Deep Learning 1

2025-2026 – Pascal Mettes

Lecture 5

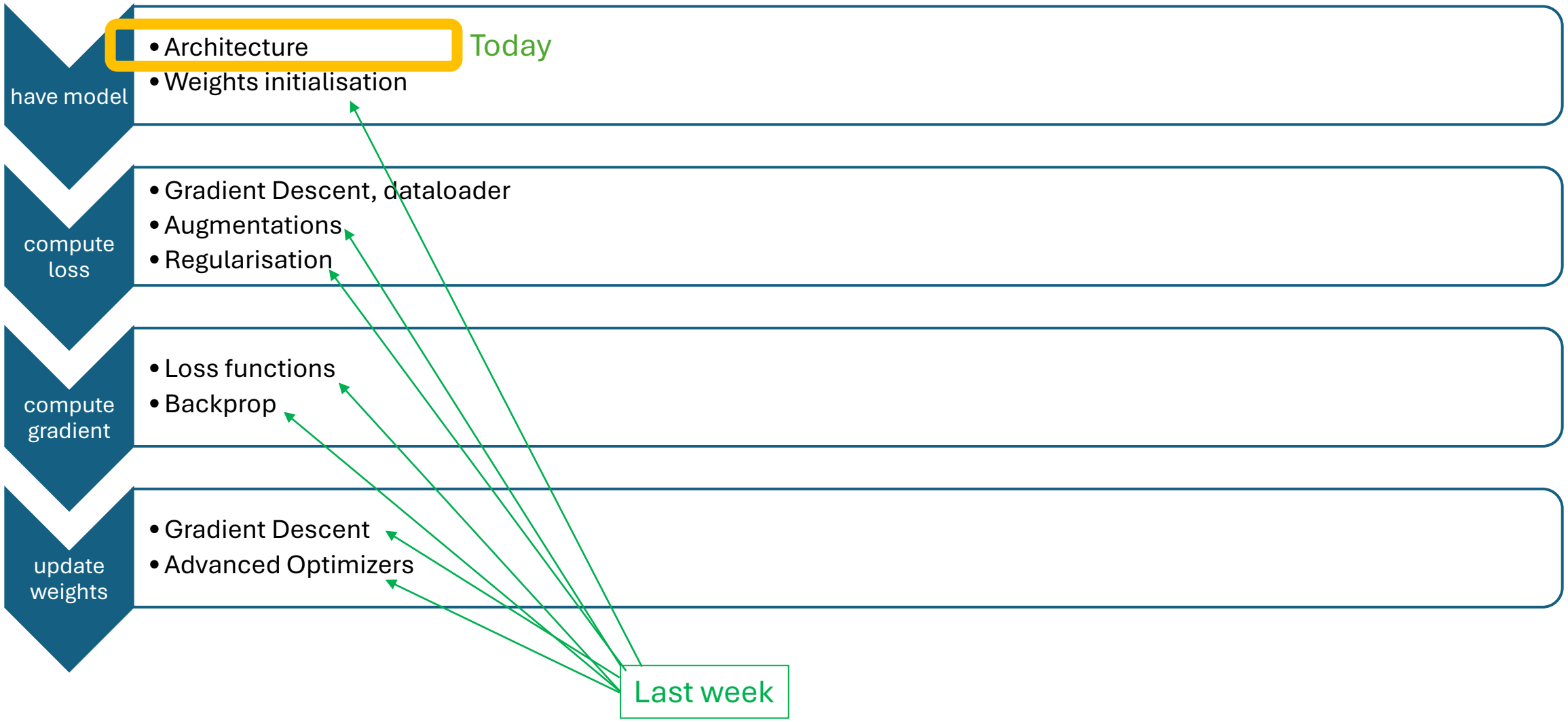
Convolutional Neural Networks

Previous lecture

Lecture	Title
1	Intro and history of deep learning
3	Deep learning optimization I
5	Convolutional deep learning
7	Graph deep learning
9	Multi-modal deep learning
11	What doesn't work in deep learning
13	Q&A

Lecture	Title
2	AutoDiff
4	Deep learning optimization II
6	Attention-based deep learning
8	From supervised to unsupervised deep learning
10	Generative deep learning
12	Non-Euclidean deep learning
14	Deep learning for videos

Where are we

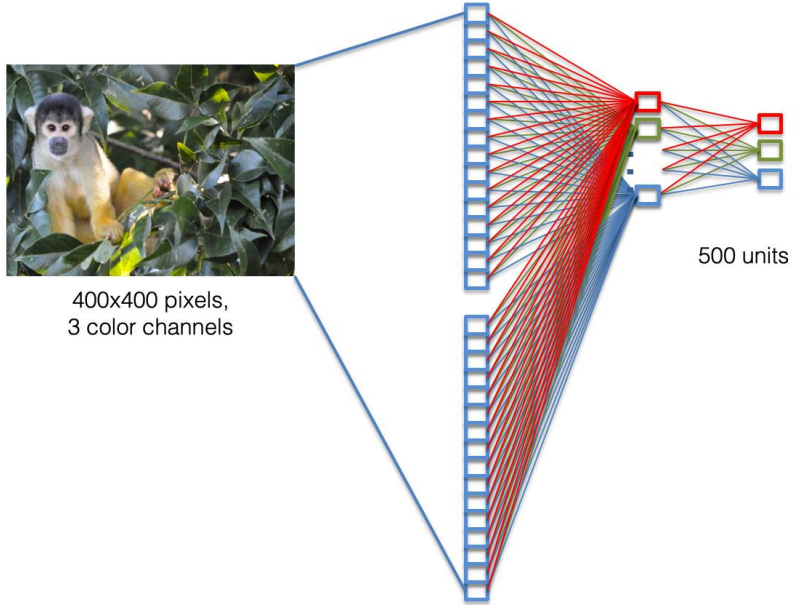

have model
• Architecture
• Weights initialisation
Today
compute loss
• Gradient Descent, dataloader
• Augmentations
• Regularisation
compute gradient
• Loss functions
• Backprop
update weights
• Gradient Descent
• Advanced Optimizers
Last week

MLPs and real world data

Multi-layer perceptrons / feedforward networks assume vectorized data.

Consider an image of 400x400 pixels with 3 color channels.

How many parameters needed for a 1-layer networks with 500 hidden units?

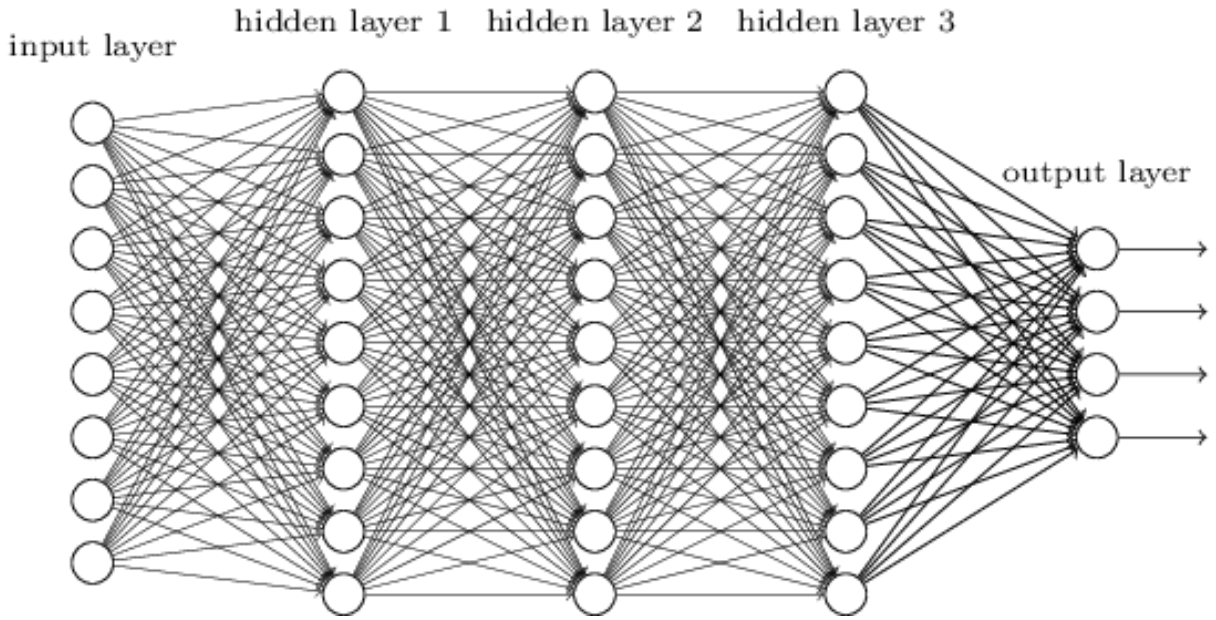


MLPs and real world data

From this fully-connected model, do we really need all the edges?

Can some of these be “shared” (equal weight)?

Can prior knowledge (“inductive biases”) be incorporated into the design?



The data that we need for deep learning is not in the form of feature vector. Feature vectors are data that have been already manipulated by human. Deep learning operates with raw data

The inductive bias is a structure in our architecture that should be reflected in the data. This should help the learning

The convolution

We have a signal $x(t)$ and a weighting function $w(a)$

We can generate a new function $s(t)$ by the following equation:

$$s(t) = \int x(a)w(t-a)da$$

We refer to $w(a)$ *as a filter or a kernel*. This operation is called convolution.

The convolution operation is typically denoted with asterisk:

$$s(t) = (x * w)(t)$$

Convolution vs linear operators

convolution is a linear layer but done locally many times

Linear operation: $f(x, w) = x^T w$

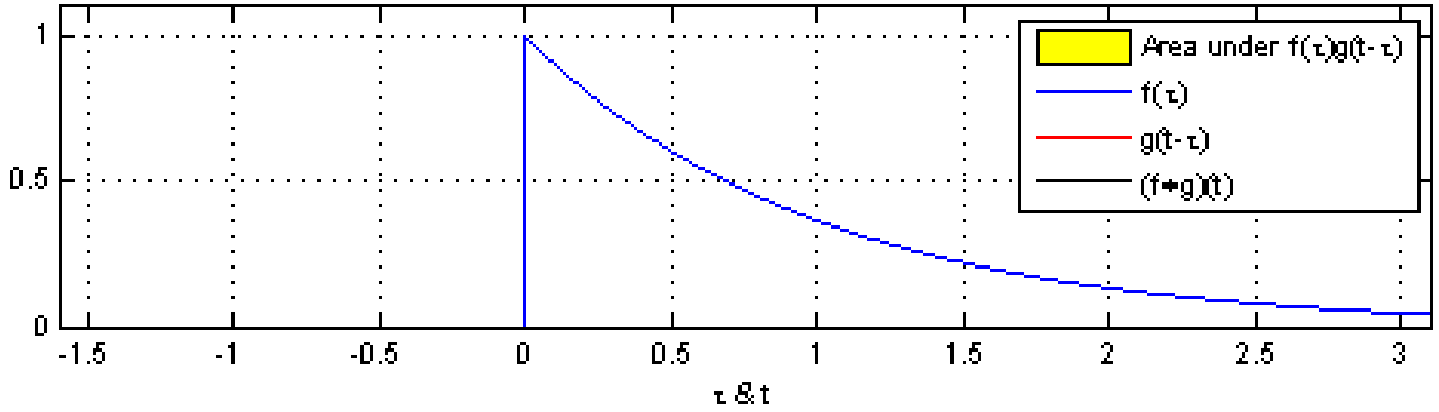
- Global operation, separate weight per feature
- Dimensionality of w = dimensionality of x
- 1 output value

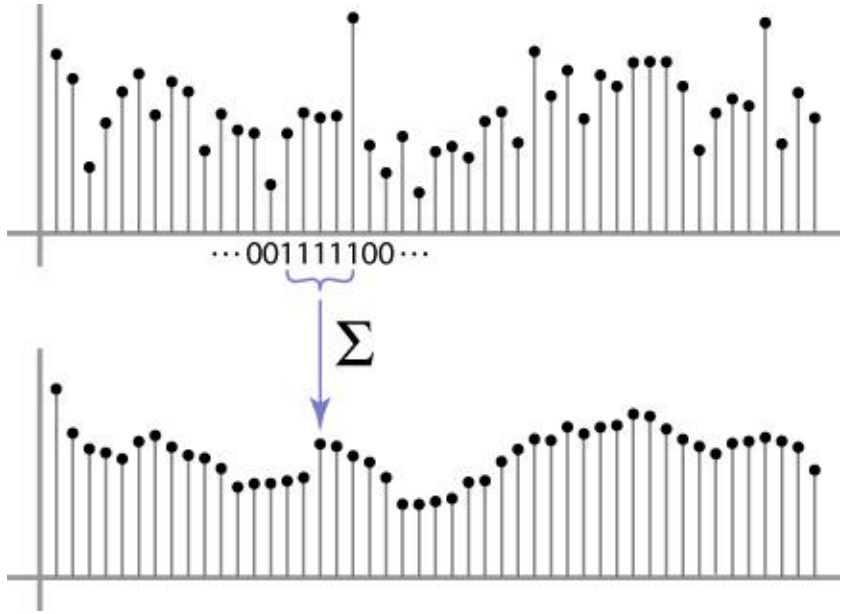
Convolutional operation: $f(x, w) = x * w$

- Local operation, shared weights over local regions
- Dimensionality of w much smaller than dimensionality of x
- Output (almost?) same size as input

1D convolutions

The convolution $(f * g)(t)$ of two functions $f(t)$ and $g(t)$ *computes the overlap in area*.





It is taking the average of the signal (smoothing), always use even (or odd?) number?? don't get it

2D convolutions

For a two-dimensional image I as our input, we want to use a two-dimensional kernel K:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n)$$

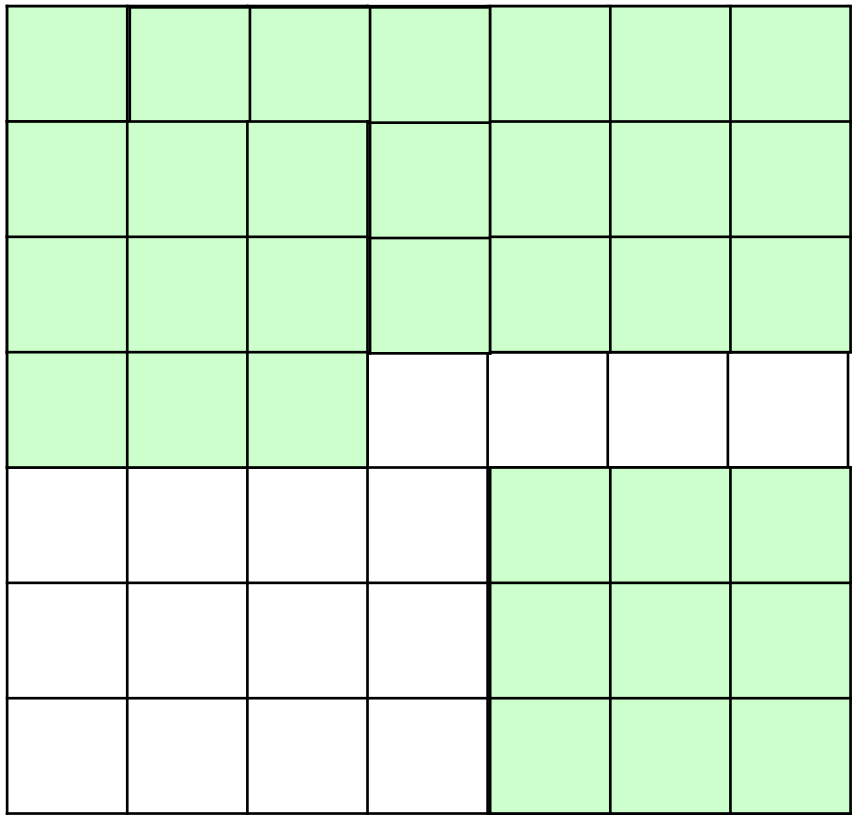
Convolution is commutative, and we can equivalently write:

$$S(i,j) = (K * I)(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n)$$

Neural networks libraries implement cross-correlation:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n)K(m,n)$$

2D convolution example



Input image: 7x7

Filter size: 3x3

Do the convolution by sliding the filter over all possible image locations.

What is the size of the output?

Other 2D convolution example

$$F[x,y] \quad \star \quad H[a,b] \qquad\qquad G[x,y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$\frac{1}{9}$$

1	1	1
1	1	1
1	1	1

$$G = H \star F$$

Other 2D example

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$F[x, y]$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

$G[x, y]$

Source: D. Lowe

Let’s test your convolution intuition

Original

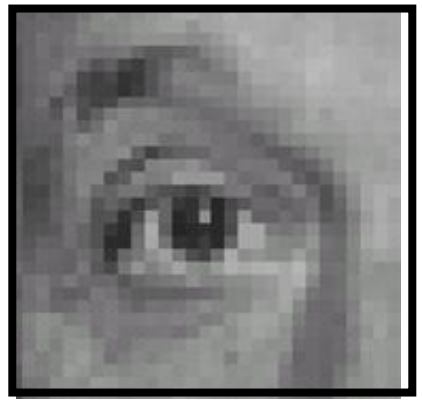
0	0	0
0	1	0
0	0	0

Filtered
(no change)

Let’s test your convolution intuition

Original

0	0	0
0	0	1
0	0	0

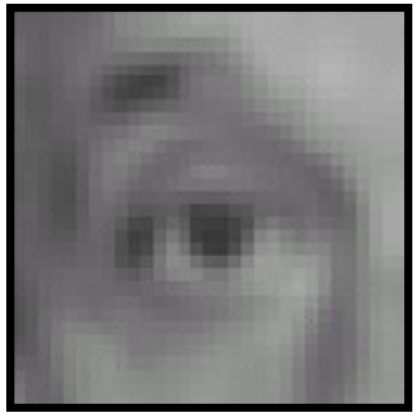


Filtered
(shift left)

Let’s test your convolution intuition

Original

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$



Filtered
(blur)

Let’s test your convolution intuition

Original

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Filtered
(sharpening)

Motivations for convolutions

Sparse interaction, or local connectivity.

- *The receptive field of the neuron, or the filter size.*
- *The connections are local in space (width and height), but full in depth.*
- *A set of learnable filters.*

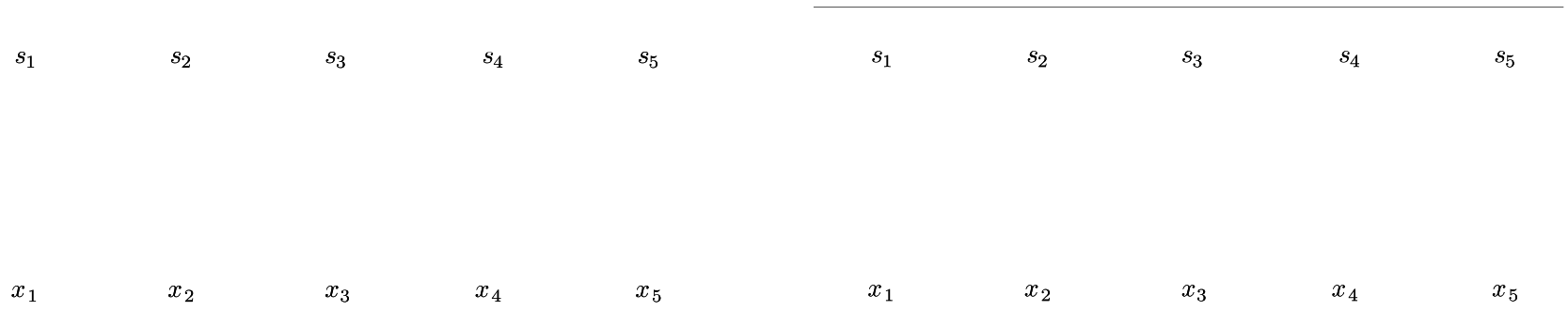
Parameters sharing, the weights are tied.

Equivariant representation (spatially): same operation at different places.

1. Sparsity

Sparse interaction, or local connectivity

- This is accomplished by making the kernel smaller than the input.
- reduces the memory requirements of the model
- improves its statistical efficiency.



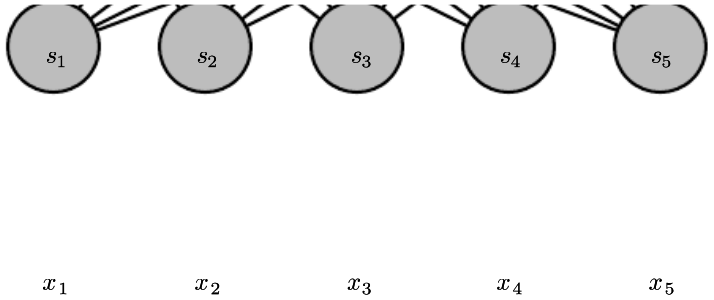
sparse connection

full connection

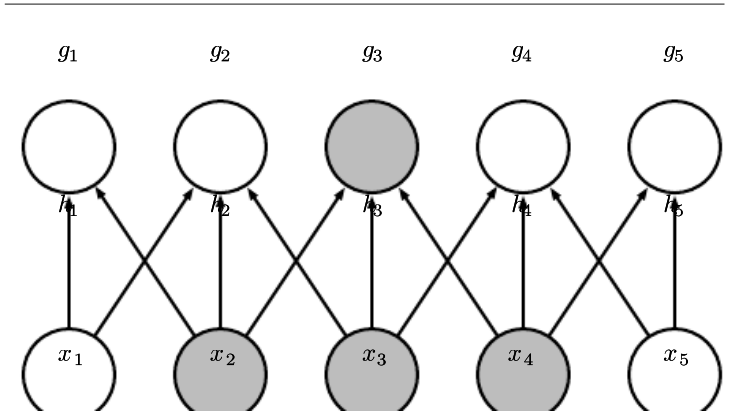
1. Sparsity

Sparse interaction, or local connectivity.

- Receptive field is the kernel/filter size.
- The receptive field of the units in the deeper layers of a convolutional network is larger than the receptive field of the units in the shallow layers.



convolution with a kernel of width 3

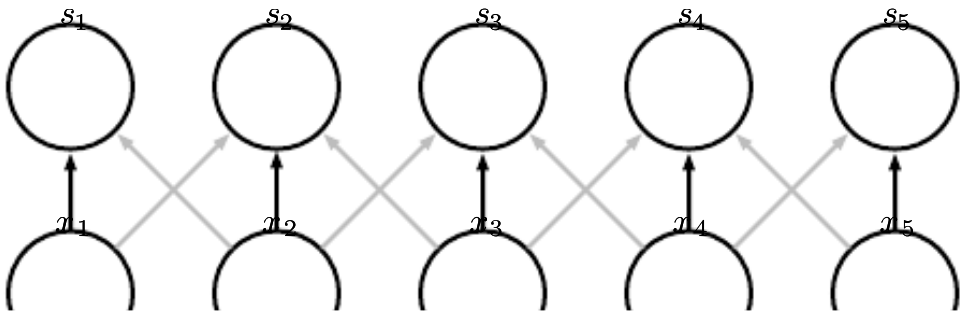


receptive field of the units in the deeper layers

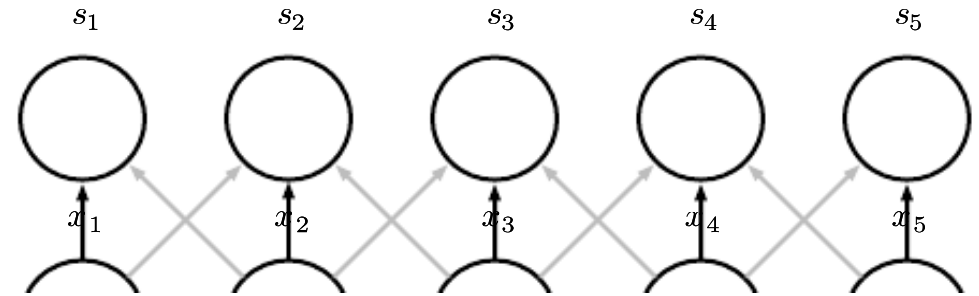
2. Parameter sharing

Parameters sharing, the weights are tied.

- refers to using the same parameter for more than one function in a model.
- each member of the kernel is used at every position of the input.



parameter sharing



no parameter sharing

3. Equivariance

Equivariant representation

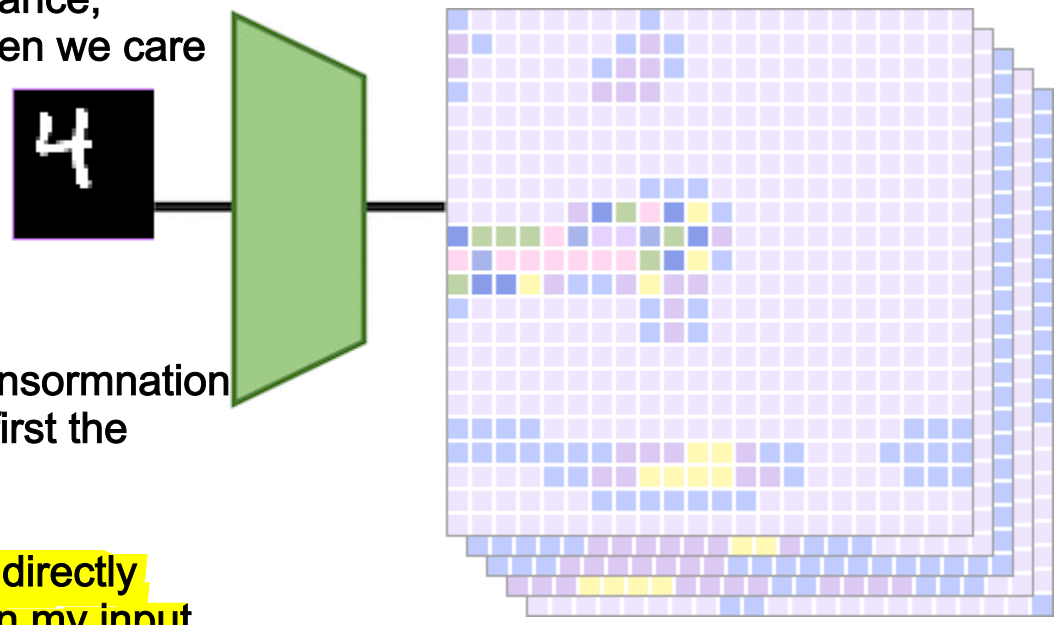
- *Parameter sharing causes the layer to have equivariance to translation.*
- *A function is equivariant if the input changes, the output changes in the same way.*
- *Why do we want equivariance to translation?*

all of the deep learning is about invariance, (invariance of the inputs). But very often we care also of equivariance.

x - > f(x)
| |
g(x) -.> f(g(x))

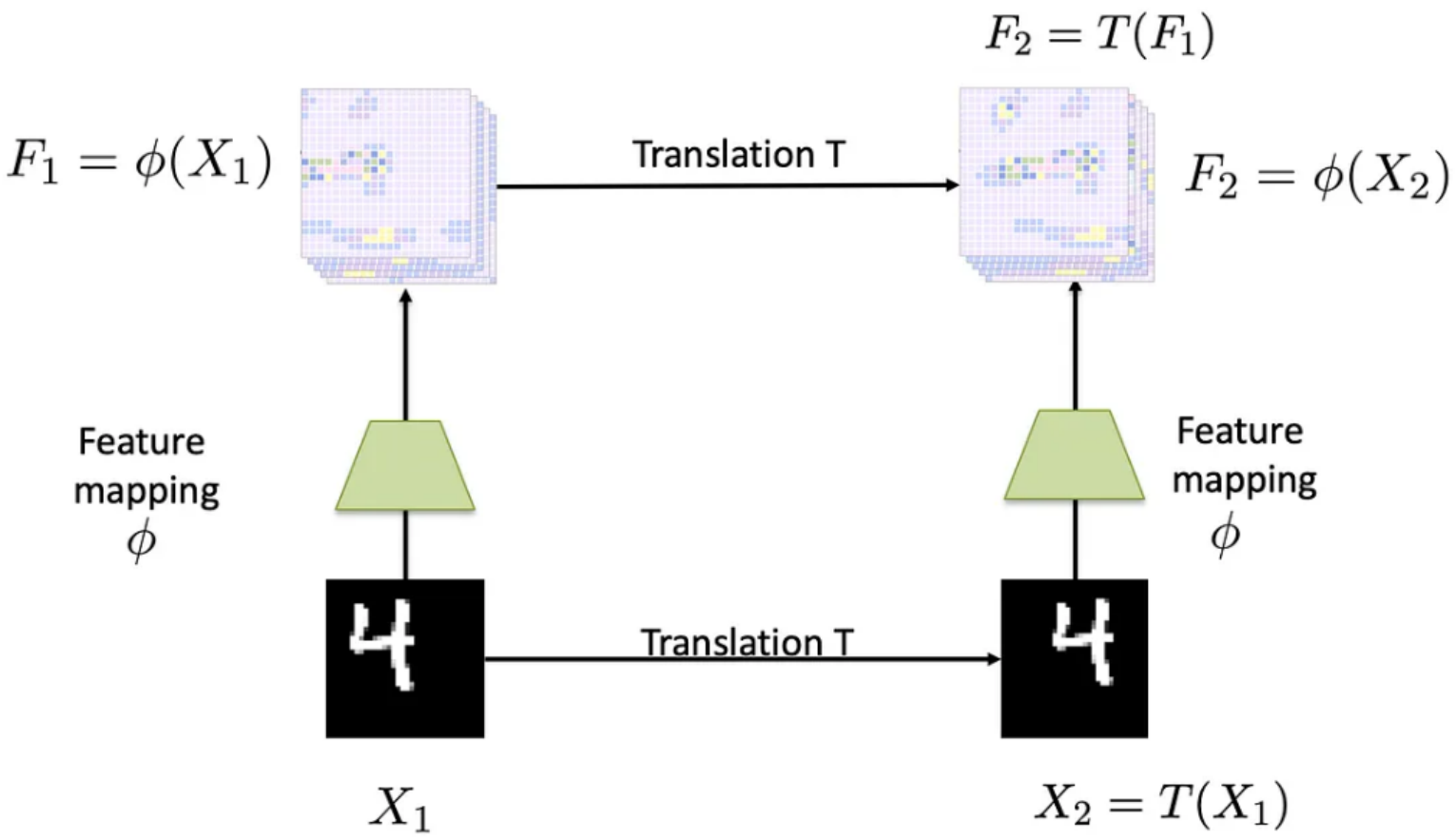
It doesn't mean if I do first a group transormnation and the apply te function or if I apply first the function and then the transformation

The amount changing in my output is directly proportional to the amount changing in my input



Our real objective is to find a neural mapping from images to predictions, which is invariant to all different geometric transformations to which objects could be subject to, for instance translations, rotations and projective distortions.

an equivariant mapping is a mapping which preserves the algebric structure of a transformation. As a particular case, a translation equivariant mapping is a mapping which, when the input is translated, leads to a translated mapping



Dealing with borders

We can’t convole border pixels, as filter windows extends beyond the image.

As is, this means that each convolution makes the image output smaller.

Solution: re-introduce a set of border pixels for every convolution.

zero-padding is the most weird to use because you add pixels which are not even in the range of the others, but it is the most widely used, so apparently it is not a big deal

Zero padding

Wrap around

Copy

Reflect

Convolutional networks pipeline

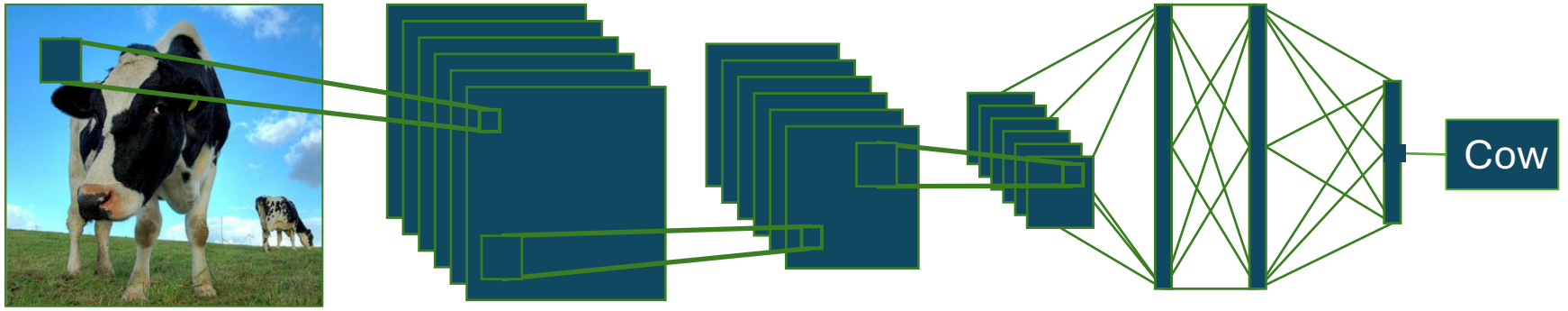
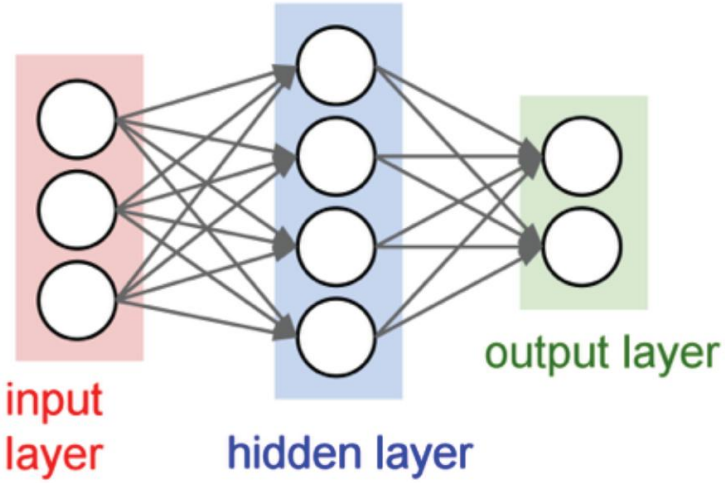


Image is the input, which should go through layers and ultimately predict label.

We want to *learn* the filter values to help us recognize classes.

3D Activations

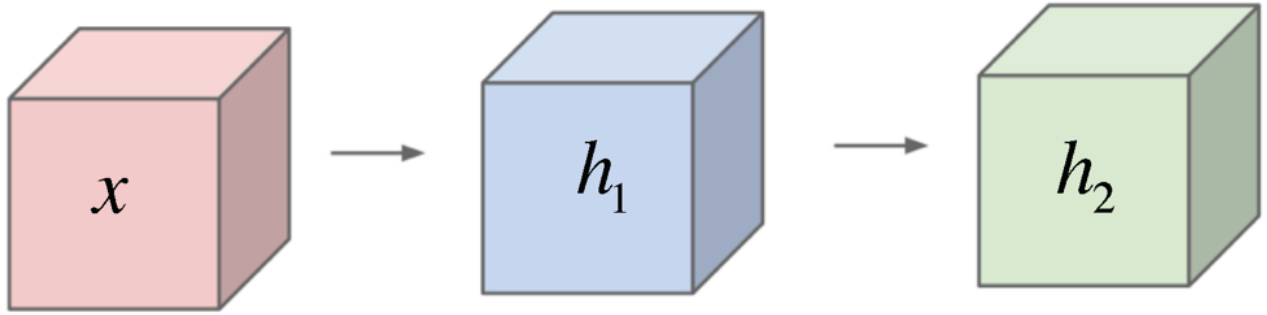
before:



(1D vectors)

with images now we have tensors with 3 channels

now:

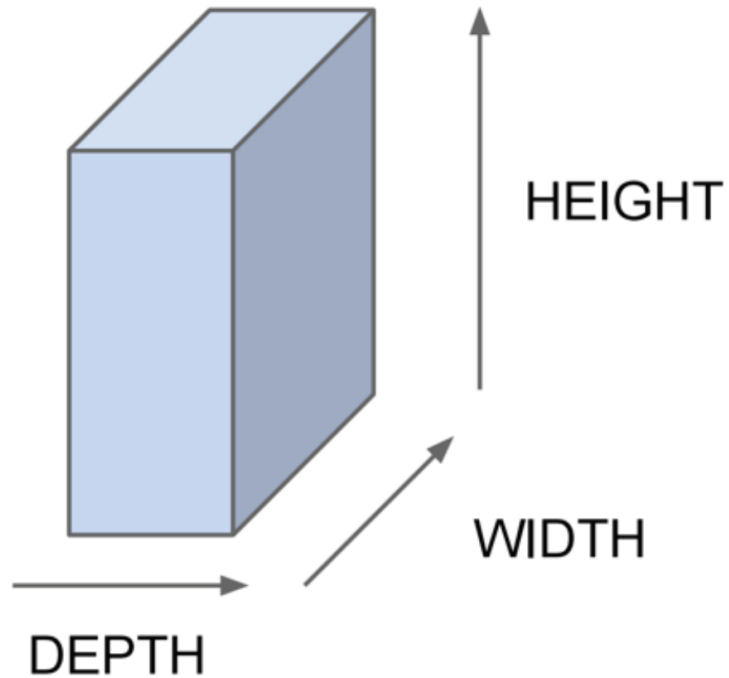


(3D arrays)

Figure: Andrej Karpathy

3D Activations

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

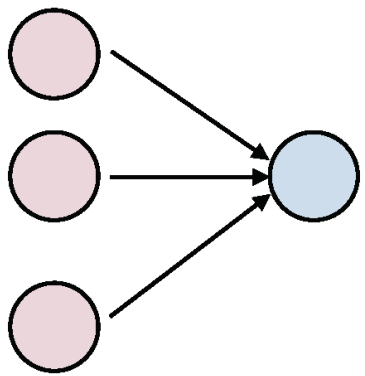


For example, a CIFAR-10 image is a 3x32x32 volume (3 depth — RGB channels, 32 height, 32 width)

Figure: Andrej Karpathy

3D Activations

1D Activations:



3D Activations:

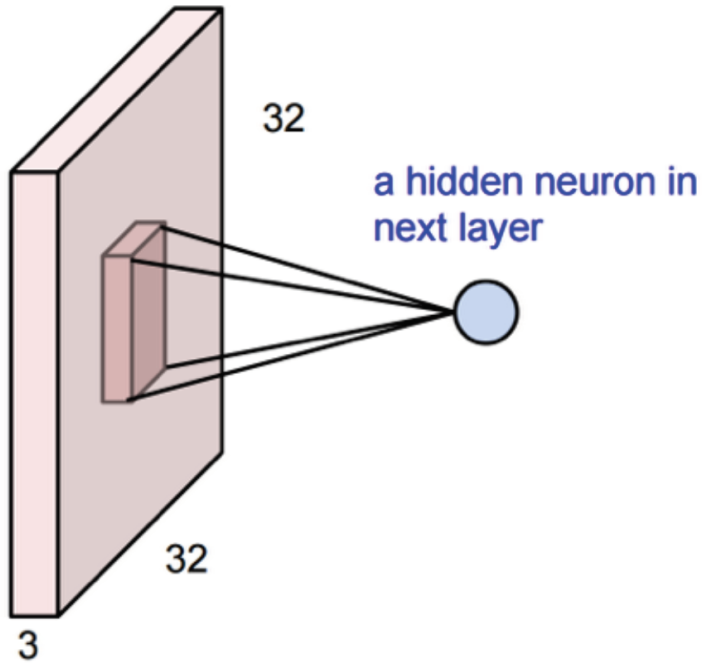
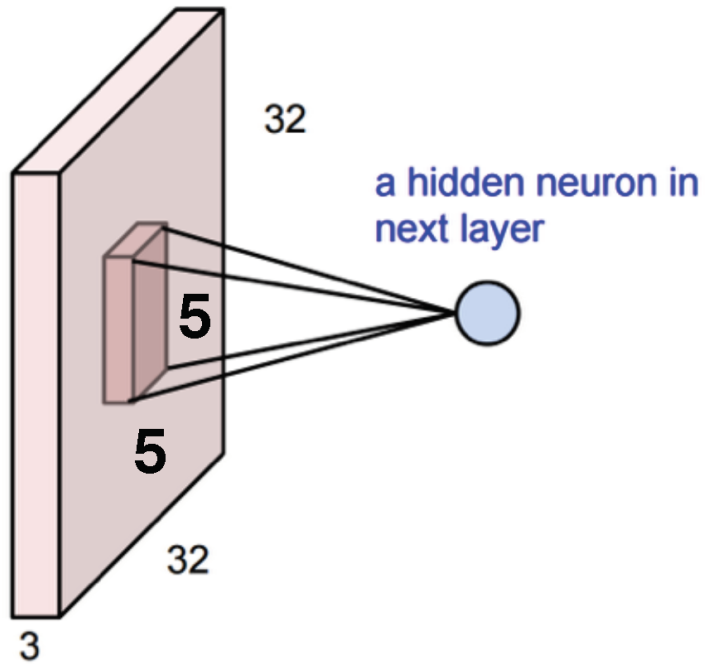


Figure: Andrej Karpathy

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

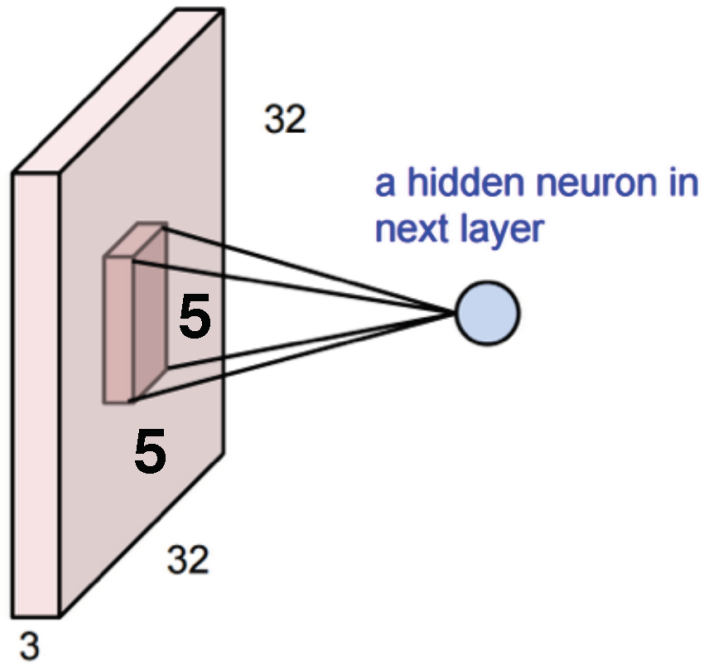


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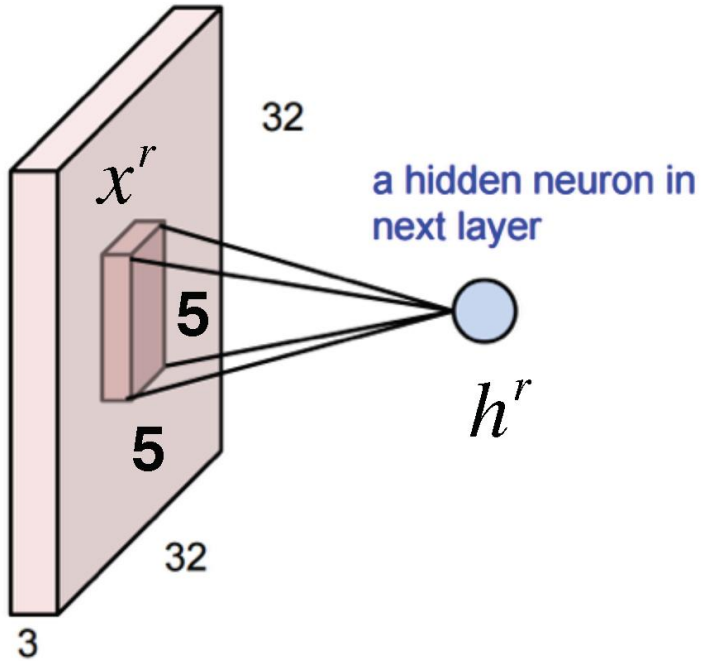
Figure: Andrej Karpathy

3D Activations



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

With output neuron h^r

Then the output is:

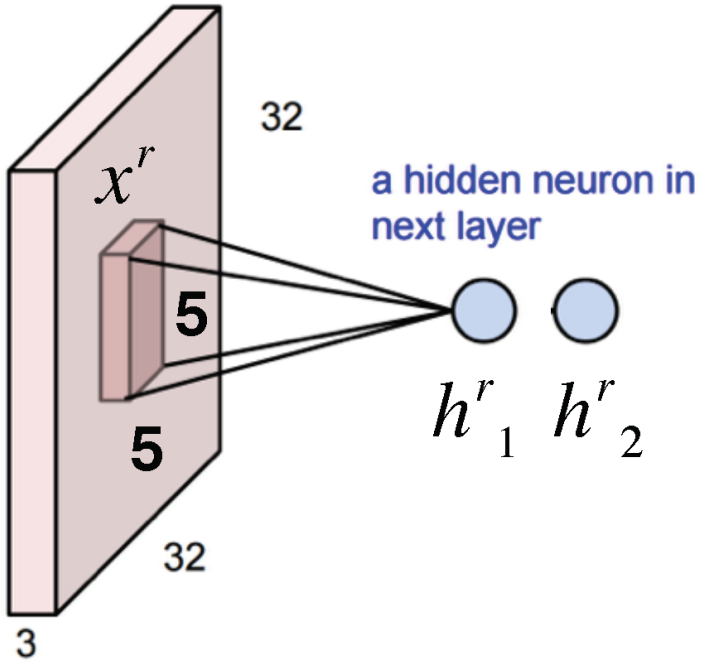
$$h^r = \sum_{ijk} x^r{}_{ijk} W_{ijk} + b$$

Sum over 3 axes

Figure: Andrej Karpathy

3D Activations

each individual filters create 1 output values, if i need multiple outputs i need multiple filters



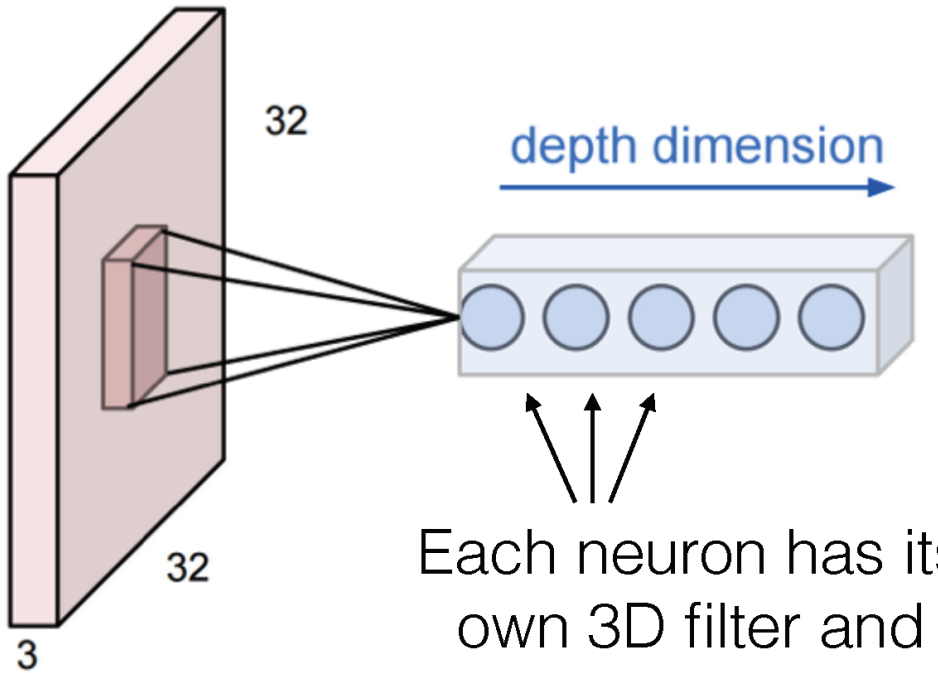
With **2** output neurons

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

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

Figure: Andrej Karpathy

3D Activations



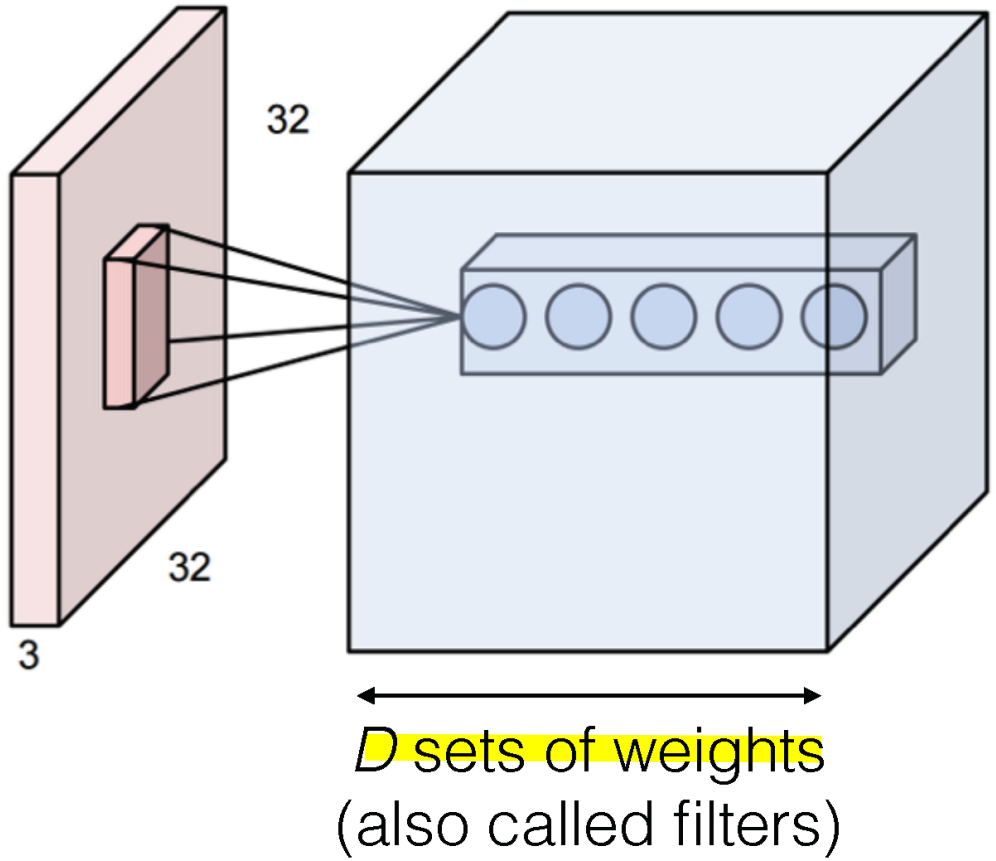
Each neuron has its own 3D filter and own (scalar) bias

We can keep adding more outputs

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

Figure: Andrej Karpathy

3D Activations



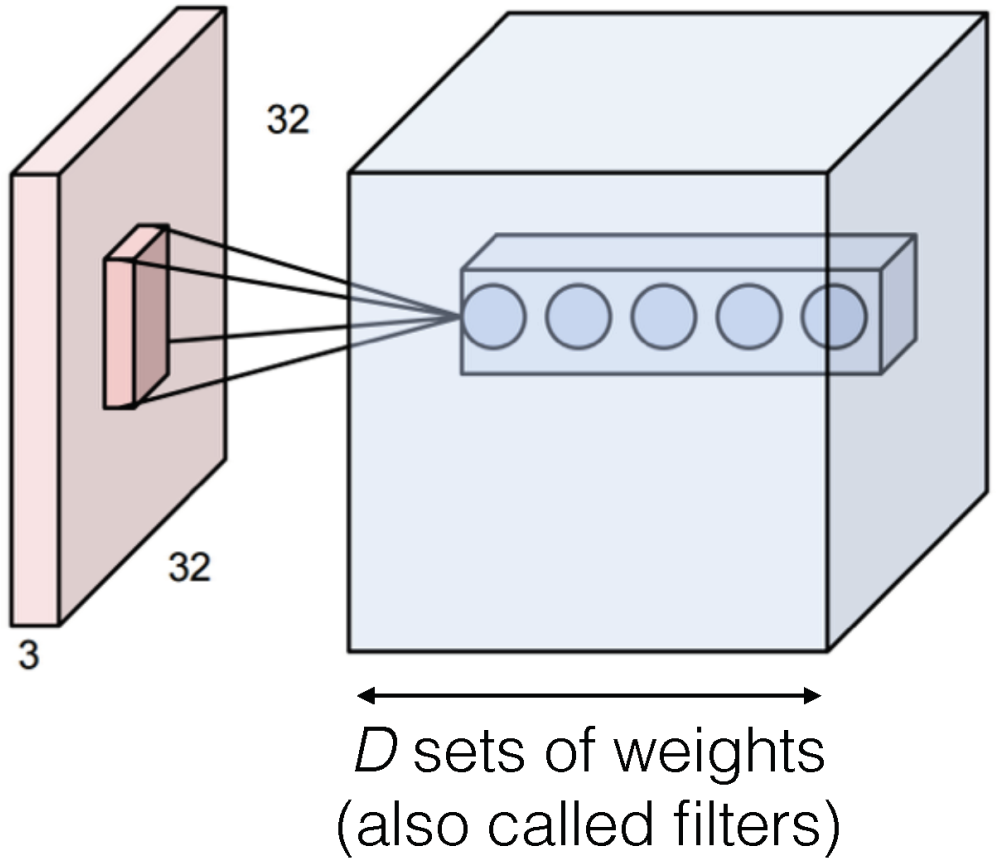
Now repeat this across the input

Weight sharing:

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

Figure: Andrej Karpathy

3D Activations



With weight sharing, this is called **convolution**

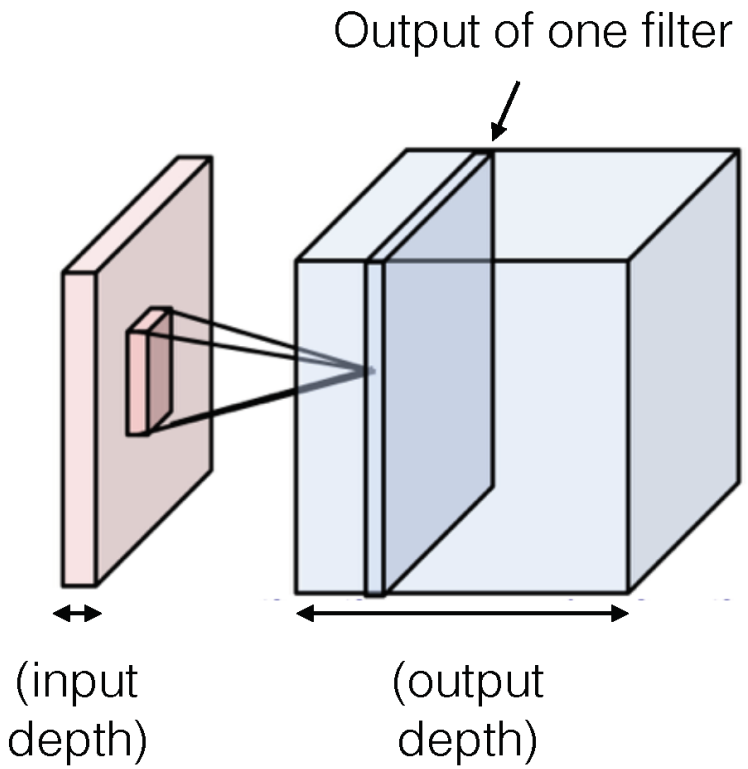
Without weight sharing, this is called a **locally connected layer**

Figure: Andrej Karpathy

each filter is one slice, it creates its own image which is of 1 channel dimension. Typically the value of channels is much higher compared to the one of the input

the weight are 4 dimensionals

3D Activations



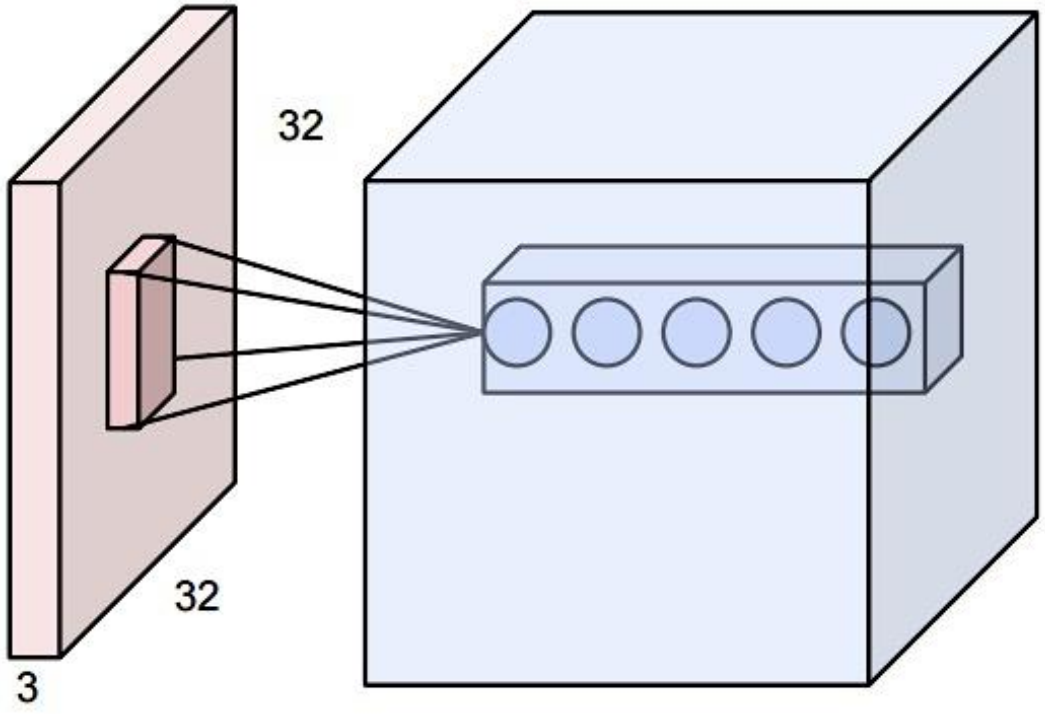
One set of weights gives one slice in the output

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)

Quick test



Q1: What does the 3 mean?

RGB

Q2: What is the output size for D filters (with padding)?

32x32xD

Q3: Does the output size depend on the input size or the filter size (with padding)?

Input size

Filters and layer dimensionality

First layer:

Input: 32x32x3 and A filters of size 5x5x3

Output: 32x32xA

Second layer:

Input: 32x32xA and B filters of size 5x5x[?]

Output size: 32x32x[?]

3D Activations

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

(Input)

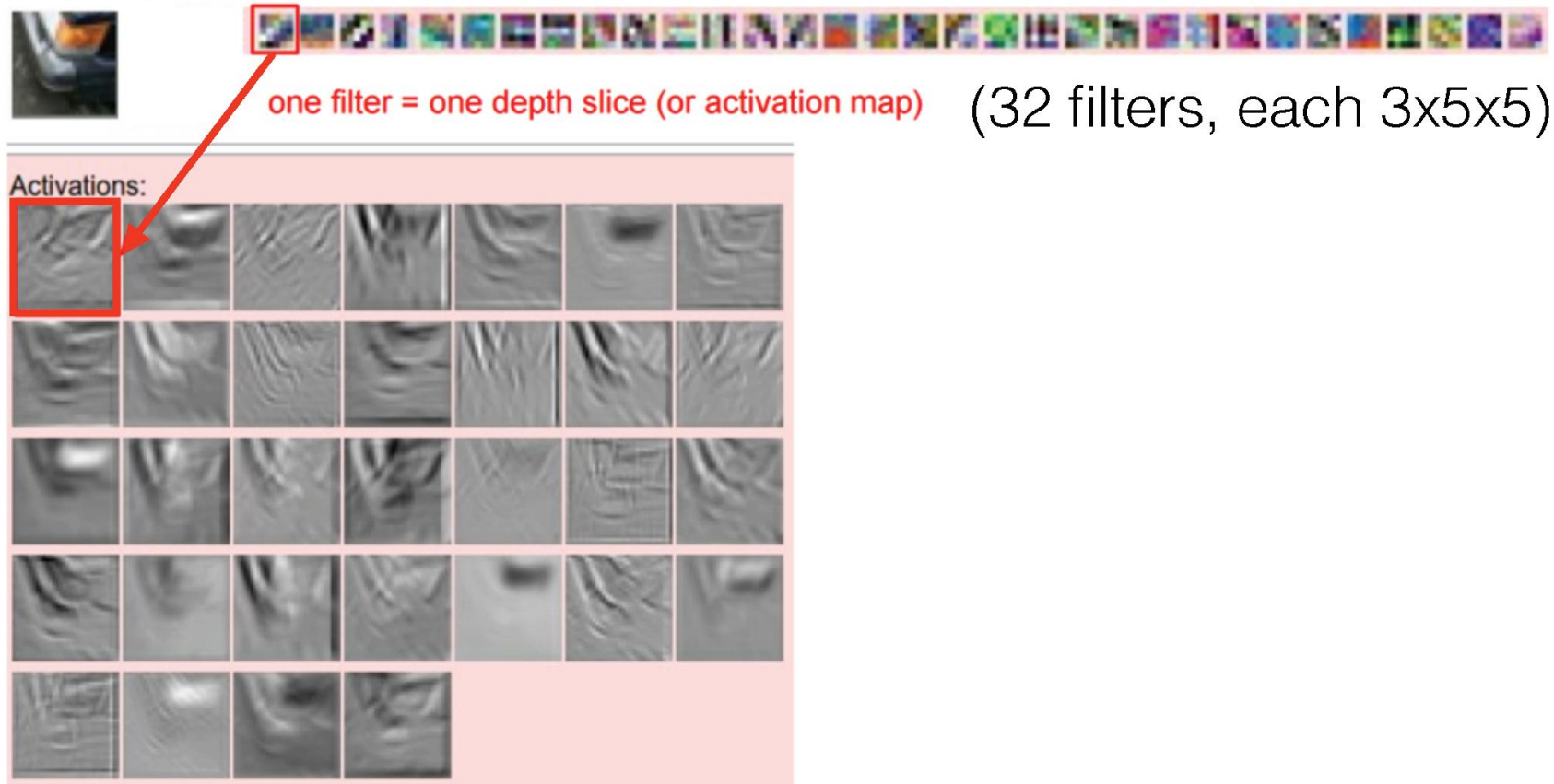


Figure: Andrej Karpathy

3D Activations

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

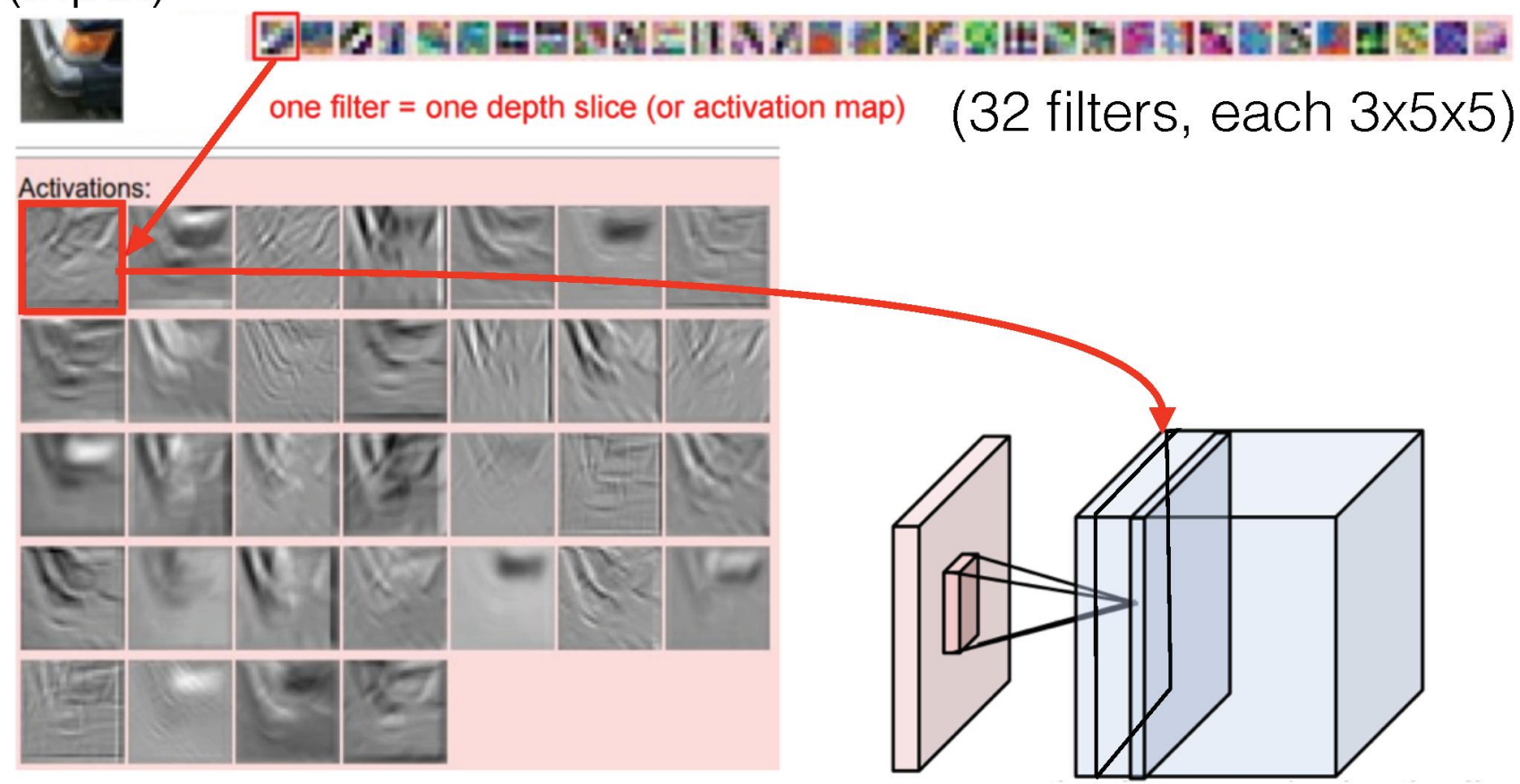


Figure: Andrej Karpathy

3D Activations

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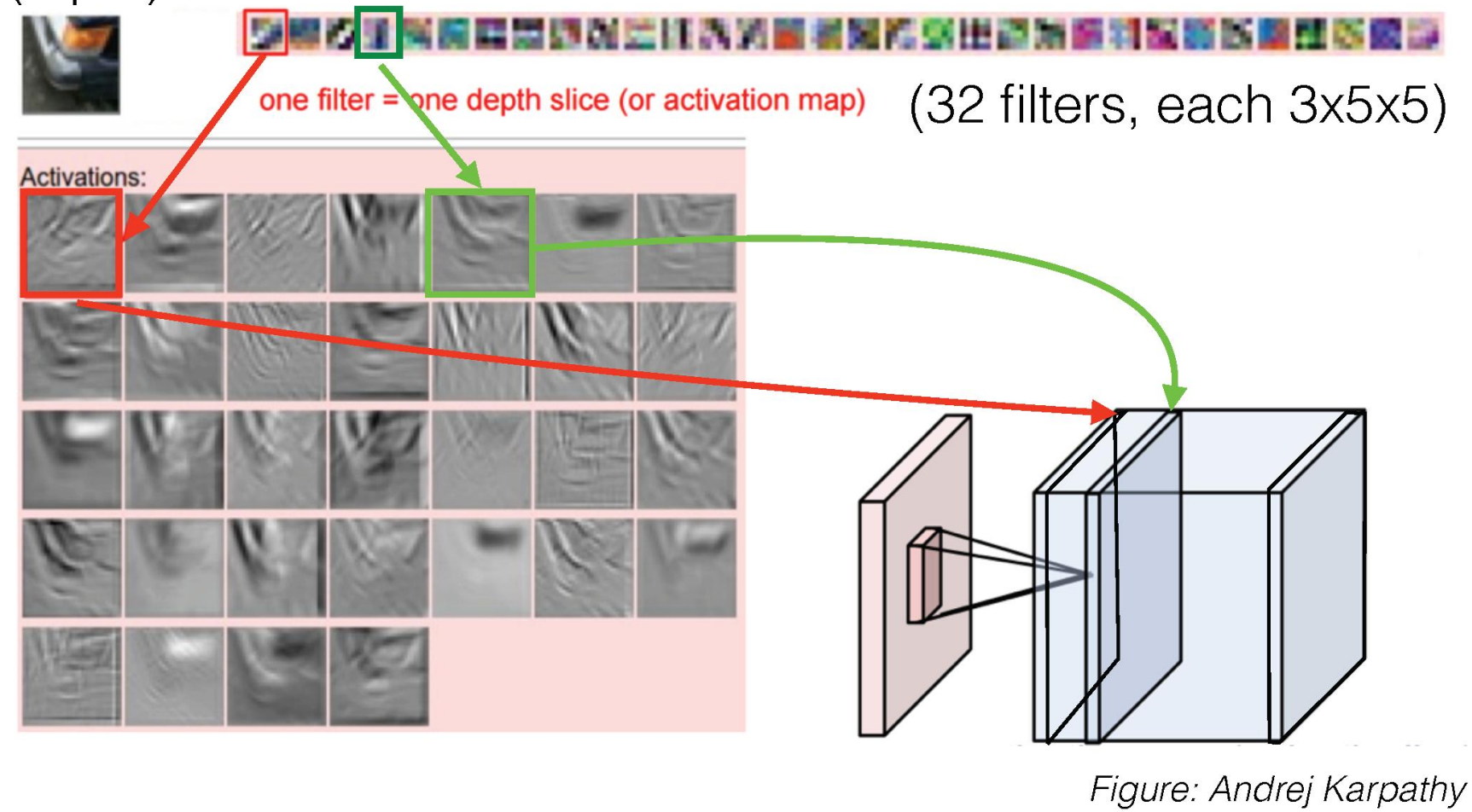

Figure: Andrej Karpathy

3D Activations

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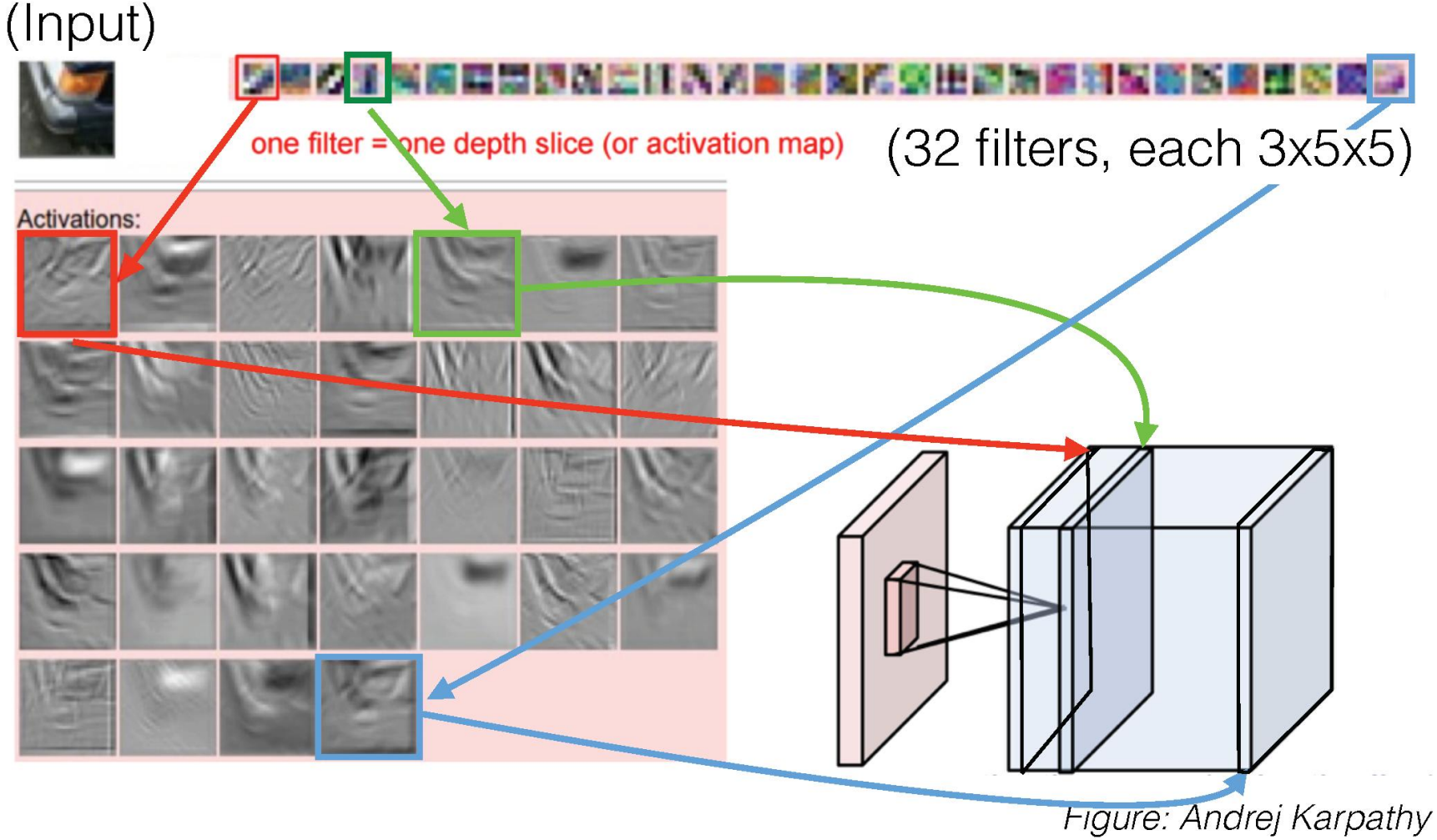
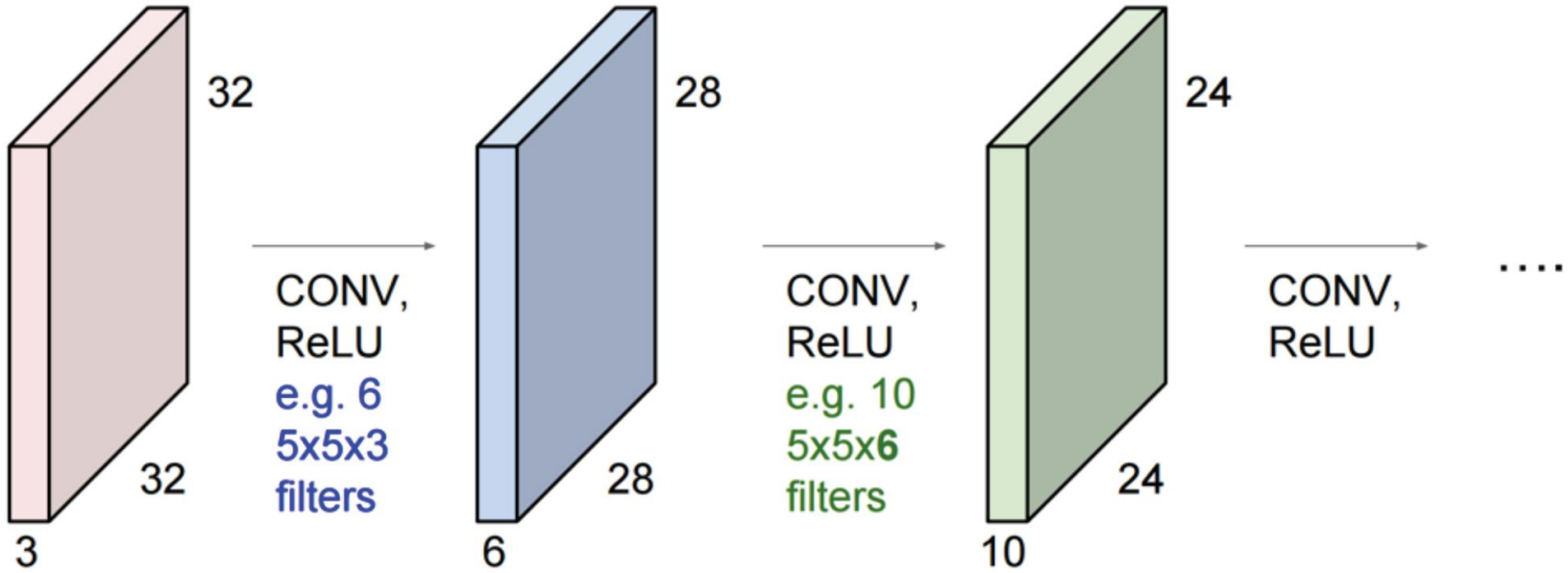


Figure: Andrej Karpathy

Putting it together

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



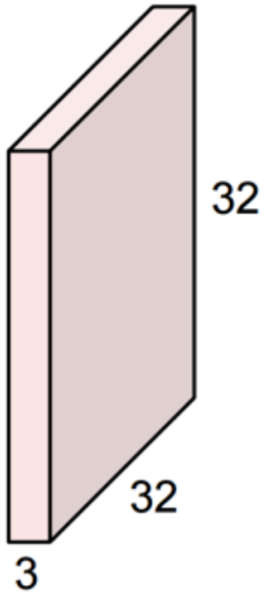
if no padding the output dimension is input-kern_size+1

Putting it together

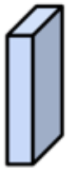
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image



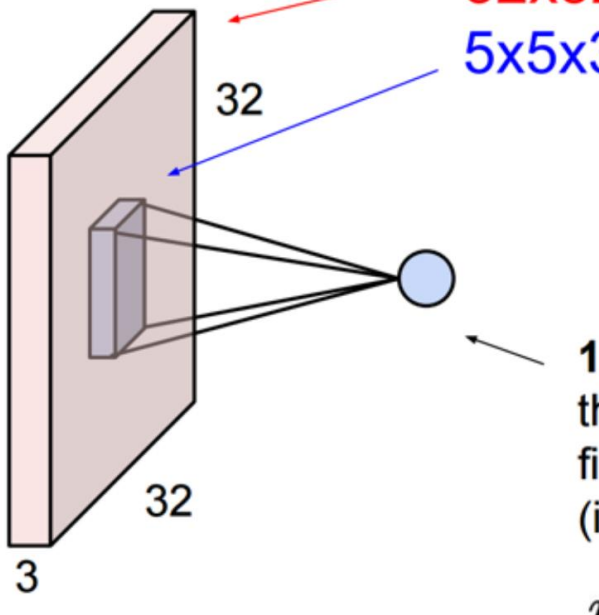
5x5x3 filter



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

Putting it together

Convolution Layer



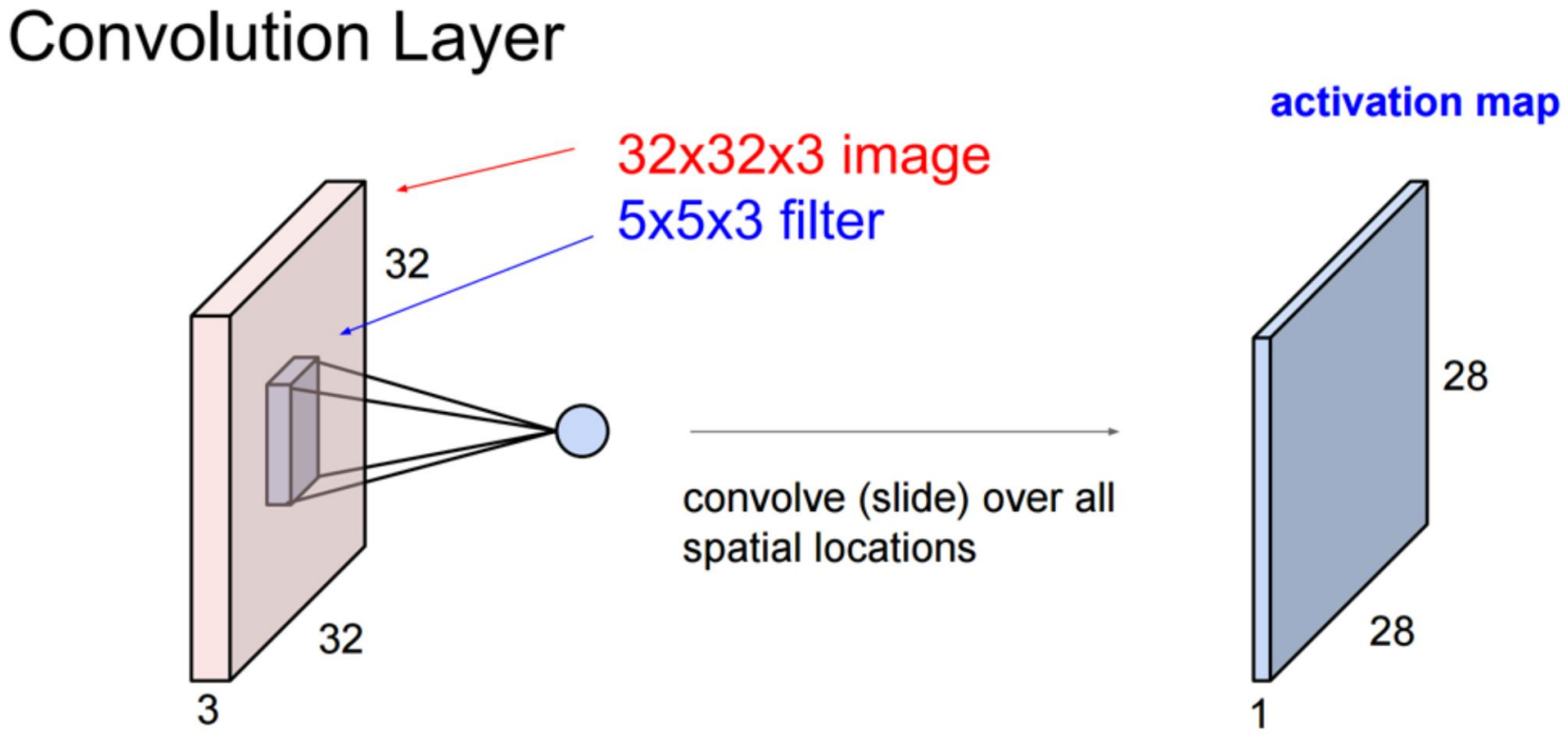
32x32x3 image

5x5x3 filter w

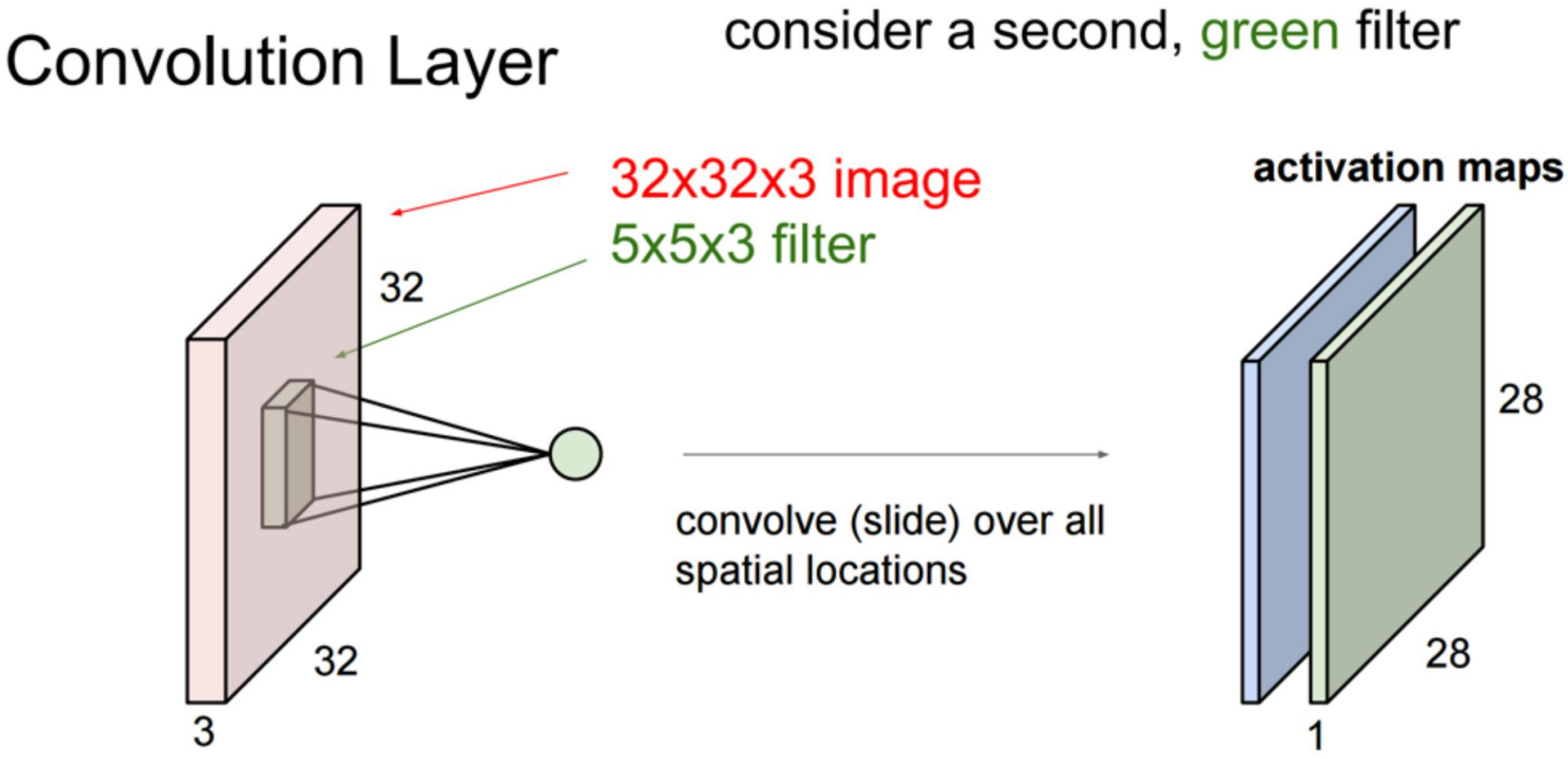
1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Putting it together

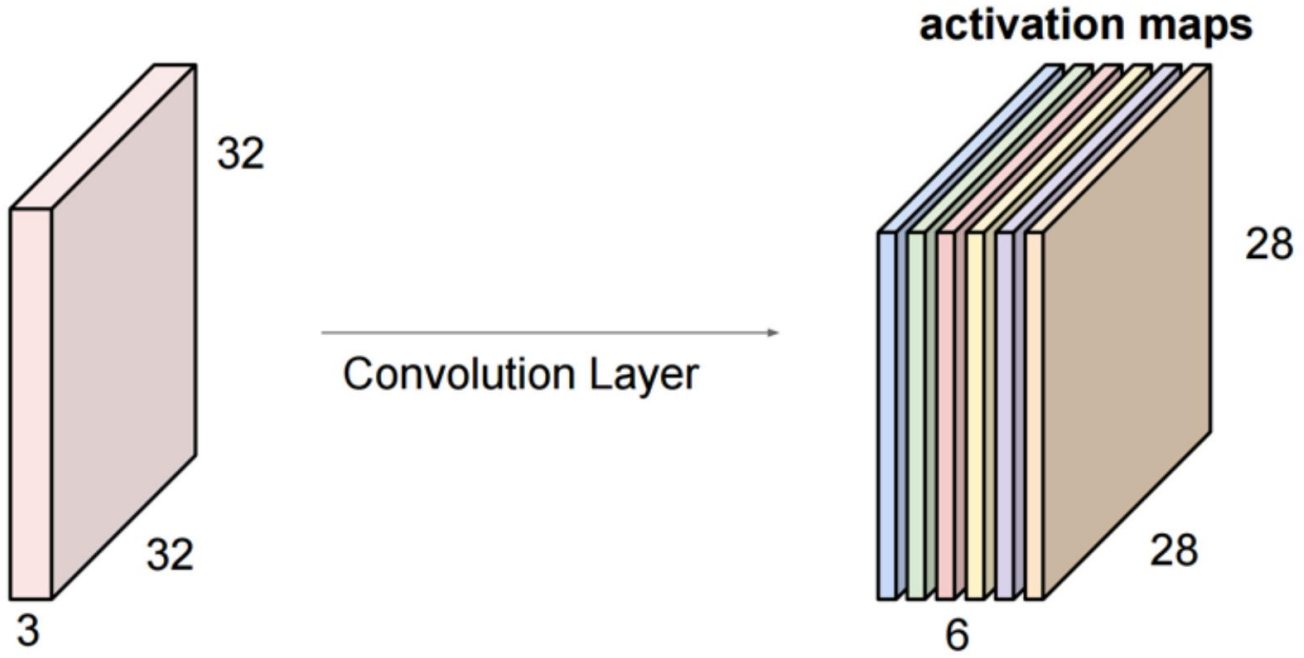


Putting it together



Putting it together

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!

Break

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?

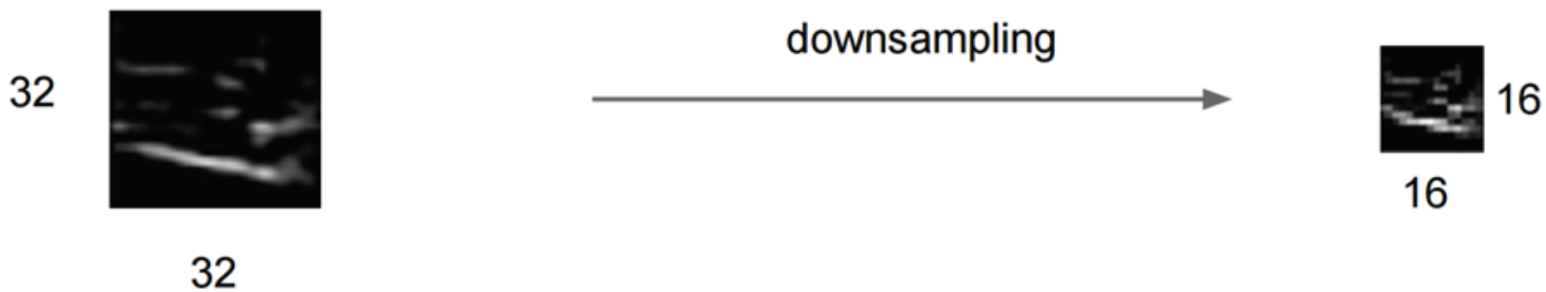
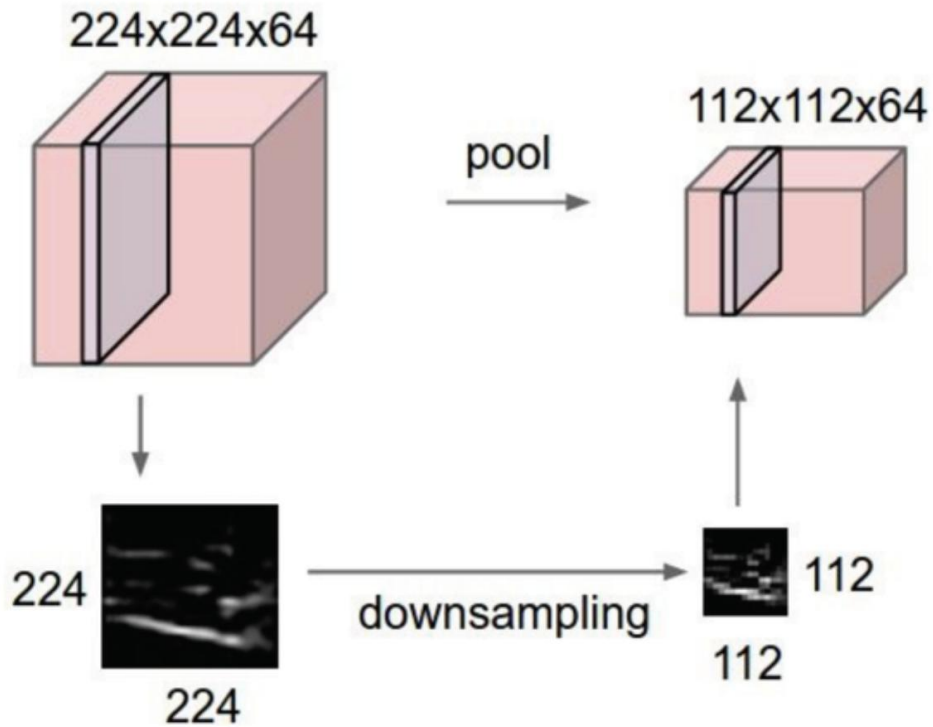


Figure: Andrej Karpathy

Pooling

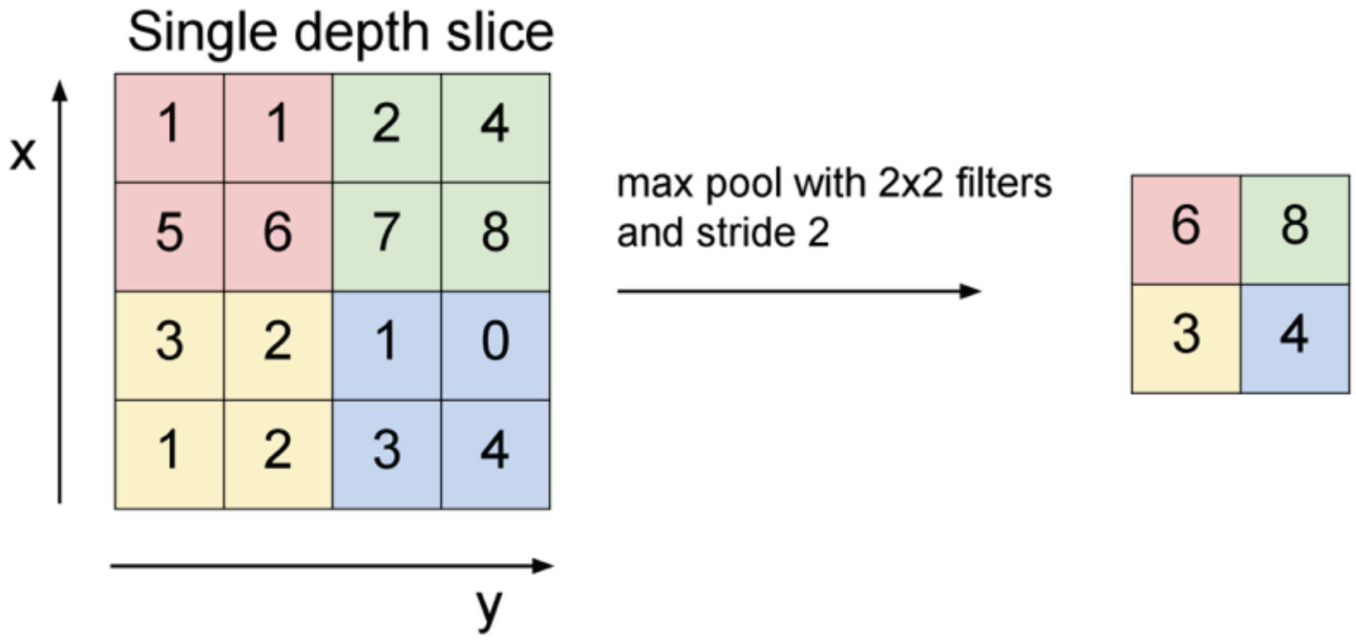
- makes the representations smaller and more manageable
- operates over each activation map independently:



Max Pooling

Why max pooling and not average?

We want to keep the information where the activation is higher



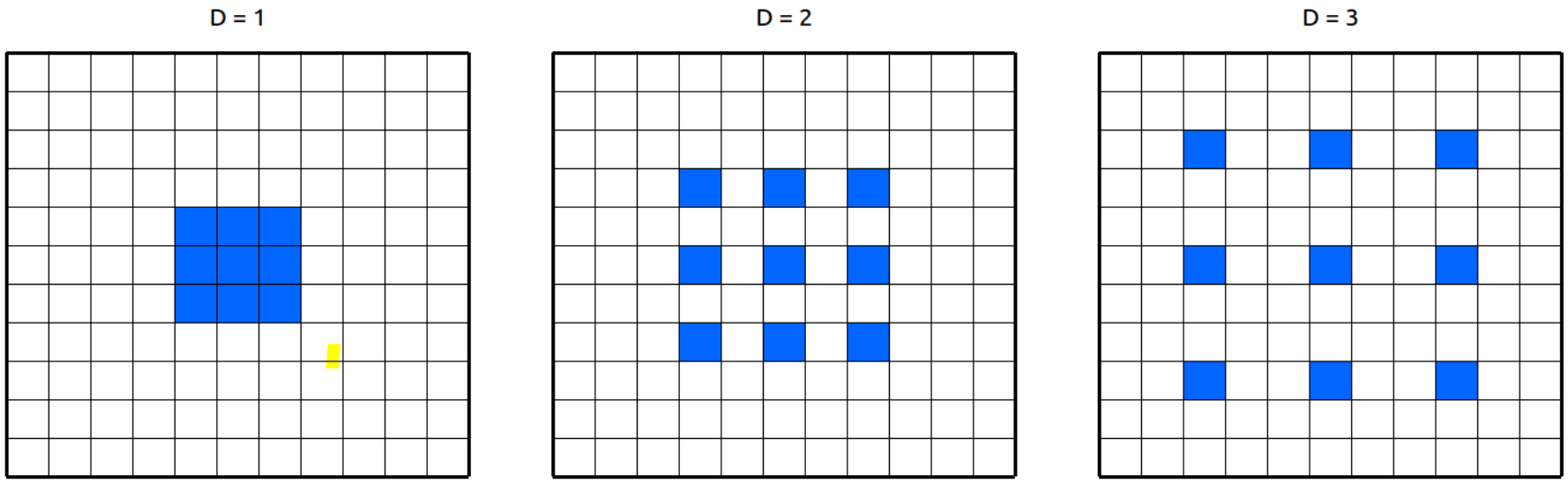
What's the backprop rule for max pooling?

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

Figure: Andrej Karpathy

Dilated convolutions

Enlarge receptive field without increasing parameter count.



1x1 convolutions

Generally, the goal of a convolutional layer is to learn local spatial filters.

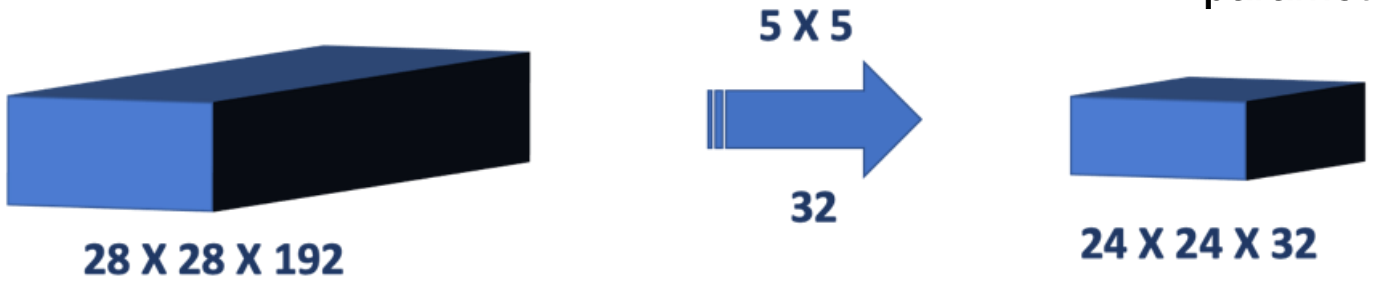
Special case: 1x1 convolutions.

Example: input is [32x32x3], then a 1x1 convolution is a 3-D dot product.

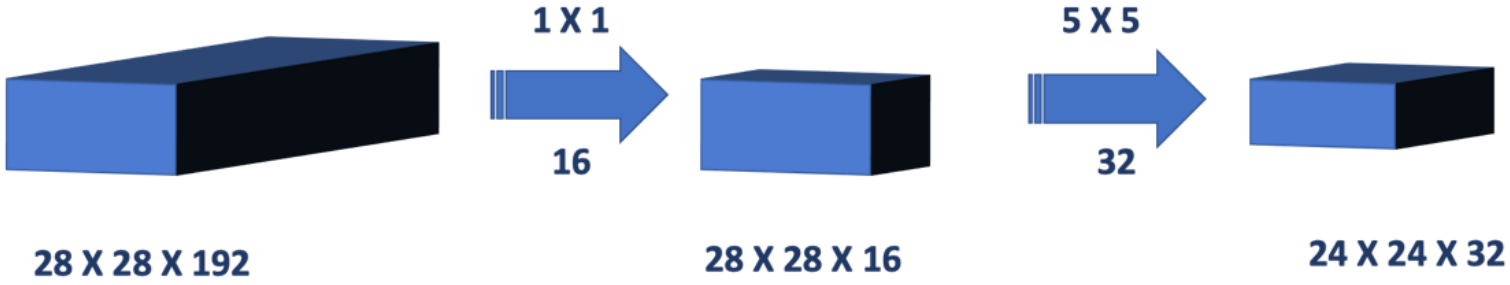
1x1 convolutions learn to mix information across channels.

1x1 convolutions

to redice the number of channels I could do convolution with a fewer number of channels (depth) but this cost me a lot of operation and weight parameters



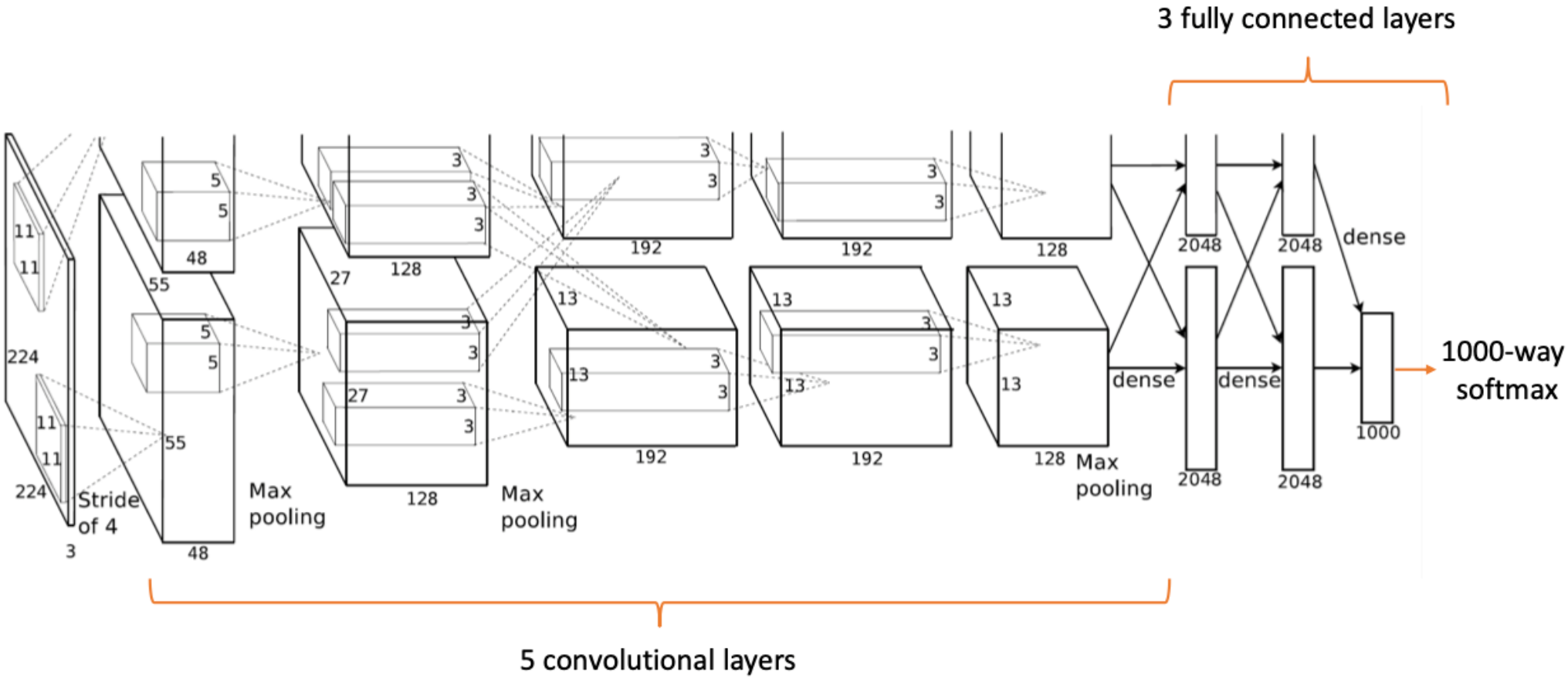
Number of Operations : (28X28X32) X (5X5X192) = 120.422 Million Ops



Number of Operations for 1 X 1 Conv Step : (28X28X16) X (1X1X192) = 2.4 Million Ops
Number of Operations for 5 X 5 Conv Step : (28X28X32) X (5X5X16) = 10 Million Ops
Total Number of Operations = 12.4 Million Ops

A more practical approach is to use a linear node for each of the input channel I want and use it to reduce the dimension with much less parameters

AlexNet

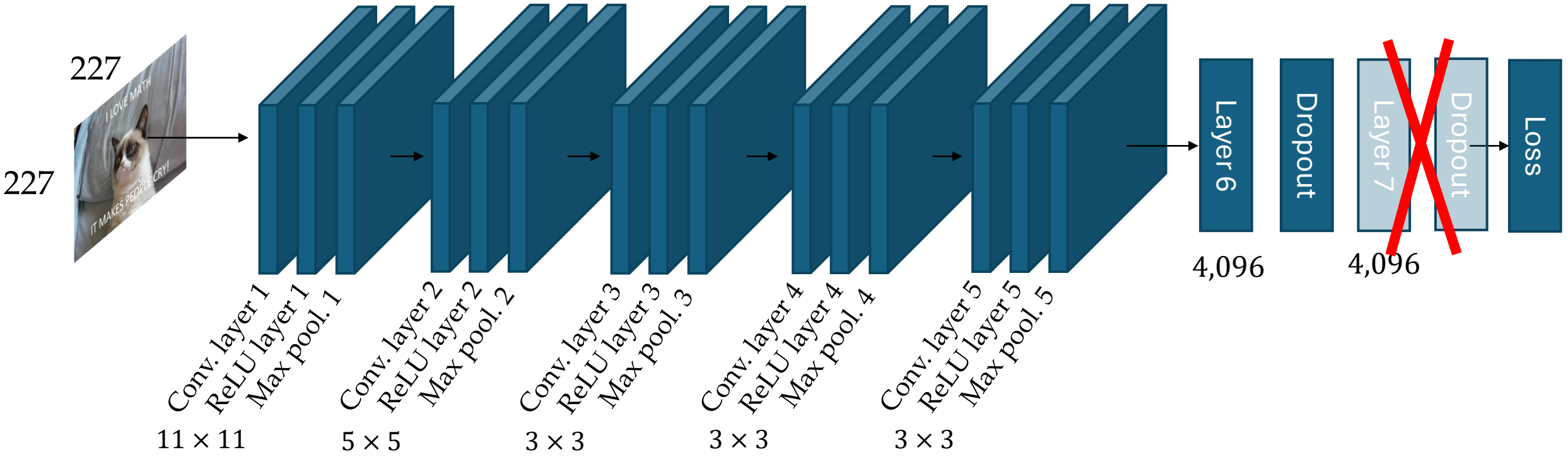


Where are most of the parameters?

Almost all the parameters are in the fully connected layer

Removing parameters

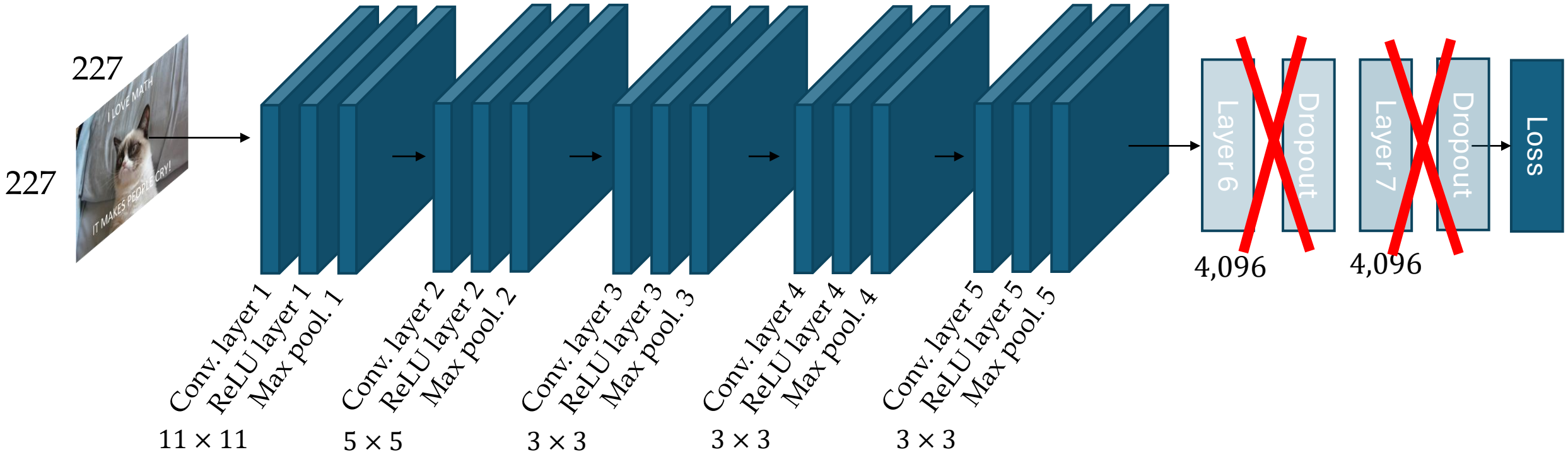
1.1% drop in performance, 16 million less parameters



Removing parameters

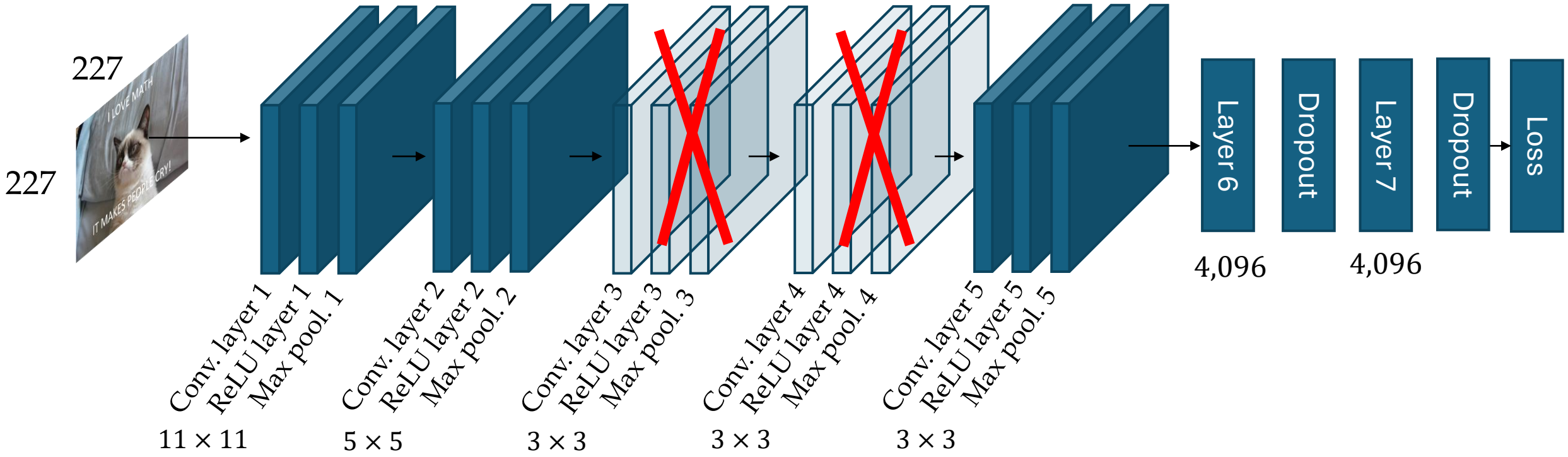
I drop most of my parameters but I perform almost the same

5.7% drop in performance, 50 million less parameters



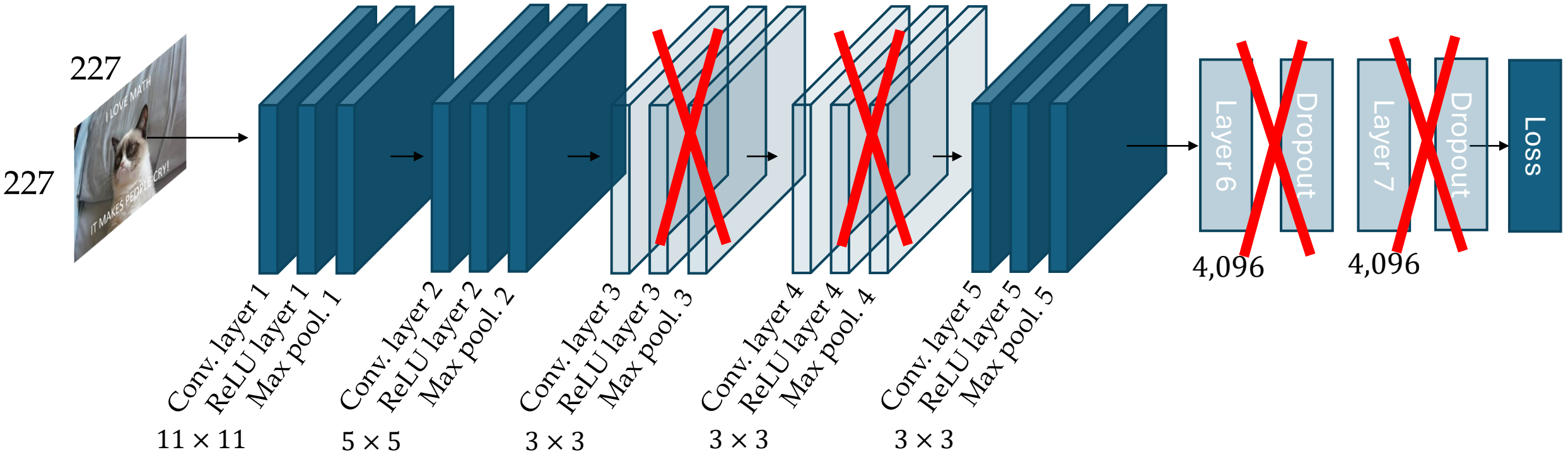
Removing parameters

3.0% drop in performance, 1 million less parameters. Why?



Removing parameters

33.5% drop in performance. Depth is crucial.



Key ingredient for deeper networks: residuals

these elements are everywhere and rule out most of deep learning.

Let's say we have the neural network nonlinearity $a = F(x)$.

maybe it is easier to learn the difference instead of the transformation

Perhaps easier to learn a function $a = F(x)$ to model differences $a \sim \delta y$ than to model absolutes $a \sim y$.

Otherwise, you may need to model the magnitude and the direction of activations

Think of it like in input normalization → you normalize around 0

Think of it like in regression → you model differences around the mean value

"Residual idea": Let neural networks explicitly model difference mappings

$$F(x) = H(x) - x \Rightarrow H(x) = F(x) + x$$

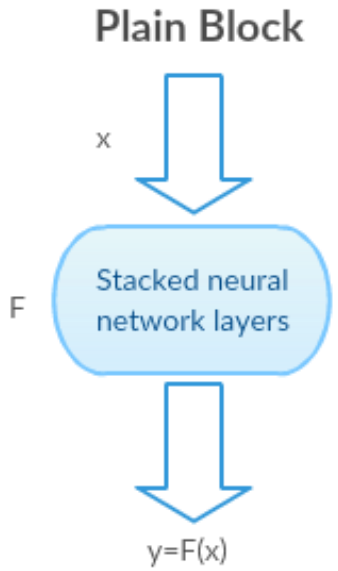
$F(x)$ are the stacked nonlinearities

x is the input to the nonlinear layer.

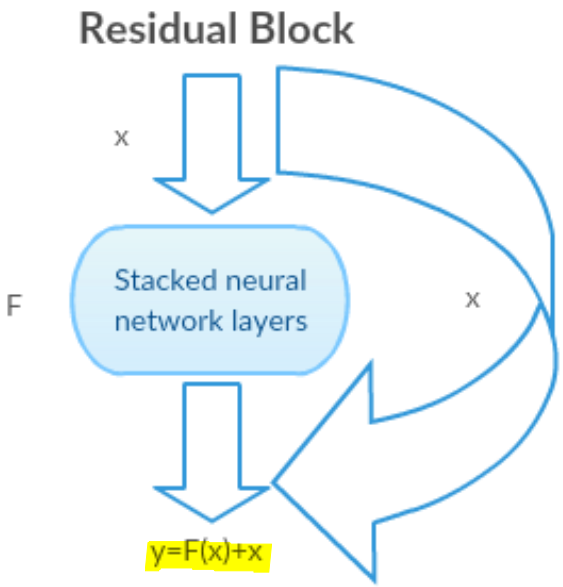
to add the input, the output must be of the same size. So we usually apply it after two conv layers so that we can transform the output of the first back into the dimension of its input, in order to be able to sum it afterwards

The residual block

They're useful because solves the problem of vanishing gradients, when I do backprop the derivative of H(x) wrt x will be the der of F plus 1, this one avoid the gradient to become too small



Hard to get F(x)=x and make y=x an identity mapping



Easy to get F(x)=0 and make y=x an identity mapping

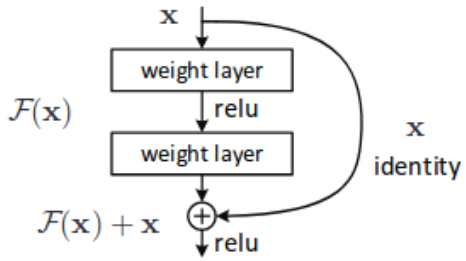
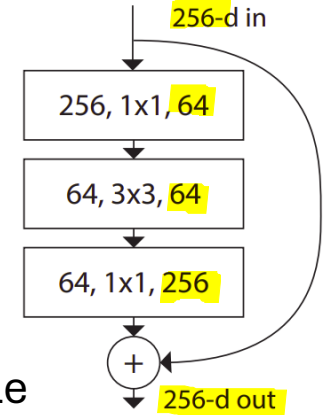


Figure 2. Residual learning: a building block.

Example



Also it has been shown that since the residual block instead of learning a complete transformation $H(x)$, layers learn the residual function $F(x)=H(x)-x$. Learning small adjustments or residuals is considerably easier than learning the full mapping, particularly as networks grow deeper. This reformulation of the learning problem reduces the complexity of the optimization landscape, allowing gradient-based algorithms to converge more rapidly and find better solutions with fewer training iterations.

Performance degration gone

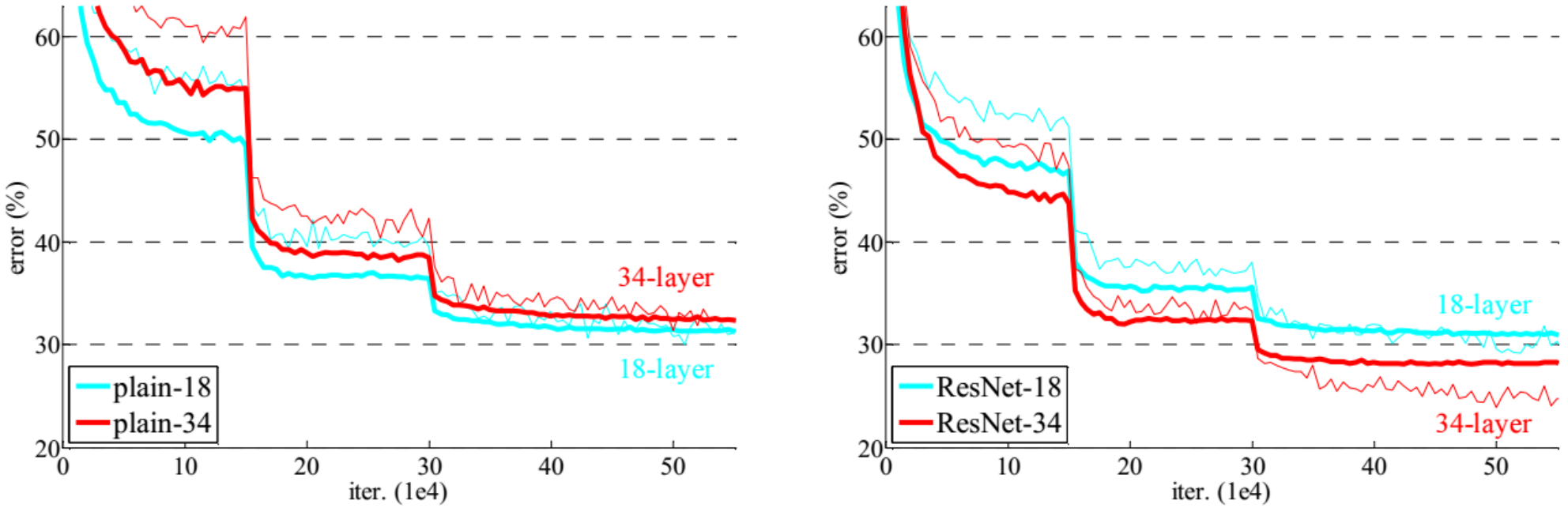
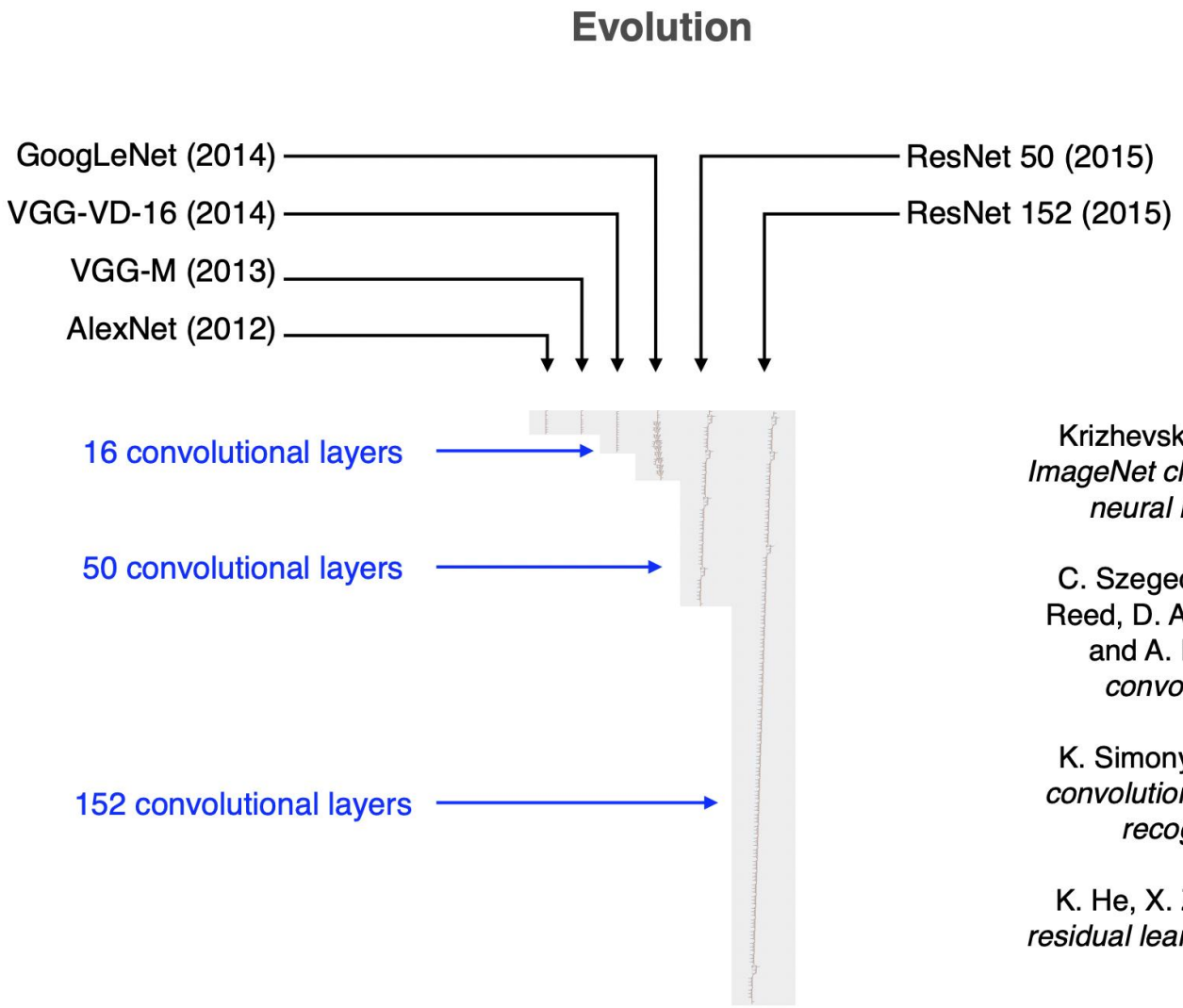


Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

ResNet is a record-breaker: (1) depth



Krizhevsky, I. Sutskever, and G. E. Hinton. *ImageNet classification with deep convolutional neural networks*. In Proc. NIPS, 2012.

C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. *Going deeper with convolutions*. In Proc. CVPR, 2015.

K. Simonyan and A. Zisserman. *Very deep convolutional networks for large-scale image recognition*. In Proc. ICLR, 2015.

K. He, X. Zhang, S. Ren, and J. Sun. *Deep residual learning for image recognition*. In Proc. CVPR, 2016.

Image credit: Andrea Vedaldi

ResNet is a record-breaker: (2) performance

Very low ImageNet errors with networks that can grow to 1000 layers.

method	top-5 err. (**test**)
VGG [41] (ILSVRC'14)	7.32
GoogLeNet [44] (ILSVRC'14)	6.66
VGG [41] (v5)	6.8
PReLU-net [13]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	**3.57**

Table 5. Error rates (%) of **ensembles**. The top-5 error is on the test set of ImageNet and reported by the test server.

ResNet is a record-breaker: (3) influence

DL1 24/25:

Deep **residual** learning for image recognition
K **He**, X Zhang, S Ren, J Sun - Proceedings of the IEEE …, 2016 - openaccess.thecvf.com
… as learning **residual** functions with … **residual networks** are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate **residual** …
☆ Save 99 Cite Cited by 242319 Related articles All 65 versions »

DL1 25/26:

Deep residual learning for **image recognition**
K He, X Zhang, S Ren, J Sun - … and **pattern recognition**, 2016 - openaccess.thecvf.com
… **Deeper** neural **networks** are more difficult to train. We present a **residual learning** framework to ease the training of **networks** that are substantially **deeper** than those used previously. …
☆ Save 99 Cite Cited by 290057 Related articles All 53 versions »

Convolutional networks beyond classification

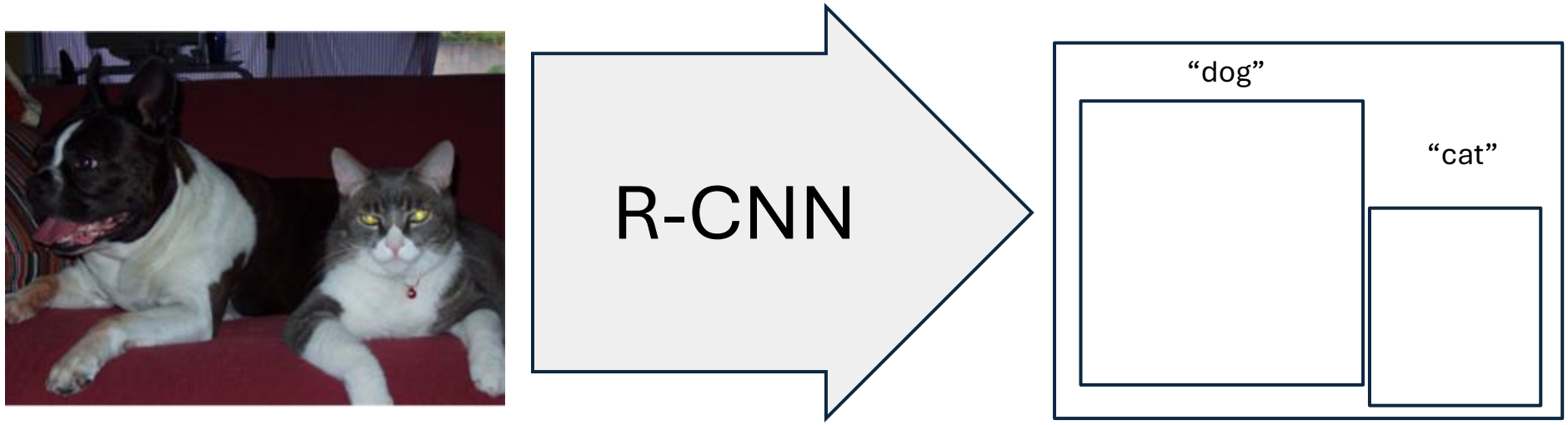
Detection, localization, and explanation

Object detection

Goal: correctly identify where the main objects are.

This task is called *object detection*.

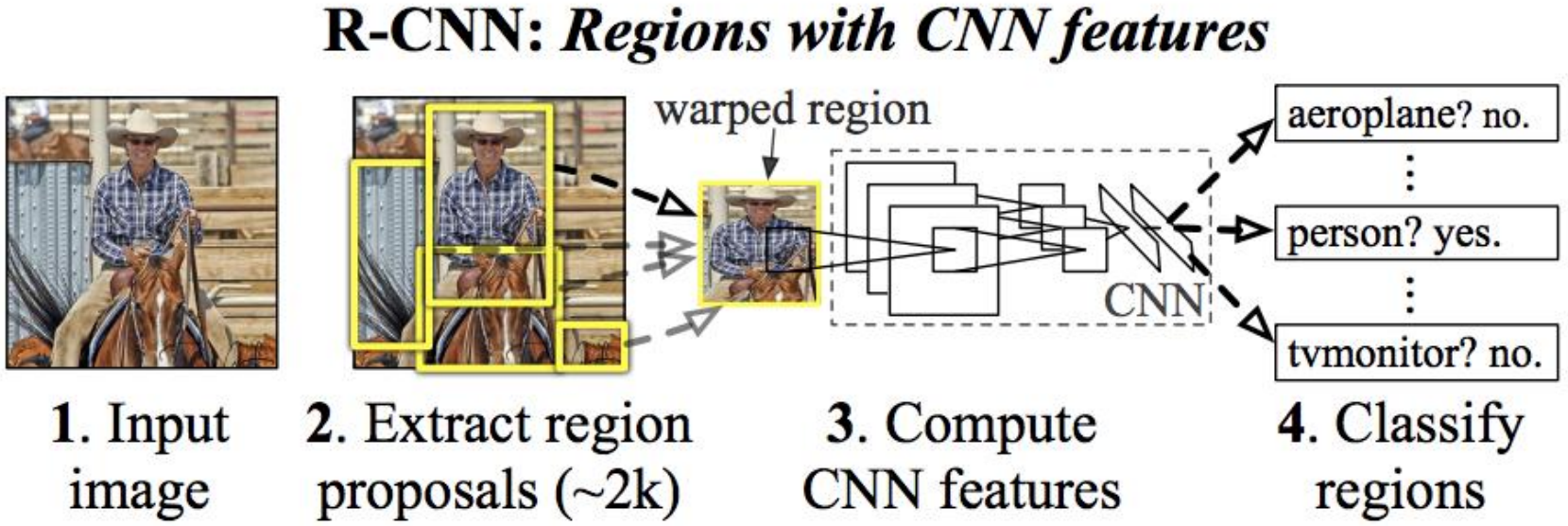
Output: bounding boxes with object classification scores.



Region-Based ConvNets (R-CNN) [2014]

Idea: each box in an image is its own image.

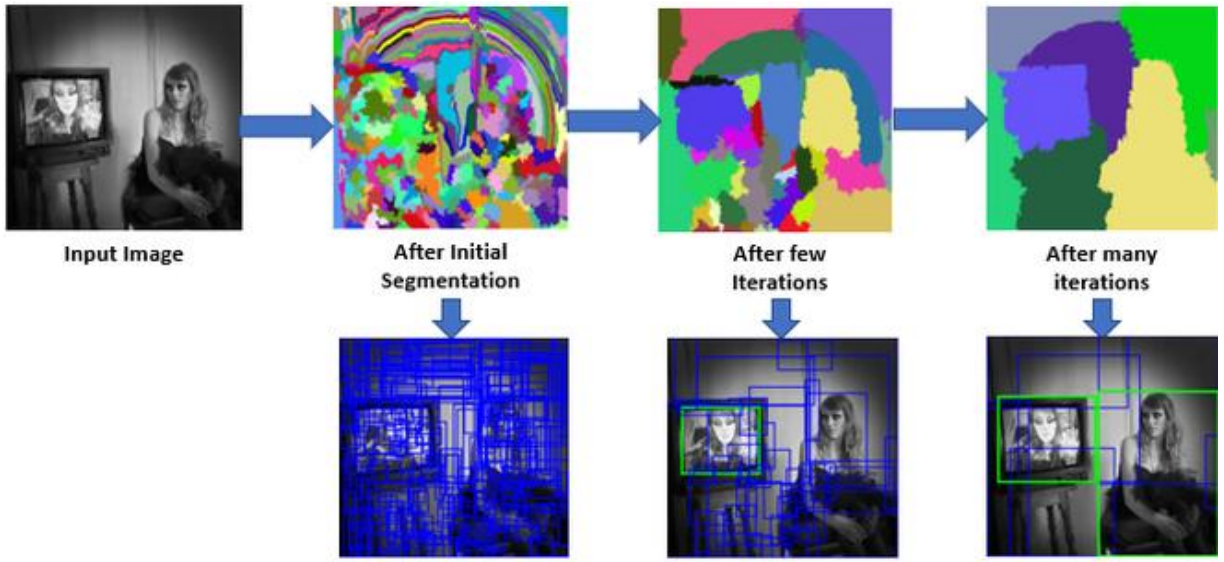
How: (1) find interesting boxes, (2) rescale each box and feed through a CNN.



Extracting region proposals

An idea from before the deep learning era. R-CNN uses an algorithm designed by the UvA: selective search.

Selective search: start from superpixels, group one-by-one. Each new grouping is a new region proposal.



Extra step: improving the region locations

Now, having found the object in the box, can we tighten the box to fit the true dimensions of the object?

We can, and this is the final step of R-CNN.

R-CNN runs a simple linear regression on the region proposal to generate tighter bounding box coordinates to get the final result.

- Inputs: sub-regions of the image corresponding to objects.
- Outputs: New bounding box coordinates for the object in the sub-region.

R-CNN summarized

R-CNN is just the following steps:

1. Generate a set of proposals for bounding boxes.

2. Run the images in the bounding boxes through a pre-trained AlexNet and finally an SVM to see what object the image in the box is.

3. Run the box through a linear regression model to output tighter coordinates for the box once the object has been classified.

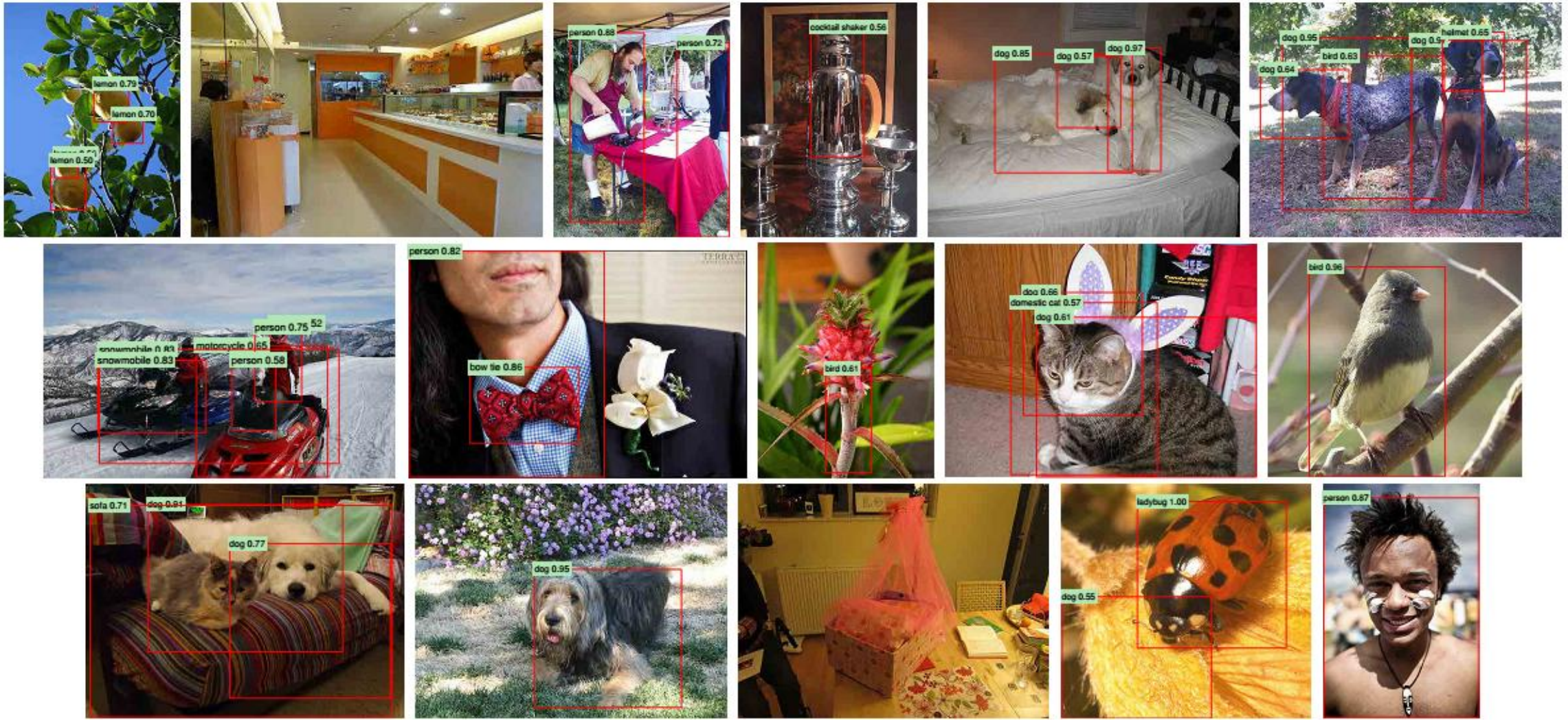
the final part of the 2 and the 3 actually happens in parallel

After the CNN extracts features from each warped region proposal and the SVM classifier determines the object class, the initial bounding boxes from selective search are often imprecise and don't tightly fit the actual objects. The linear regression model addresses this localization error by learning to predict correction offsets that adjust the bounding box coordinates.

The regression model takes the extracted CNN features from each region proposal as input and learns to predict four values that represent offsets for the bounding box coordinates. These offsets are trained to transform the original region proposal coordinates into the ground-truth bounding box coordinates. Specifically, the model is trained using the extracted features and labeled bounding boxes of each region proposal as training examples

For each object class detected, the regression predicts adjustments to the position and size of the bounding box relative to the original region proposal. This allows the final output to have much tighter and more accurate bounding boxes than what selective search initially provided, improving the mean average precision by approximately 3-4%.

R-CNN results

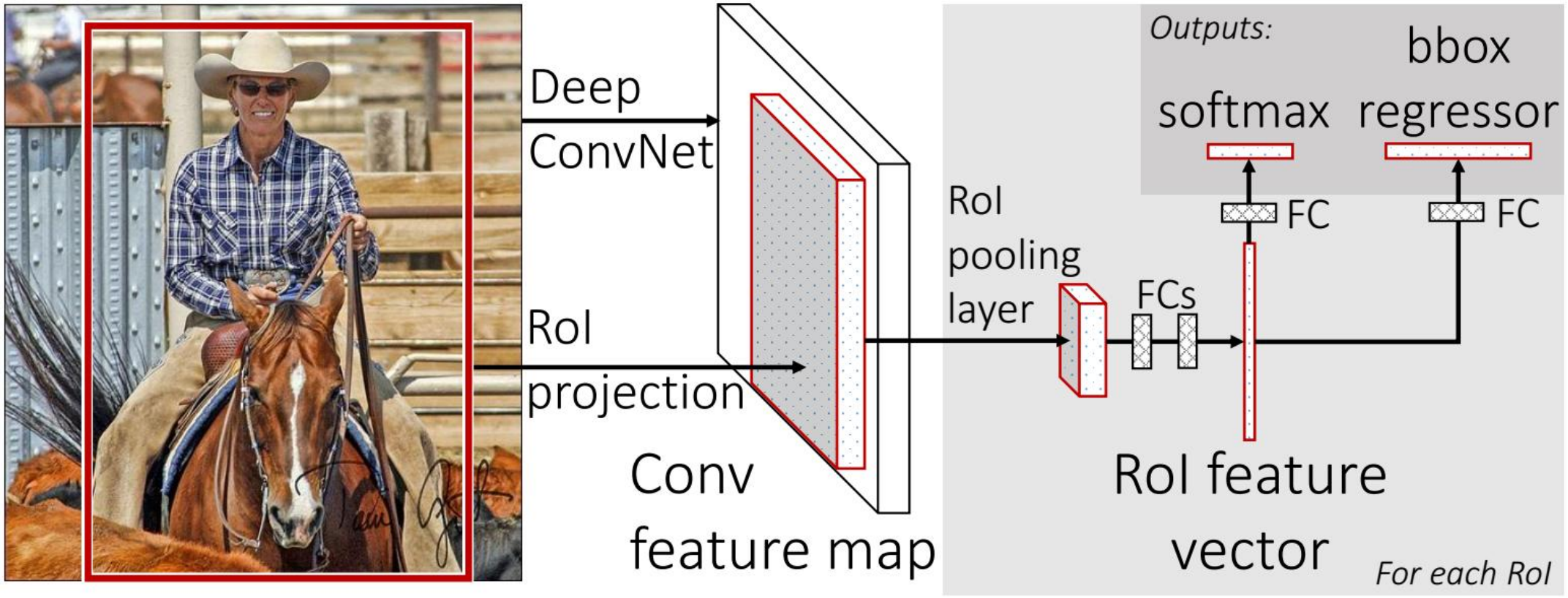


What are the two major downsides to R-CNN?

1. Each region proposal requires a new pass through the network.

2. Region proposals need to be determined a priori.

Fast R-CNN [2015]



Key to Fast R-CNN: RIOPooling

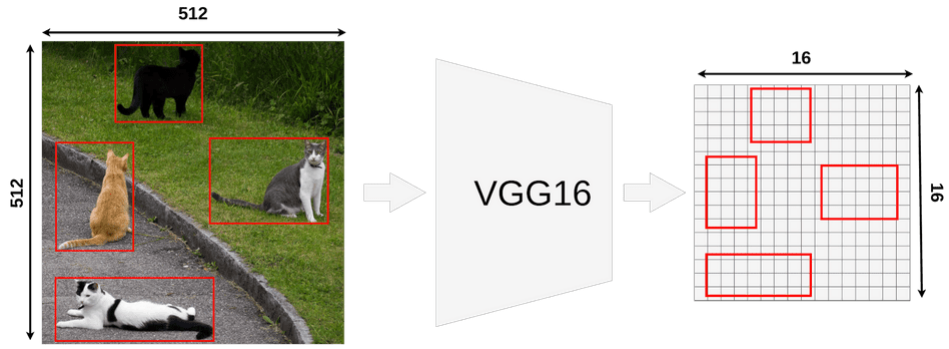
For the forward pass of the CNN, a lot of proposed regions for the image invariably overlapped …

… causing us to run the same CNN computation again and again (~2000 times!).

Why not run the CNN just once per image and then find a way to share that computation across the ~2000 proposals?

Region of Interest pooling

RoIPool shares the forward pass of a CNN for an image across its subregions.



In the image above, notice how the CNN features for each region are obtained by selecting a corresponding region from the CNN's feature map.

Then, the features in each region are pooled (usually using max pooling). So, all it takes us is one pass of the original image as opposed to ~2000!

Now region proposal are extracted use Selective search (or other onCPU algorith,) directly from the feature map.

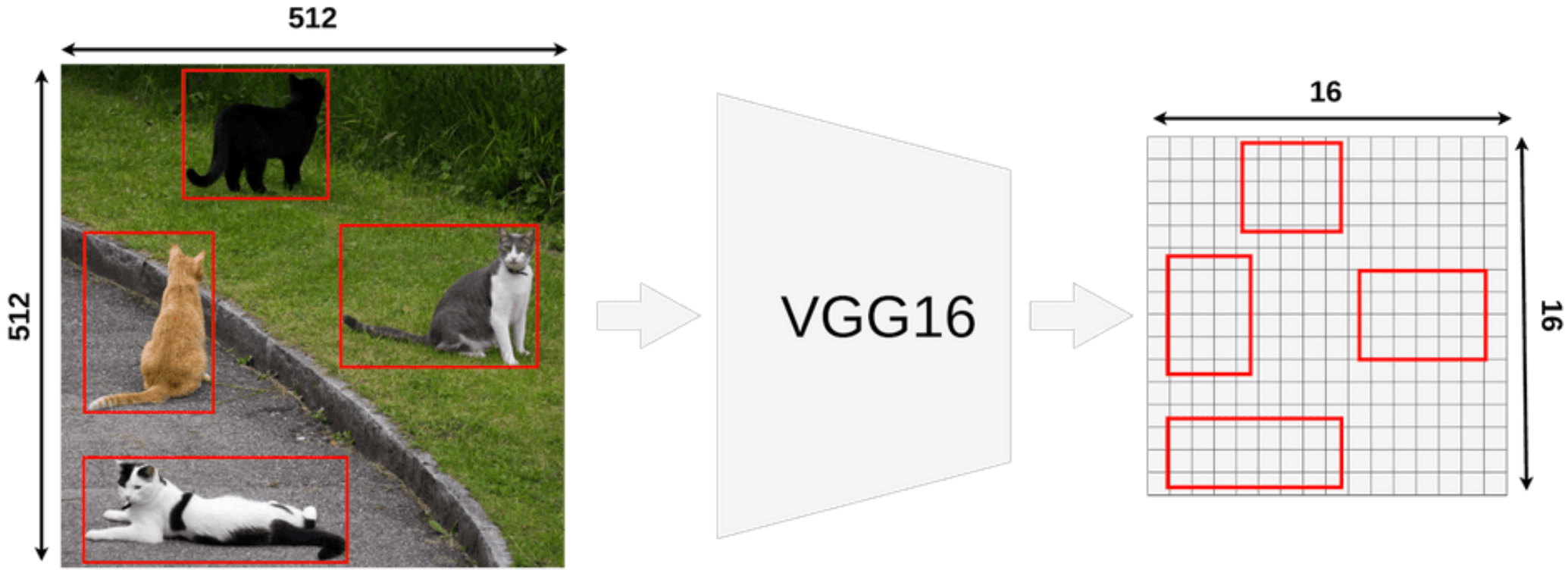
RoI pooling works by dividing the proposal region on the feature map into a grid and using max pooling within each grid cell. This produces a fixed-size feature map from each proposal, regardless of its original size. The output is then flattened into a feature vector.

Each feature vector is passed through fully connected layers, which split into two branches:

Classification branch: Predicts class scores (via softmax) for each proposal.

Bounding box regression branch: Predicts position and size offsets to refine the bounding box, making it fit the object better.

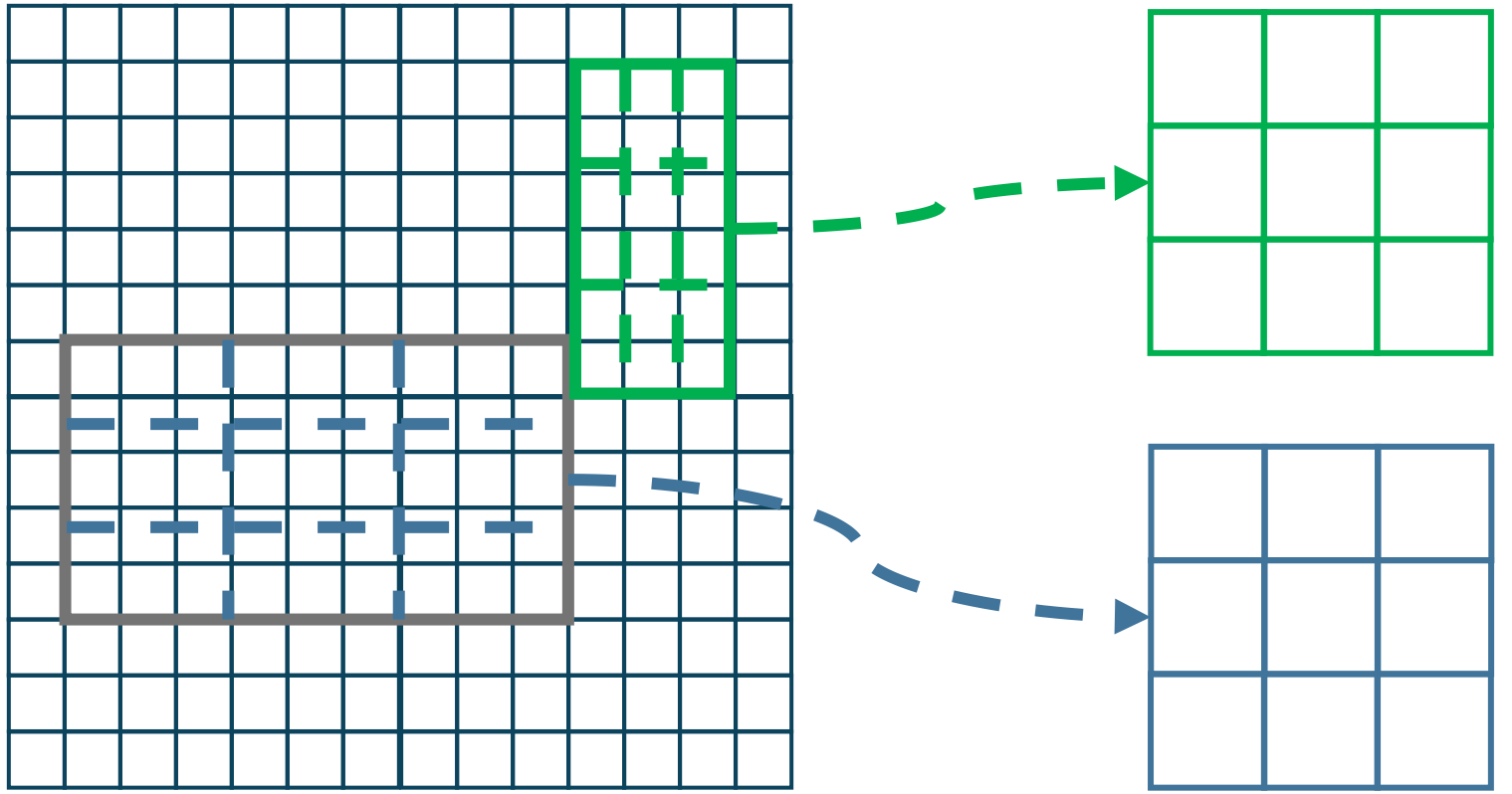
Region of Interest pooling



Region of Interest pooling

Divide feature map in TxT cells.

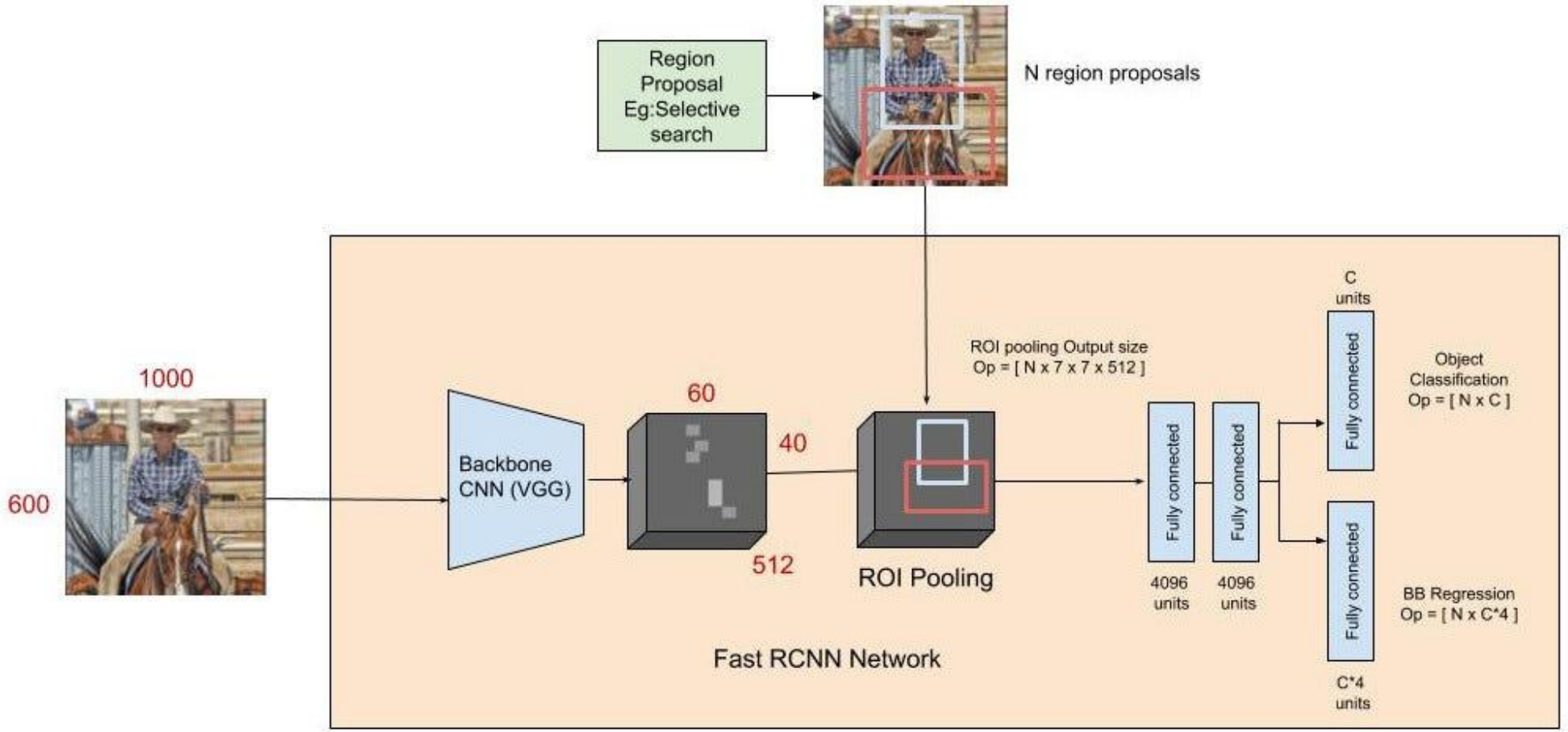
The cell size will change depending on the size of the candidate location.



revise

Always 3x3 no matter the size of candidate location

Second key to Fast R-CNN: joint training



Fast R-CNN: step-by-step

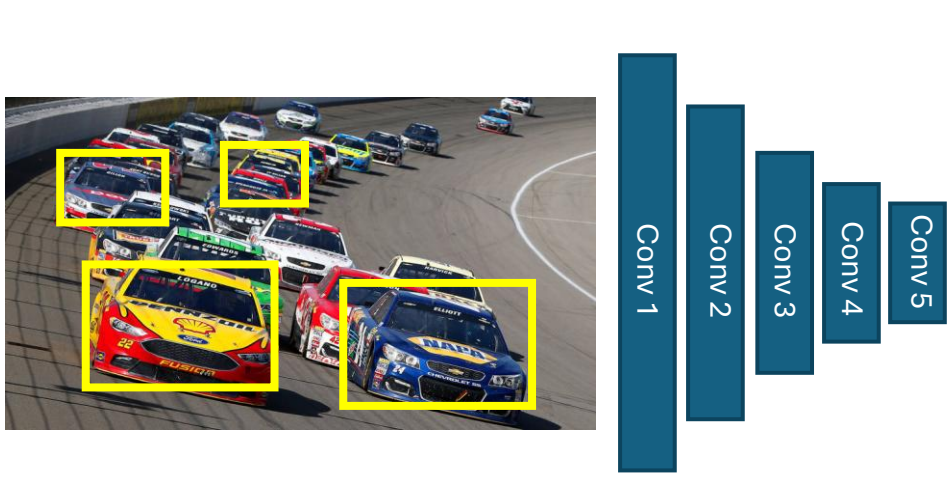
Process the whole image up to conv5.

Conv 5 feature map

Fast R-CNN: step-by-step

Process the whole image up to conv5.

Compute possible locations for objects.

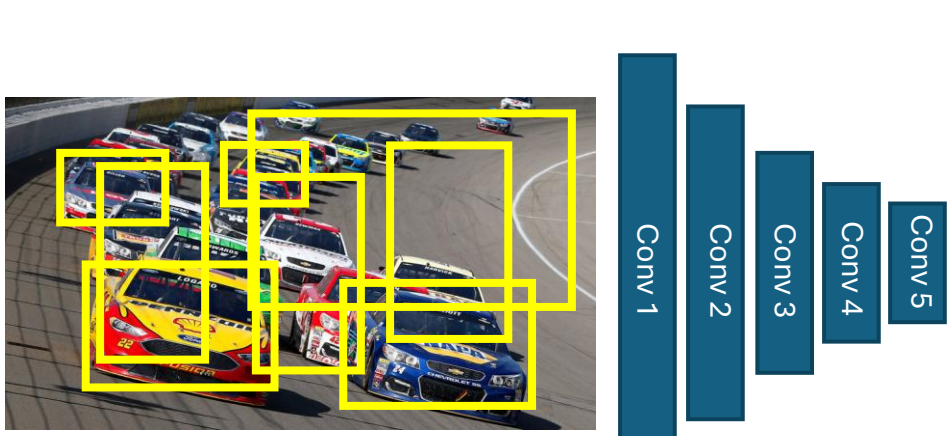


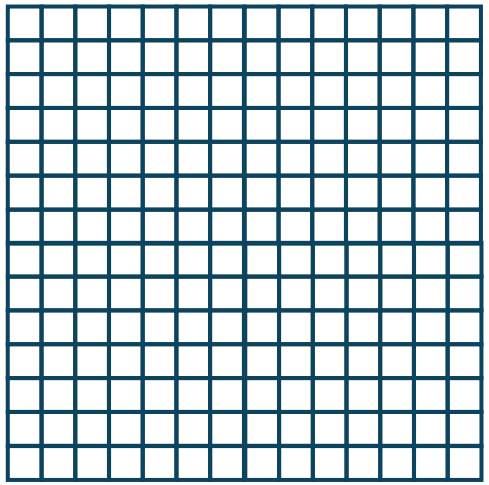
Conv 5 feature map

Fast R-CNN: step-by-step

Process the whole image up to conv5.

Compute possible locations for objects (some correct, most wrong).





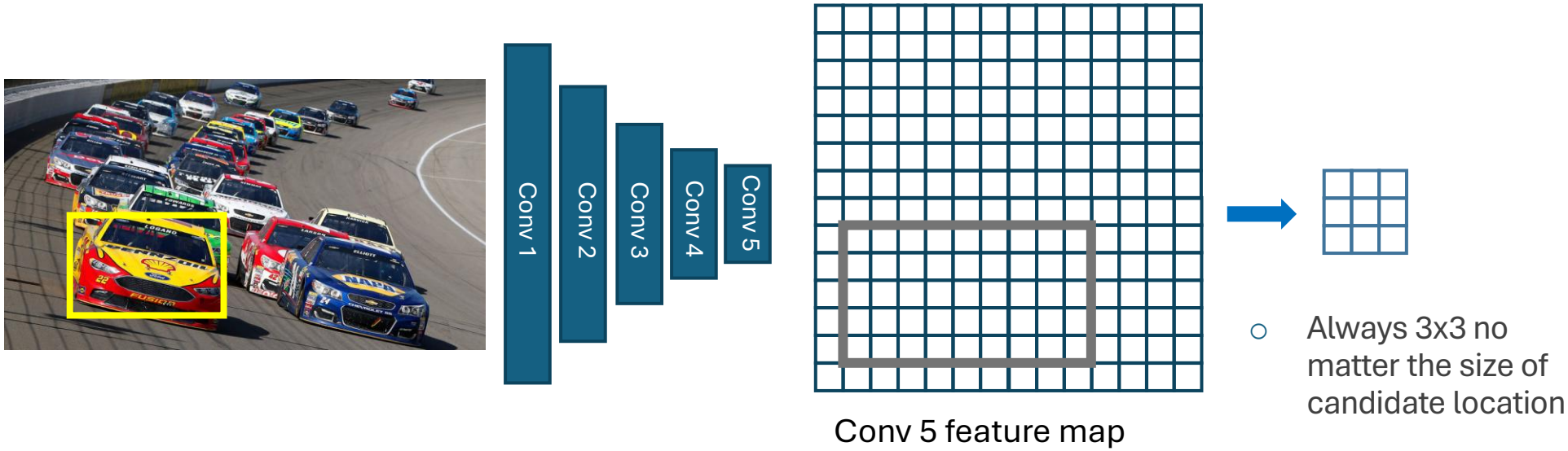
Conv 5 feature map

Fast R-CNN: step-by-step

Process the whole image up to conv5.

Compute possible locations for objects.

Given single location → ROI pooling module extracts fixed length feature.



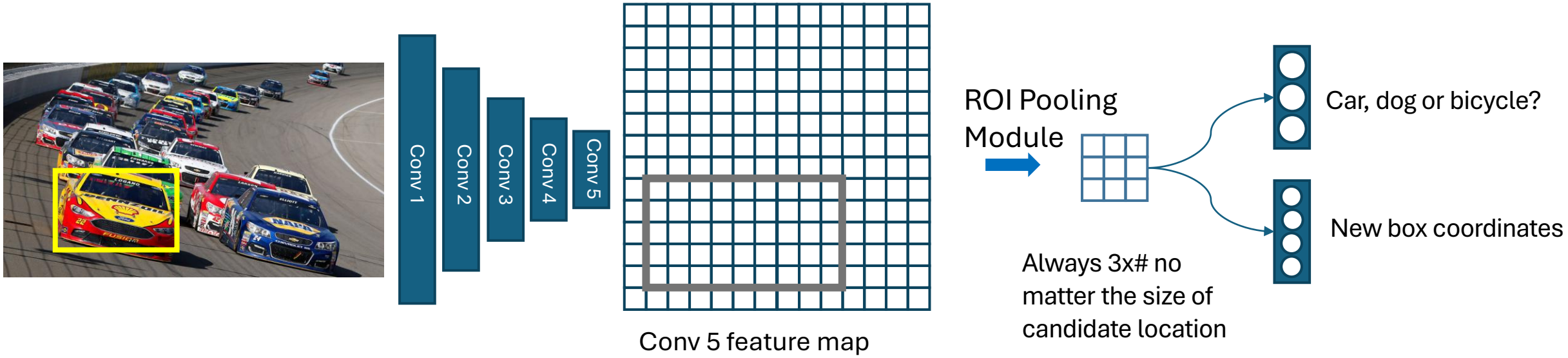
Fast R-CNN: step-by-step

Process the whole image up to conv5.

Compute possible locations for objects.

Given single location → ROI pooling module extracts fixed length feature.

Connect to two final layers, 1 for classification, 1 for box refinement.



Pros and cons of Fast R-CNN

Reuse convolutions for different candidate boxes

Compute feature maps only once

Region-of-Interest pooling

Define stride relatively → box width divided by predefined number of "poolings" T

Fixed length vector

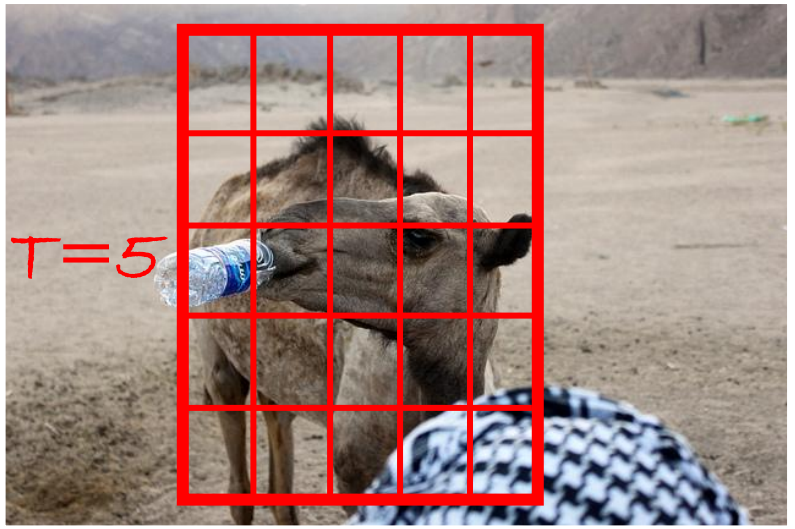
"End-to-end" training!

(Very) Accurate object detection

(Very) Faster

- Less than a second per image

External box proposals needed



Faster R-CNN [2017]

Still a bottleneck: the region proposer.

First step: generating a bunch of potential bounding boxes/regions.

In Fast R-CNN, these proposals were created using Selective Search, a fairly slow process that was found to be the bottleneck of the overall process…

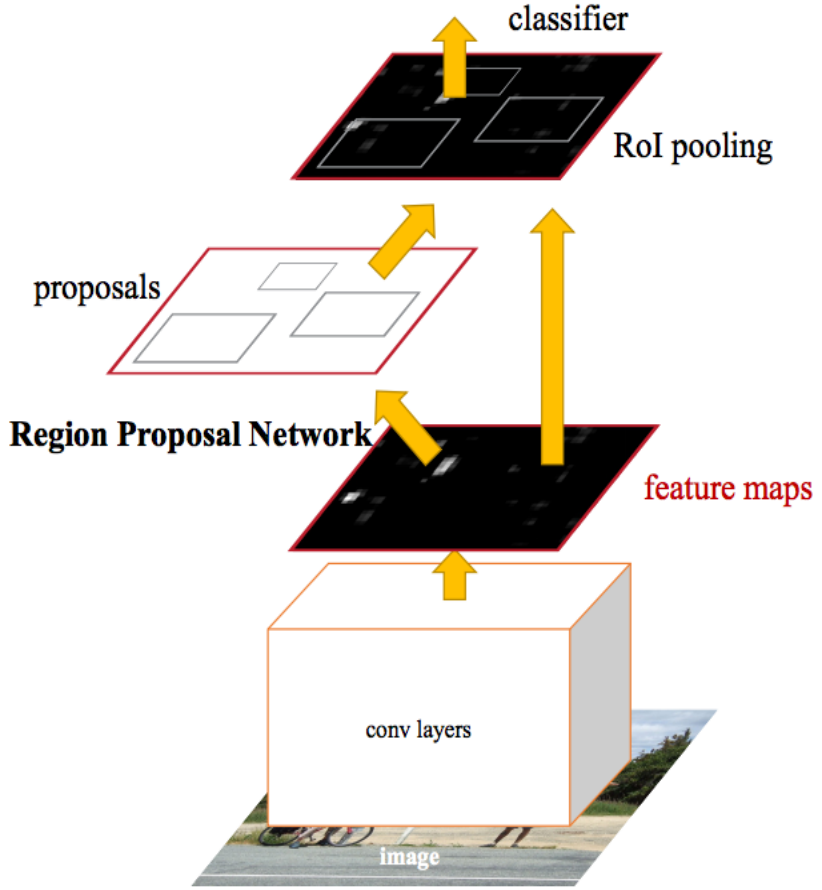
Faster R-CNN

Faster R-CNN adds a Fully Convolutional Network on top of the features of the CNN creating what's known as the Region Proposal Network.

The **Region Proposal Network** works by passing a sliding window over the CNN feature map and at each window, outputting *k* potential bounding boxes and scores for how good each of those boxes is expected to be.

In such a way, we create *k* such common aspect ratios we call anchor boxes. For each such anchor box, we output one bounding box and score per position in the image.

We then pass each such bounding box that is likely to be an object into Fast R-CNN to generate a classification and tightened bounding boxes.

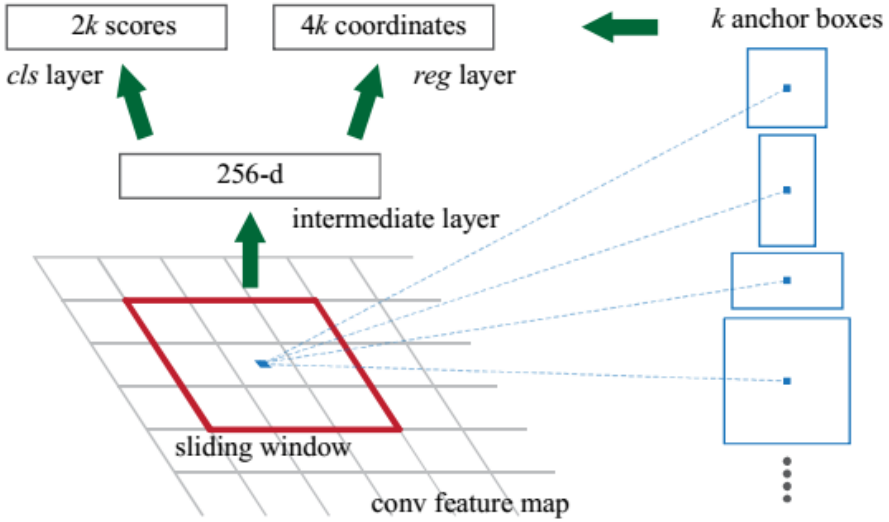


Faster R-CNN

Fast R-CNN → external candidate locations.

Faster R-CNN → deep network proposes candidate locations.

Slide the feature map → k anchor boxes per slide.



Region Proposal Network

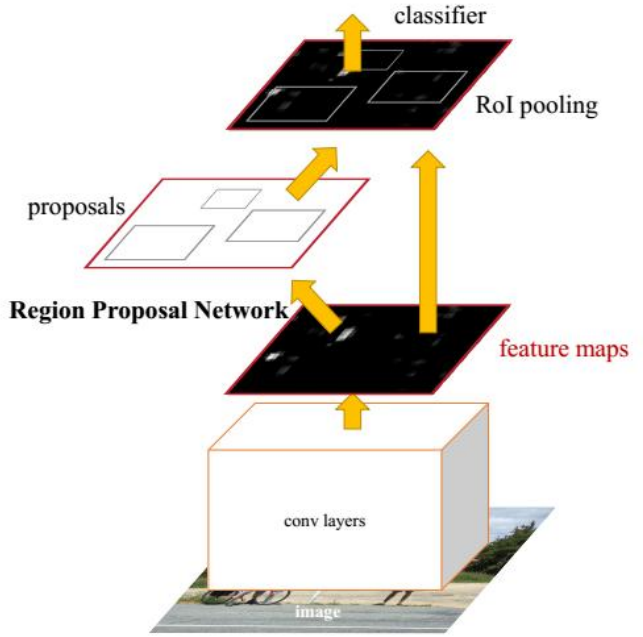


Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the 'attention' of this unified network.

Focal loss

Cross-entropy is a problem for object detection.

Many boxes evaluated, a lot of small losses lead to a huge bias.

Solution: add an exponent to the cross-entropy term!

The exponent control how much the probability on x axis influence the loss

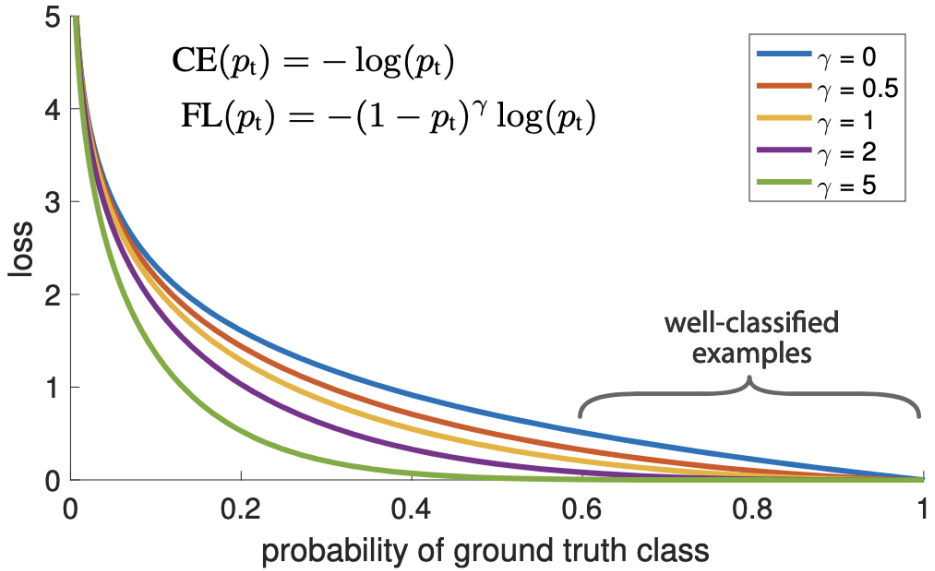


Figure 1. We propose a novel loss we term the *Focal Loss* that adds a factor $(1 - p_t)^{\gamma}$ to the standard cross entropy criterion. Setting $\gamma > 0$ reduces the relative loss for well-classified examples ($p_t > .5$), putting more focus on hard, misclassified examples. As our experiments will demonstrate, the proposed focal loss enables training highly accurate dense object detectors in the presence of vast numbers of easy background examples.

Mask R-CNN

Extending Faster R-CNN for Pixel Level Segmentation.

So far, we've seen how we've been able to use CNN features in many interesting ways to effectively locate different objects in an image with bounding boxes.

Can we extend such techniques to go one step further and locate exact pixels of each object instead of just bounding boxes?

This problem is known as *image segmentation*.

Mask R-CNN

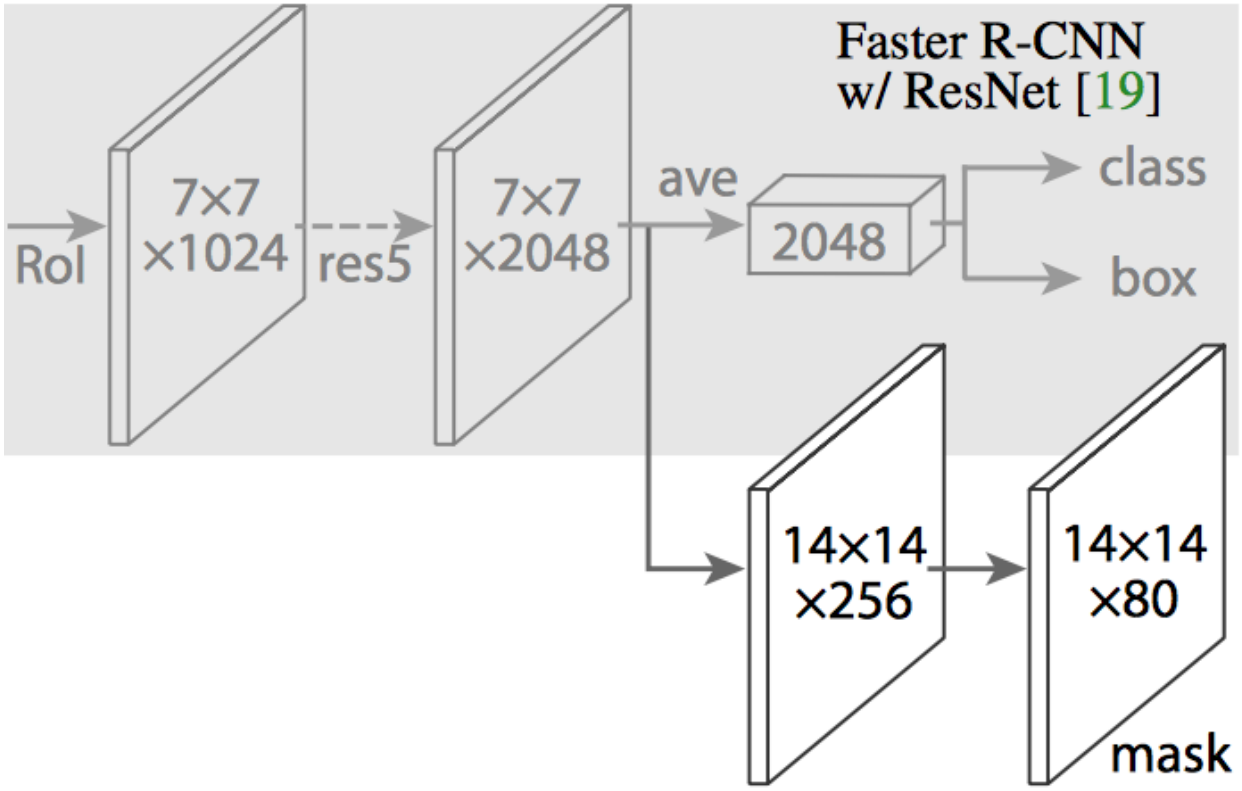
Given that Faster R-CNN works so well for object detection, could we extend it to also carry out pixel level segmentation?

Mask R-CNN does this by adding a branch to Faster R-CNN that outputs a binary mask that says whether or not a given pixel is part of an object.

Here are its inputs and outputs:

- Inputs: CNN Feature Map.
- Outputs: Matrix with 1s on all locations where the pixel belongs to the object and 0s elsewhere (this is known as a binary mask).

Mask R-CNN

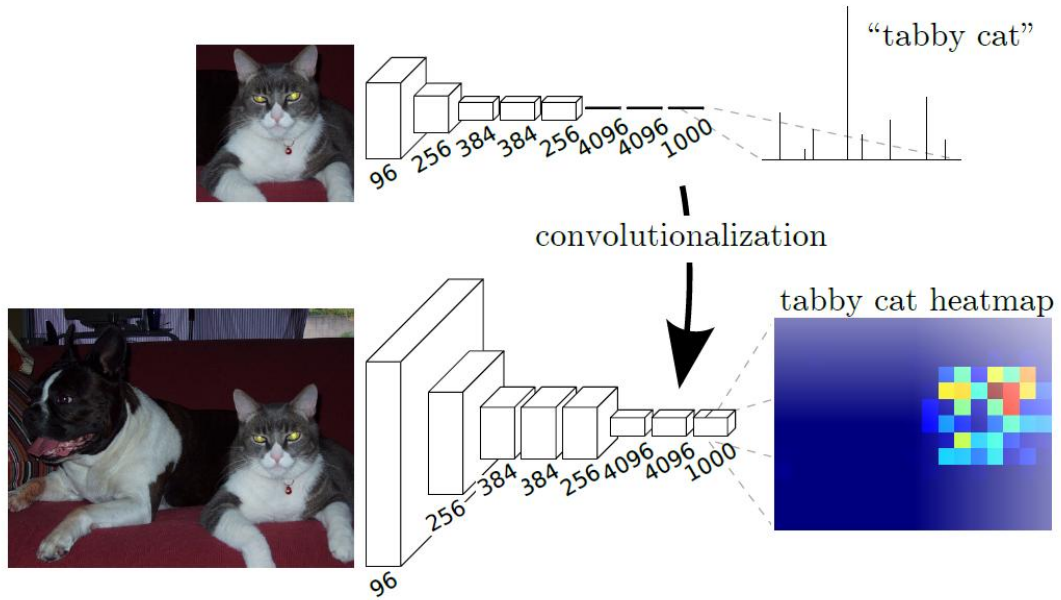

Faster R-CNN
w/ ResNet [19]
RoI
7×7
×1024
res5
7×7
×2048
ave
2048
class
box
14×14
×256
14×14
×80
mask

person1.00
person.99
person.99
person1.00
person1.00
skateboard.91
handbag.81
skateboard.83
umbrella.97
umbrella.97
person.99
person.98
umbrella1.00
backpack.95
backpack.96
handbag.85
umbrella.96
umbrella.99
umbrella.98
handbag.97
backpack.98
bicycle.93
person1.00
baseball bat.99
baseball bat.98
dog1.00
baseball bat.85
person.98
surfboard1.00
surfboard.98
person.74
zebra.99
zebra.99
zebra.88
zebra1.00
person.99
frisbee1.00
person.80
person.82
chair.98
dining table.78
chair.95
cup.71
chair.87
chair.97
chair.94
wine glass.91
wine glass.93
wine glass.83
cup.96
cup.91
dining table.75
kite.98
kite.81
kite1.00
kite.82
kite.97
kite.99
kite.84
kite.93
handbag.80
elephant1.00
elephant.97
elephant.99
traffic light.99
traffic light.71
handbag.88
handbag.99
tie.85
person.88
tv.98
bottle.97
wine glass.99
wine glass1.00
dining table.95
potted plant.92
bird.93
bench.97
handbag.73
person.78

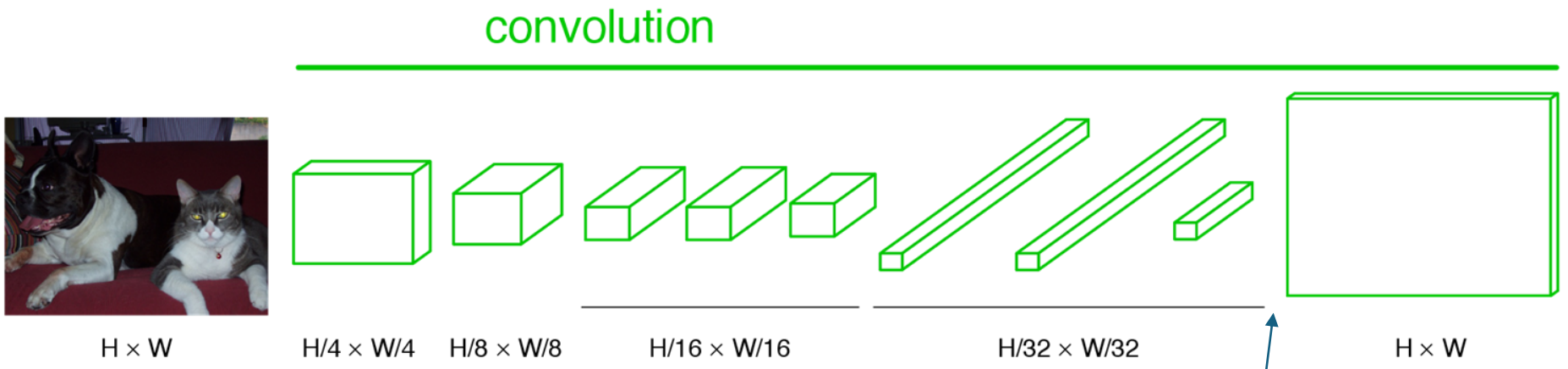
Towards pixel-level classification

Mask R-CNN classifies pixels within boxes.

Instead of first detecting objects and then segmenting them, can we also just classify each pixel directly to get a full segmentation mask?



From a bottleneck back to a full image



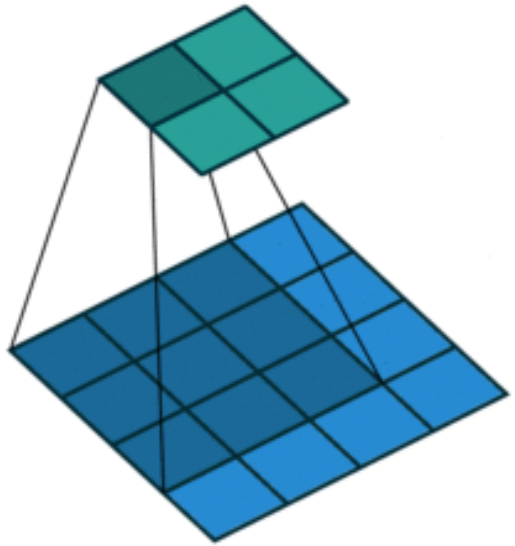
I want my output size equal to the input size

Some upsampling algorithm to return us to H x W

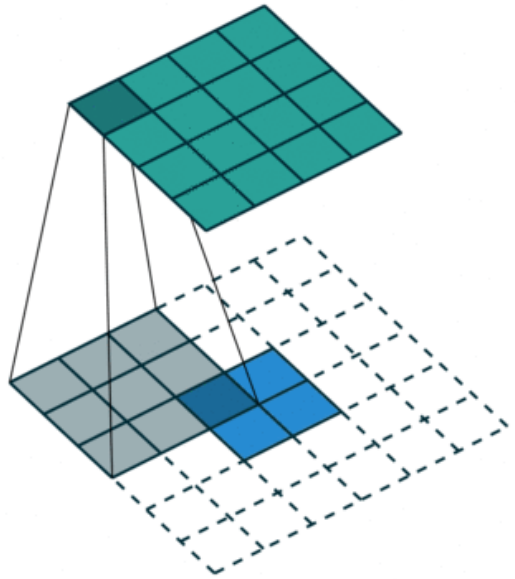
Deconvolutions

Output →

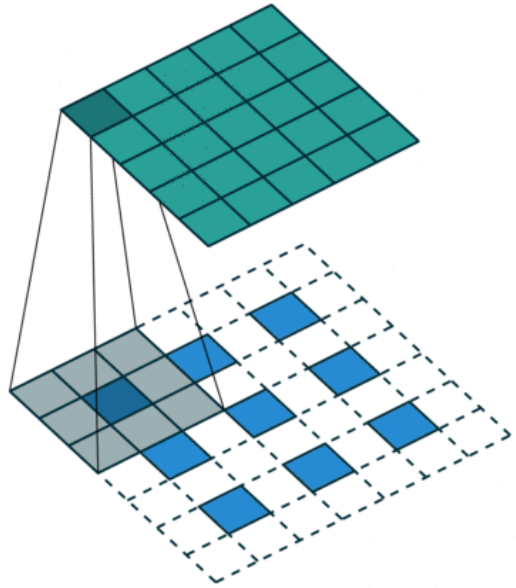
Image →



Convolution
No padding, no strides



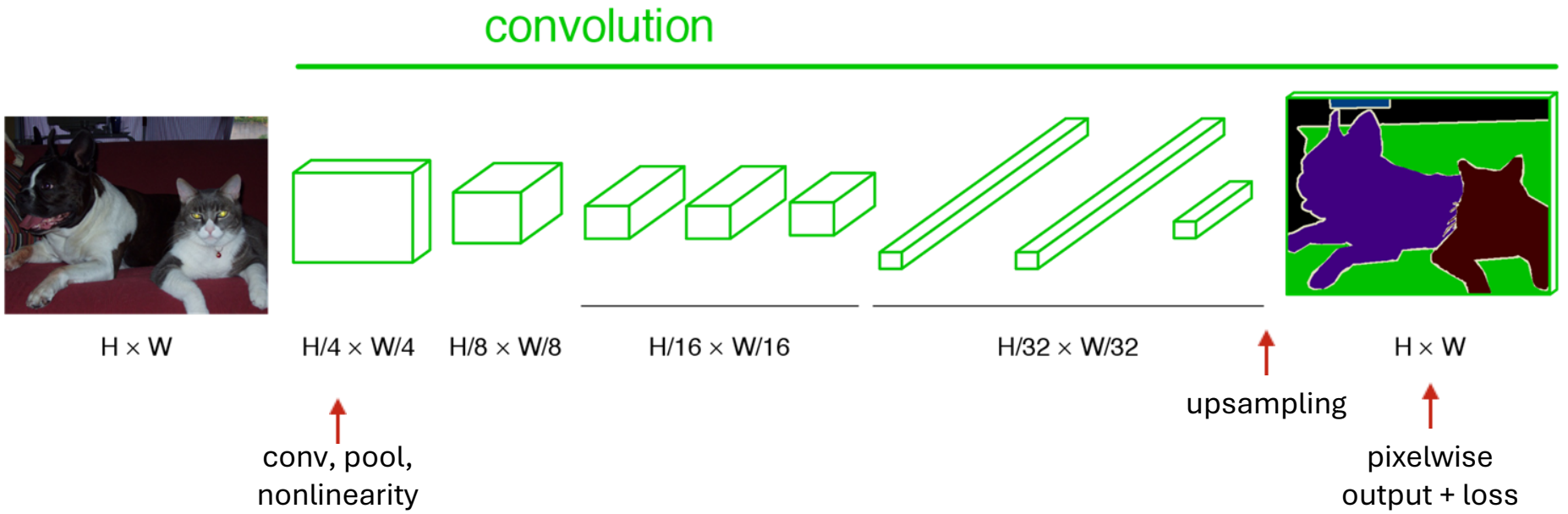
Upconvolution
Padding, no strides



Upconvolution
Padding, strides

More visualizations: https://github.com/vdumoulin/conv_arithmetic

End-to-end pixel-level optimization



This lecture

Convolutions.

Convolutional networks.

Convolutional networks for detection and segmentation.

Learning and reflection

Chapter 9, Deep Learning Book

Chapter 10, Understanding Deep Learning Book

Learning and reflection

Understanding Deep Learning: Chapter 10

Understanding Deep Learning: Chapter 11

Next lecture

Lecture	Title	Lecture	Title
1	Intro and history of deep learning	2	AutoDiff
3	Deep learning optimization I	4	Deep learning optimization II
5	Convolutional deep learning	6	Attention-based deep learning
7	Graph deep learning	8	From supervised to unsupervised deep learning
9	Multi-modal deep learning	10	Generative deep learning
11	What doesn't work in deep learning	12	Non-Euclidean deep learning
13	Q&A	14	Deep learning for videos

Thank you