvNet Structure

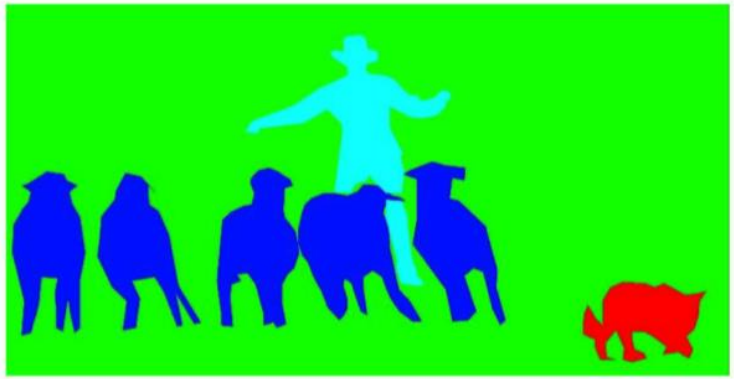
- ConvNets stack CONV,POOL,FC layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Typical architectures look like

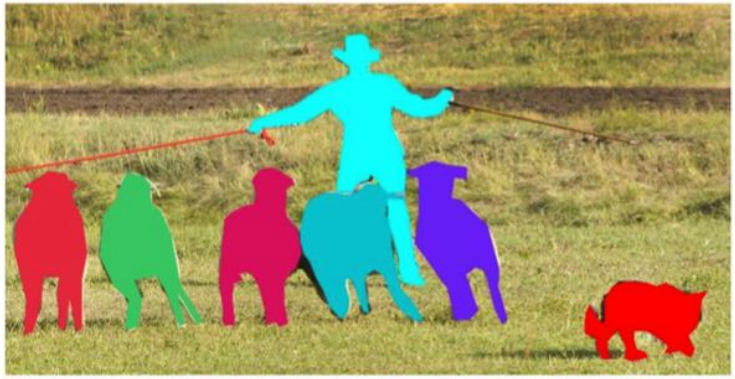
  [(CONV-RELU)*N-POOL?]*M-(FC-RELU)*K,SOFTMAX

  where N is usually up to ~5, M is large, 0 <= K <= 2.
  - but recent advances such as ResNet/GoogLeNet challenge this paradigm

Other Tasks Using Convnets







Figures from Lin et al. (2015)

Other Tasks Using Convnets

Generative models of images

- Generative adversarial nets
- Variational autoencoders
- Autoregressive models (PixelCNN)

Questions?

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