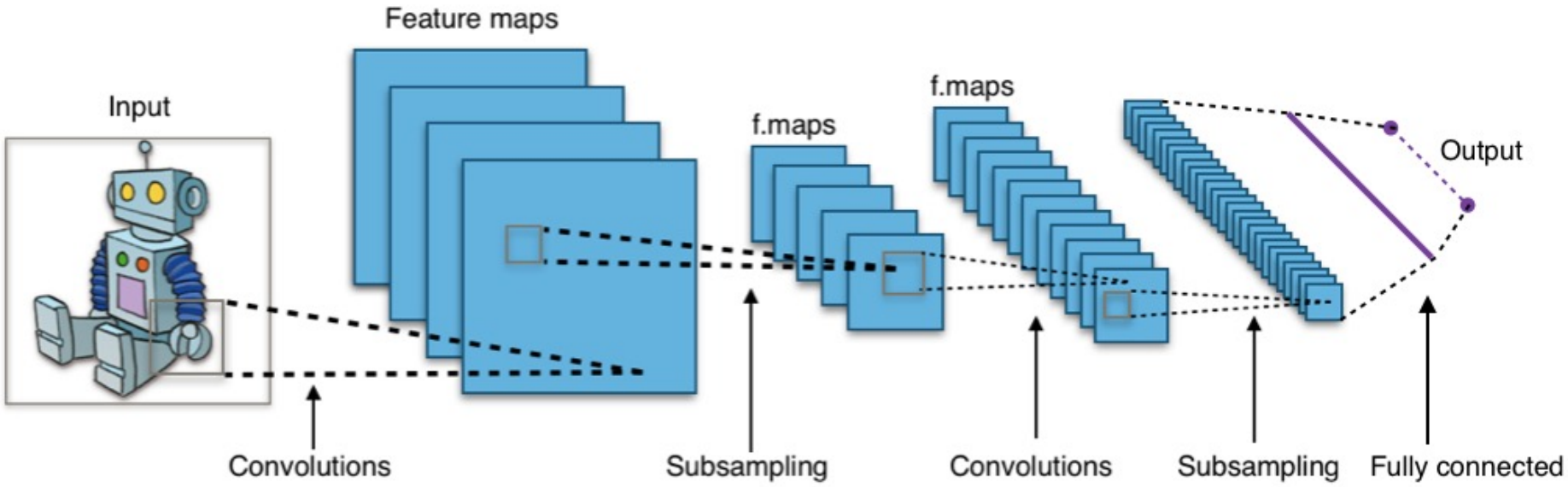
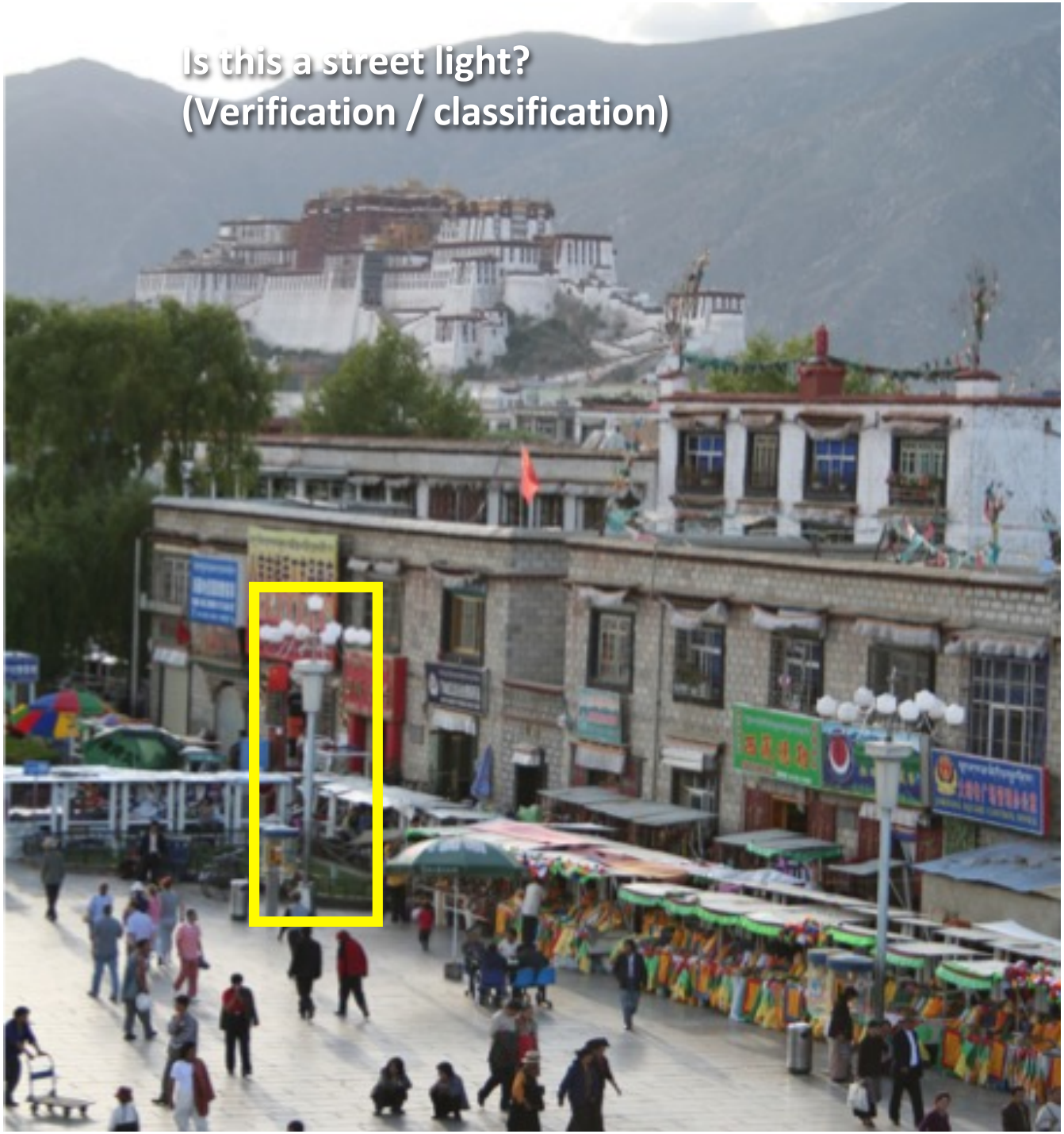
Convolutional neural networks

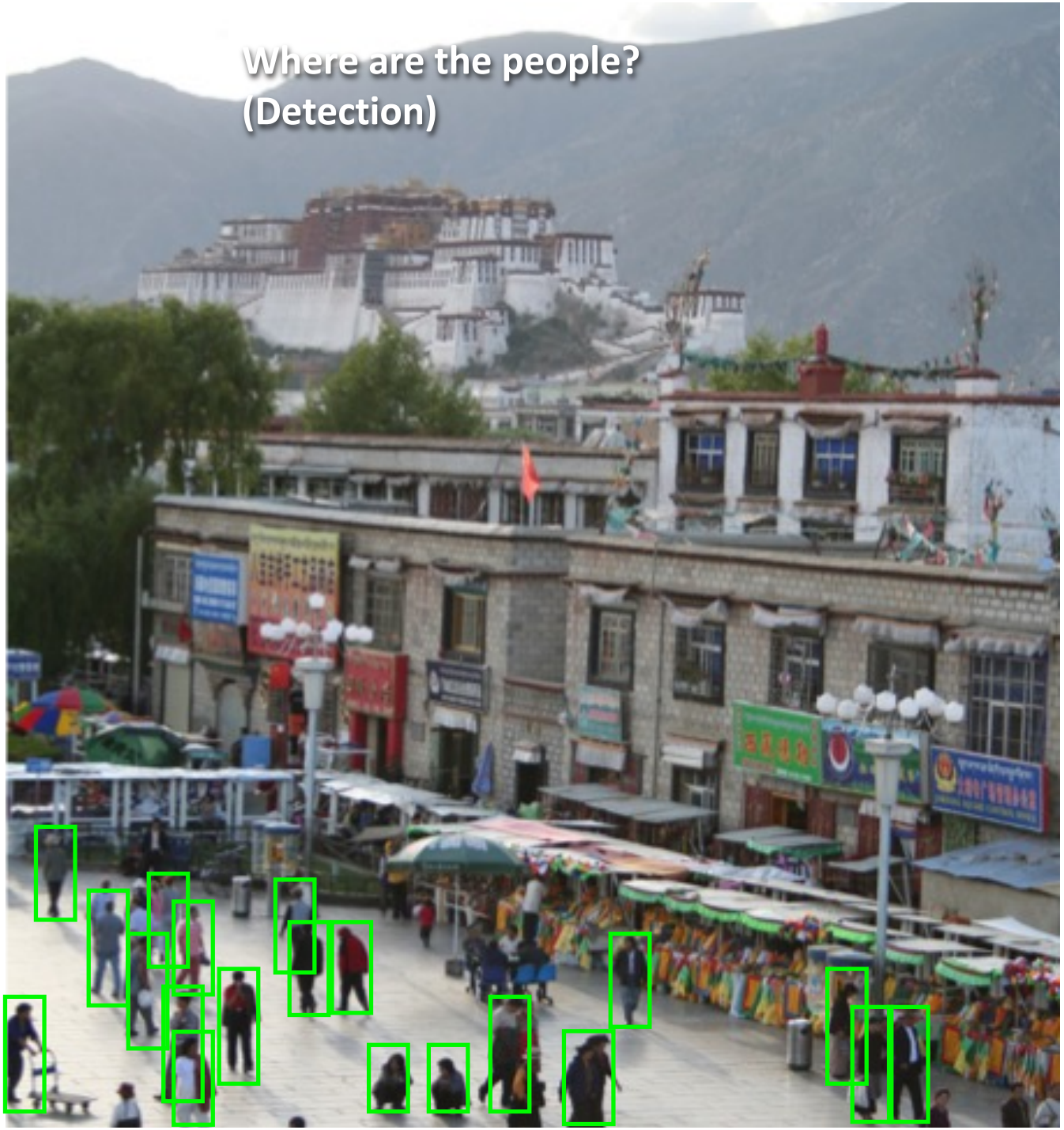


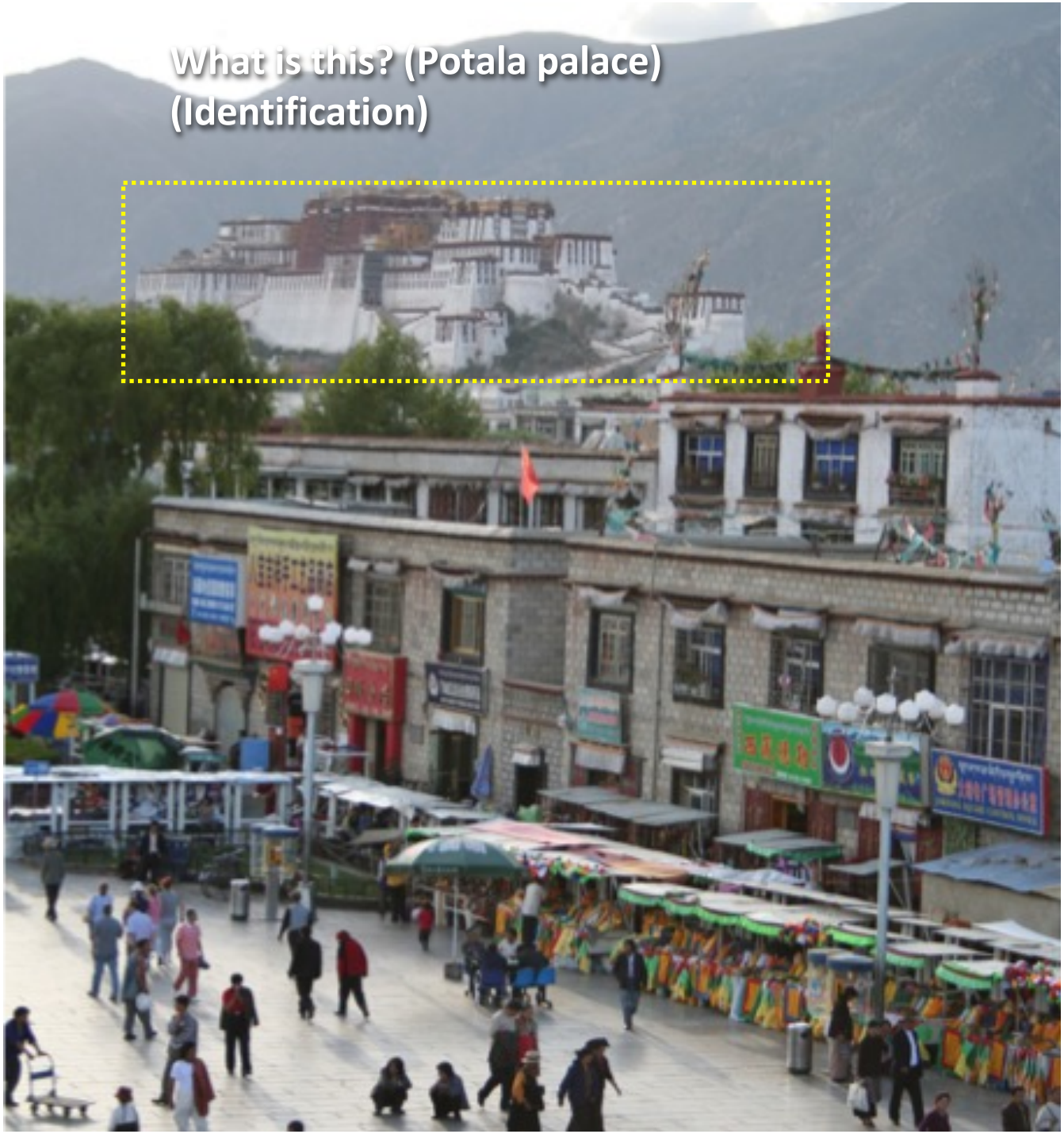
Overview of today's lecture

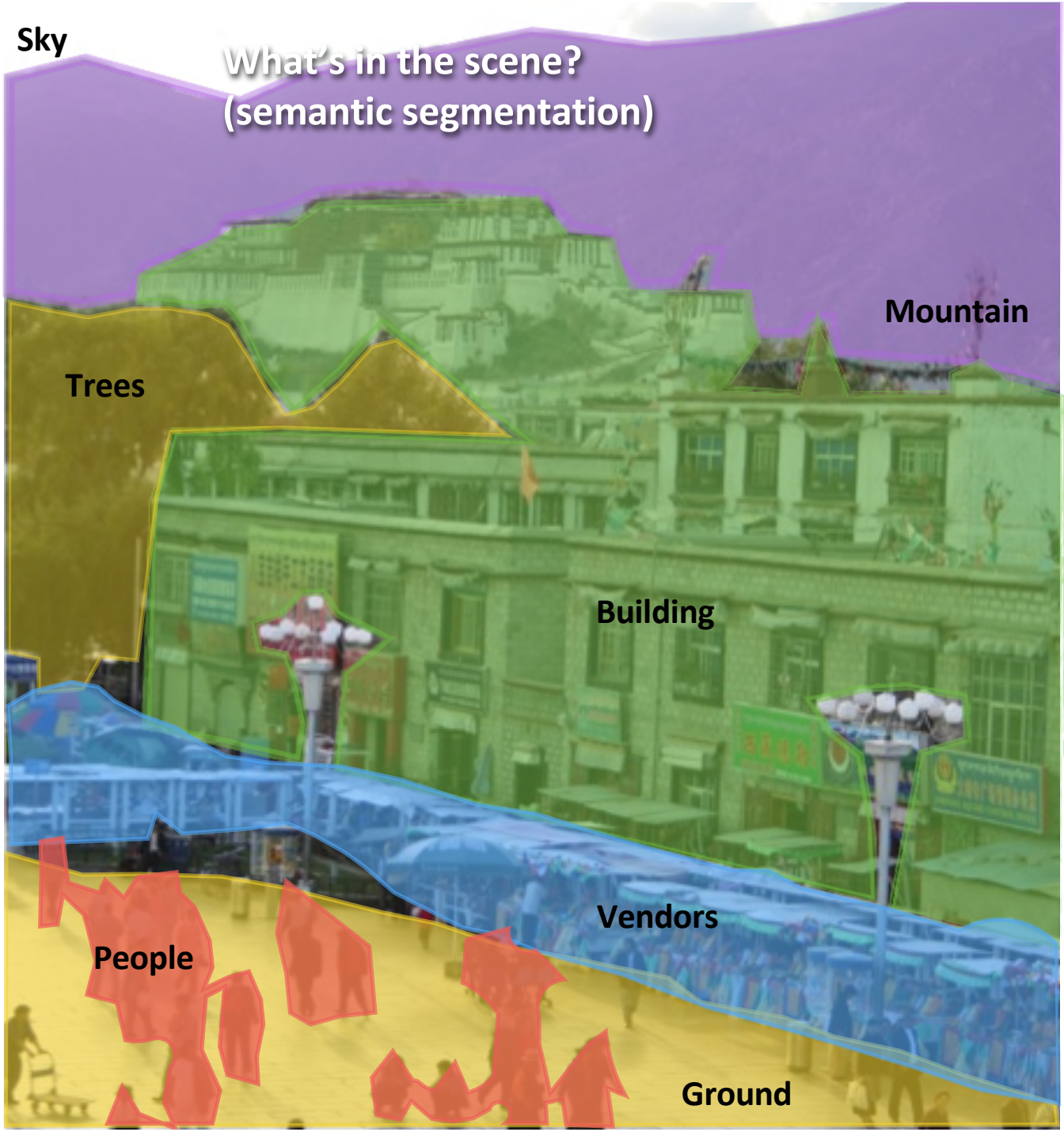
- What is recognition?
- Convolutional Neural Networks (CNNs / ConvNets)
- Training ConvNets.

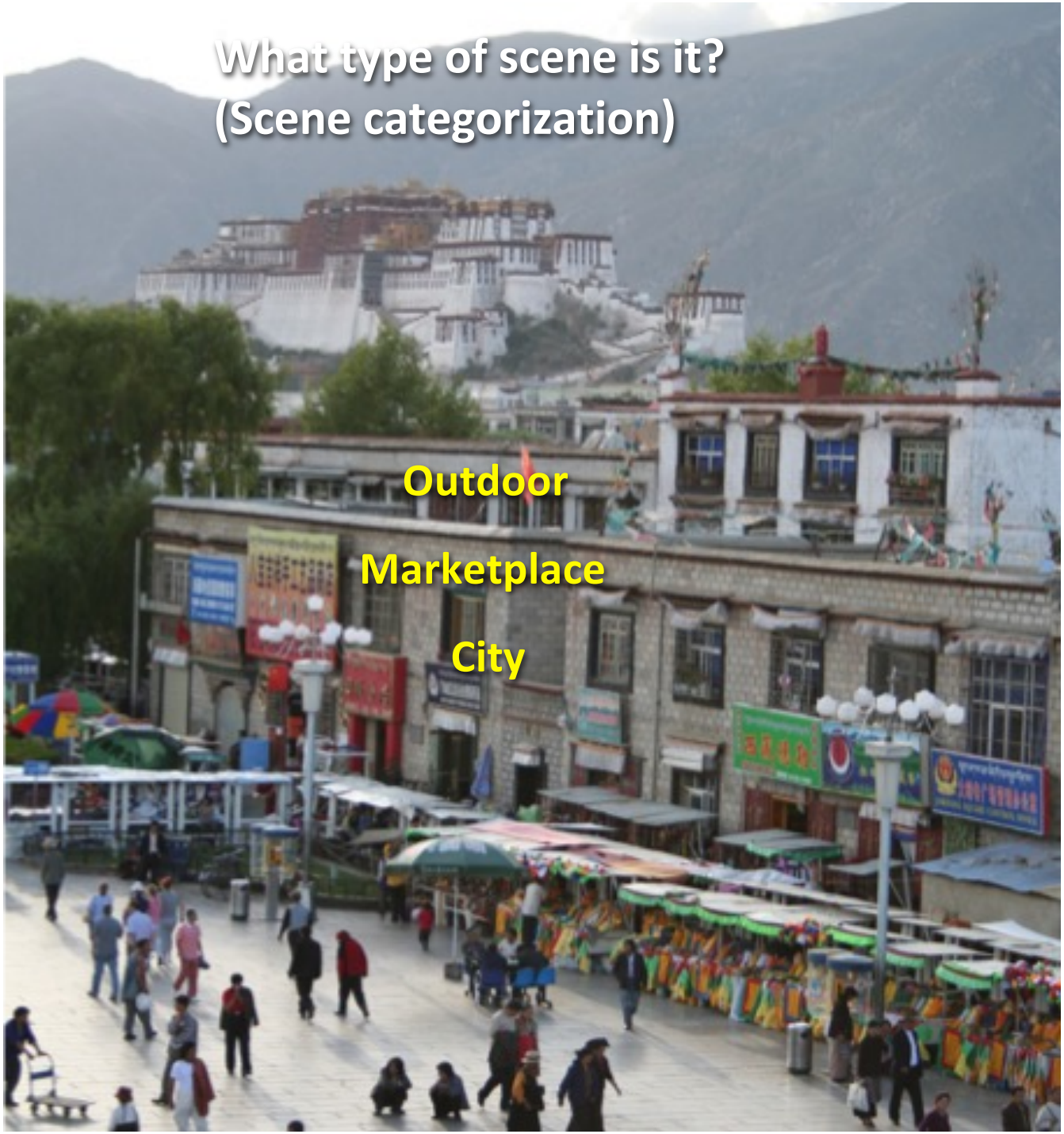
Recognition


Is this a street light?
(Verification / classification)

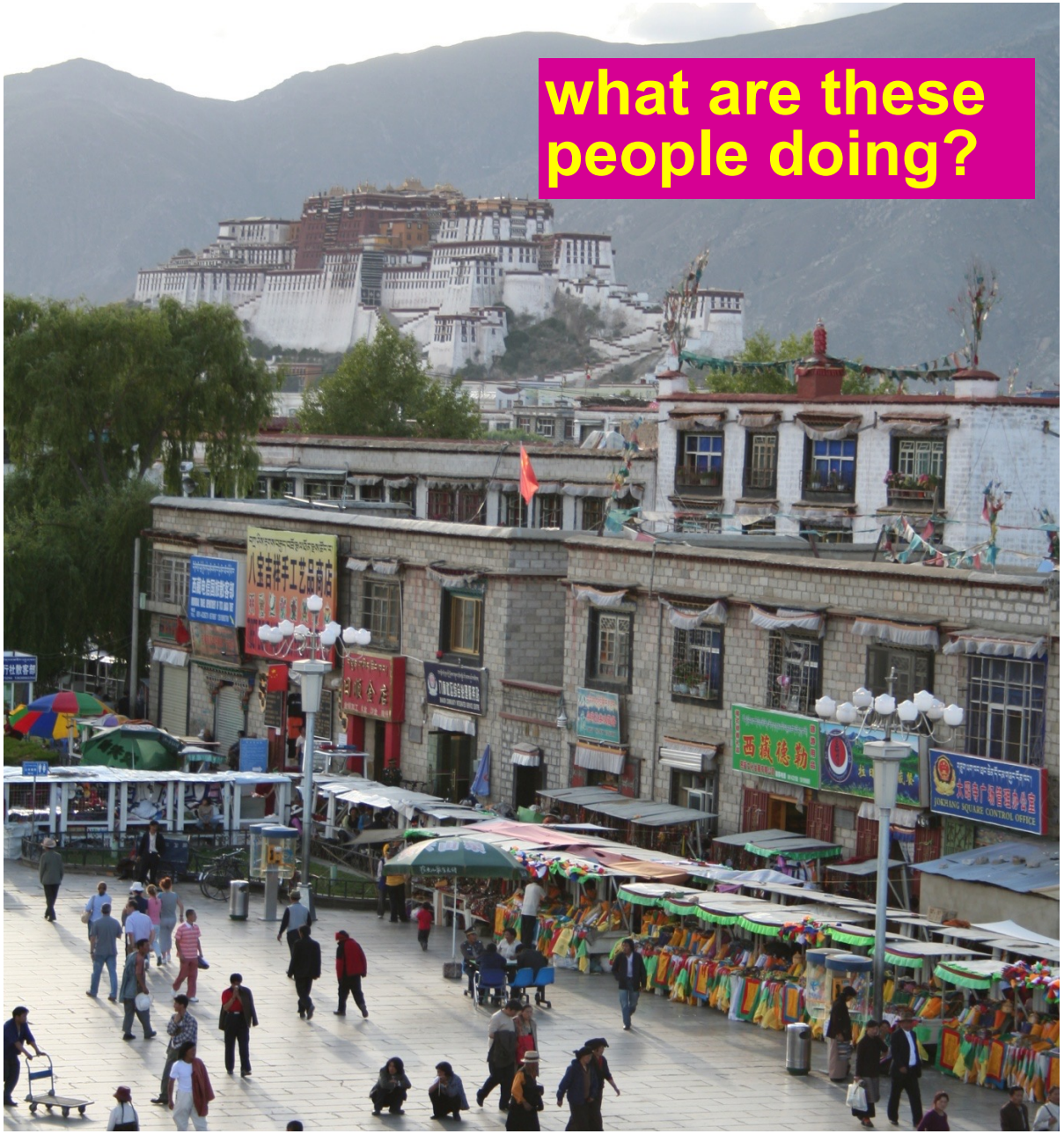

Where are the people?
(Detection)


What is this? (Potala palace)
(Identification)


Sky
What's in the scene?
(semantic segmentation)
Mountain
Trees
Building
Vendors
People
Ground

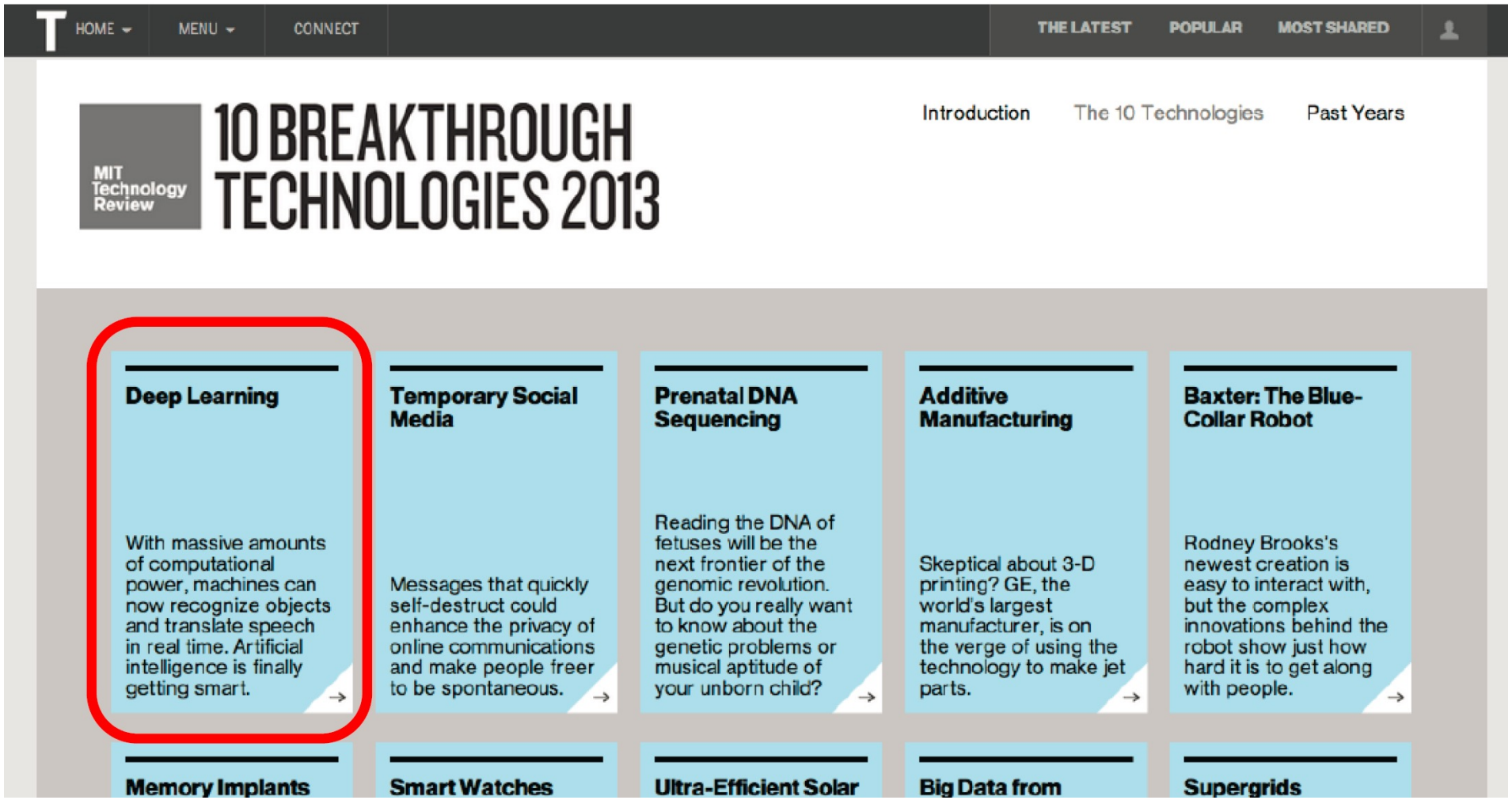

What type of scene is it?
(Scene categorization)
Outdoor
Marketplace
City

Activity / Event Recognition



Convolutional Neural Networks

Motivation


HOME
MENU
CONNECT
THE LATEST
POPULAR
MOST SHARED
MIT Technology Review
10 BREAKTHROUGH TECHNOLOGIES 2013
Introduction
The 10 Technologies
Past Years
Deep Learning
With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.
Temporary Social Media
Messages that quickly self-destruct could enhance the privacy of online communications and make people freer to be spontaneous.
Prenatal DNA Sequencing
Reading the DNA of fetuses will be the next frontier of the genomic revolution. But do you really want to know about the genetic problems or musical aptitude of your unborn child?
Additive Manufacturing
Skeptical about 3-D printing? GE, the world's largest manufacturer, is on the verge of using the technology to make jet parts.
Baxter: The Blue-Collar Robot
Rodney Brooks's newest creation is easy to interact with, but the complex innovations behind the robot show just how hard it is to get along with people.
Memory Implants
Smart Watches
Ultra-Efficient Solar
Big Data from
Supergrids

(Unrelated) Dog vs Food

[Karen Zack, @teenybiscuit]

(Unrelated) Dog vs Food

[Karen Zack, @teenybiscuit]

CNNs in 2012: “SuperVision” (aka “AlexNet”)

“AlexNet” — Won the ILSVRC2012 Challenge

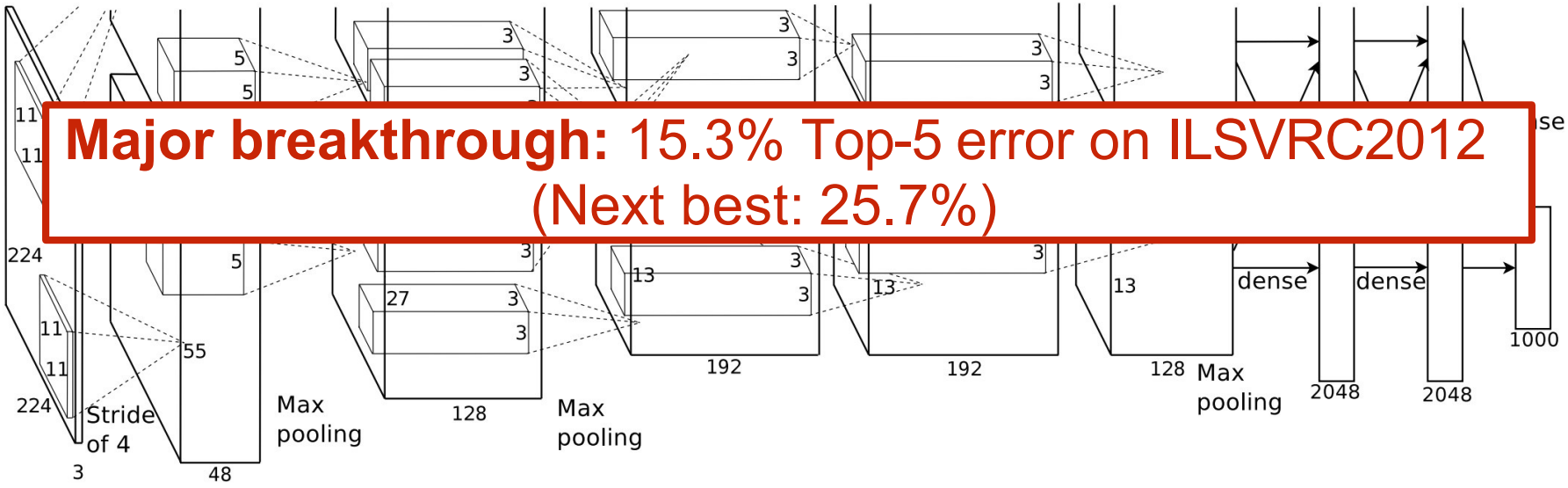
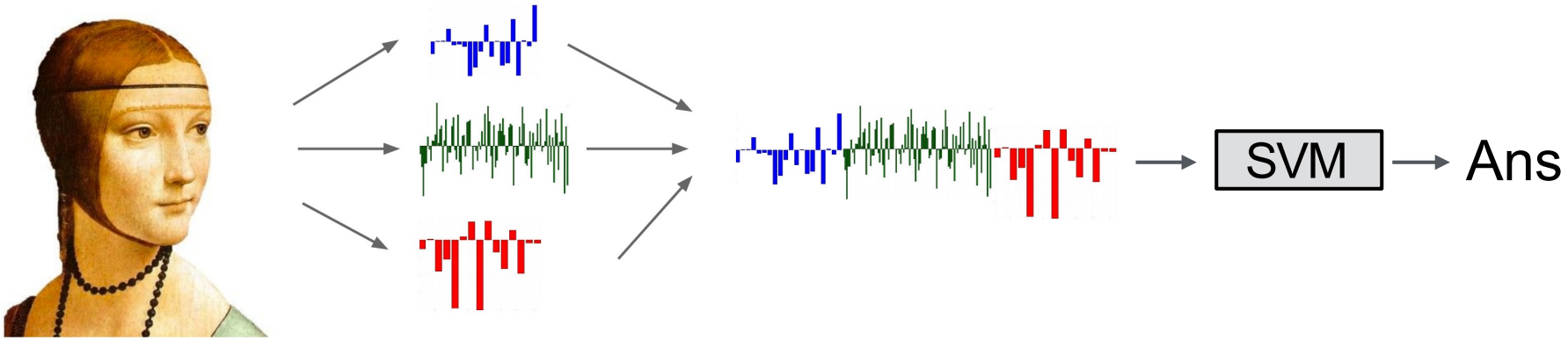


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network’s input is 150,528-dimensional, and the number of neurons in the network’s remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

[Krizhevsky, Sutskever, Hinton. NIPS 2012]

Recap: Before Deep Learning



Input Pixels | *Extract Features* | *Concatenate into a vector* ***x*** | *Linear Classifier*

The last layer of (most) CNNs are linear classifiers

Input Pixels

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

Key: perform enough processing so that by the time you get to the end of the network, the classes are linearly separable

ConvNets

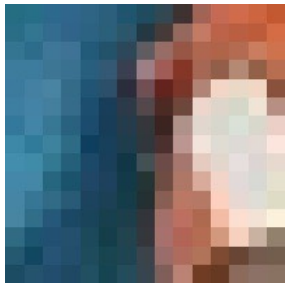
They’re just neural networks with
3D activations and weight sharing

What is an image?

What is an image?

A (color) image is a 3D tensor of numbers.

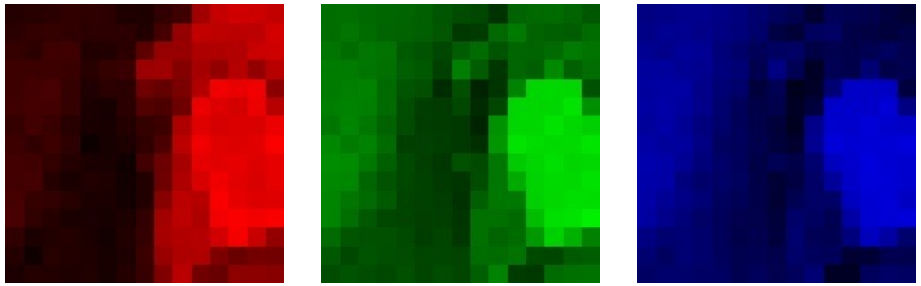
What is an image?



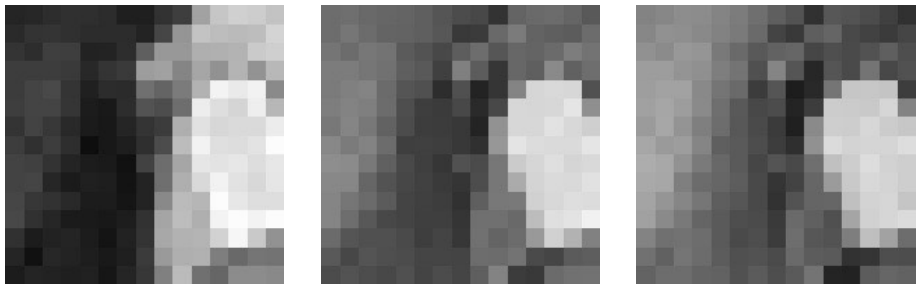
color image patch

How many bits are the intensity values?

red green blue



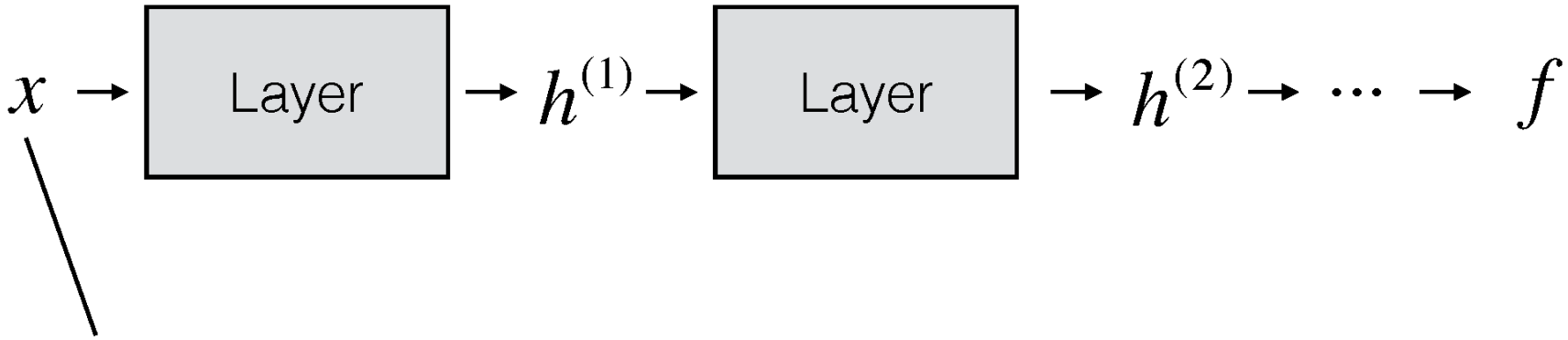
colorized for visualization



actual intensity values per channel

Each channel is a 2D array of numbers.

What shape should the activations have?



- The input is an image, which is 3D (RGB channel, height, width)

- We could flatten it to a 1D vector, but then we lose structure

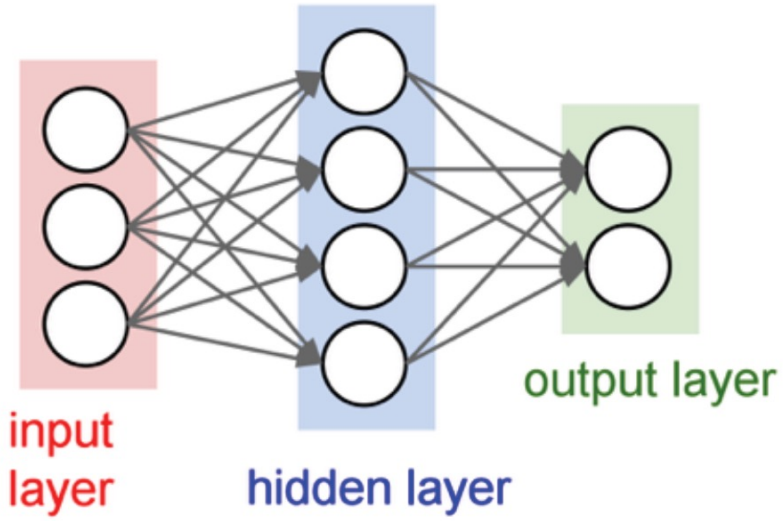
- What about keeping everything in 3D?

ConvNets

They’re just neural networks with
3D activations and weight sharing

3D Activations

before:



(1D vectors)

Figure: Andrej Karpathy

3D Activations

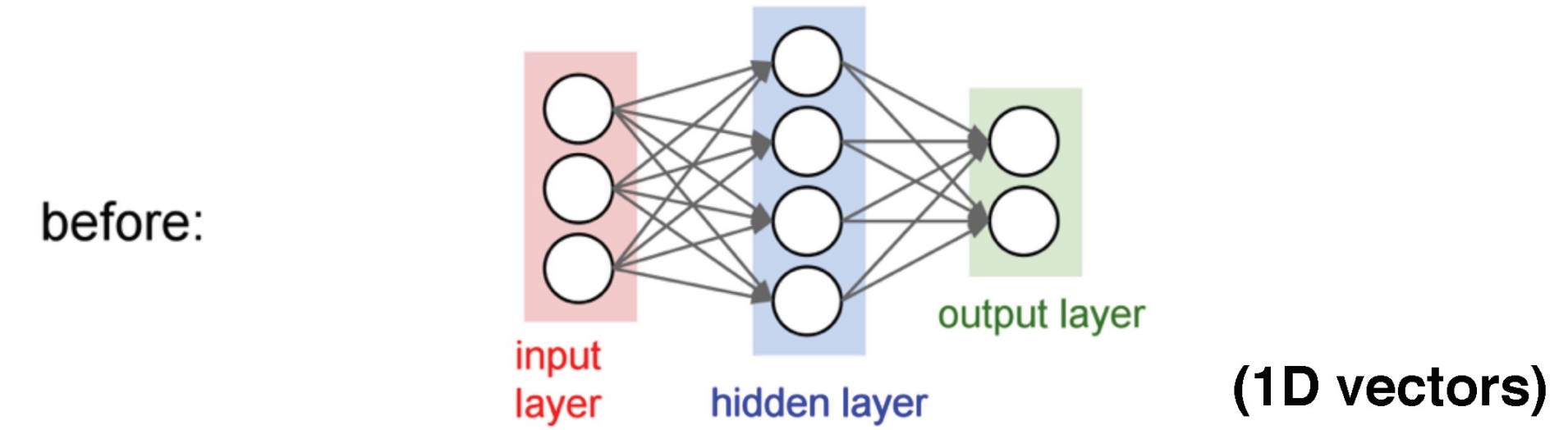


Figure: Andrej Karpathy

3D Activations

All Neural Net activations arranged in **3 dimensions:**

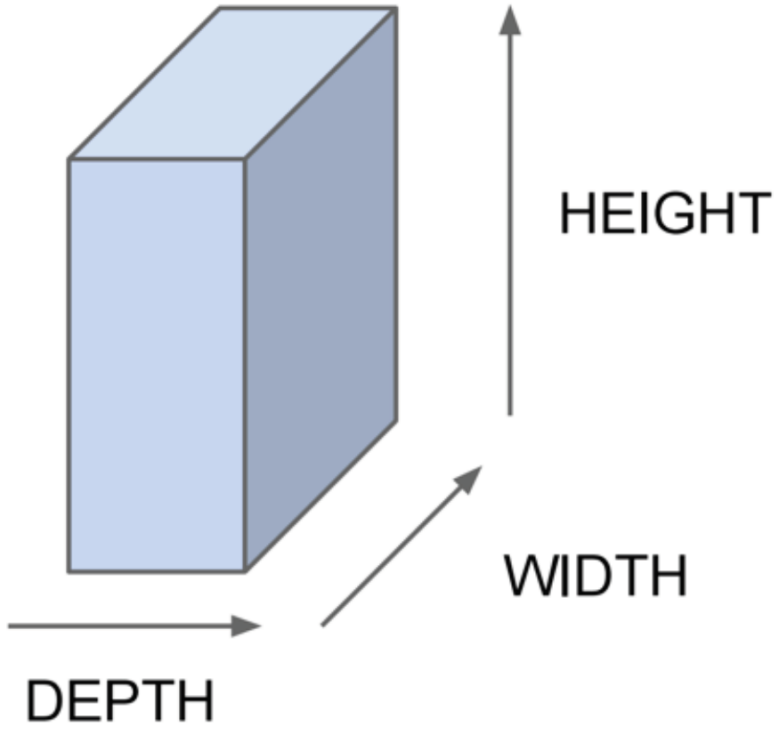
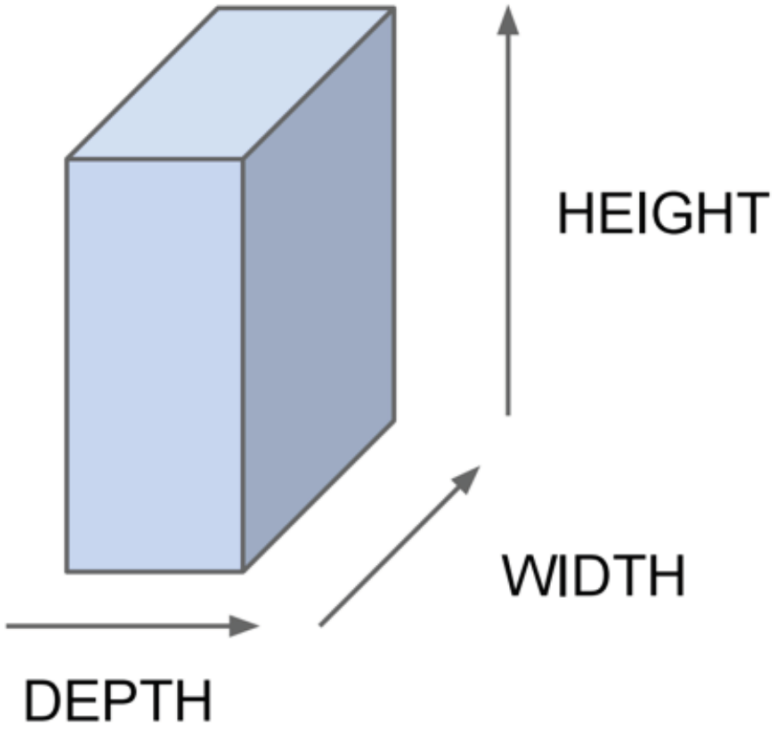


Figure: Andrej Karpathy

3D Activations

All Neural Net activations arranged in **3 dimensions:**

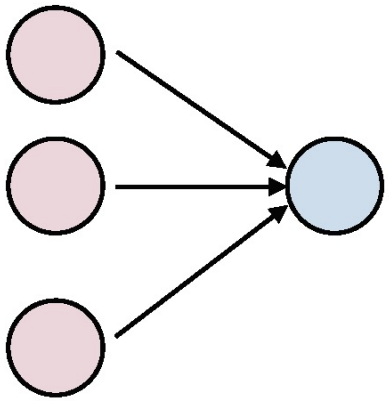


For example, a CIFAR-10 image is a 3x32x32 volume (3 depth — RGB channels, 32 height, 32 width)

Figure: Andrej Karpathy

3D Activations

1D Activations:



3D Activations:

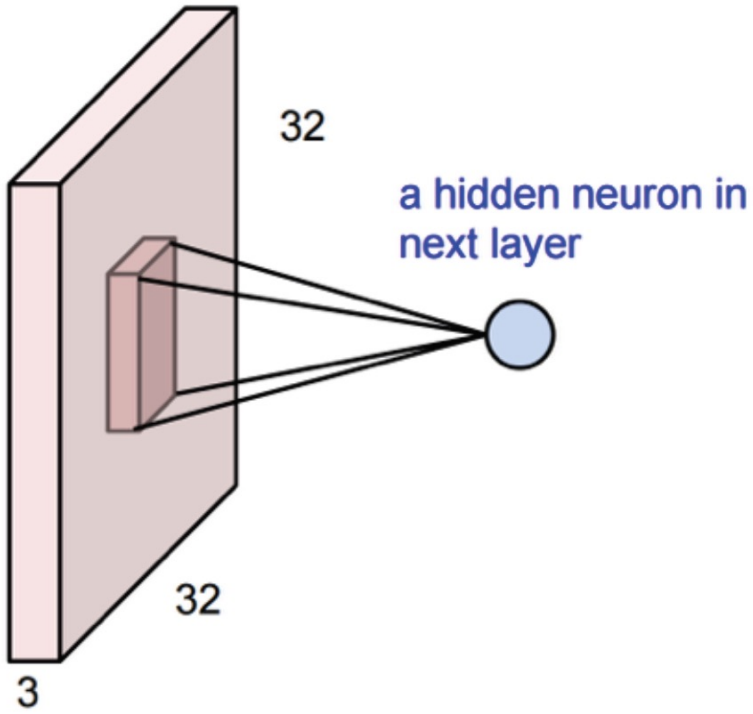
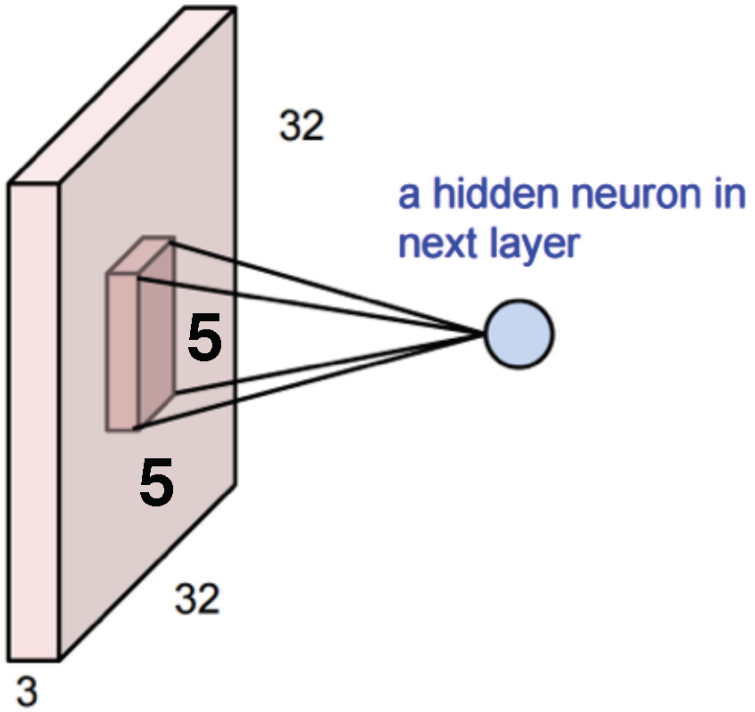


Figure: Andrej Karpathy

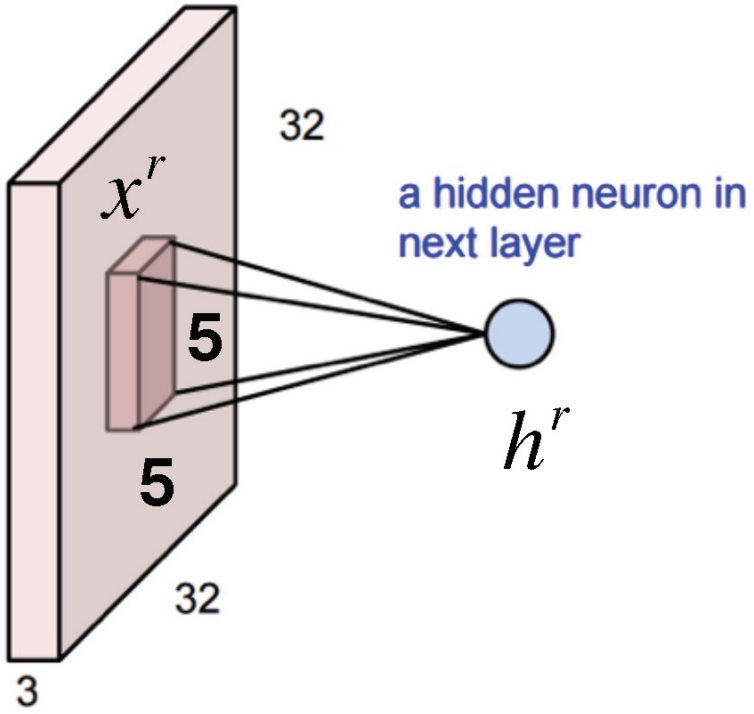
3D Activations



- 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)

Figure: Andrej Karpathy

3D Activations



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

With output neuron h^r

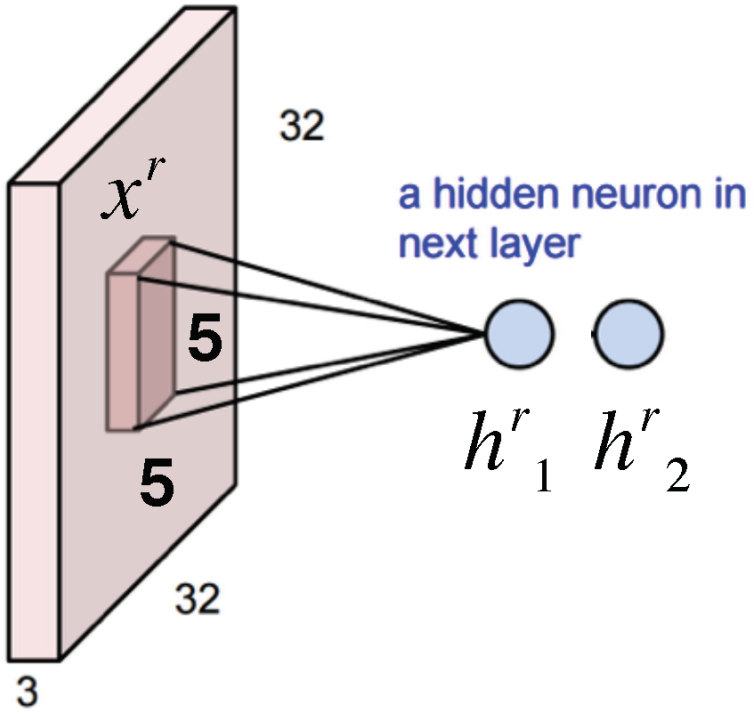
Then the output is:

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

Sum over 3 axes

Figure: Andrej Karpathy

3D Activations



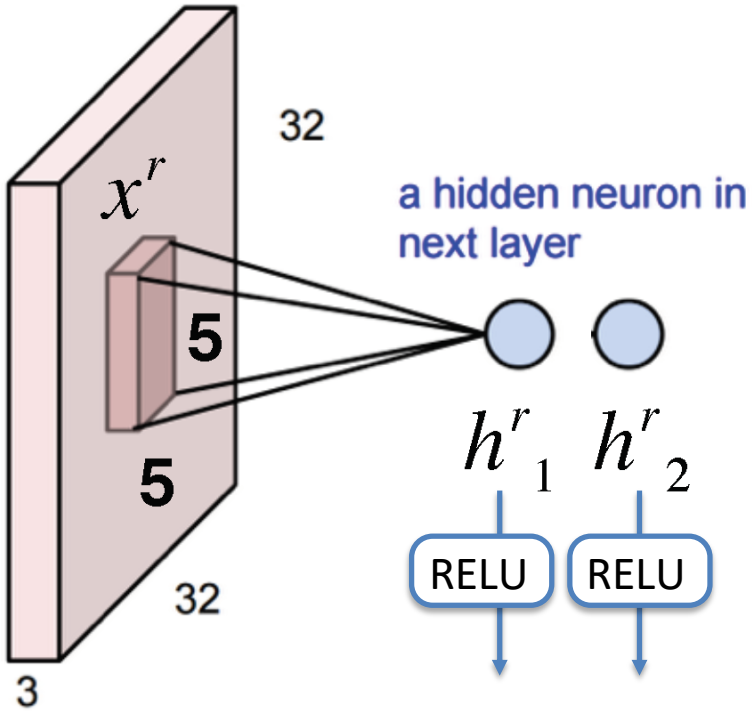
With **2** output neurons

$$h^r{}_1 = \sum_{ijk} x^r{}_{ijk} W_{1ijk} + b_1$$

$$h^r{}_2 = \sum_{ijk} x^r{}_{ijk} W_{2ijk} + b_2$$

Figure: Andrej Karpathy

3D Activations



With **2** output neurons

$$h^r{}_1 = \sum_{ijk} x^r{}_{ijk} W_{1ijk} + b_1$$

$$h^r{}_2 = \sum_{ijk} x^r{}_{ijk} W_{2ijk} + b_2$$

Apply non-linear function unit,
For instance, rectified linear unit:

RELU($h^r{}_1$)

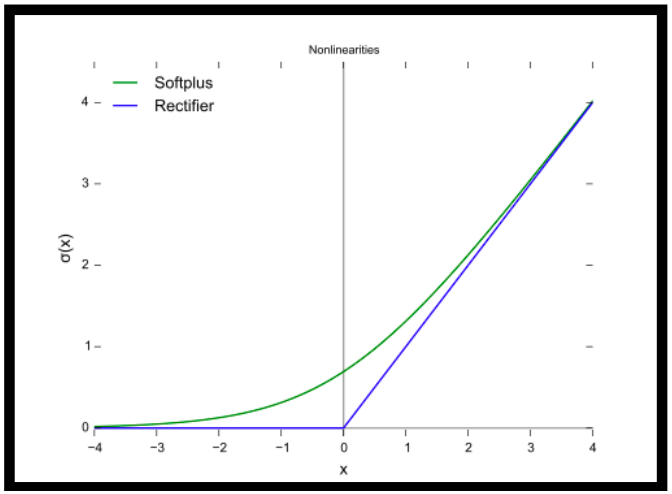
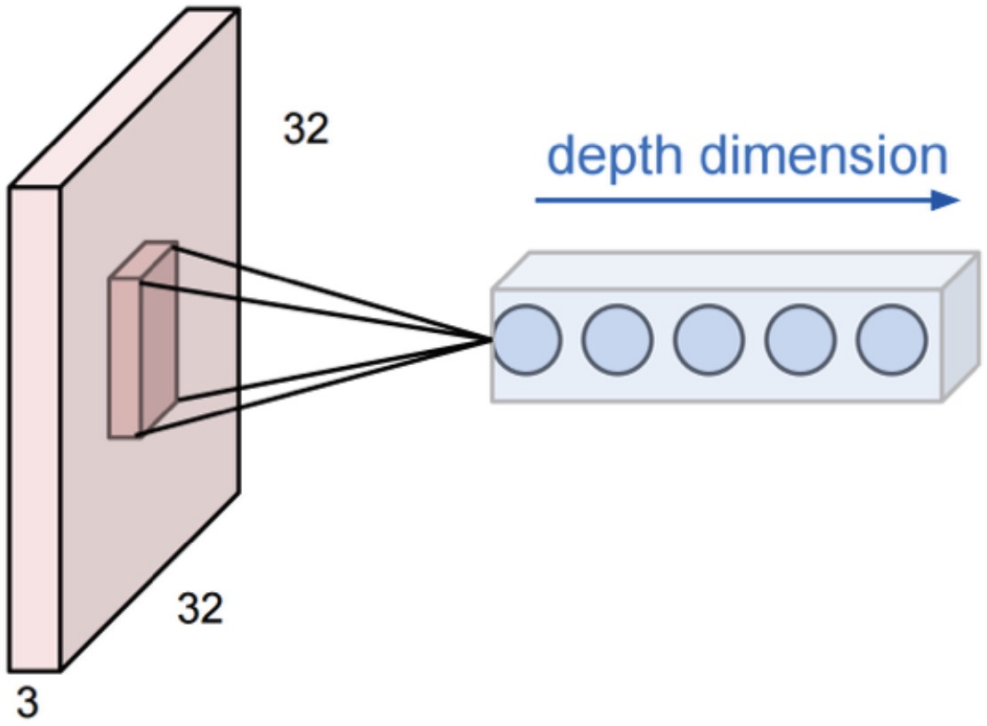


Figure: Andrej Karpathy

3D Activations

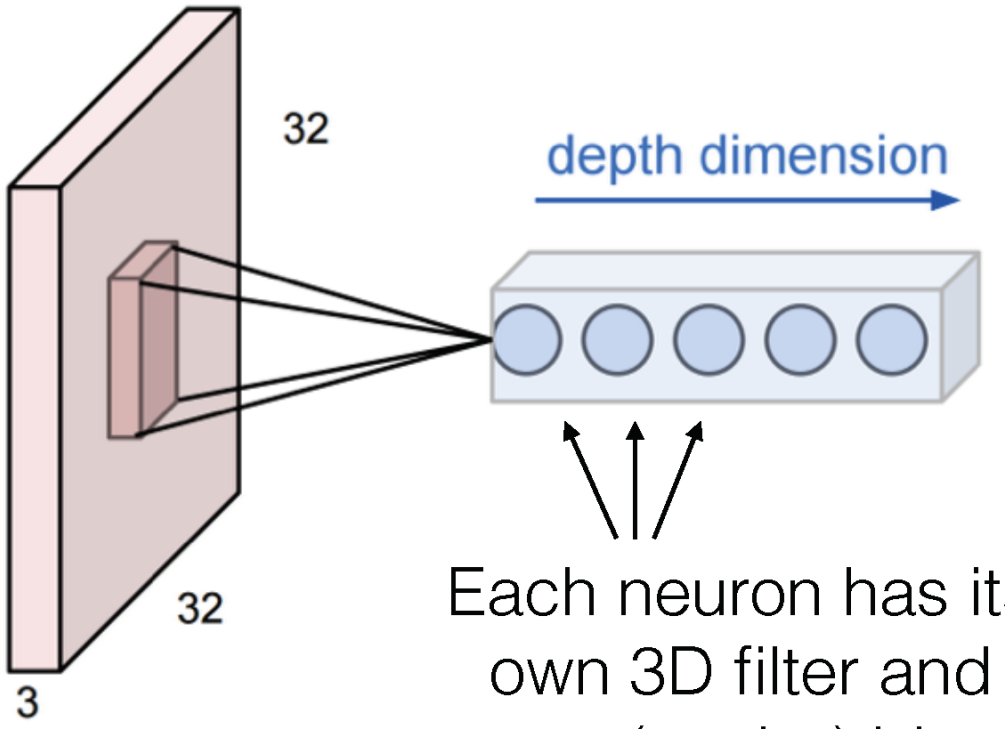


We can keep adding more outputs

These form a column in the output volume: [depth x 1 x 1]

Figure: Andrej Karpathy

3D Activations



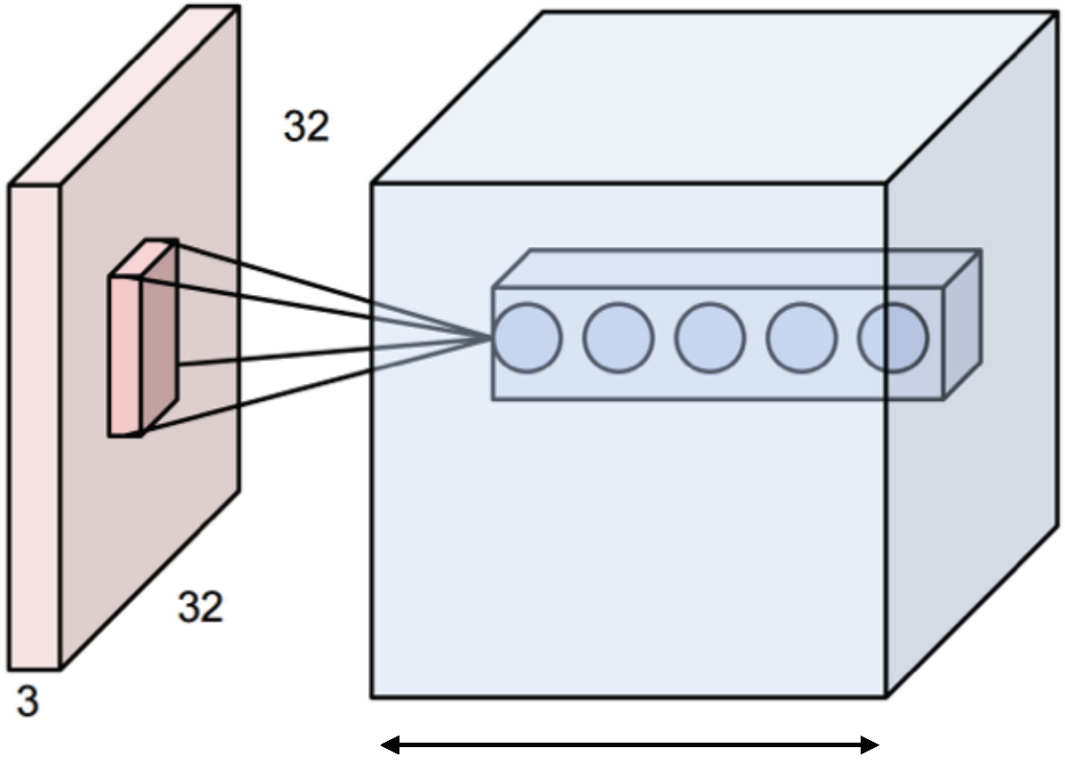
Each neuron has its own 3D filter and own (scalar) bias

We can keep adding more outputs

These form a column in the output volume: [depth x 1 x 1]

Figure: Andrej Karpathy

3D Activations

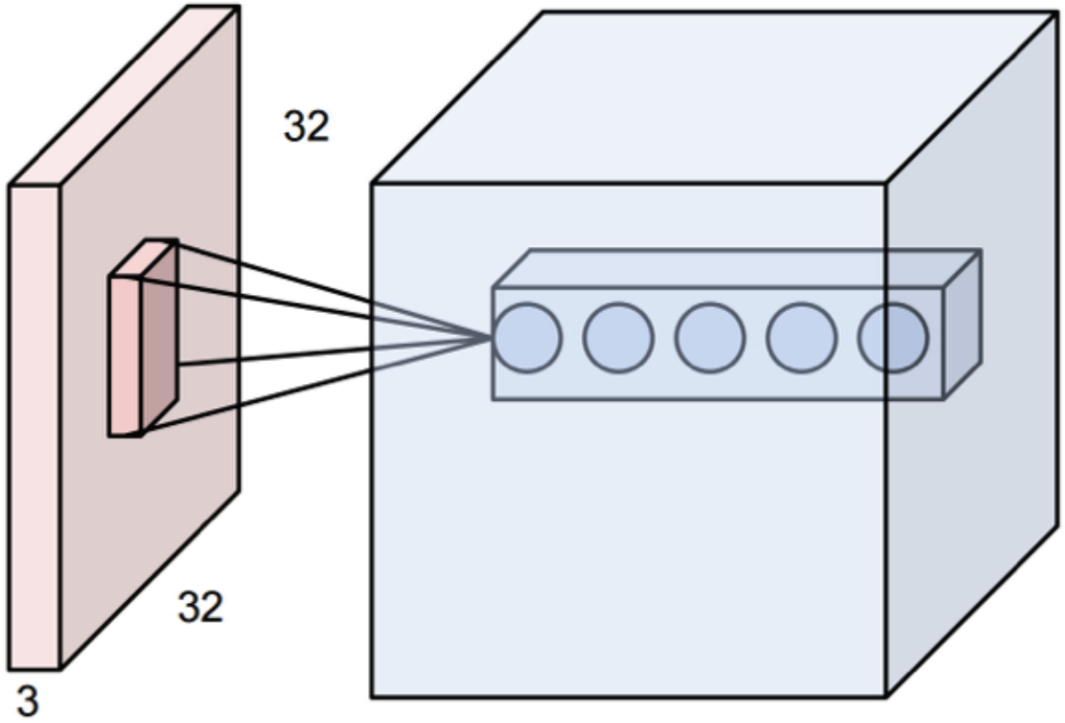


Now repeat this
across the input

D sets of weights
(also called filters)

Figure: Andrej Karpathy

3D Activations



D sets of weights
(also called filters)

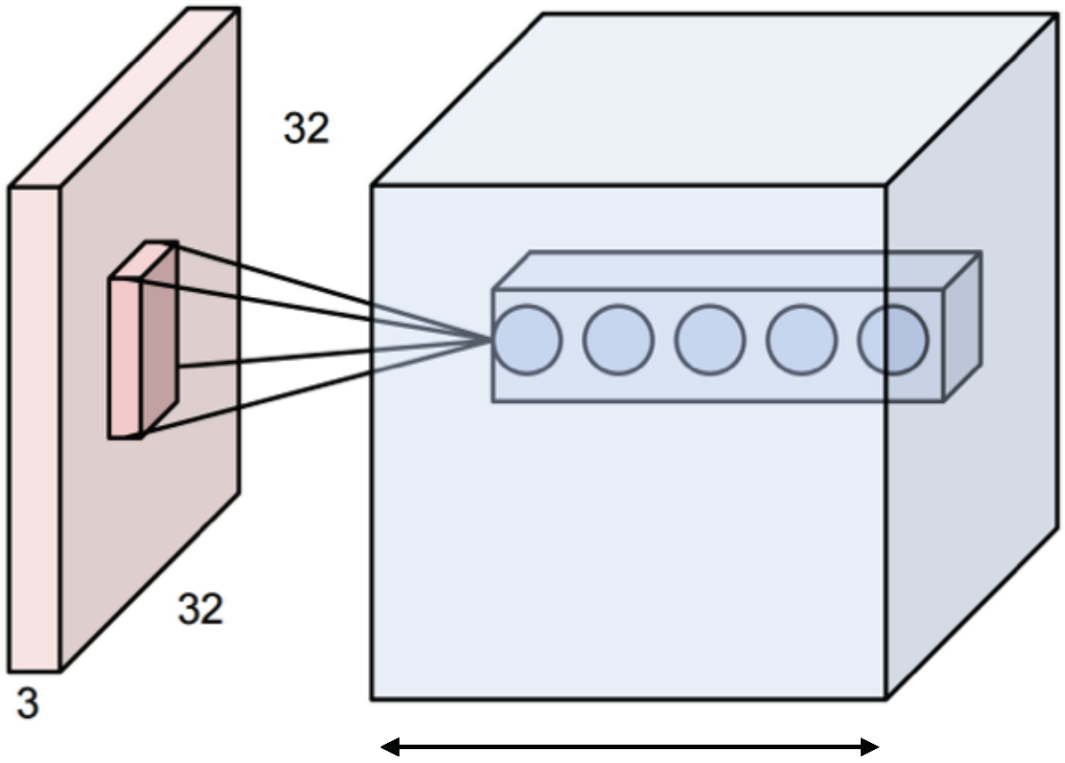
Now repeat this across the input

Weight sharing:

Each filter shares the same weights (but each depth index has its own set of weights)

Figure: Andrej Karpathy

3D Activations



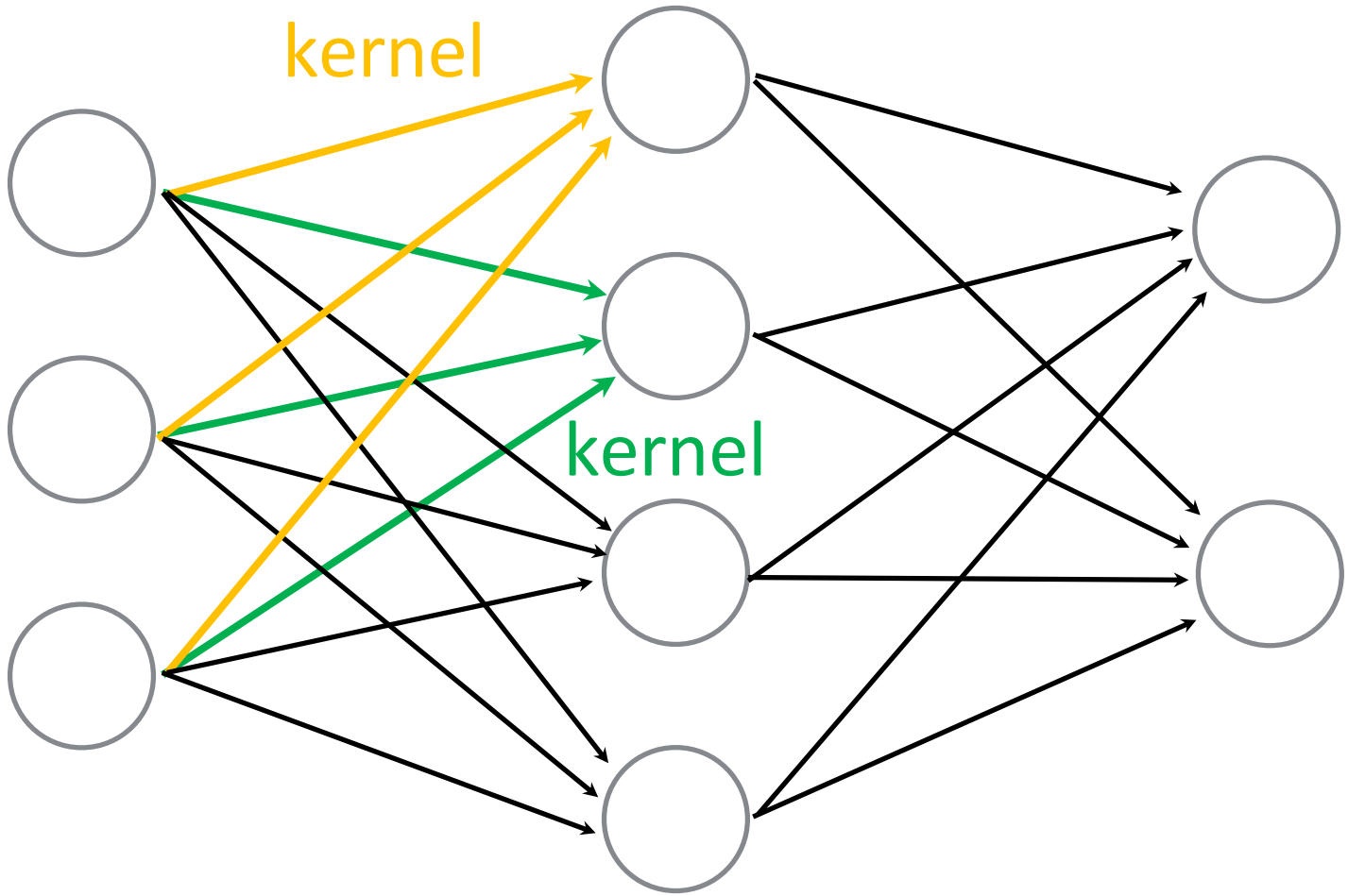
D sets of weights
(also called filters)

With weight sharing,
this is called
convolution

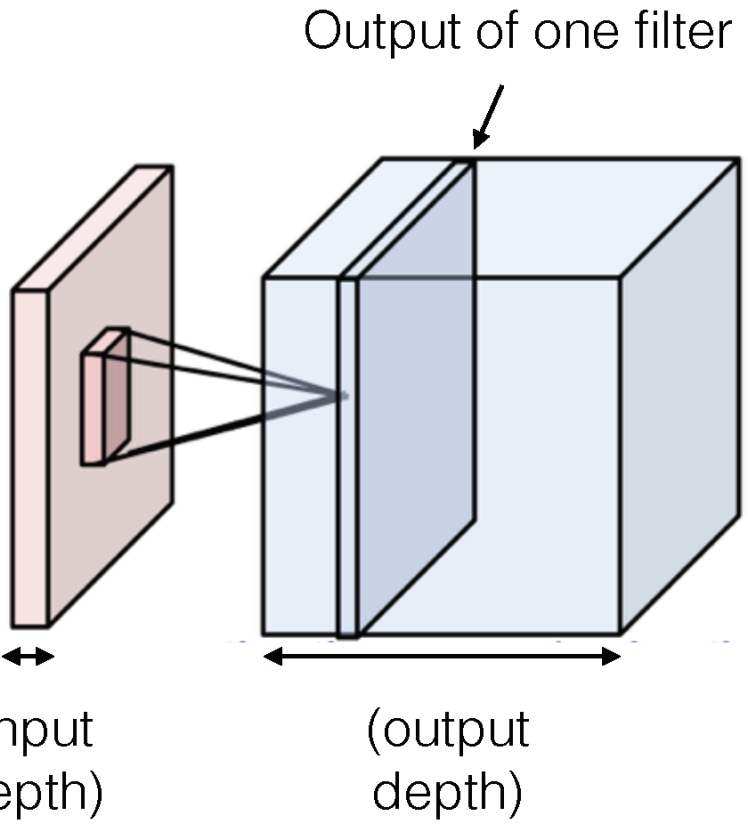
Without weight sharing,
this is called a
locally connected layer

Figure: Andrej Karpathy

Fully connected and Convolution



3D Activations

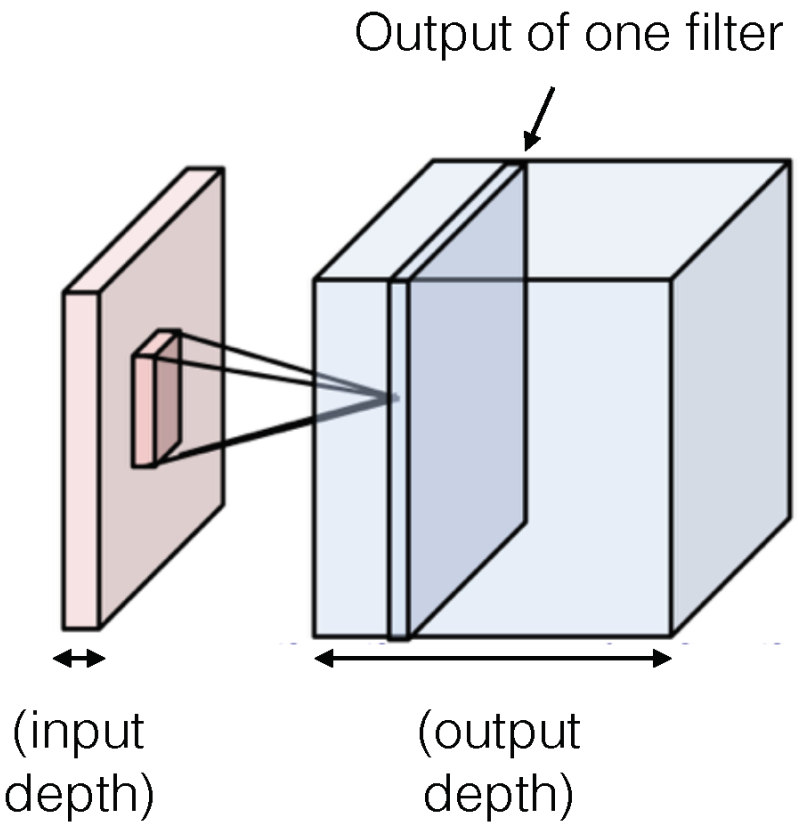


One set of weights gives one slice in the output

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

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

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)

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

3D Activations

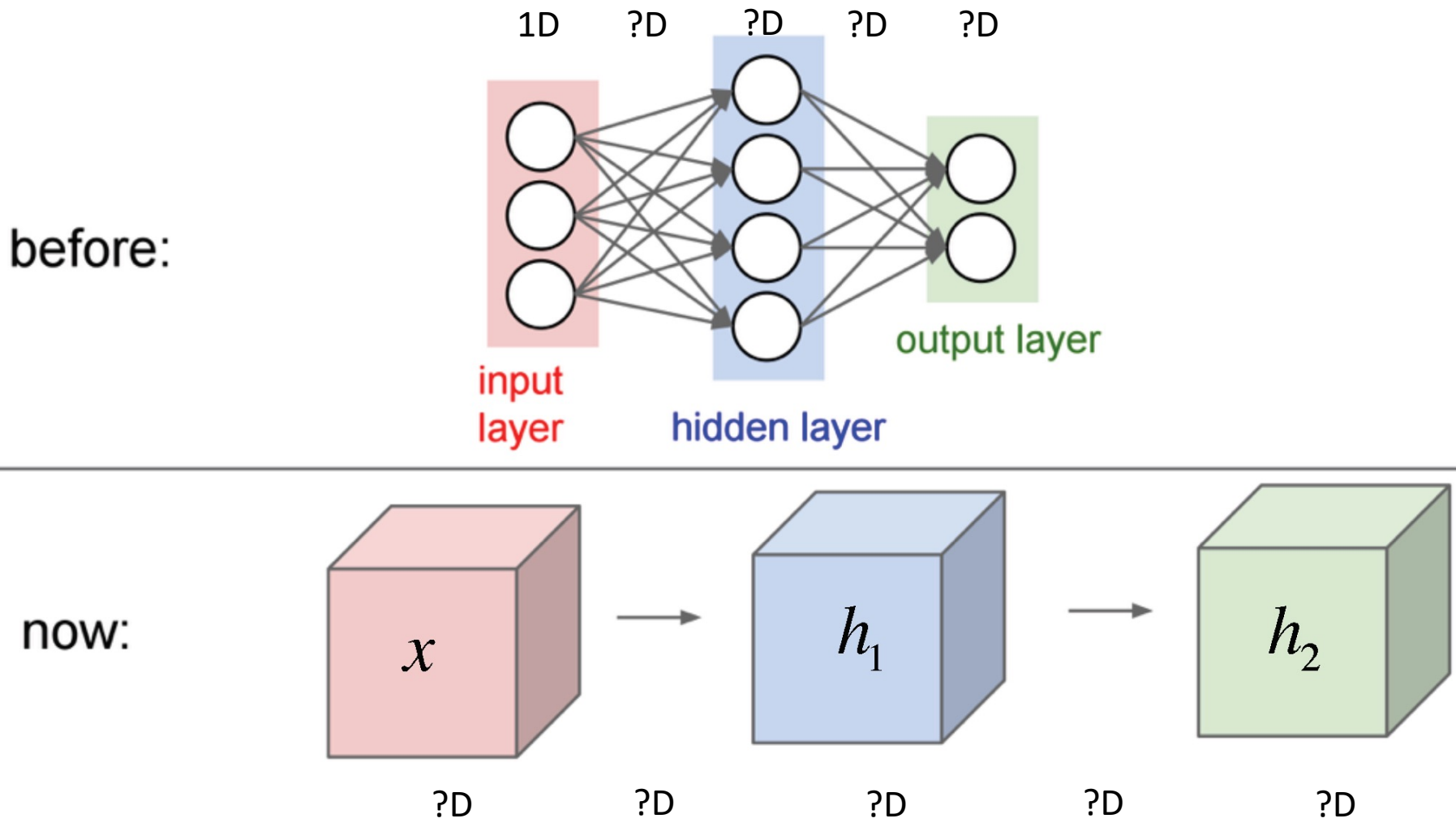


Figure: Andrej Karpathy

3D Activations

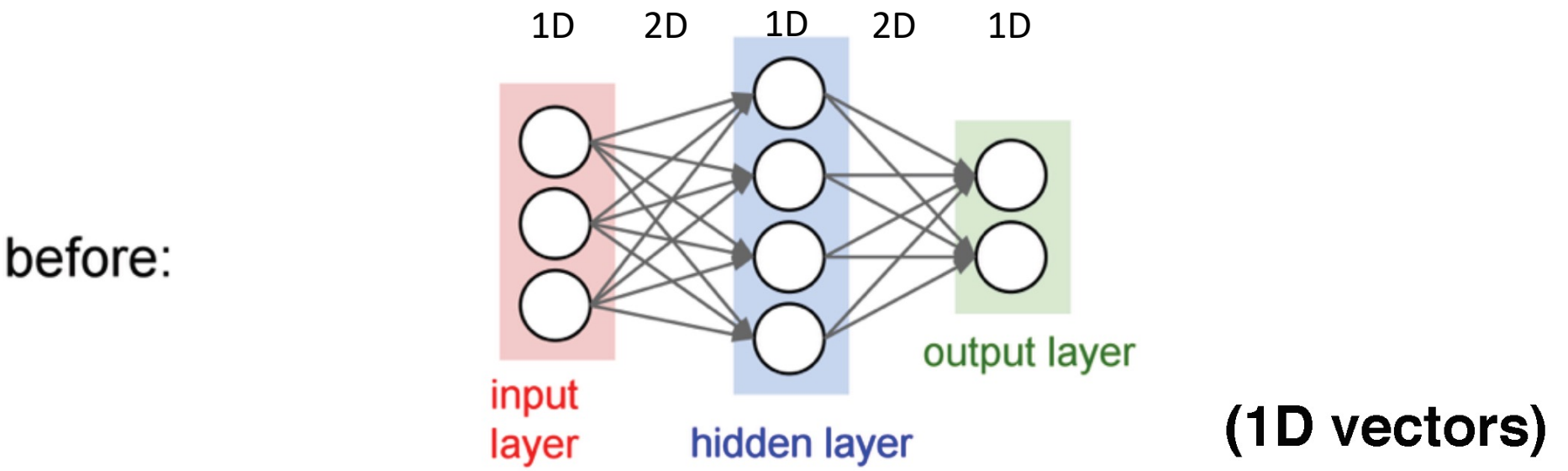


Figure: Andrej Karpathy

3D Activations

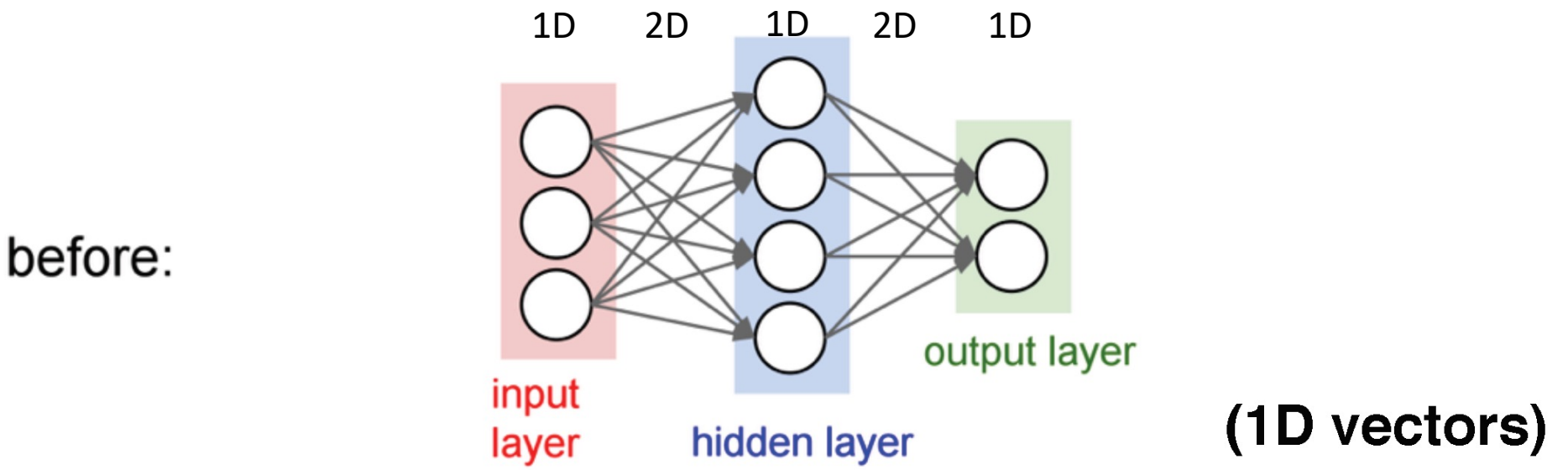


Figure: Andrej Karpathy

3D Activations

We can unravel the 3D cube and show each layer separately:

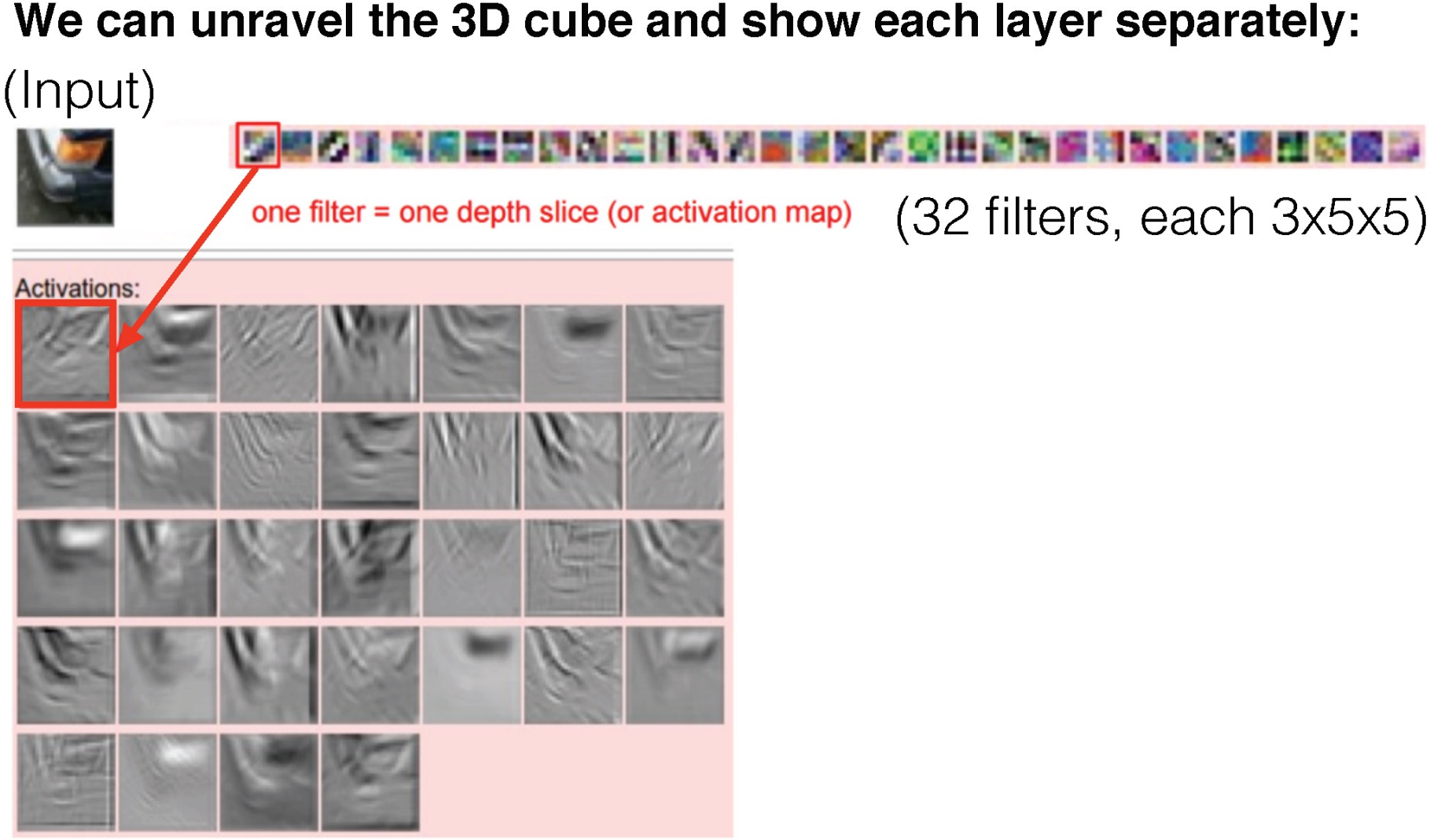


Figure: Andrej Karpathy

3D Activations

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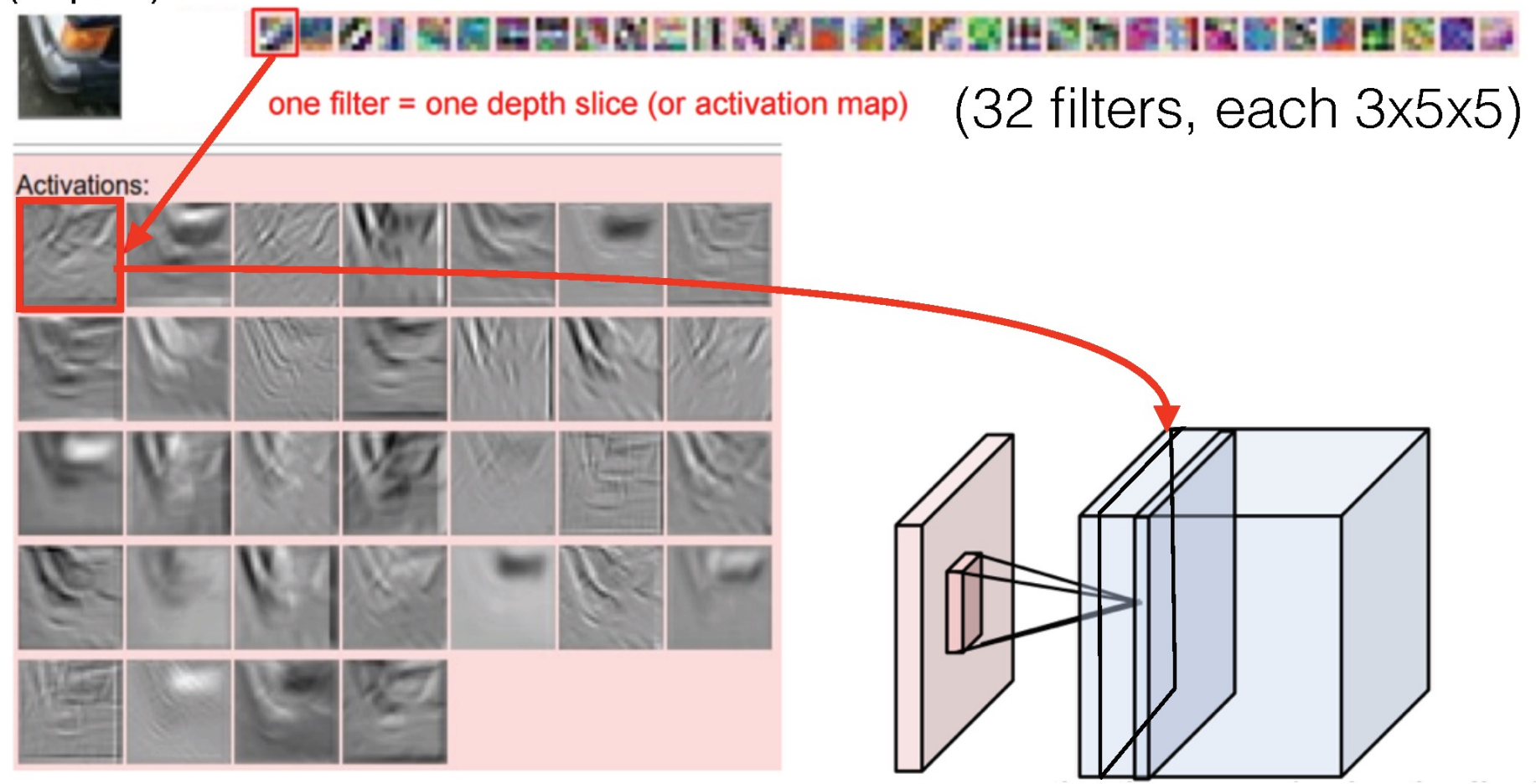

Figure: Andrej Karpathy

3D Activations

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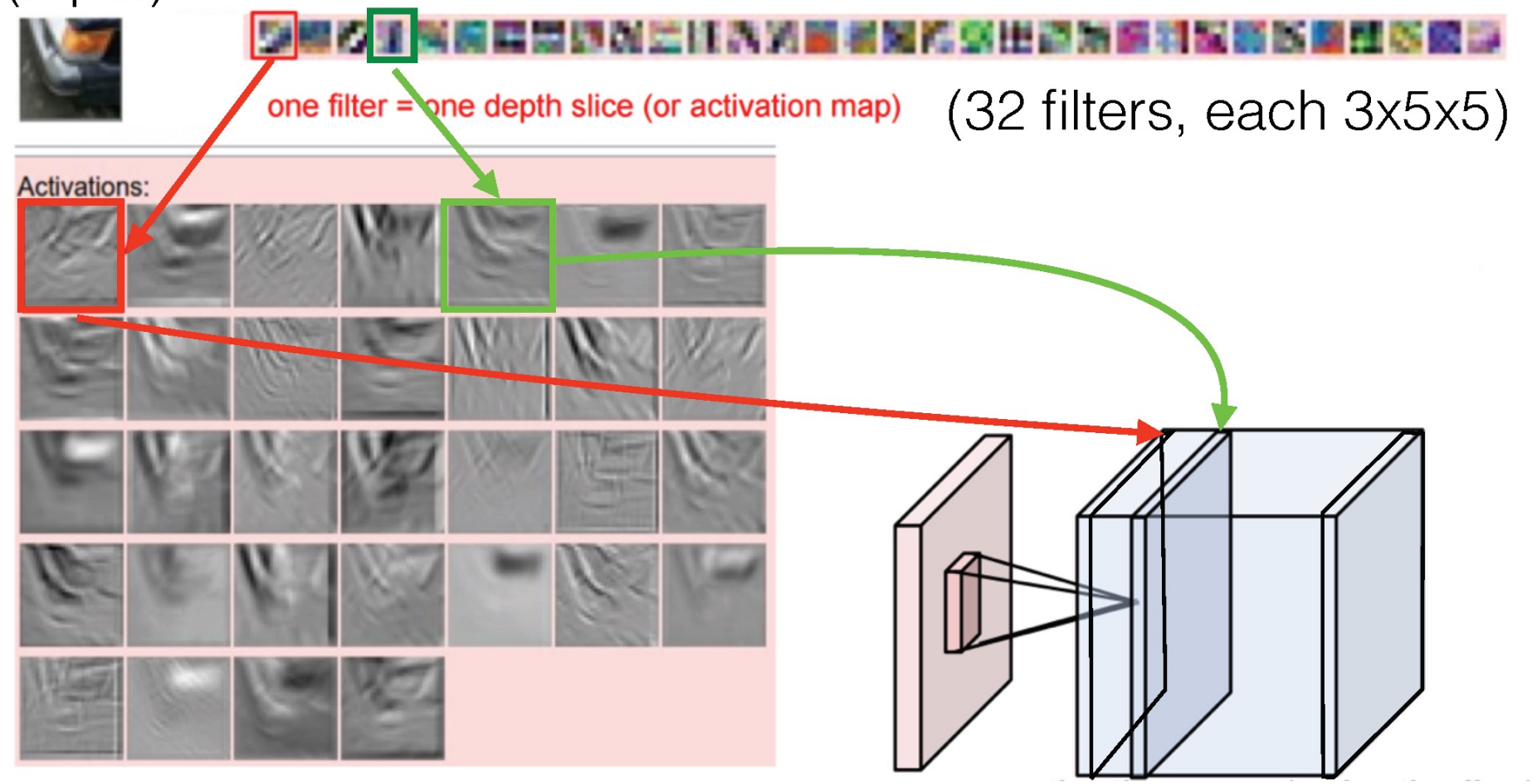


Figure: Andrej Karpathy

3D Activations

We can unravel the 3D cube and show each layer separately:

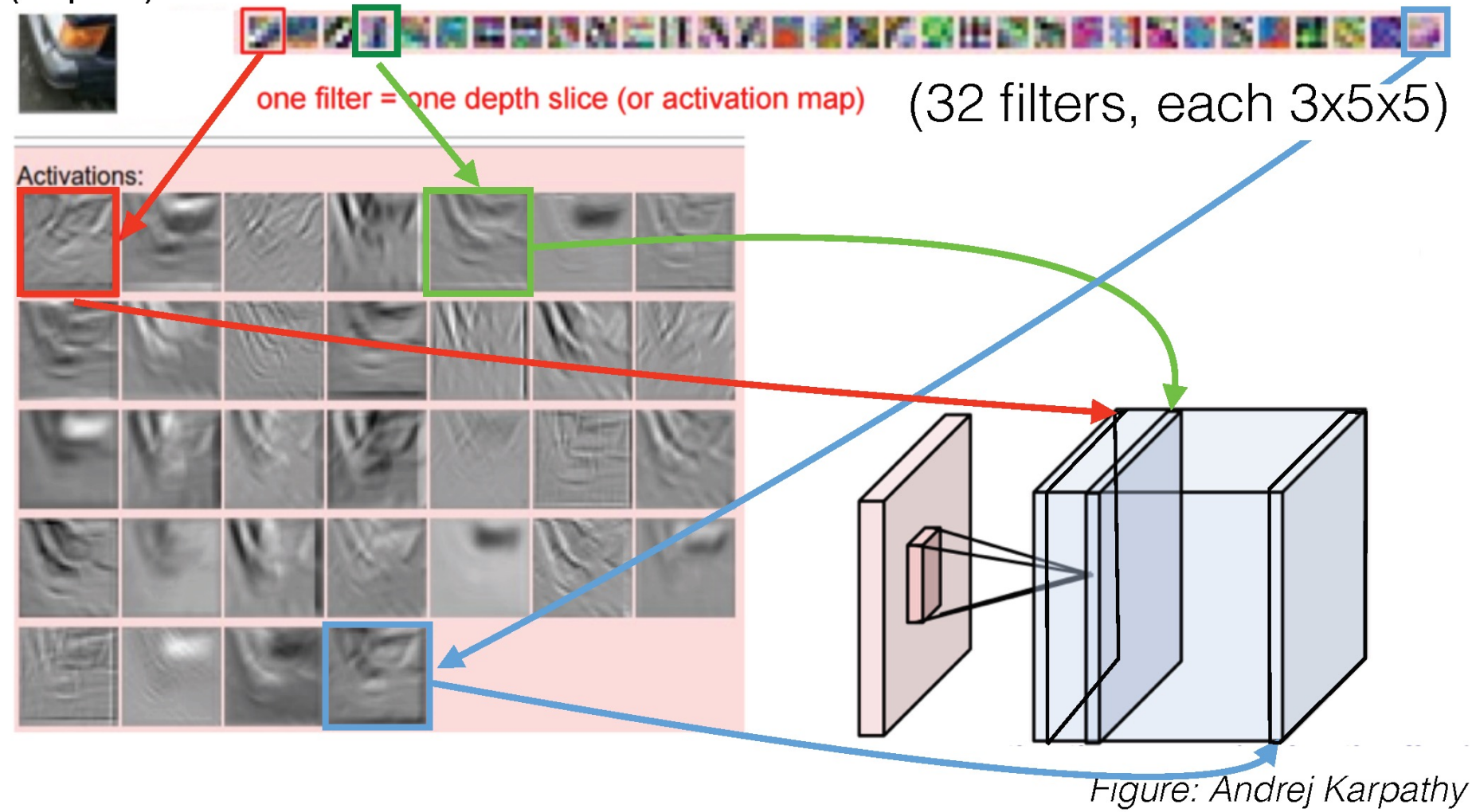
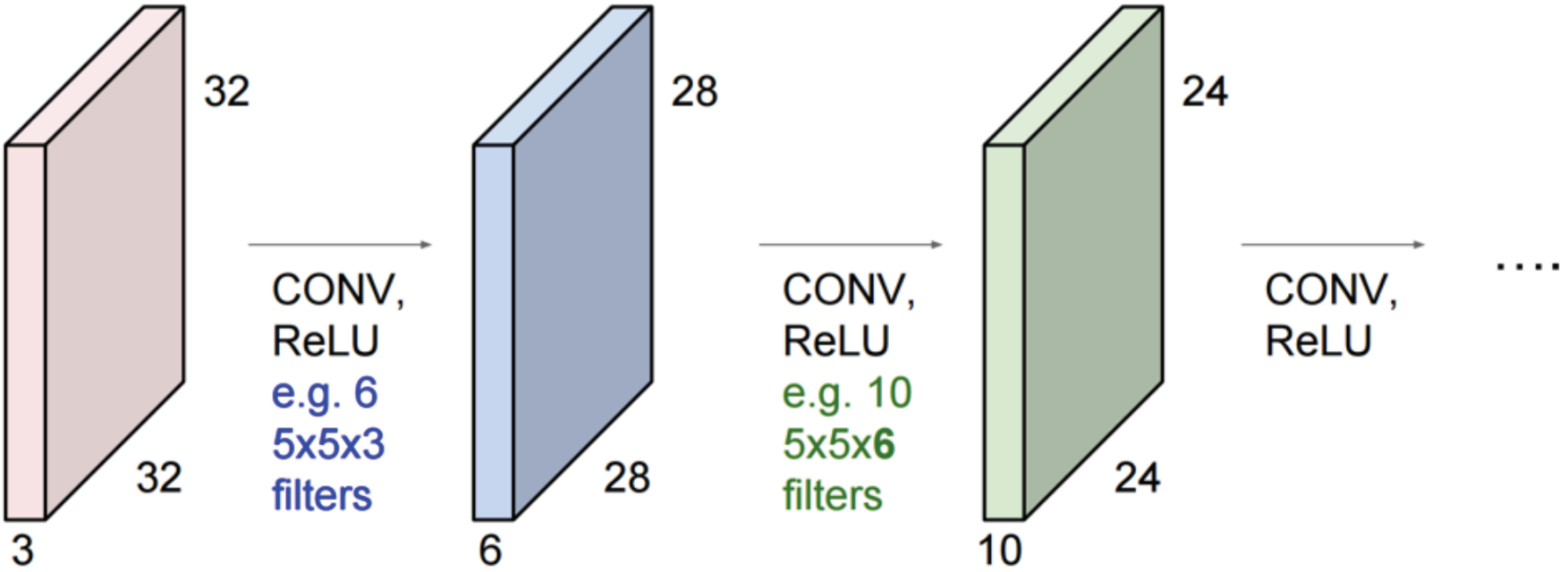


Figure: Andrej Karpathy

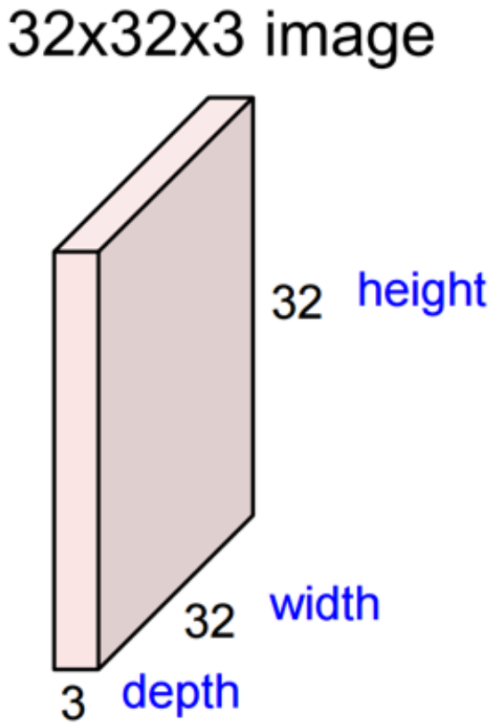
(Recap)

A **ConvNet** is a sequence of convolutional layers, interspersed with activation functions (and possibly other layer types)



(Recap)

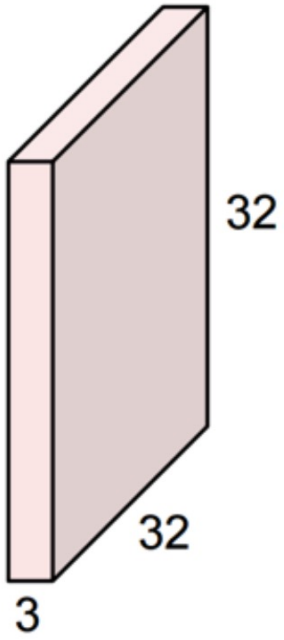
Convolution Layer



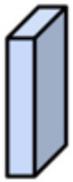
(Recap)

Convolution Layer

32x32x3 image



5x5x3 filter



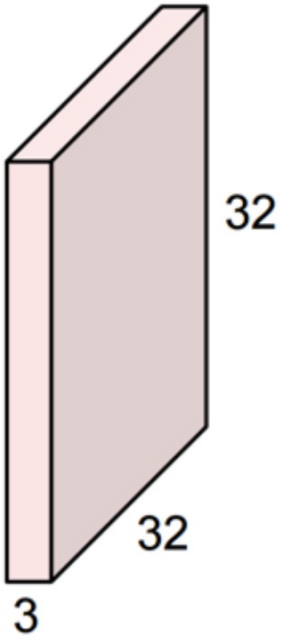
Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

(Recap)

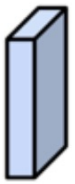
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image



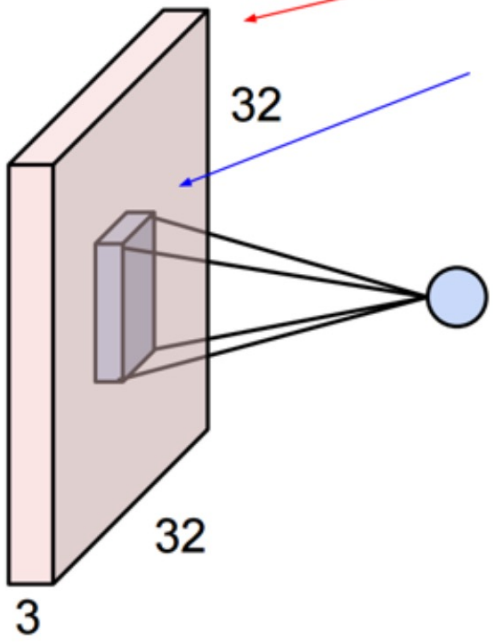
5x5x3 filter



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

(Recap)

Convolution Layer



32x32x3 image

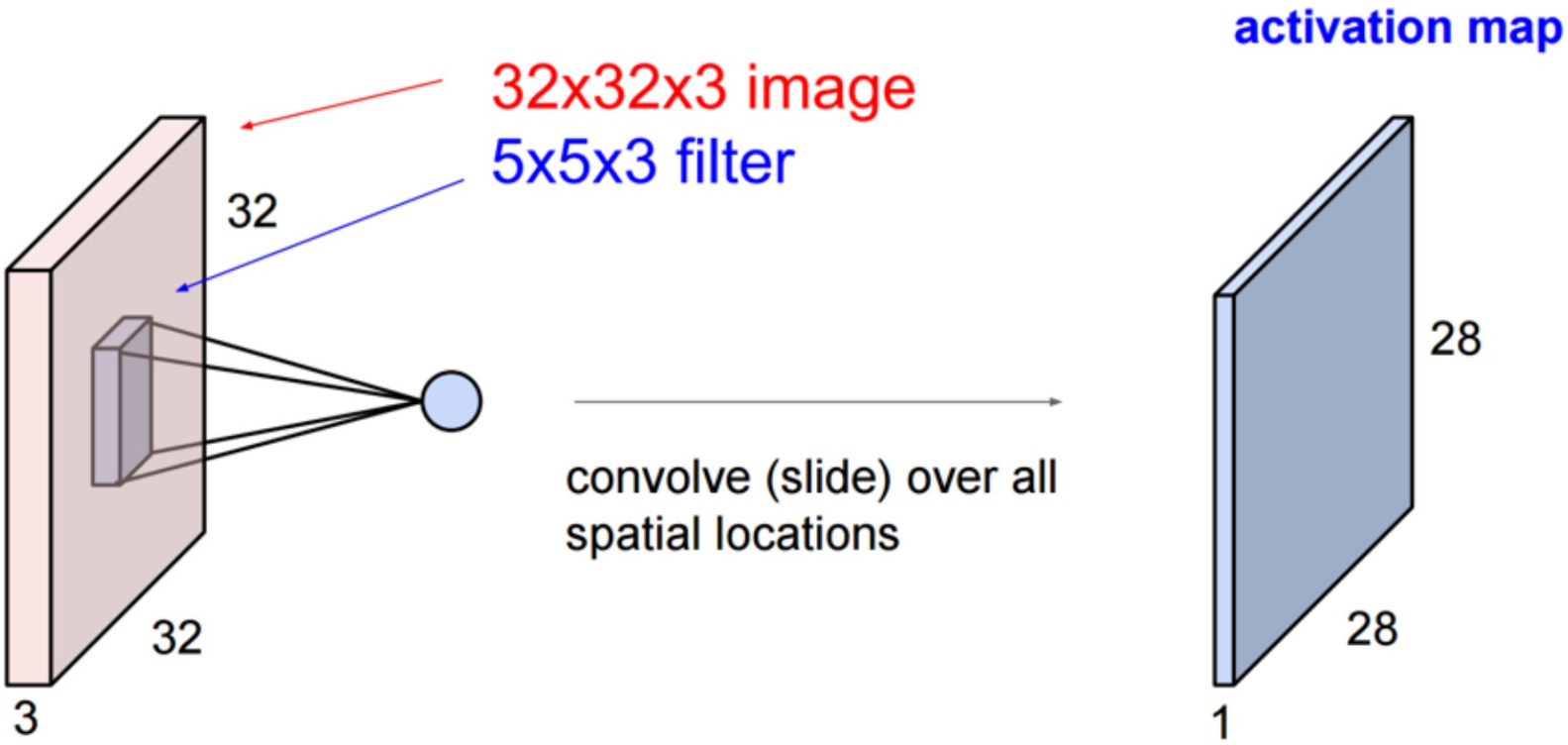
5x5x3 filter w

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)

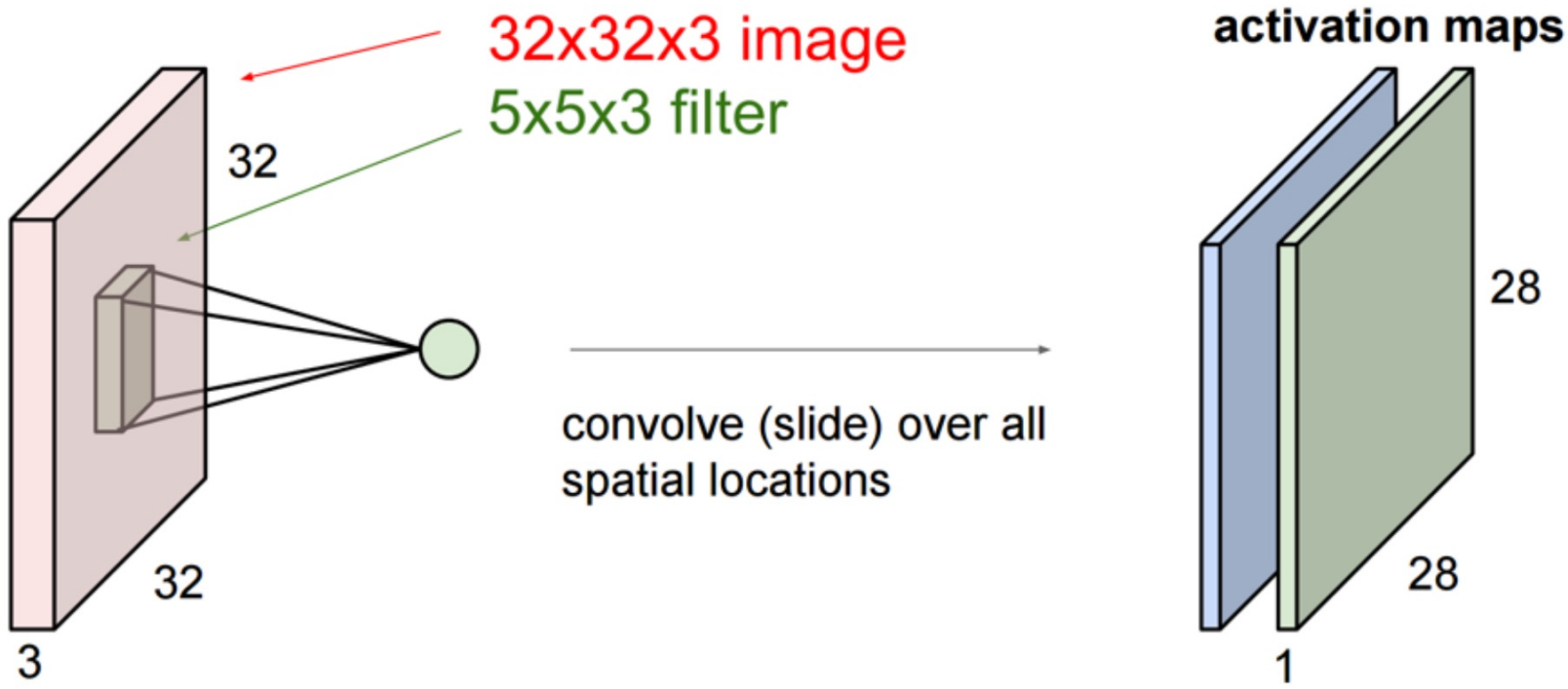
Convolution Layer



(Recap)

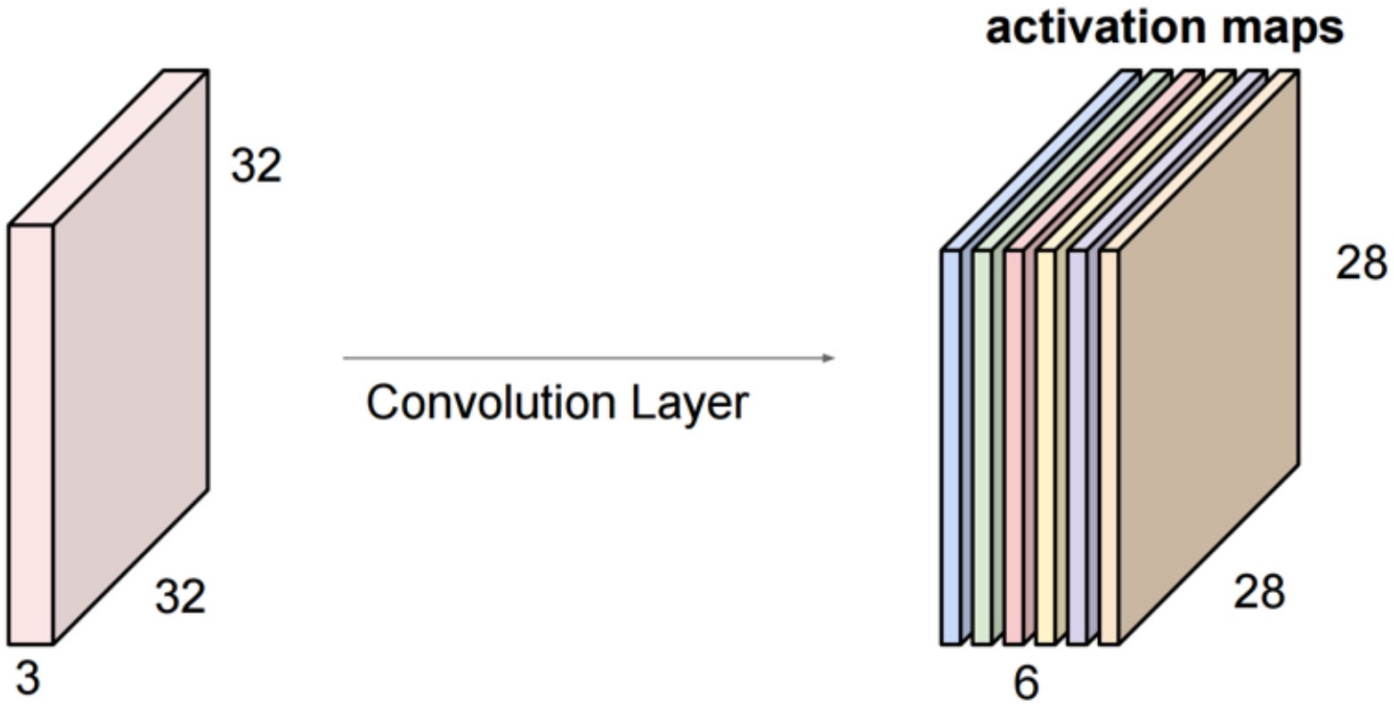
Convolution Layer

consider a second, green filter



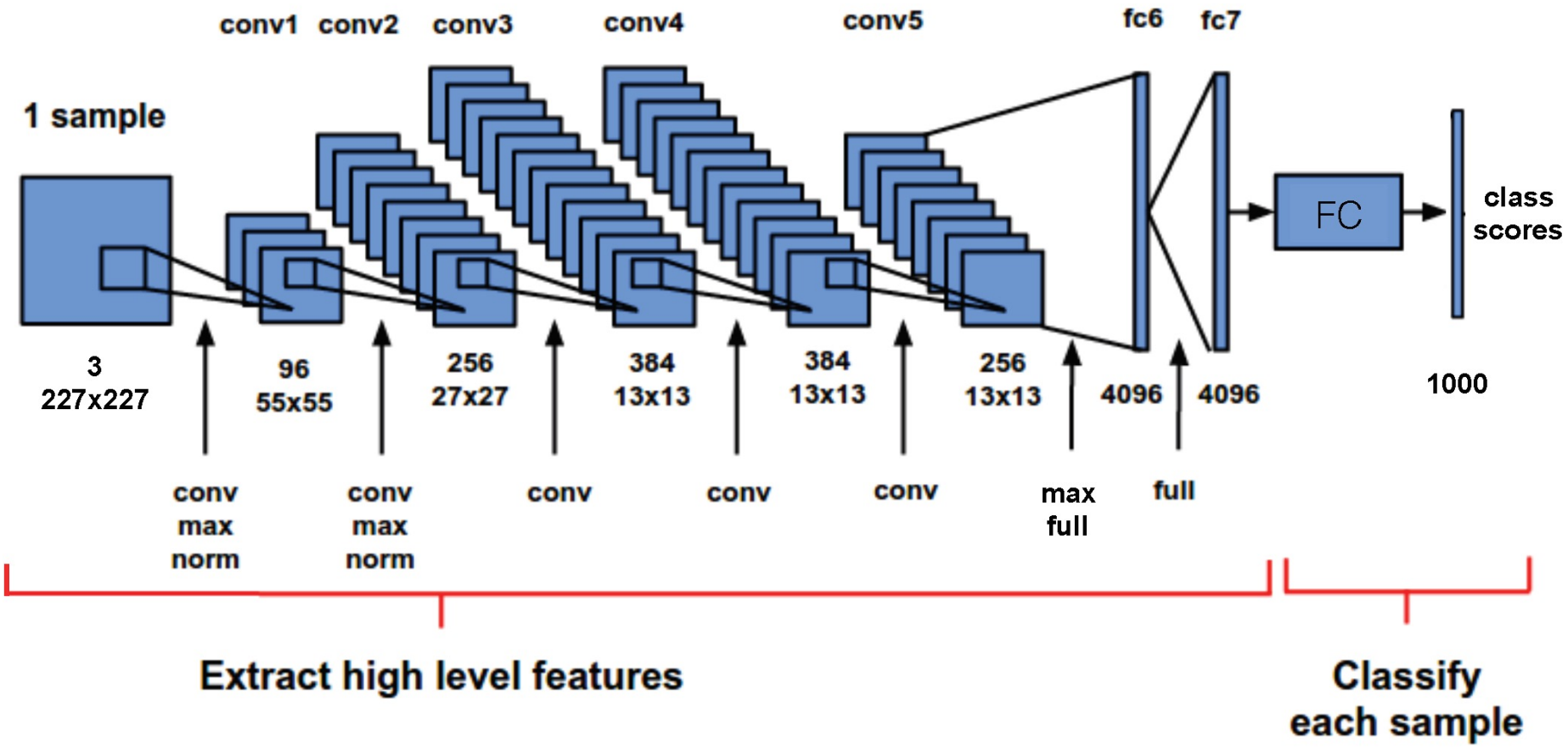
(Recap)

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

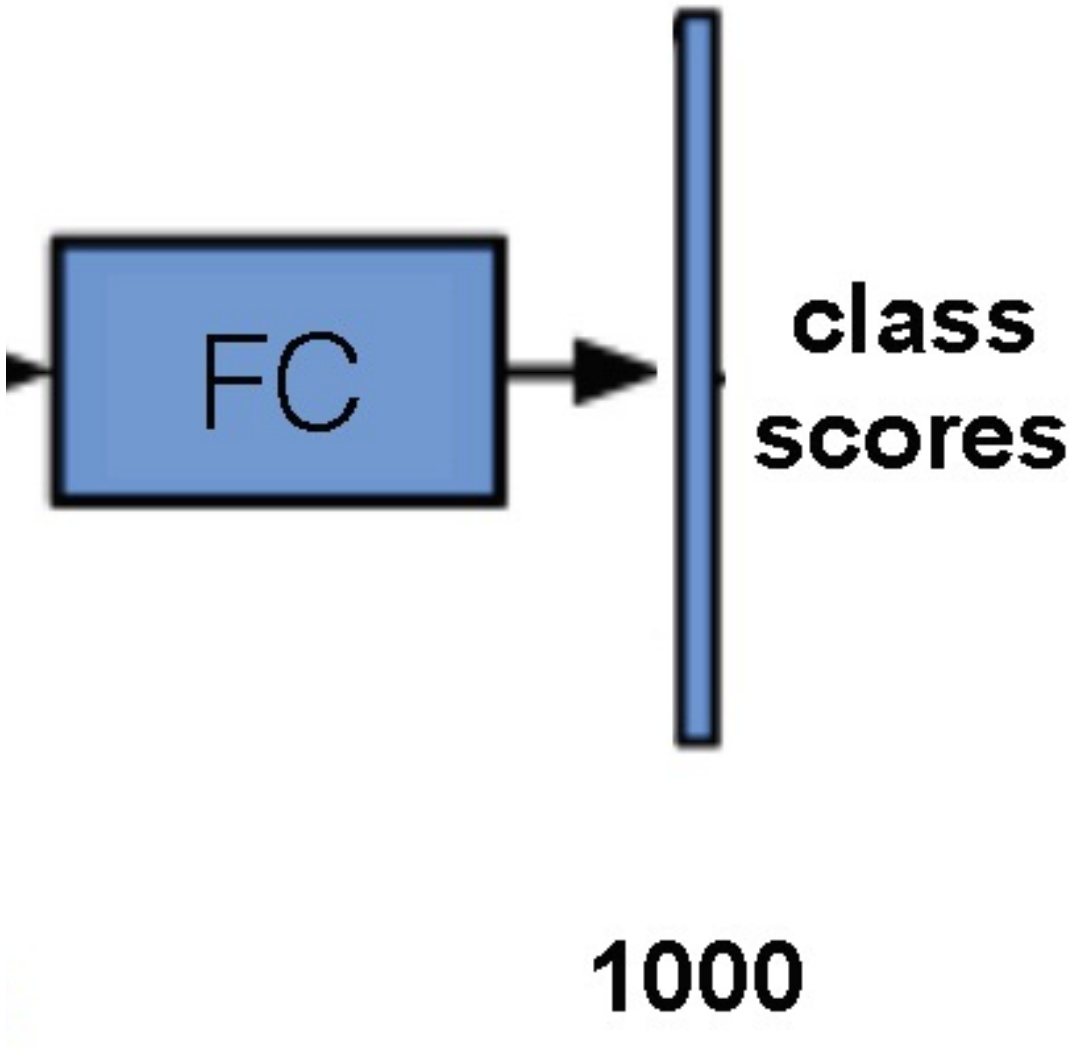


We stack these up to get a "new image" of size 28x28x6!

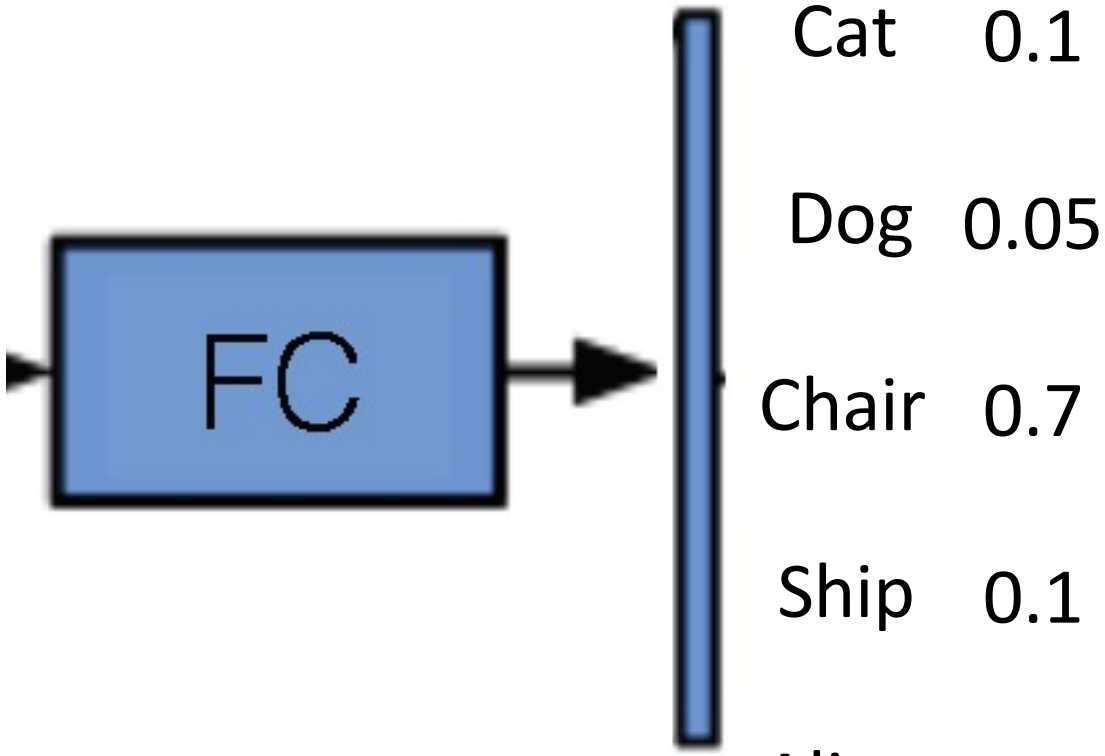
Typical entire architecture



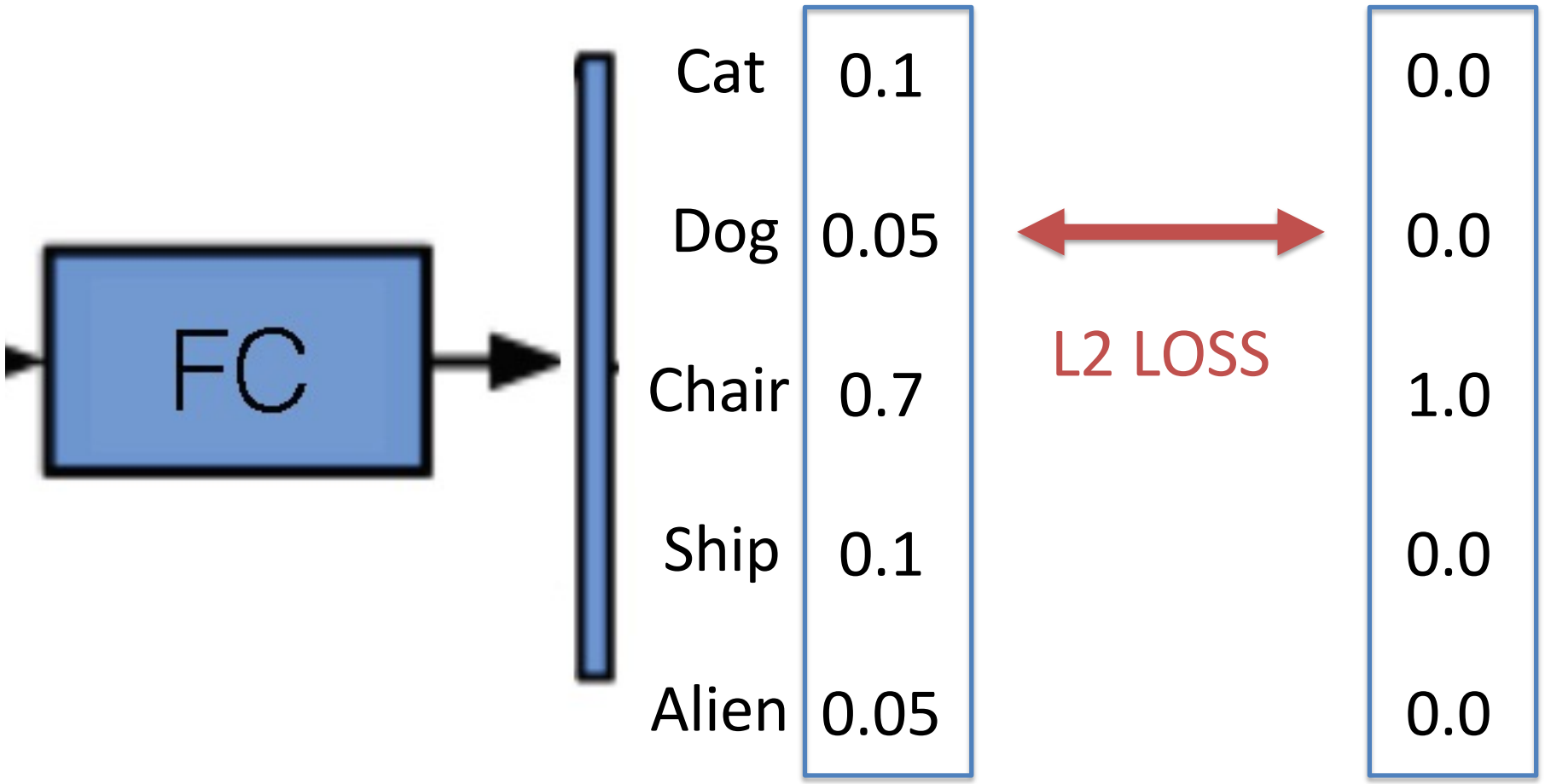
Typical entire architecture



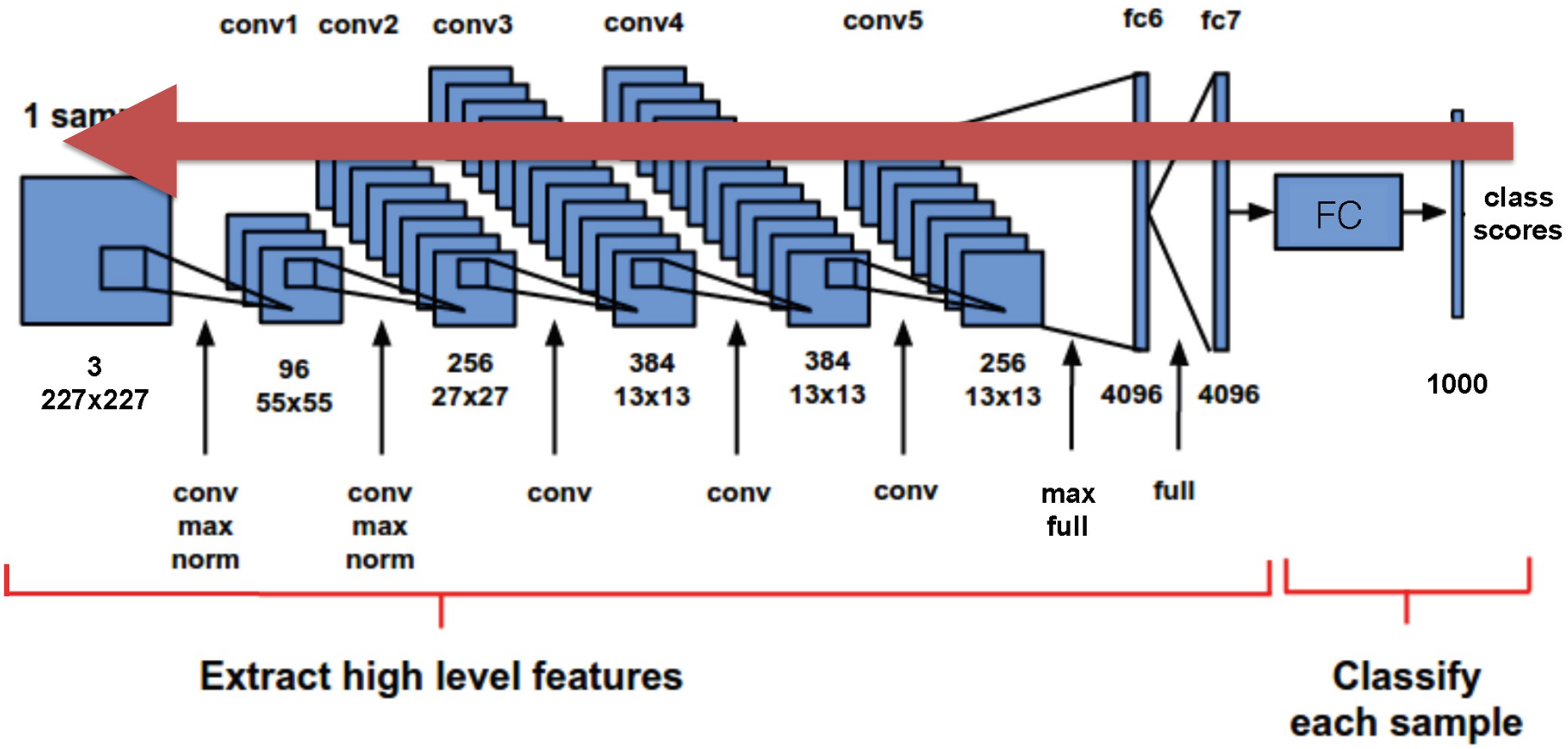
Typical entire architecture



Typical entire architecture



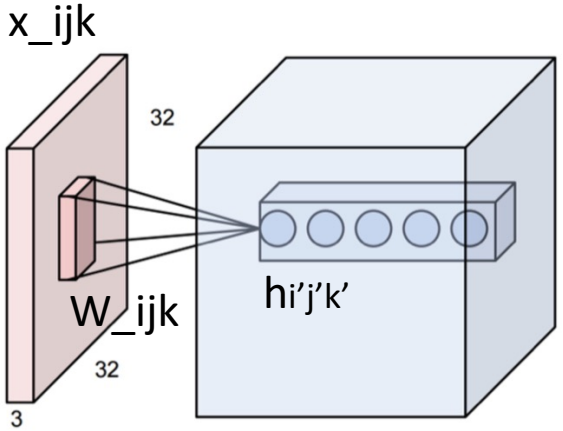
Typical entire architecture



Demos

- http://cs231n.stanford.edu/
- http://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html

Back propagation



Given gradients of the right layer

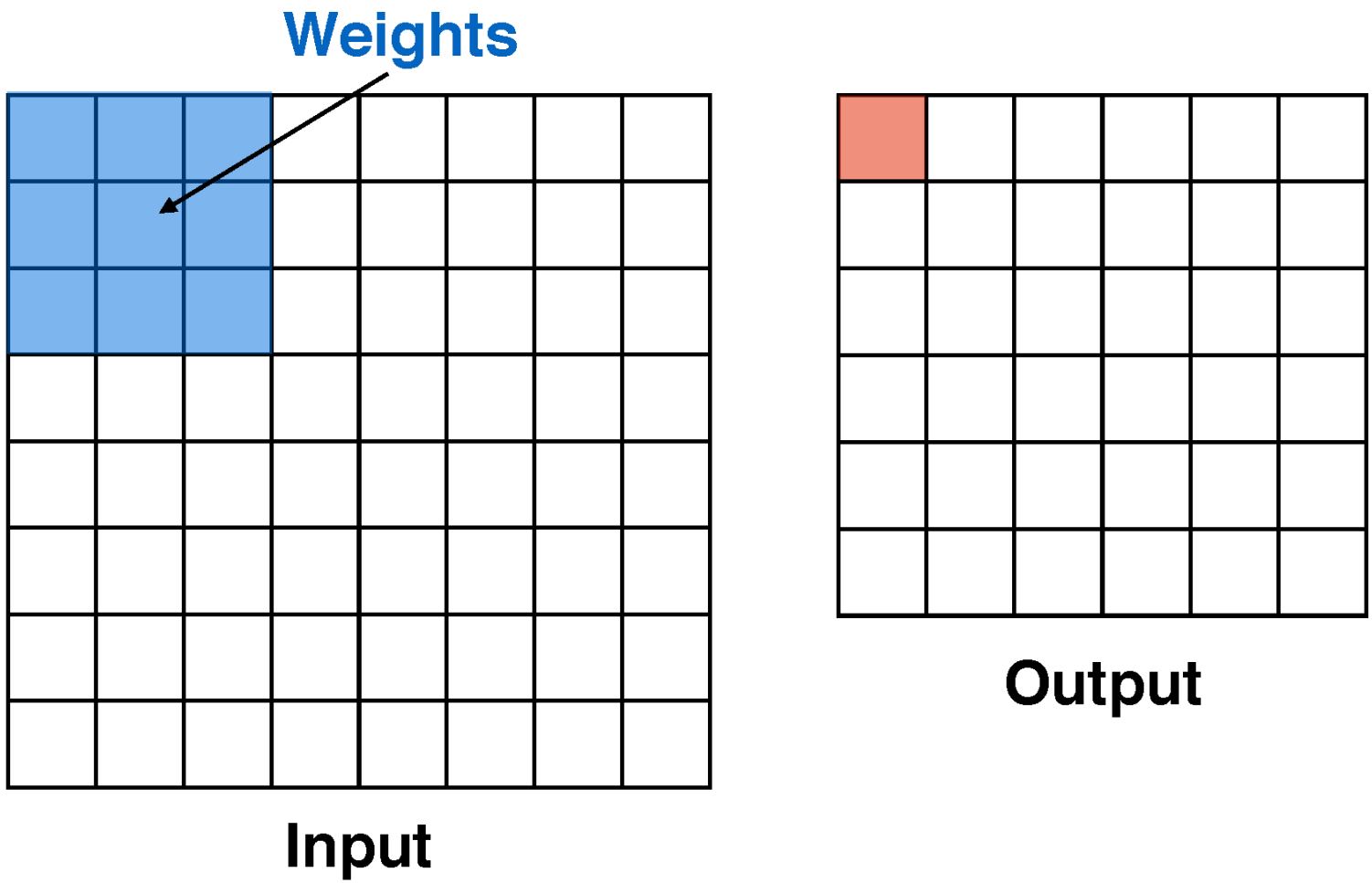
$$\frac{\partial \mathcal{L}}{\partial h_{i'j'k'}}$$

$$h_{i'j'k'} = \sum_{ijk} x_{ijk} W_{ijk} + b$$

$$\frac{\partial \mathcal{L}}{\partial x_{i'j'k'}} = \frac{\partial \mathcal{L}}{\partial h_{i1\,j1\,k1}} \frac{\partial h_{i1\,j1\,k1}}{\partial x_{i'j'k'}} + \frac{\partial \mathcal{L}}{\partial h_{i2\,j2\,k2}} \frac{\partial h_{i2\,j2\,k2}}{\partial x_{i'j'k'}} + \frac{\partial \mathcal{L}}{\partial h_{i3\,j3\,k3}} \frac{\partial h_{i3\,j3\,k3}}{\partial x_{i'j'k'}} + \ldots$$

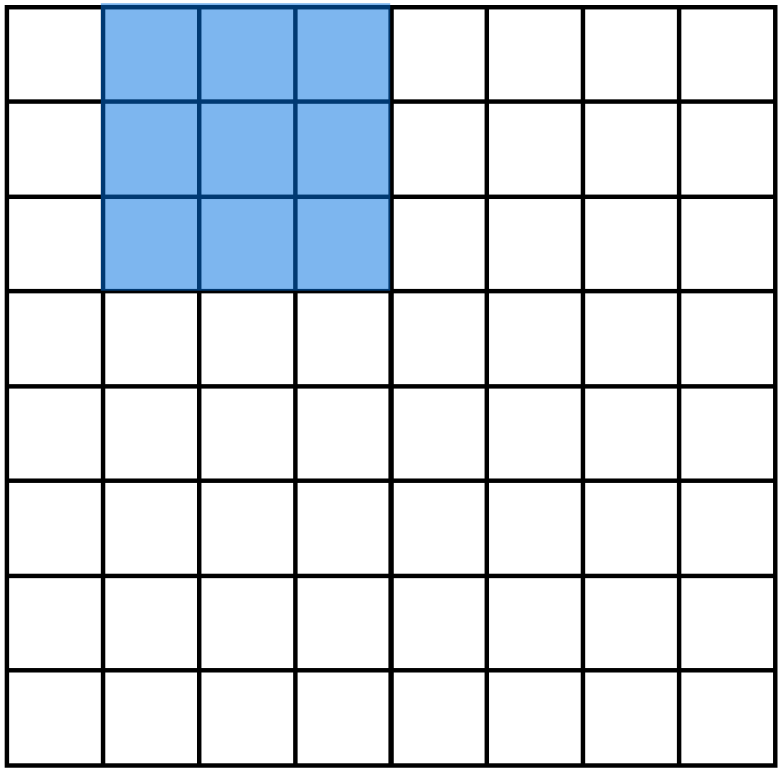
Convolution: Stride

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

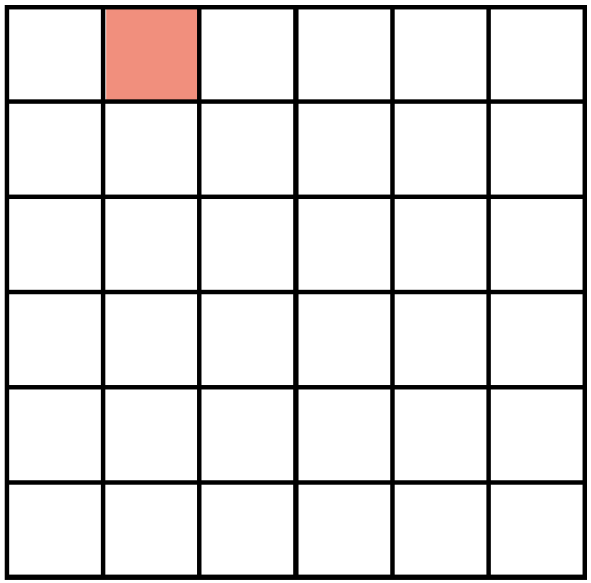


Convolution: Stride

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



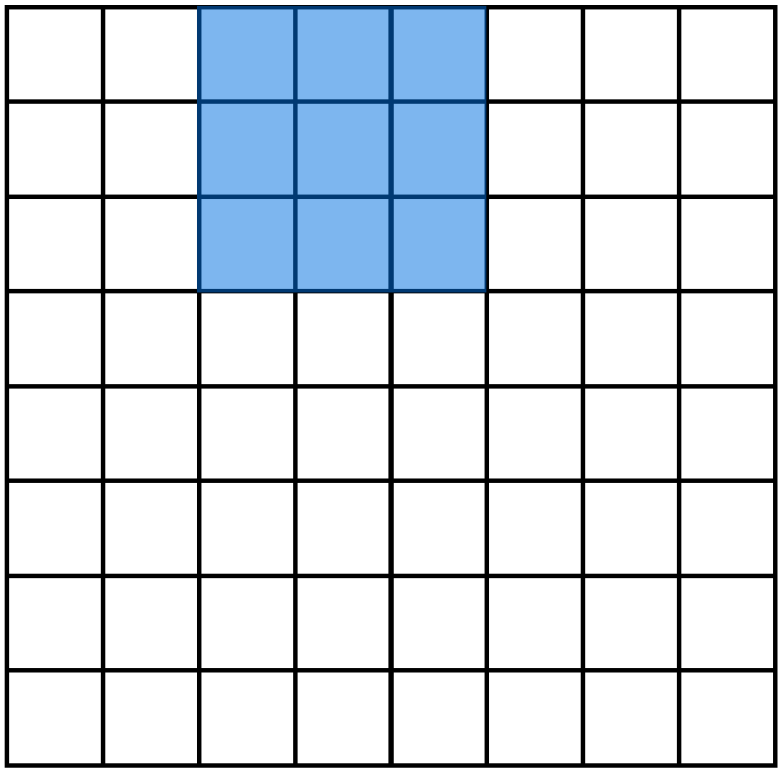
Input



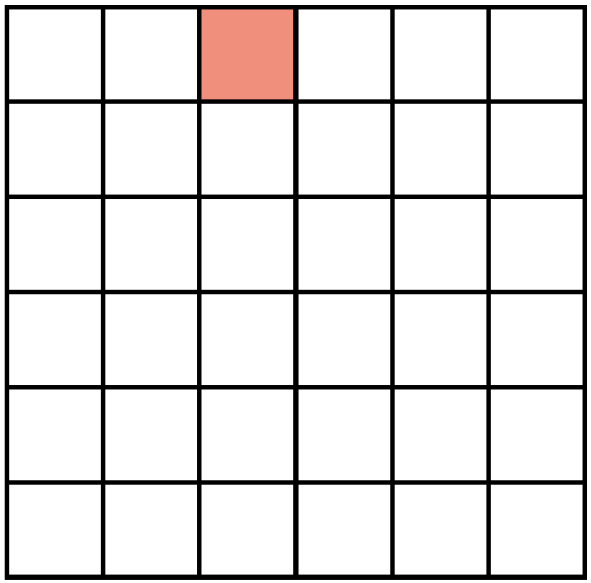
Output

Convolution: Stride

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



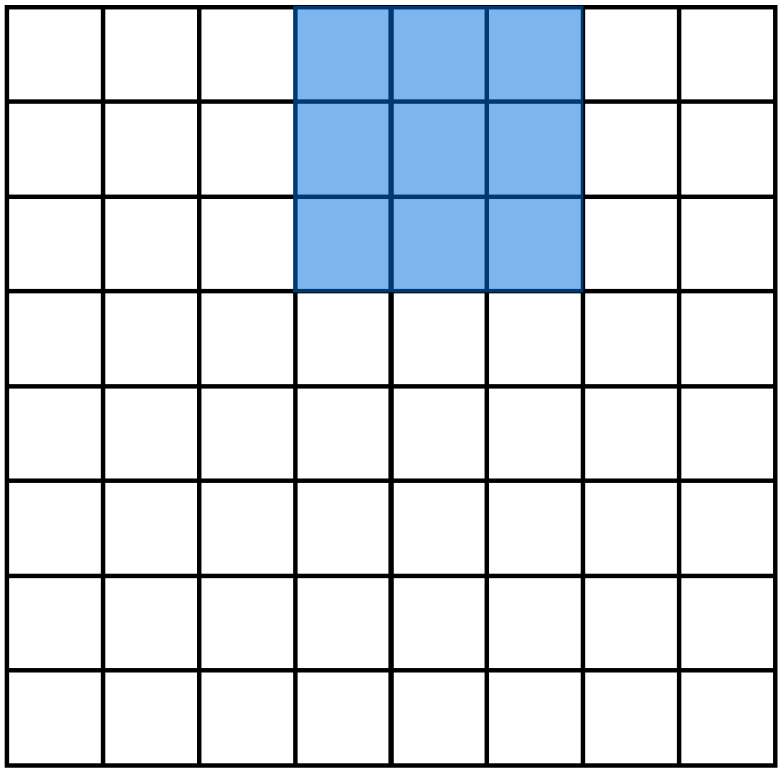
Input



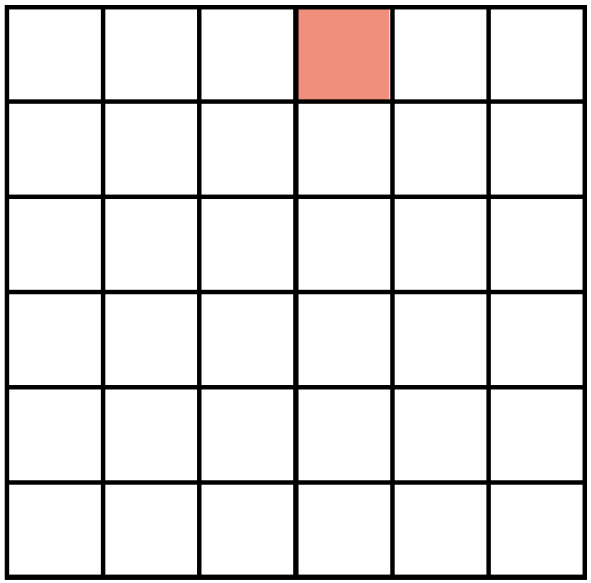
Output

Convolution: Stride

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



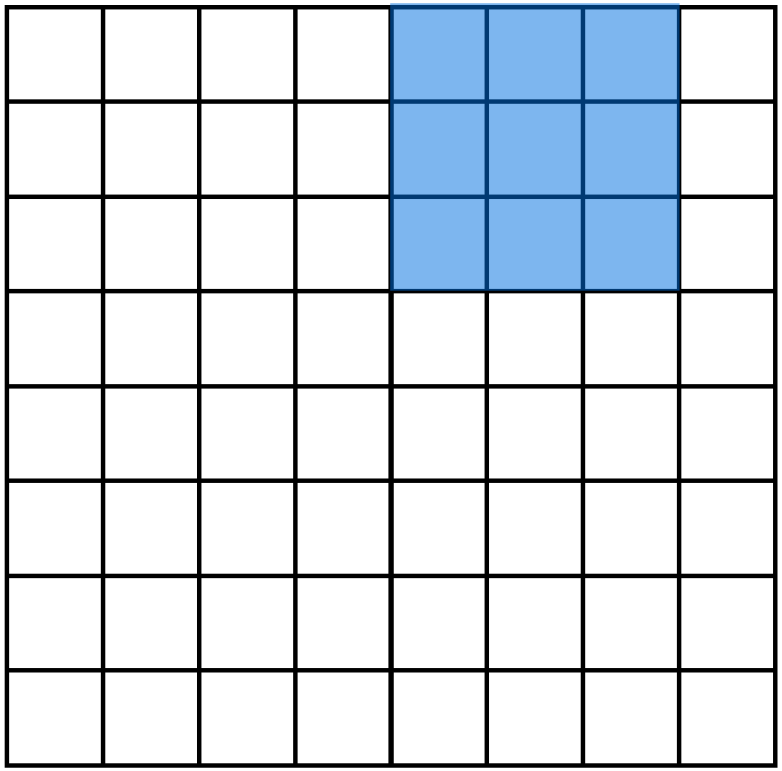
Input



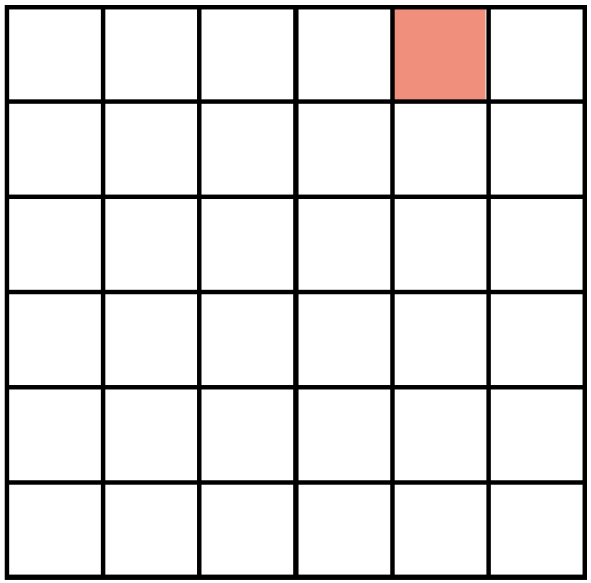
Output

Convolution: Stride

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



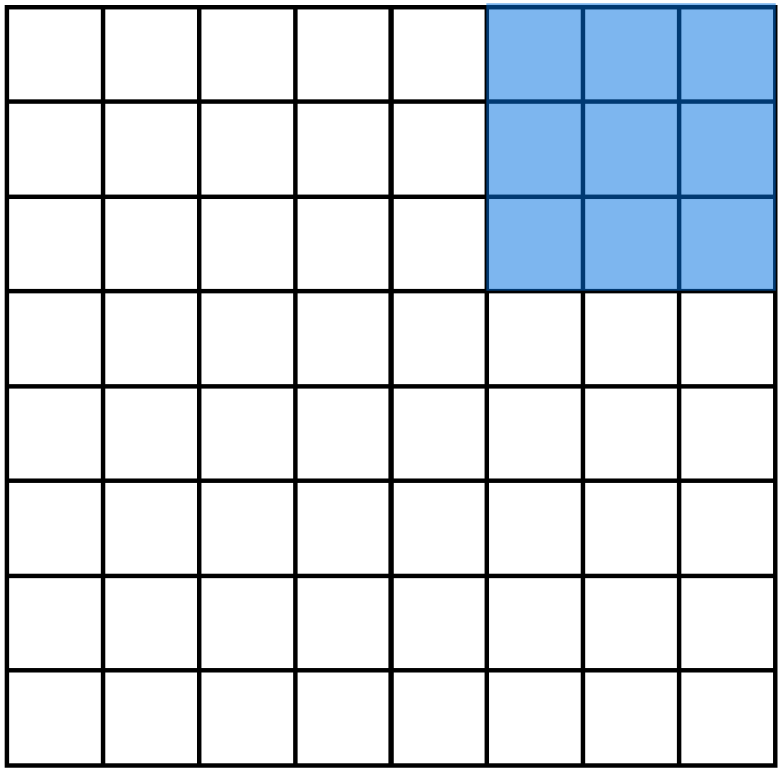
Input



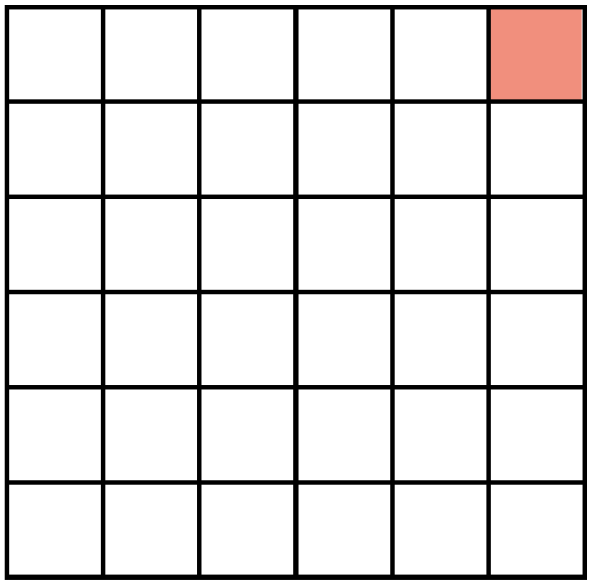
Output

Convolution: Stride

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



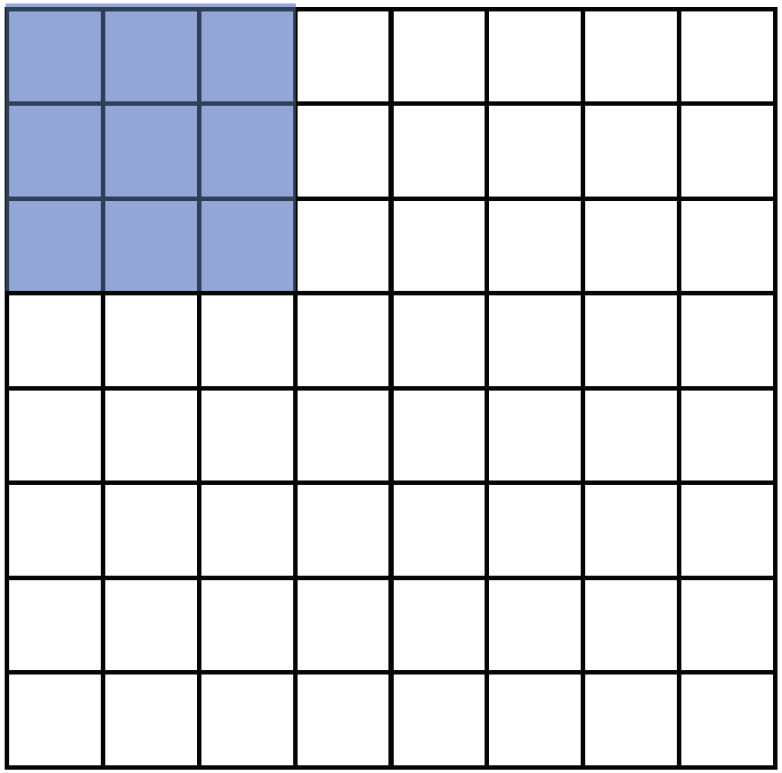
Input



Output

Convolution: Stride

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



Input

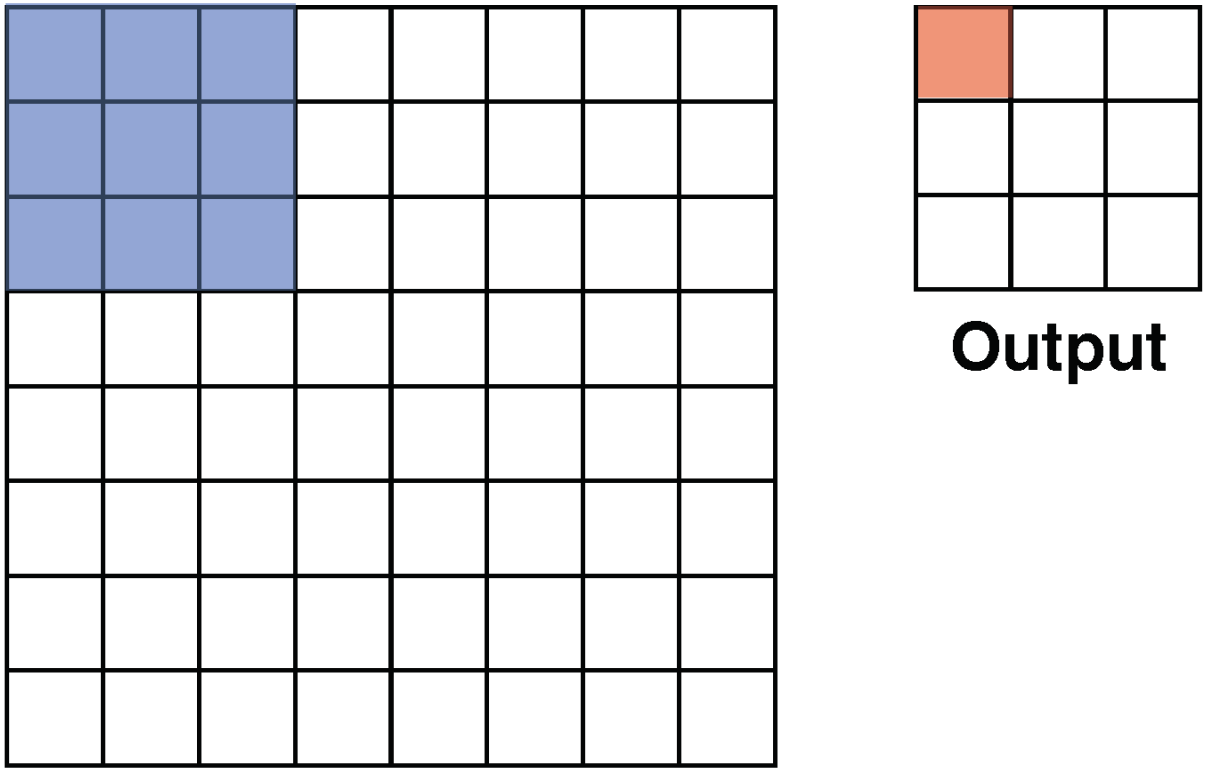
Recall that at each position, we are doing a **3D** sum:

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

(channel, row, column)

Convolution: Stride

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

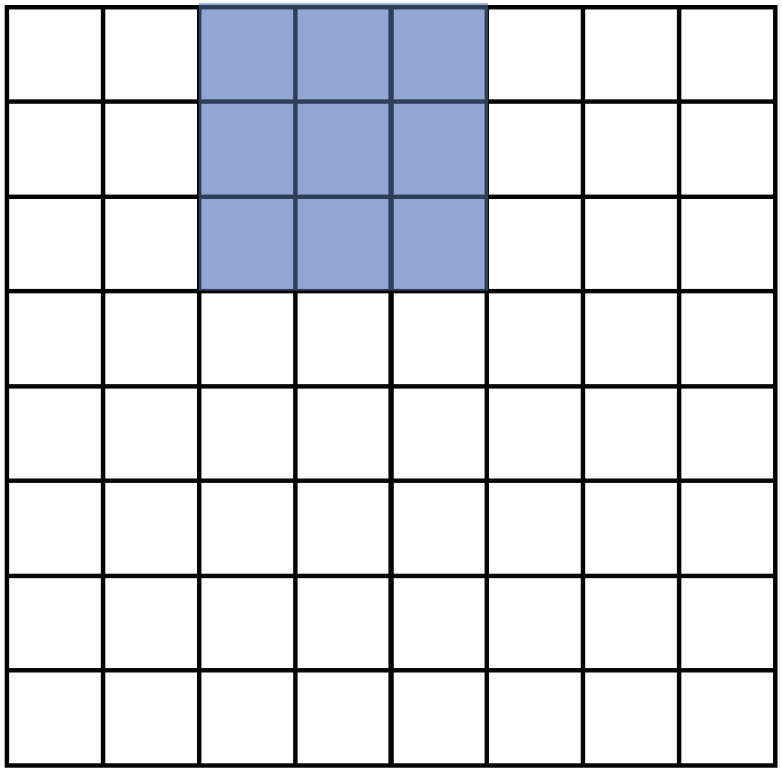


Input

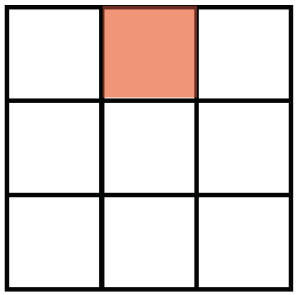
Output

Convolution: Stride

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



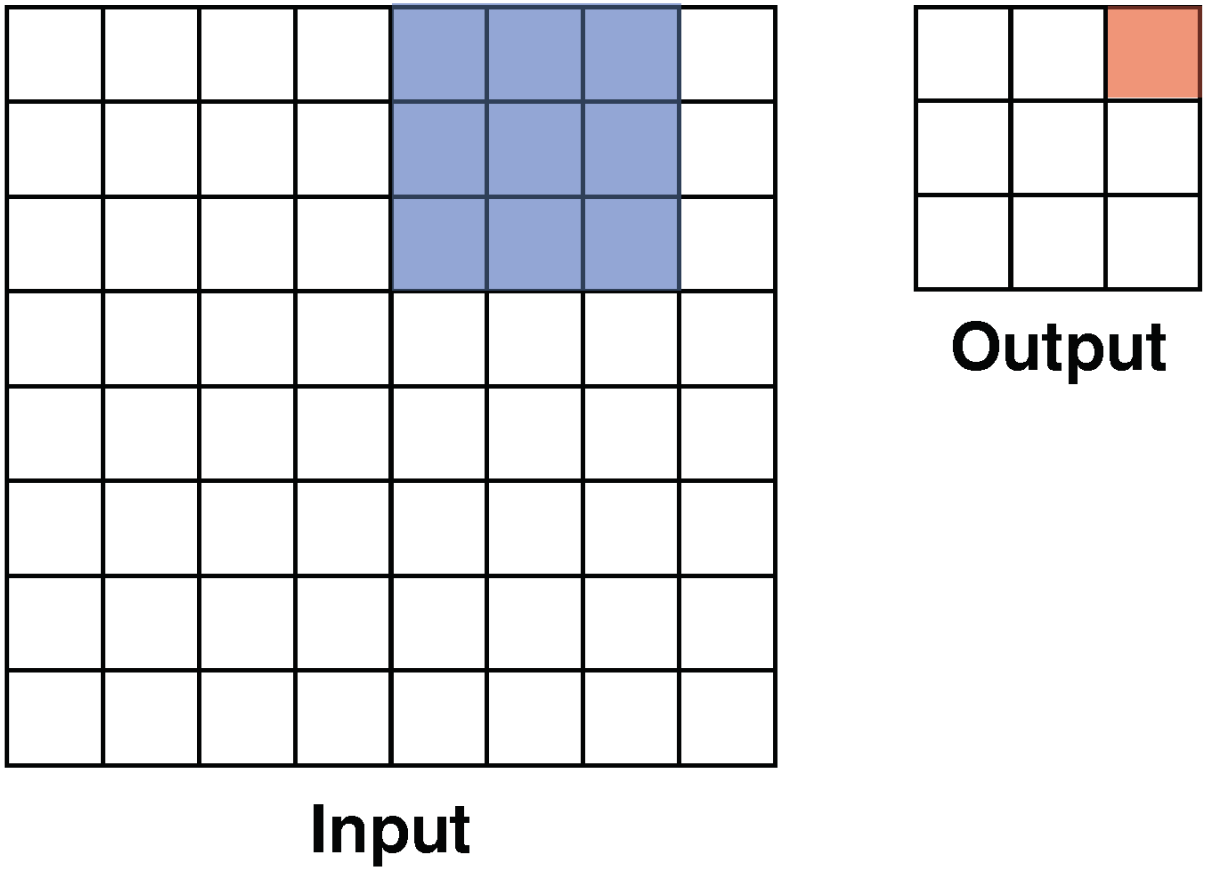
Input



Output

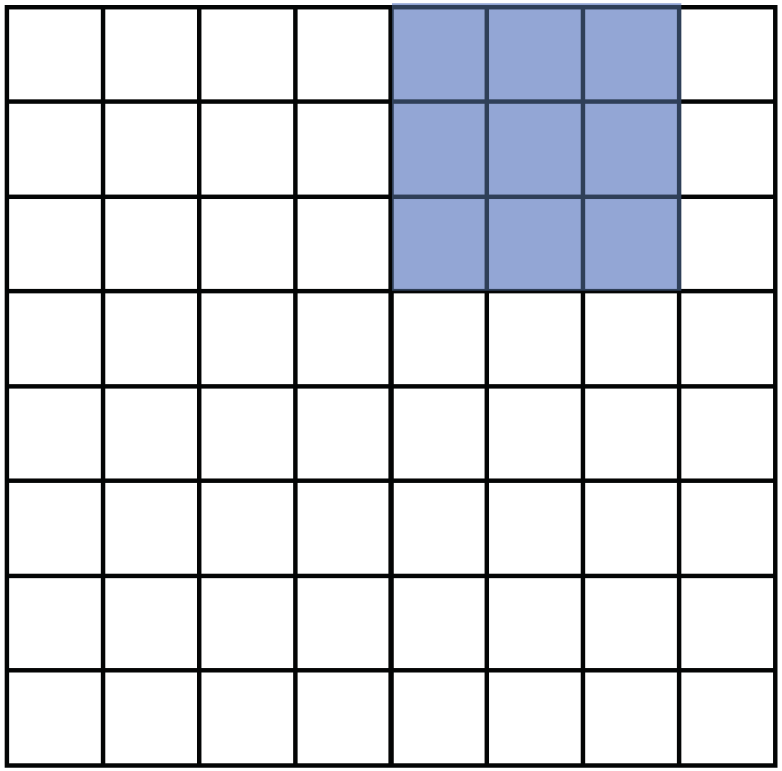
Convolution: Stride

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

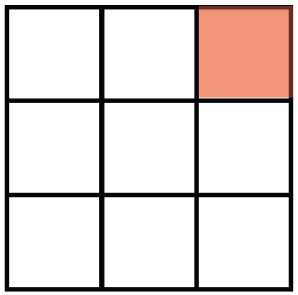


Convolution: Stride

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



Input



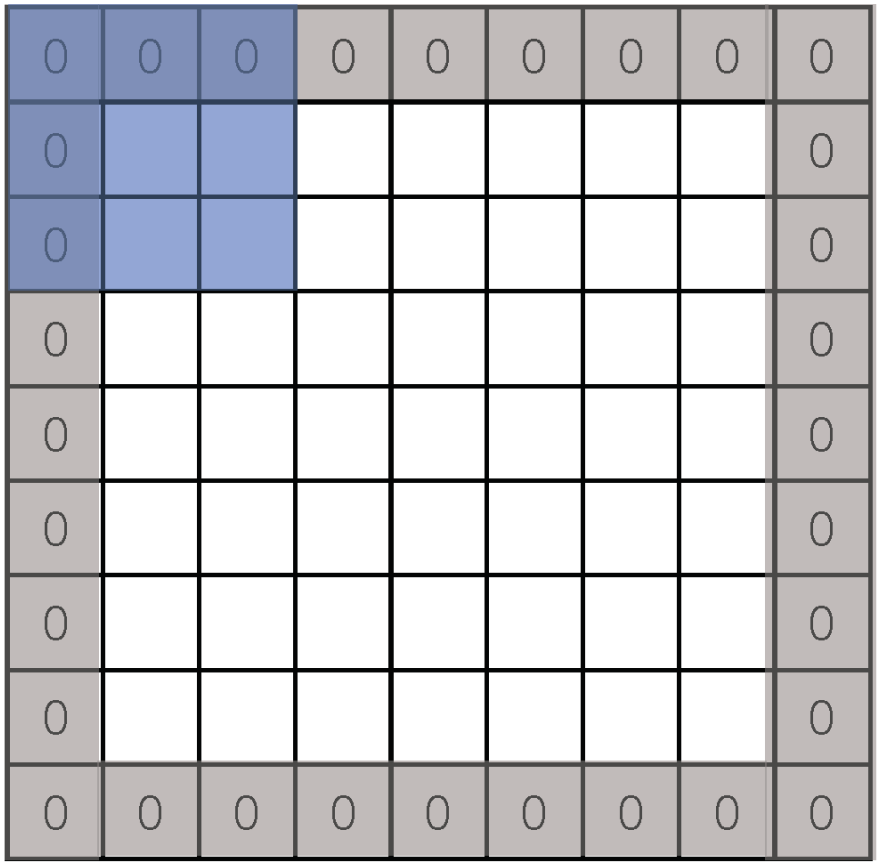
Output

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

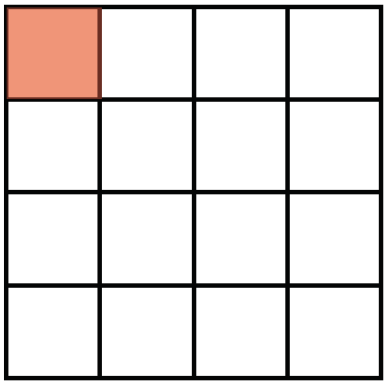
- The output is also half the size of the input

Convolution: Padding

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



Input



Output

Convolution: Padding

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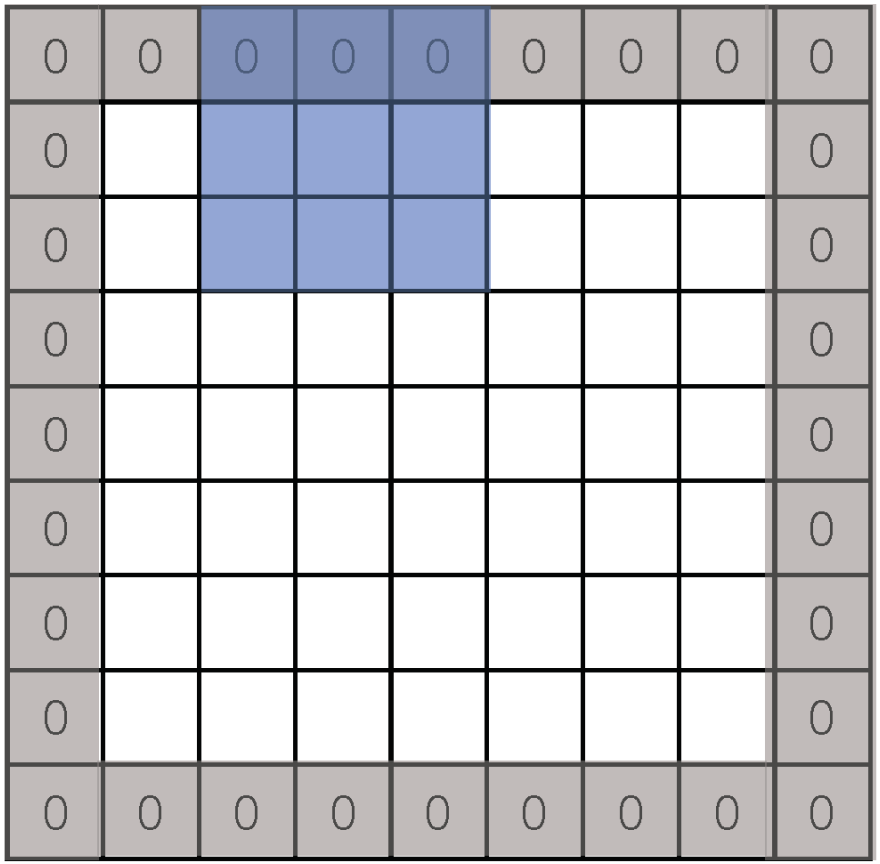
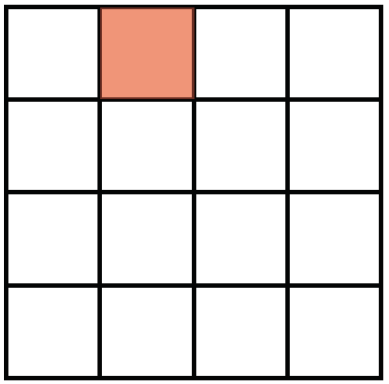


Input



Output

Convolution: Padding

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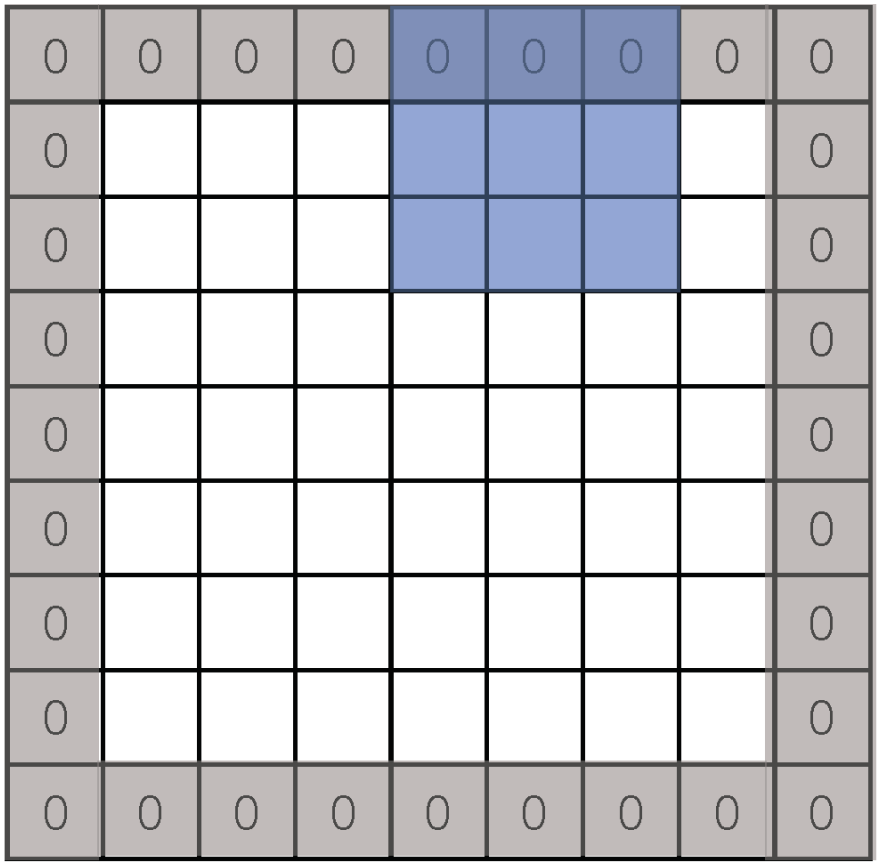
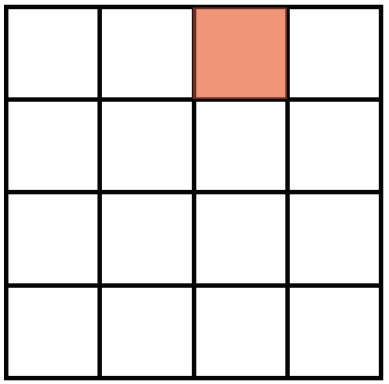


Input



Output

Convolution: Padding

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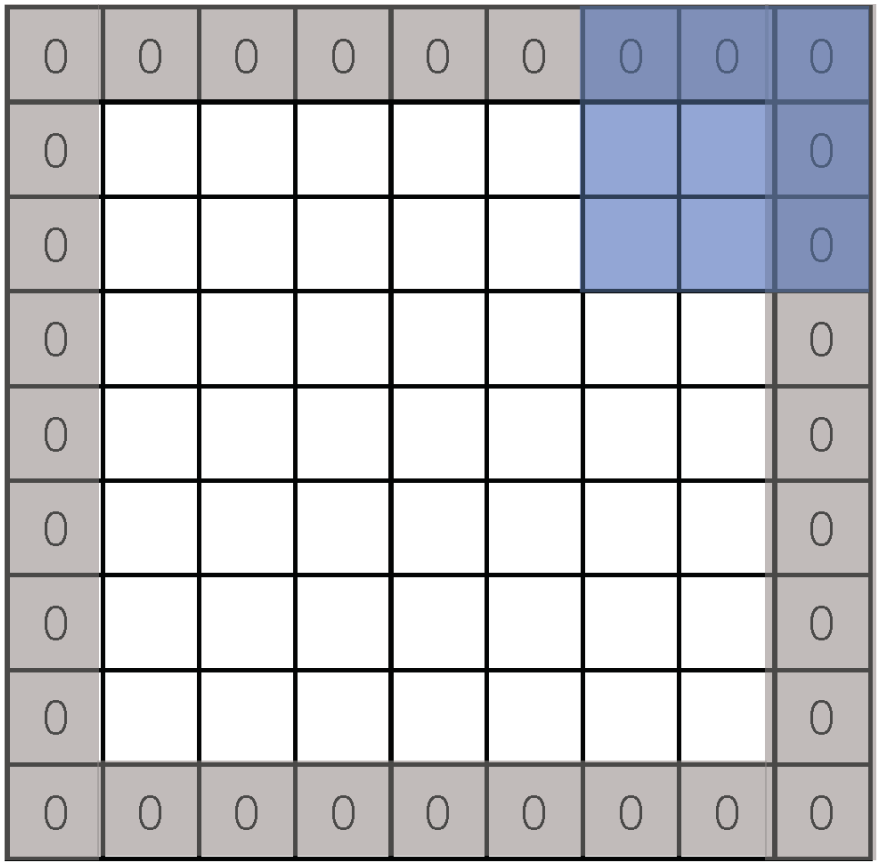
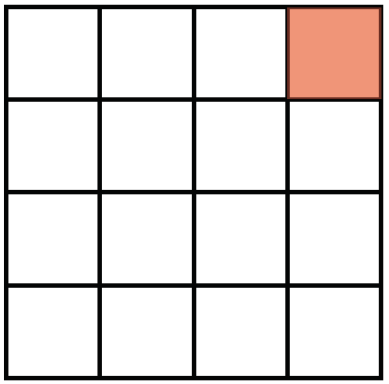
Here, **pad = 1, stride = 2**



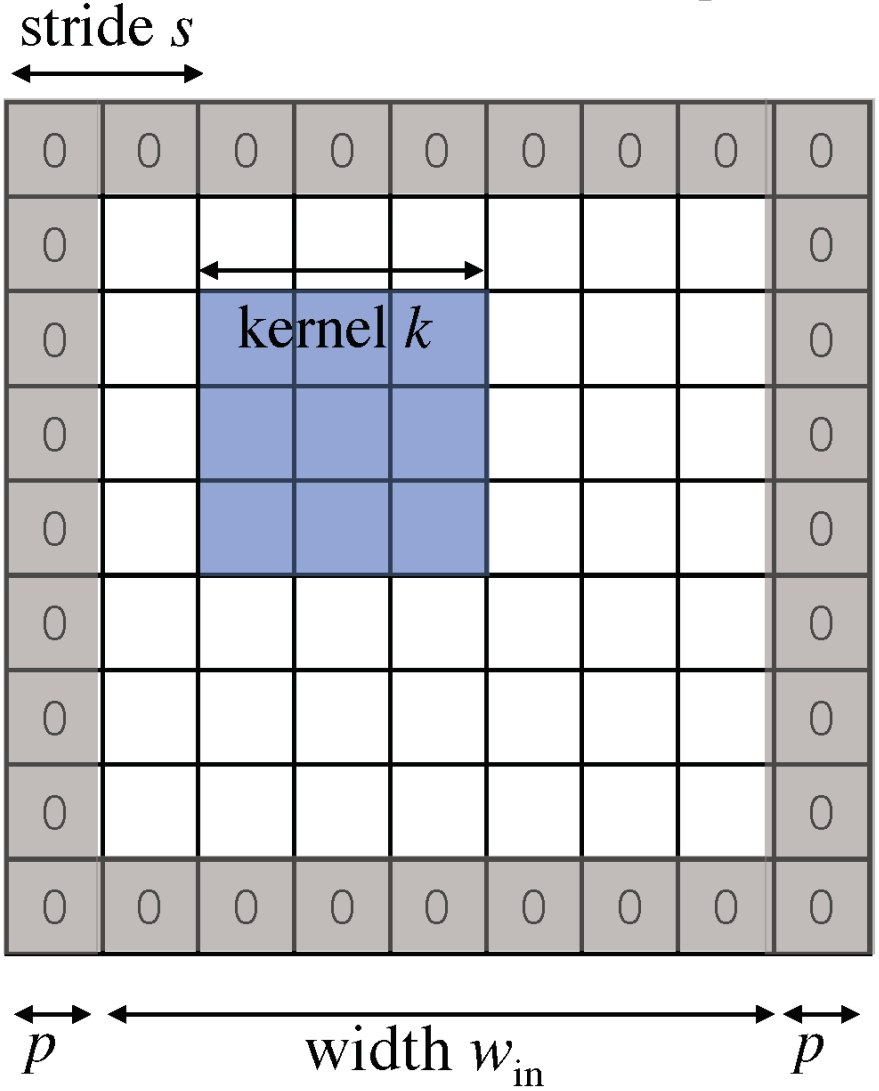
Input



Output

Convolution:

How big is the output?

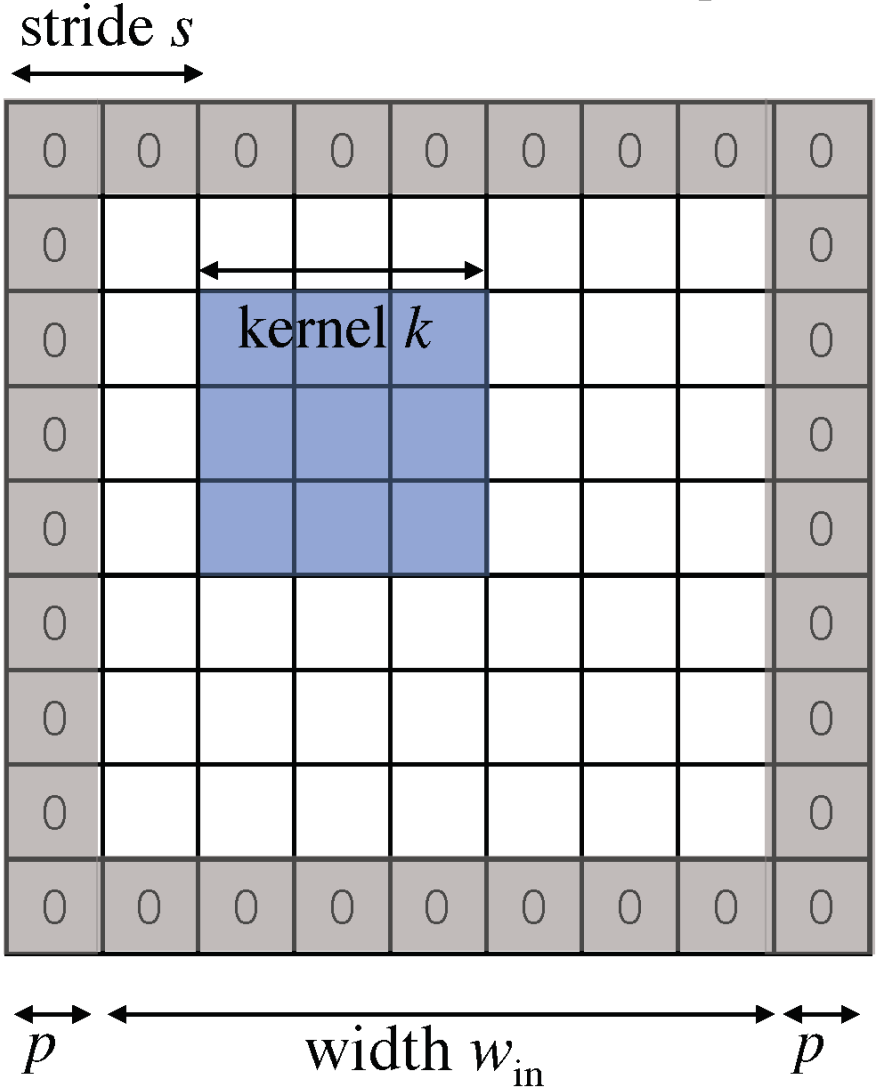


In general, the output has size:

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

Convolution:

How big is the output?



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

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?

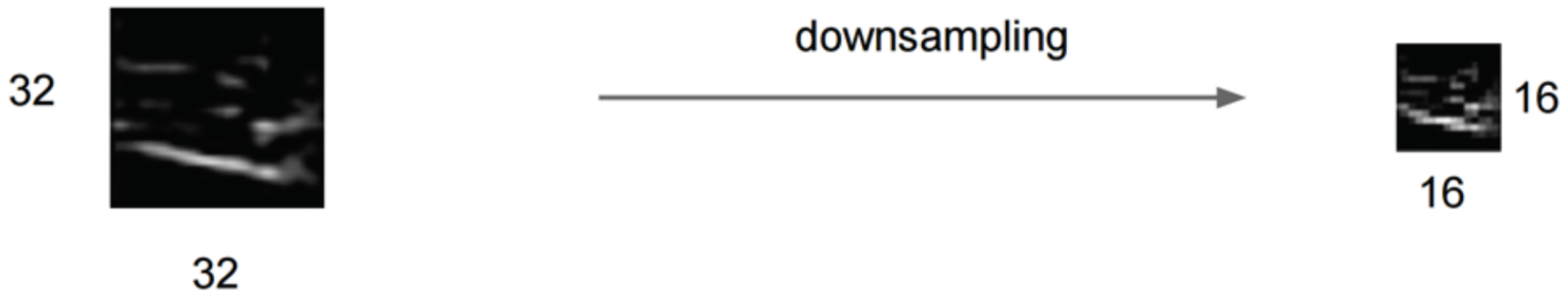
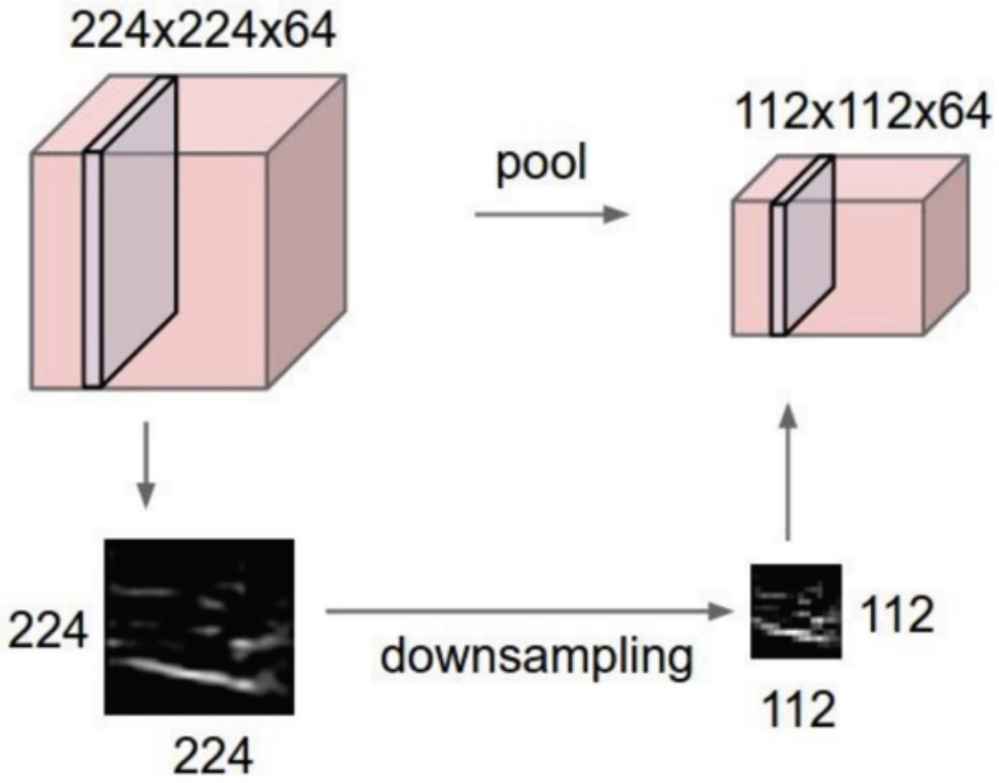


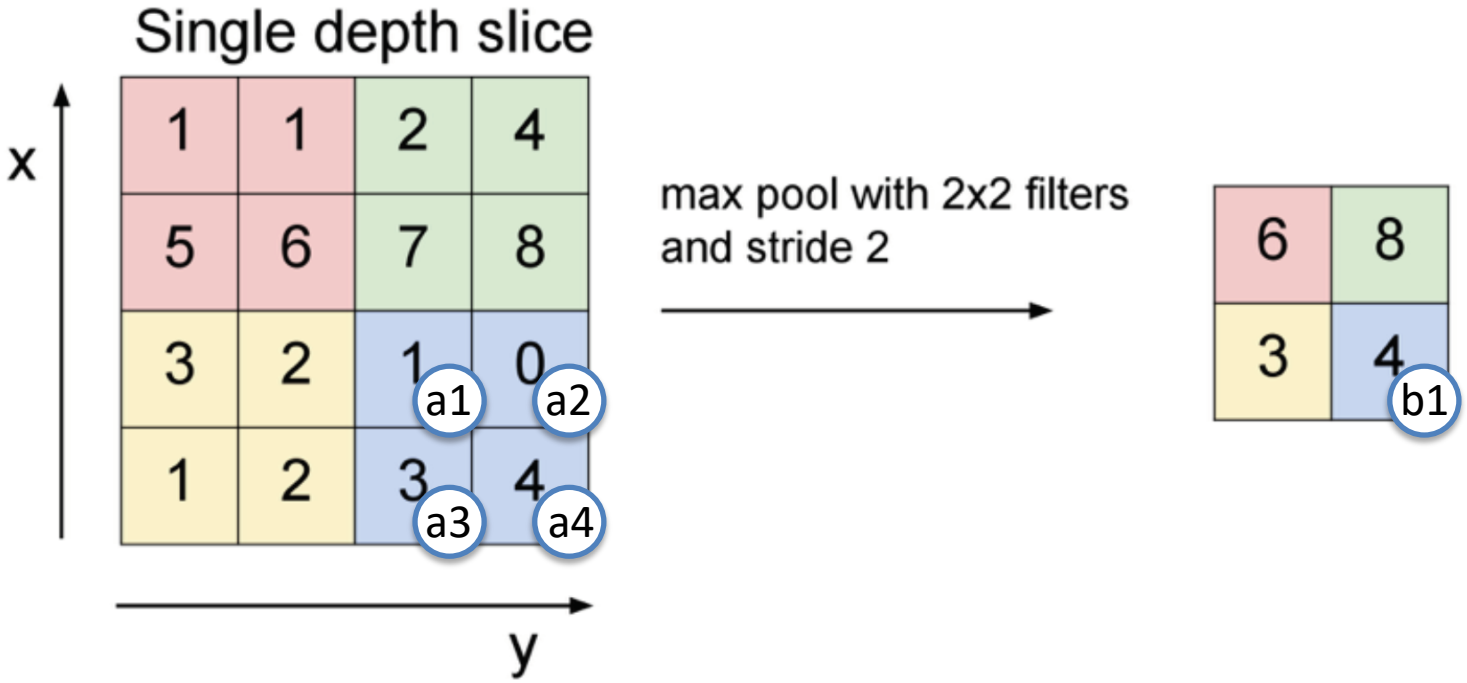
Figure: Andrej Karpathy

Pooling

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



Max Pooling

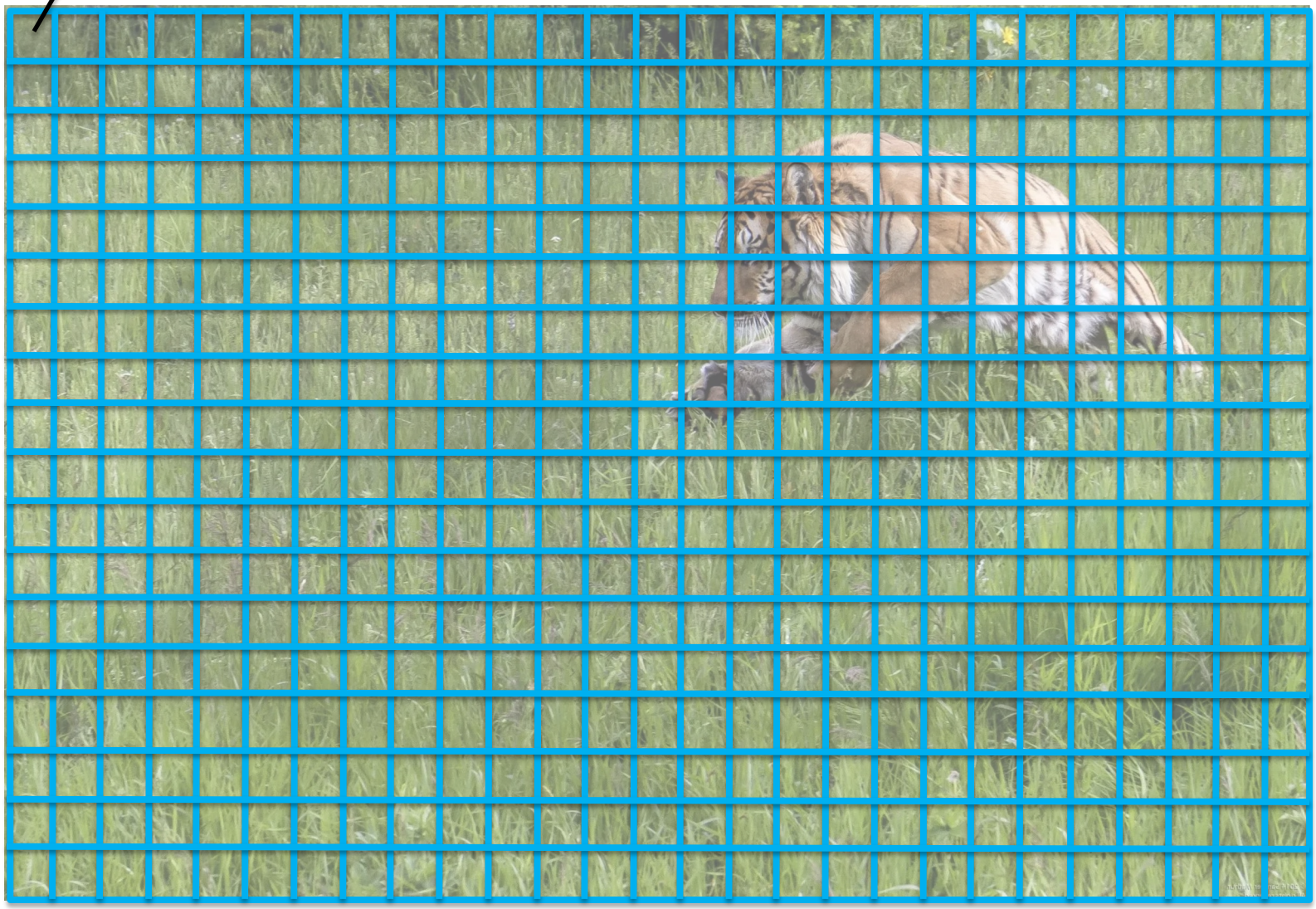


What's the backprop rule for max pooling?

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

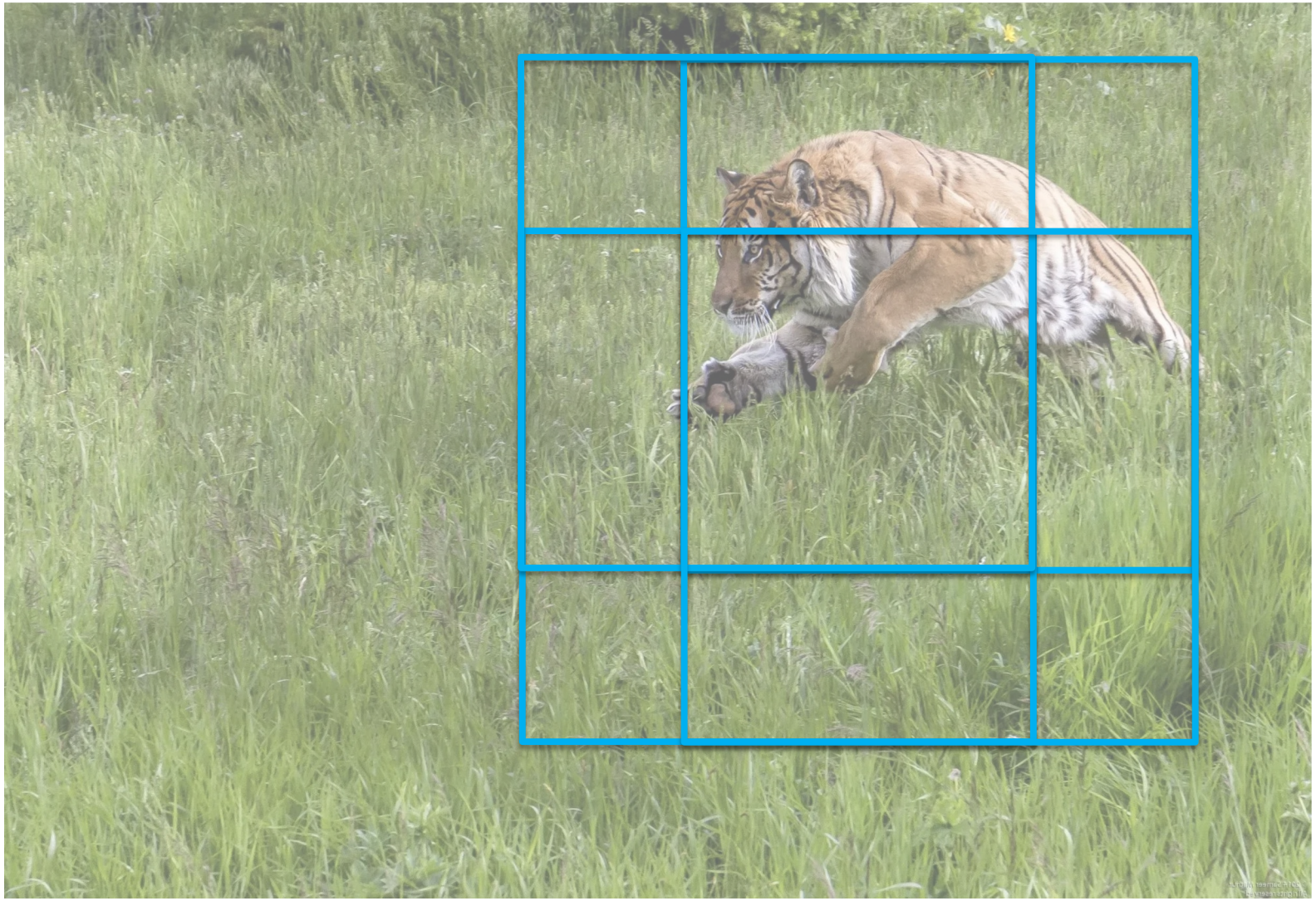
Figure: Andrej Karpathy

Max Pooling

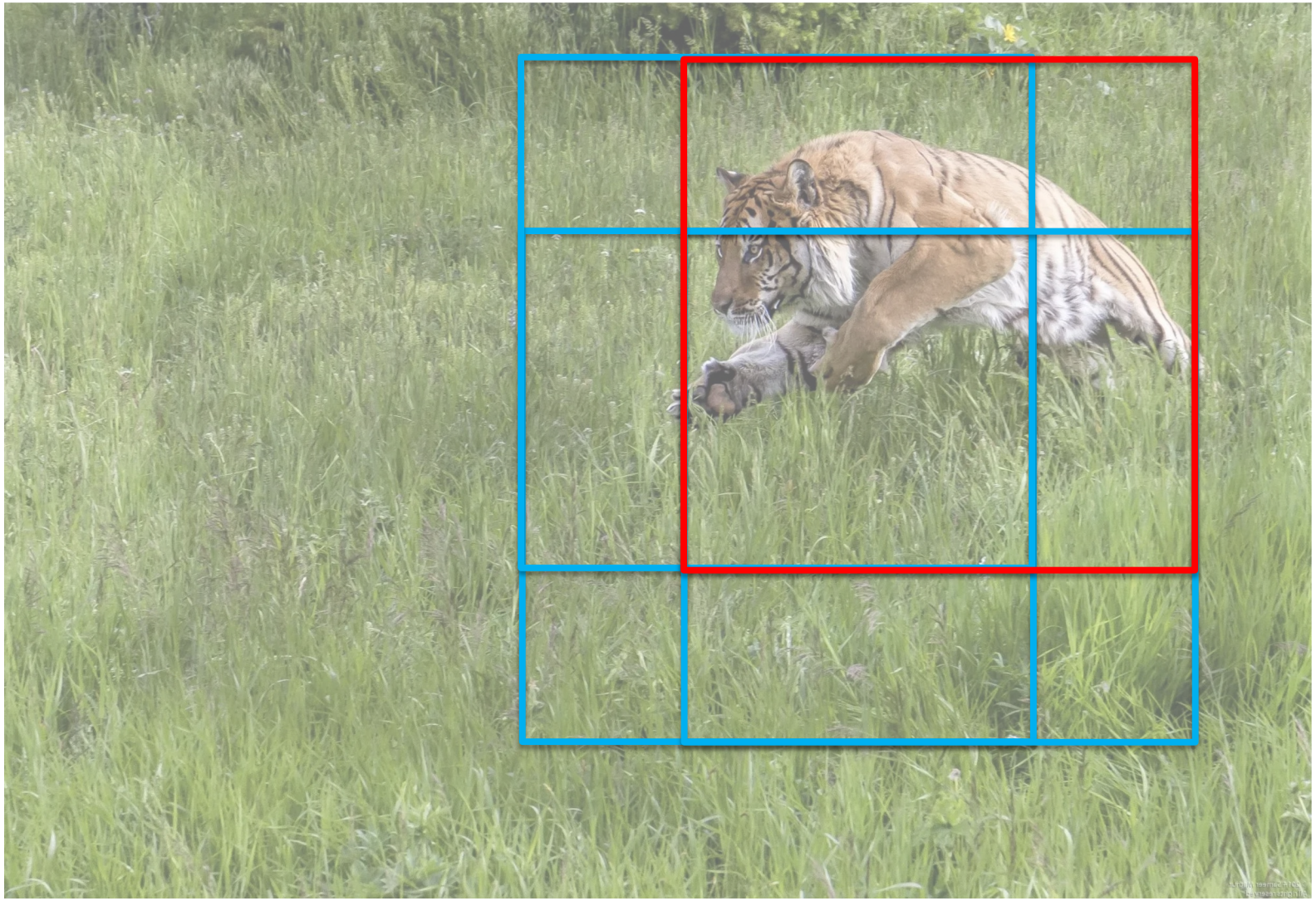


Max Pooling

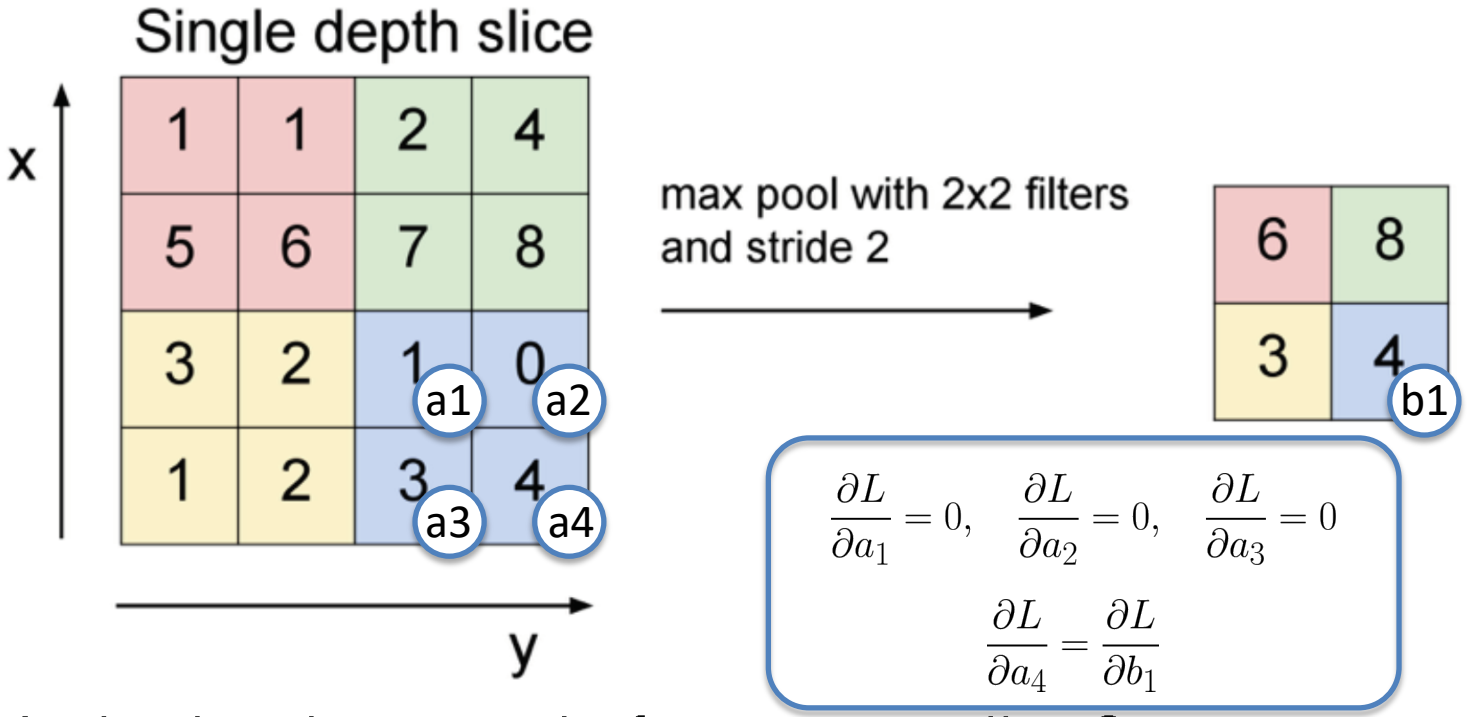
Max Pooling



Max Pooling



Max Pooling

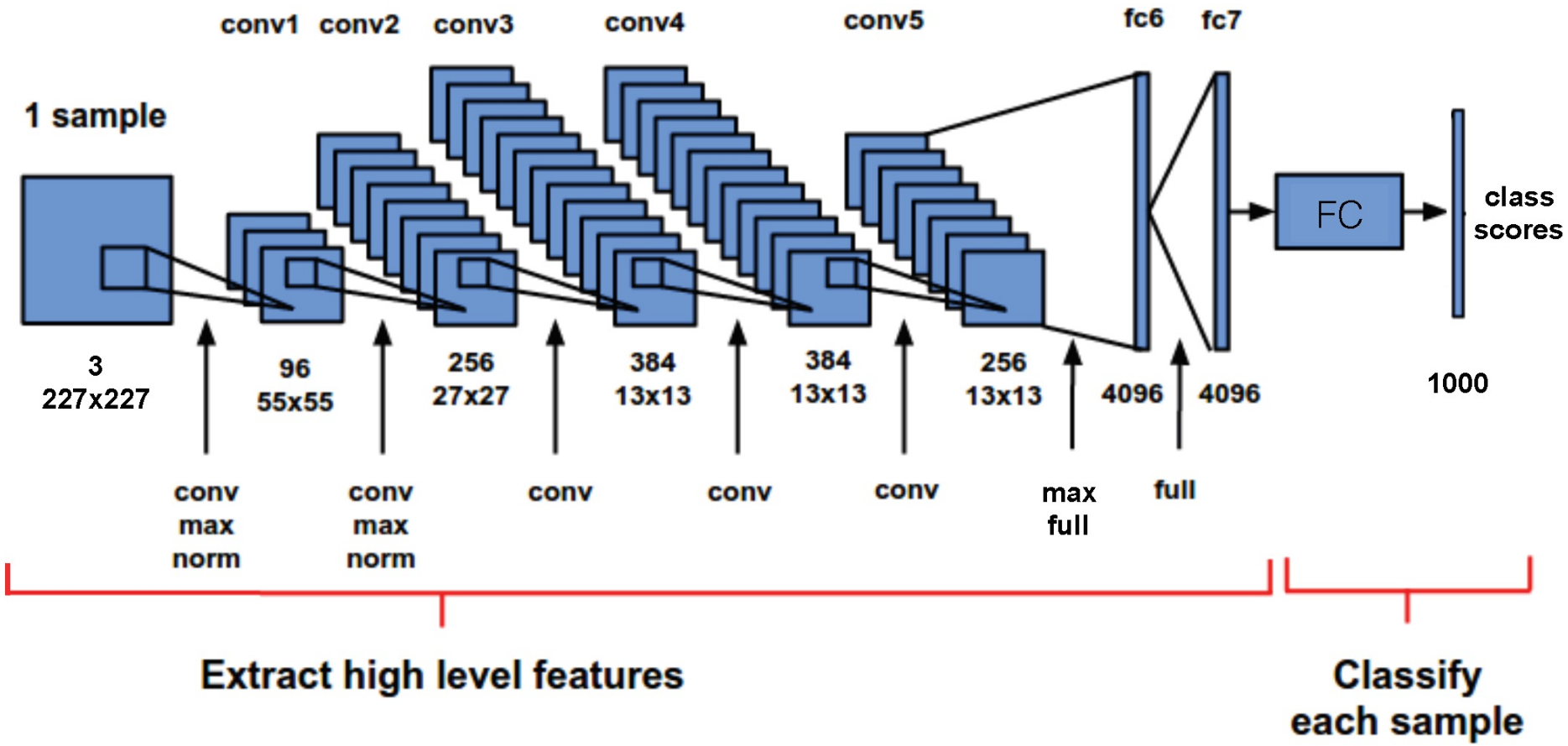


What's the backprop rule for max pooling?

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

Figure: Andrej Karpathy

Example: AlexNet [Krizhevsky 2012]



"max": max pooling
"norm": local response normalization
"full": fully connected

Figure: [Karnowski 2015] *(with corrections)*

2014

Going deeper with convolutions

Christian Szegedy
Google Inc.

Wei Liu
University of North Carolina, Chapel Hill

Yangqing Jia
Google Inc.

Pierre Sermanet
Google Inc.

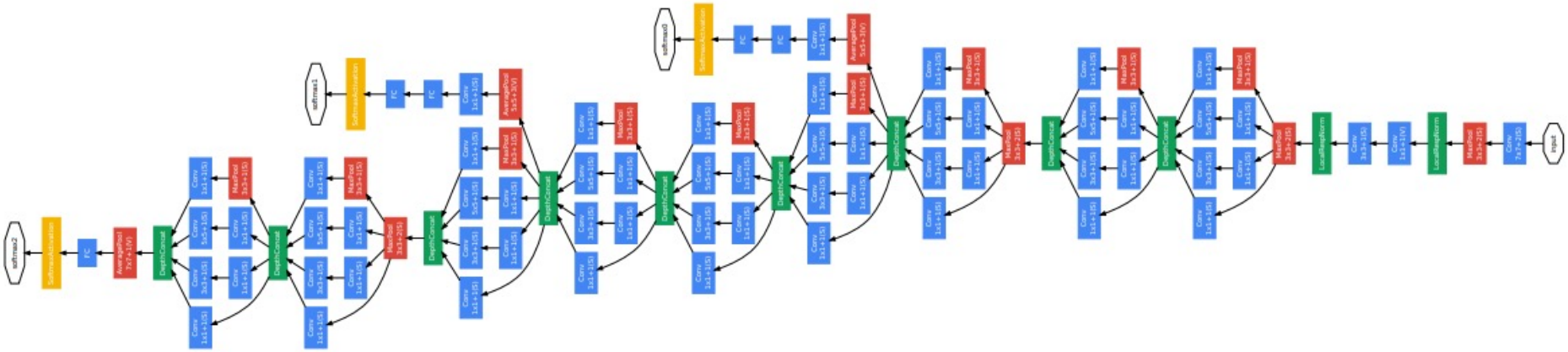
Scott Reed
University of Michigan

Dragomir Anguelov
Google Inc.

Dumitru Erhan
Google Inc.

Vincent Vanhoucke
Google Inc.

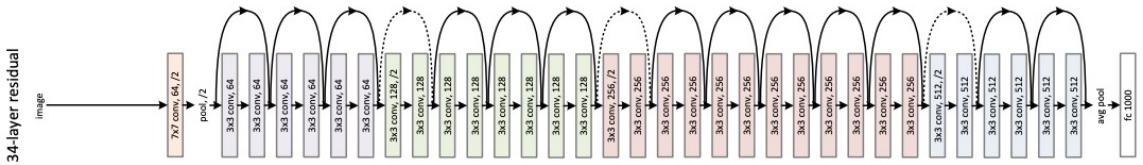
Andrew Rabinovich
Google Inc.



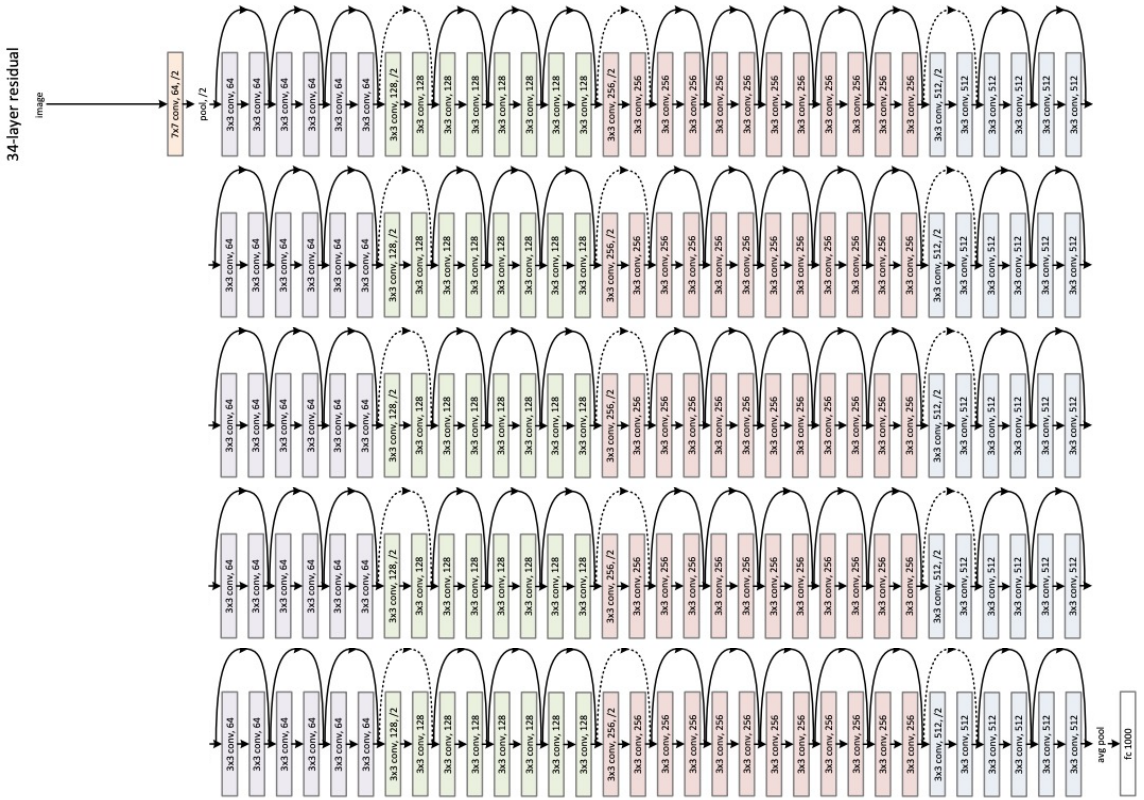
22 layers, but 12 times fewer parameters than AlexNet

2015

34 layers ResNet



152 layers ResNet



Example ConvNet

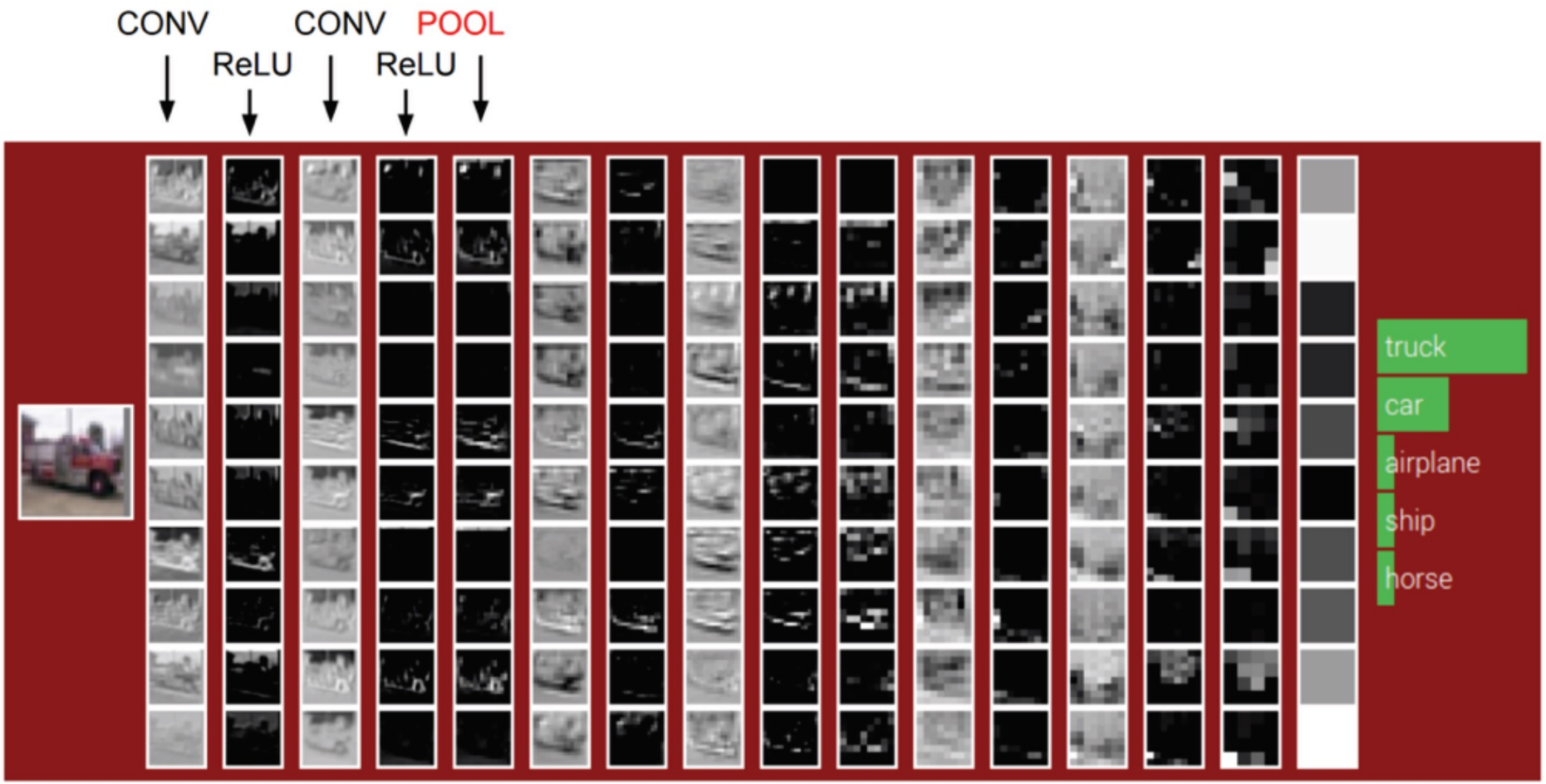


Figure: Andrej Karpathy

Example ConvNet

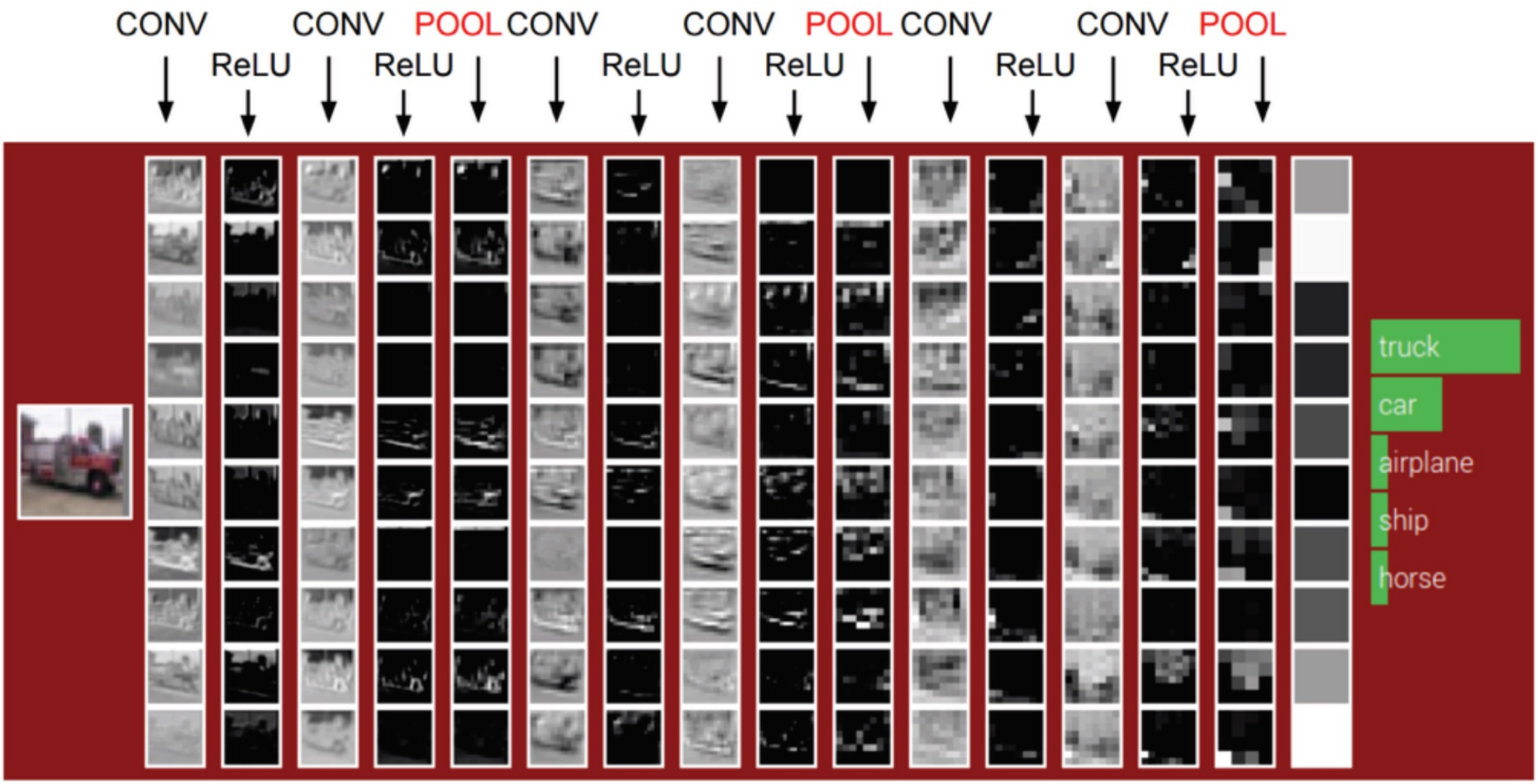


Figure: Andrej Karpathy

Example ConvNet

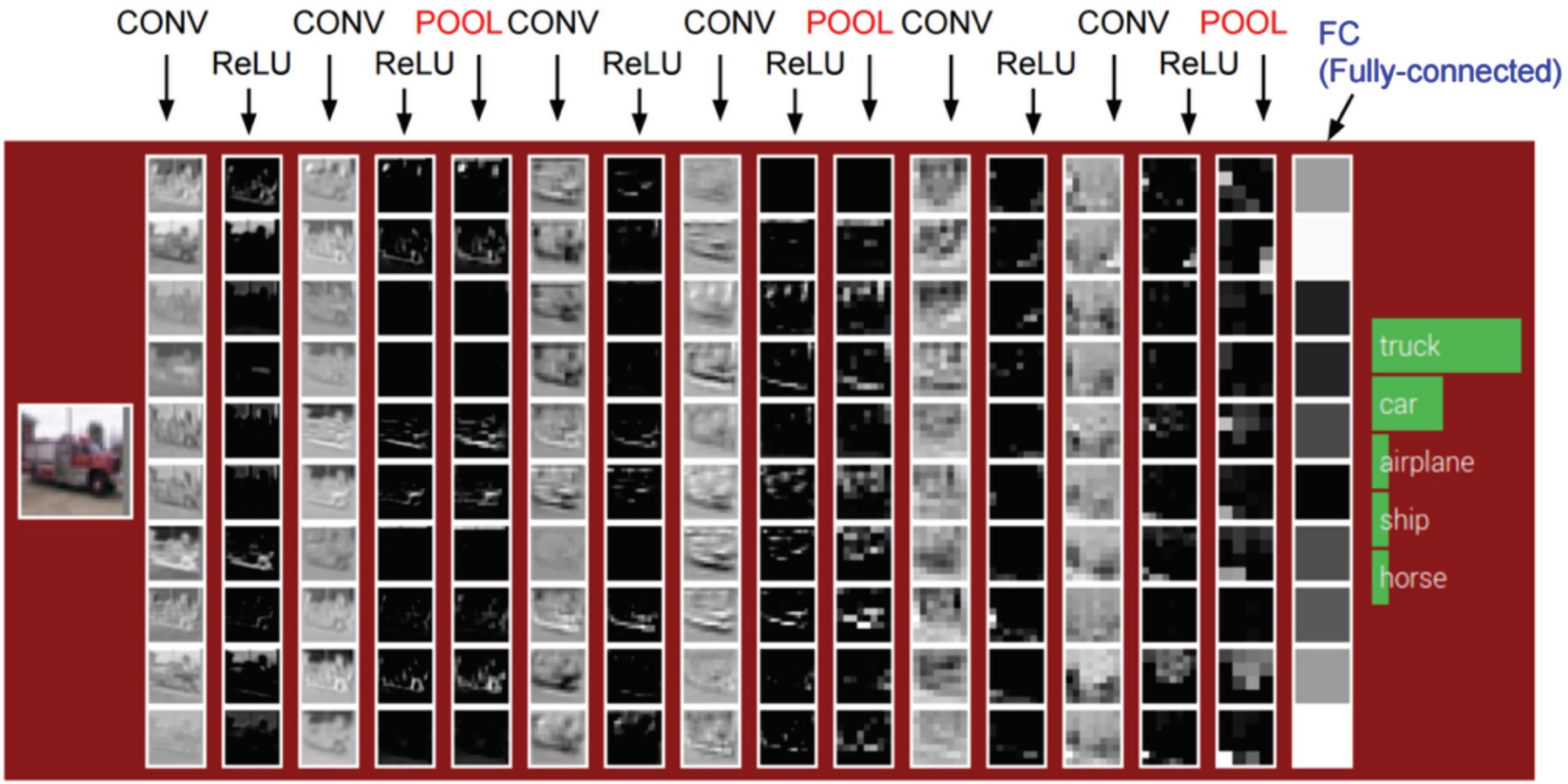
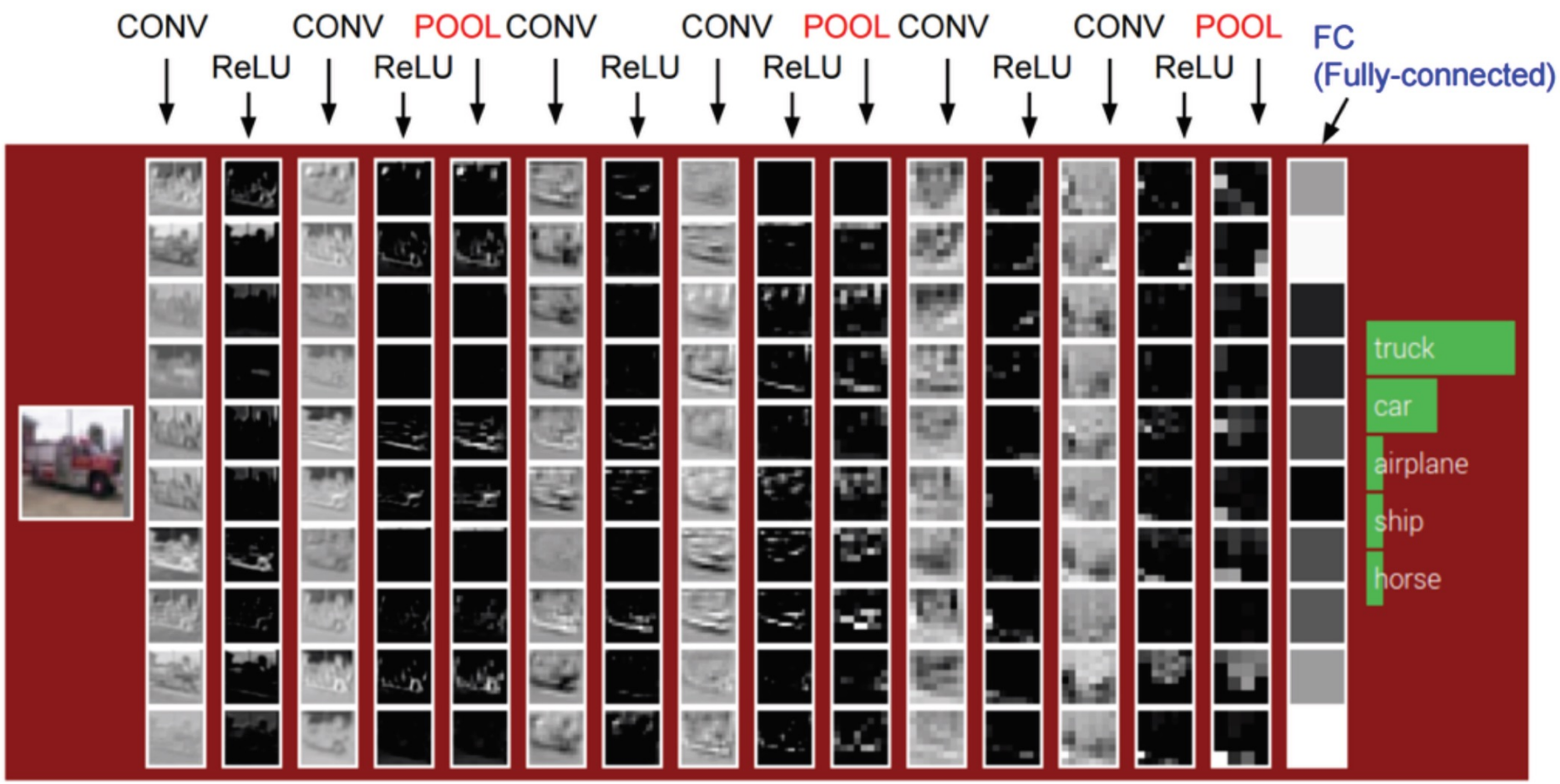


Figure: Andrej Karpathy

Example ConvNet



10x3x3 conv filters, stride 1, pad 1

2x2 pool filters, stride 2

Figure: Andrej Karpathy

Clarifai: ILSVRC 2013 winner

- Refinement of AlexNet

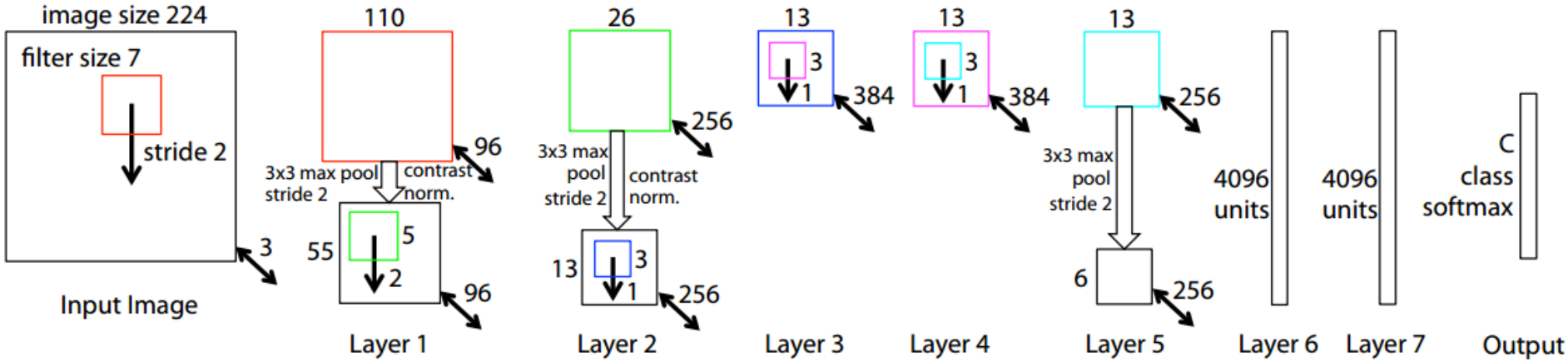
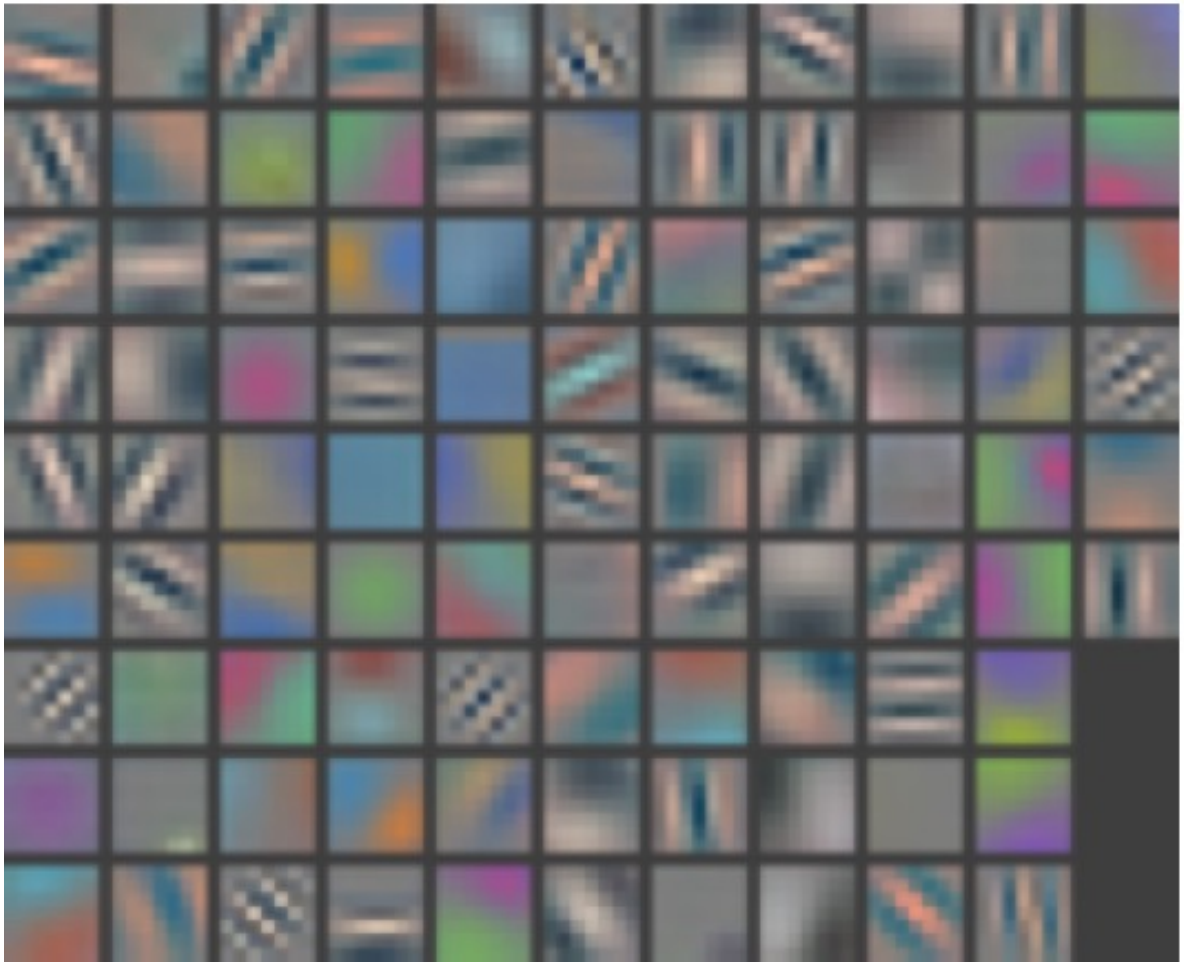


Figure 3. Architecture of our 8 layer convnet model. A 224 by 224 crop of an image (with 3 color planes) is presented as the input. This is convolved with 96 different 1st layer filters (red), each of size 7 by 7, using a stride of 2 in both x and y. The resulting feature maps are then: (i) passed through a rectified linear function (not shown), (ii) pooled (max within 3x3 regions, using stride 2) and (iii) contrast normalized across feature maps to give 96 different 55 by 55 element feature maps. Similar operations are repeated in layers 2,3,4,5. The last two layers are fully connected, taking features from the top convolutional layer as input in vector form ($6 \cdot 6 \cdot 256 = 9216$ dimensions). The final layer is a C-way softmax function, C being the number of classes. All filters and feature maps are square in shape.

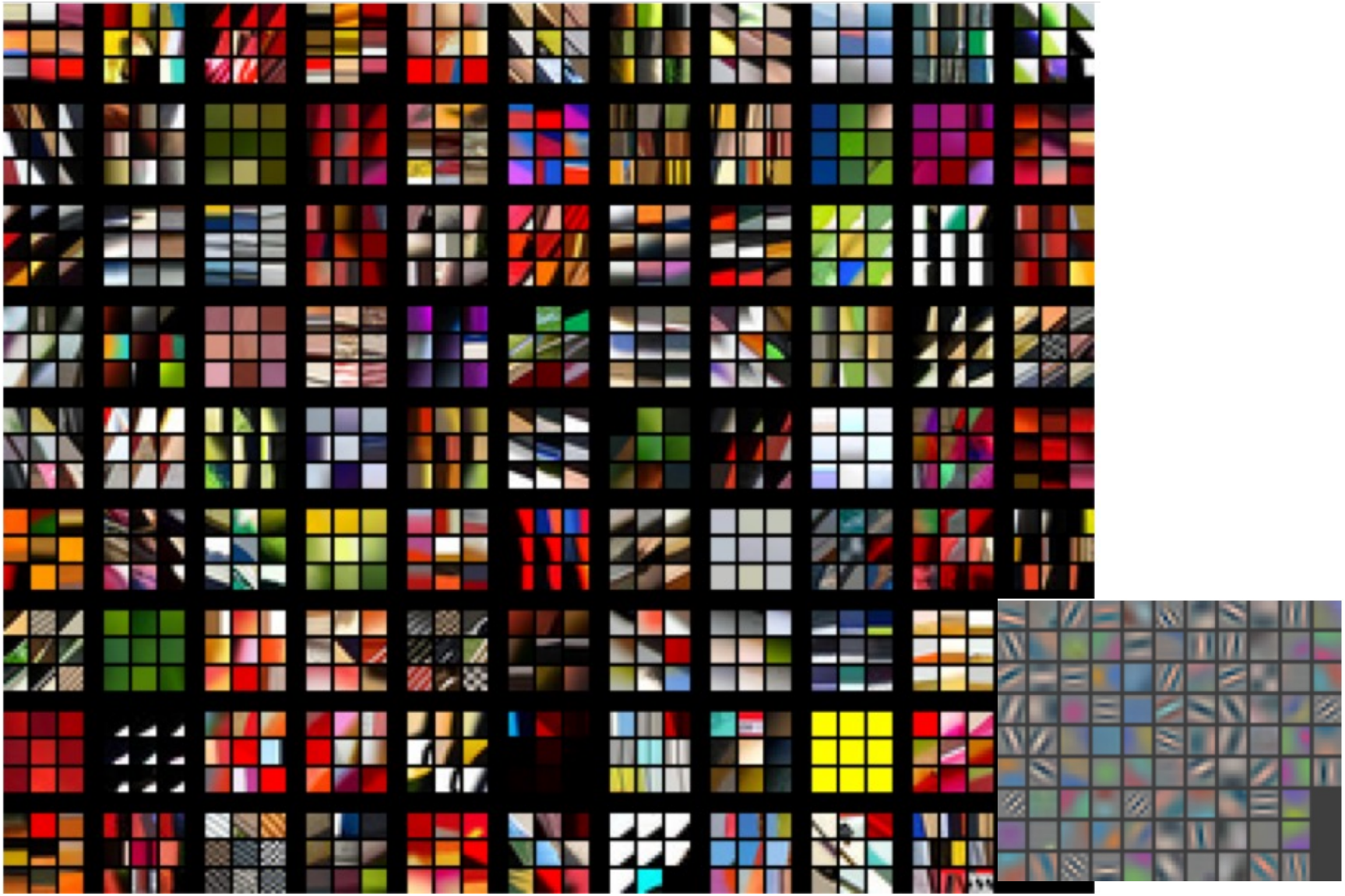
M. Zeiler and R. Fergus, Visualizing and Understanding Convolutional Networks, ECCV 2014 (Best Paper Award winner)

Layer 1 Filters



M. Zeiler and R. Fergus, Visualizing and Understanding Convolutional Networks, ECCV 2014 (Best Paper Award winner)

Layer 1: Top-9 Patches



Layer 2: Top-9 Patches

- **Patches from validation images that give maximal activation of a given feature map**


Layer 3: Top-9 Patches


Layer 4: Top-9 Patches


Layer 5: Top-9 Patches

Delving Deep into Rectifiers:
Surpassing Human-Level Performance on ImageNet Classification

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun

Microsoft Research

{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

GT: horse cart
1: horse cart
2: minibus
3: oxcart
4: stretcher
5: half track

GT: birdhouse
1: birdhouse
2: sliding door
3: window screen
4: mailbox
5: pot

GT: forklift
1: forklift
2: garbage truck
3: tow truck
4: trailer truck
5: go-kart

GT: coucal
1: coucal
2: indigo bunting
3: lorikeet
4: walking stick
5: custard apple

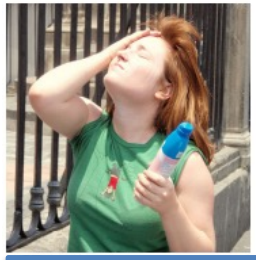
GT: komondor
1: komondor
2: patio
3: llama
4: mobile home
5: Old English sheepdog

GT: yellow lady's slipper
1: yellow lady's slipper
2: slug
3: hen-of-the-woods
4: stinkhorn
5: coral fungus

GT: torch
1: stage
2: spotlight
3: torch
4: microphone
5: feather boa

GT: banjo
1: acoustic guitar
2: shoji
3: bow tie
4: cowboy hat
5: banjo

GT: go-kart
1: go-kart
2: crash helmet
3: racer
4: sports car
5: motor scooter



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3: racer
4: sports car
5: motor scooter

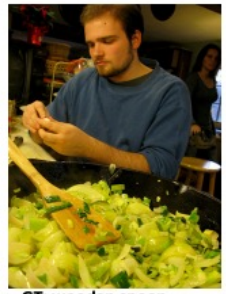
GT: mountain tent
1: sleeping bag
2: mountain tent
3: parachute
4: ski
5: flagpole

GT: geyser
1: geyser
2: volcano
3: sandbar
4: breakwater
5: leatherback turtle

GT: microwave
1: microwave
2: washer
3: toaster
4: stove
5: dishwasher

GT: sunscreen
1: hair spray
2: ice lolly
3: sunscreen
4: water bottle
5: lotion

GT: flute
1: flute
2: oboe
3: panpipe
4: trombone
5: bassoon



GT: wooden spoon
1: wok
2: frying pan
3: spatula
4: wooden spoon
5: hot pot

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(Error %)

	team	top-5 (**test**)
in competition ILSVRC 14	MSRA, SPP-nets [11]	8.06
	VGG [25]	7.32
	GoogLeNet [29]	6.66
post-competition	VGG [25] (arXiv v5)	6.8
	Baidu [32]	5.98
	MSRA, PReLU-nets	**4.94**

Table 7. The **multi-model** results for the ImageNet 2012 test set.

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