CS 1674: Intro to Computer Vision

Convolutional Neural Networks

Prof. Adriana Kovashka
University of Pittsburgh
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Plan for the next few lectures

Why (convolutional) neural networks?

Neural network basics

- Architecture
- Biological inspiration
- Loss functions
- Optimization / gradient descent
- Training with backpropagation

Convolutional neural networks (CNNs)

- Special operations
- Common architectures

Practical matters

- Tips and tricks for training
- Transfer learning
- Software packages

Understanding CNNs

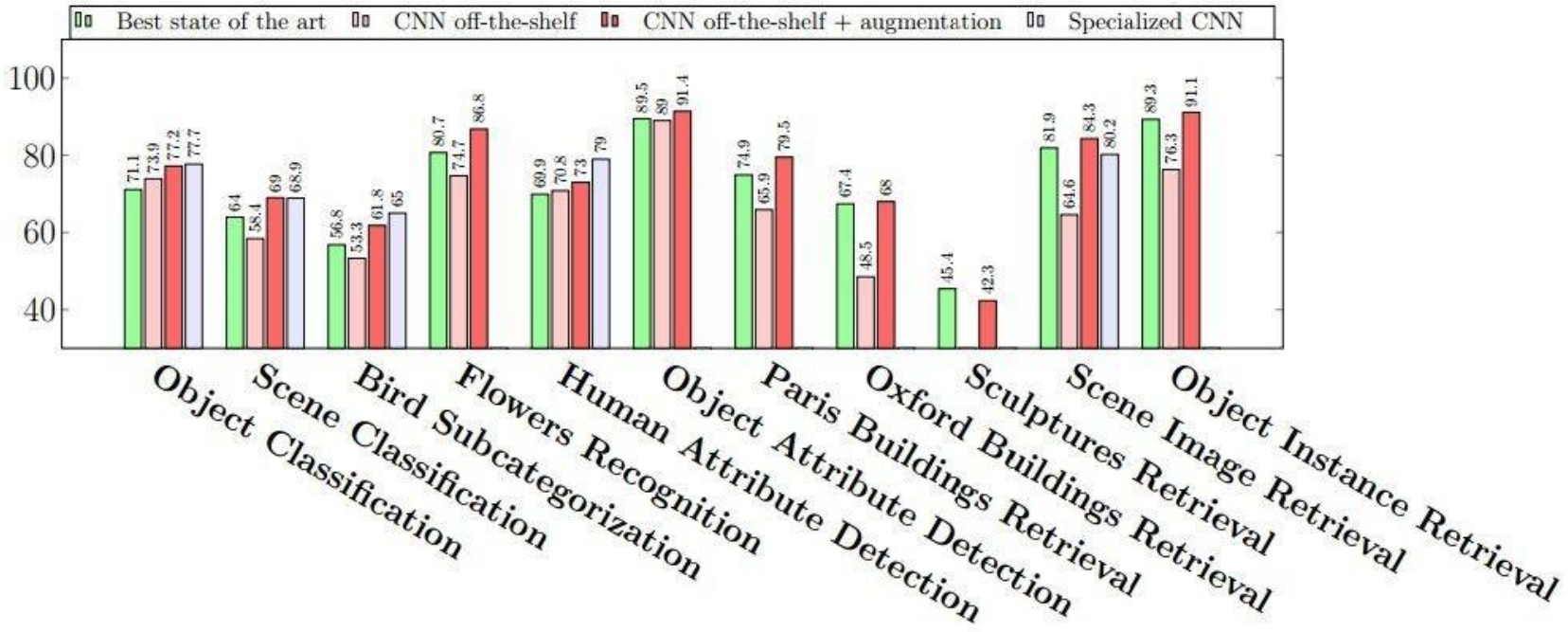
- Visualization
- Synthesis / style transfer
- Breaking CNNs

Neural network basics

Why (convolutional) neural networks?

State of the art performance on many problems

Most papers in recent vision conferences use deep neural networks



Razavian et al., CVPR 2014 Workshops

ImageNet Challenge 2012

IMAGENET

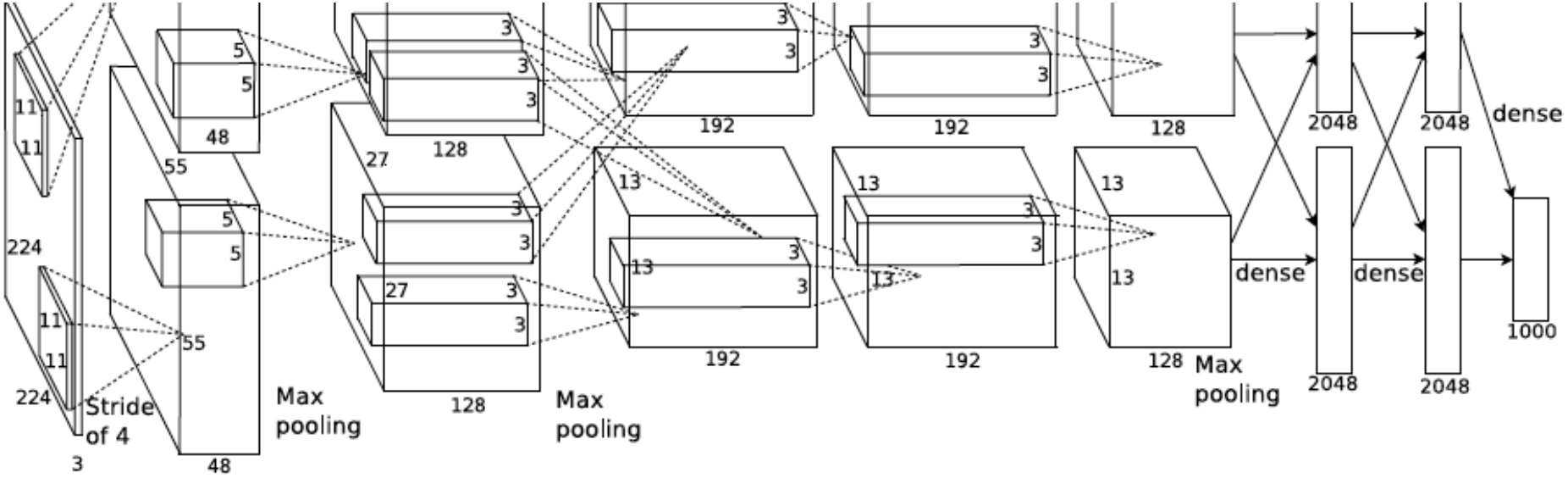
[Deng et al. CVPR 2009]

- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon Turk
- Challenge: 1.2 million training images, 1000 classes

A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

ImageNet Challenge 2012

- AlexNet: Similar framework to LeCun'98 but:
  - Bigger model (7 hidden layers, 650,000 units, 60,000,000 params)
  - More data (10^6 vs. 10^3 images)
  - GPU implementation (50x speedup over CPU)
    - Trained on two GPUs for a week
  - Better regularization for training (DropOut)



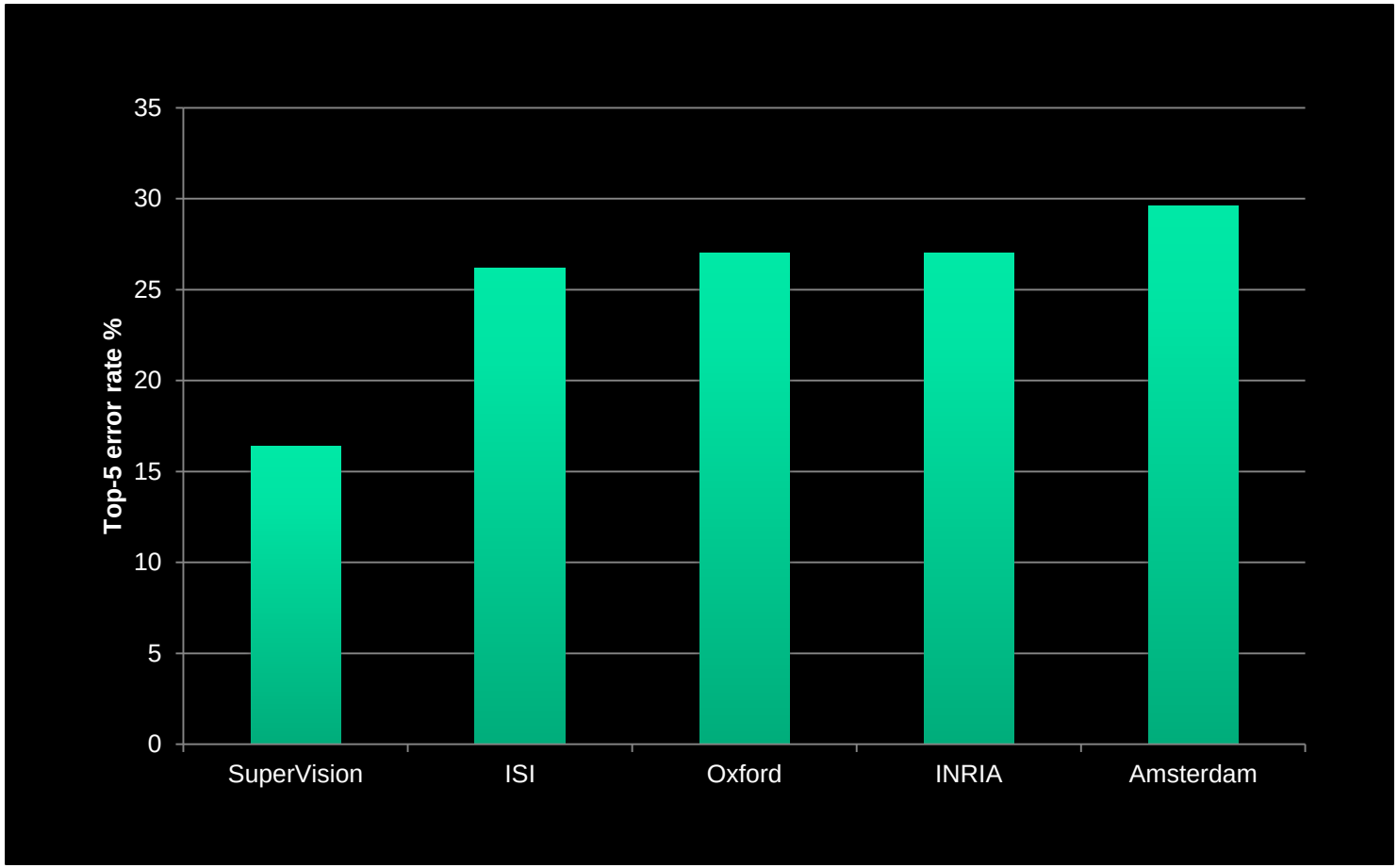
A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

Adapted from Lana Lazebnik

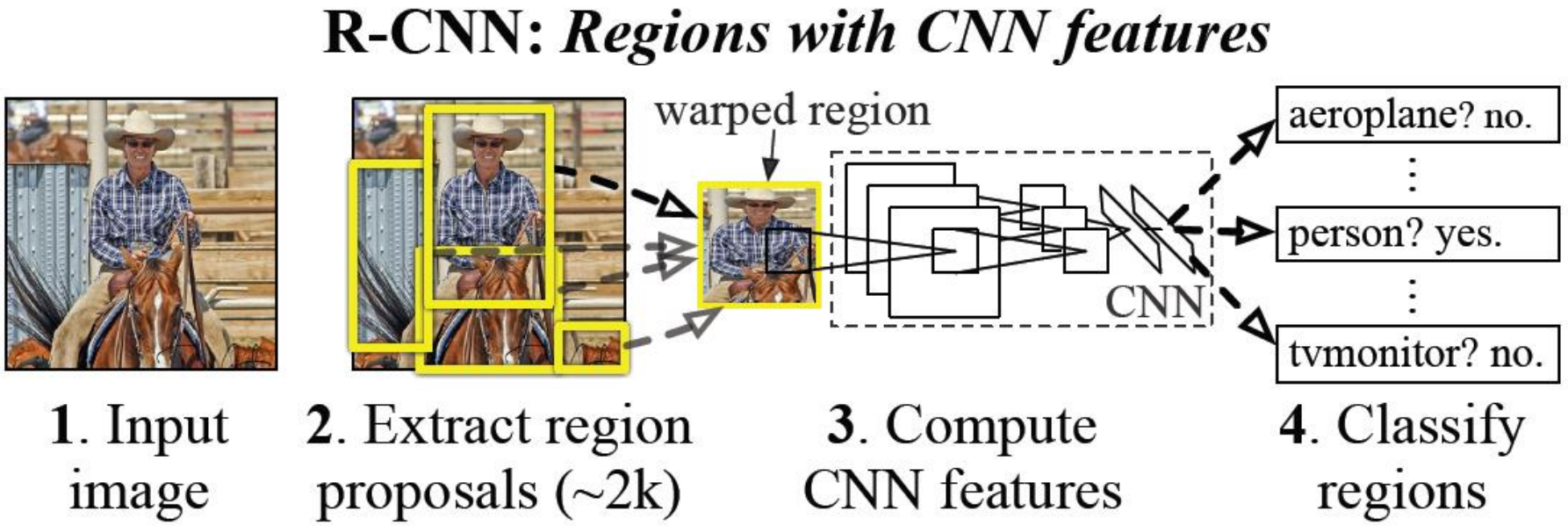
ImageNet Challenge 2012

Krizhevsky et al. -- **16.4% error** (top-5)

Next best (non-convnet) **– 26.2% error**



Example: CNN features for detection



Object detection system overview. Our system (1) takes an input image, (2) extracts around 2000 bottom-up region proposals, (3) computes features for each proposal using a large convolutional neural network (CNN), and then (4) classifies each region using class-specific linear SVMs. **R-CNN achieves a mean average precision (mAP) of 53.7% on PASCAL VOC 2010**. For comparison, Uijlings et al. (2013) **report 35.1% mAP** using the same region proposals, but with a spatial pyramid and bag-of-visual-words approach. **The popular deformable part models perform at 33.4%.**

R. Girshick, J. Donahue, T. Darrell, and J. Malik, **Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation**, CVPR 2014.

What are CNNs?

- Convolutional neural networks are a type of *neural network* with layers that perform special operations
- Used in vision but also in NLP, biomedical etc.
- Often they are *deep*

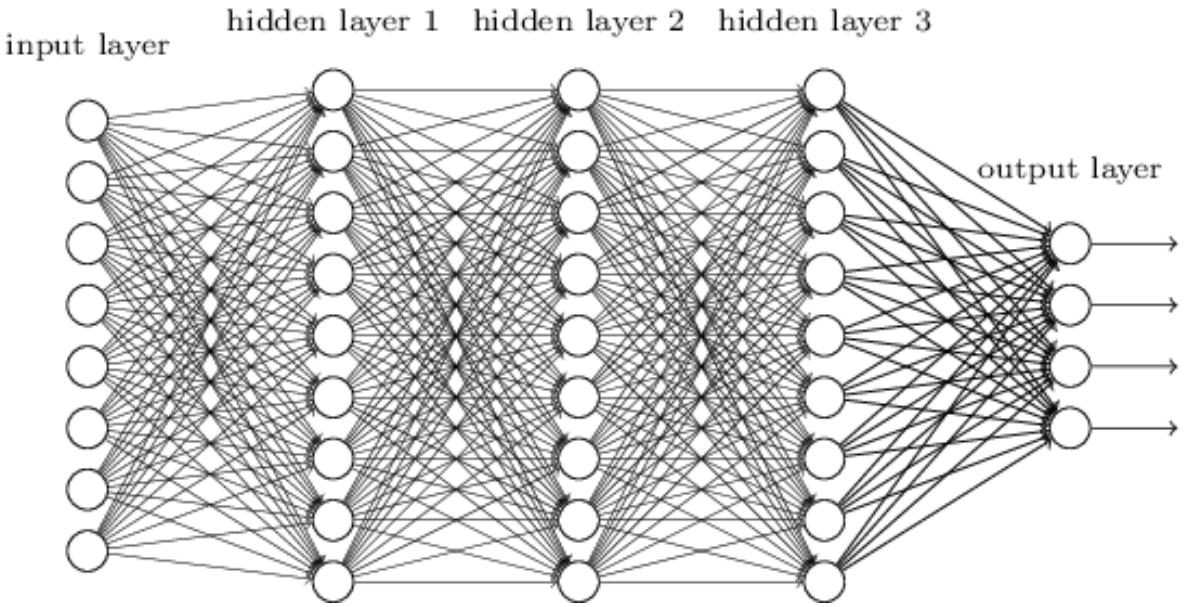
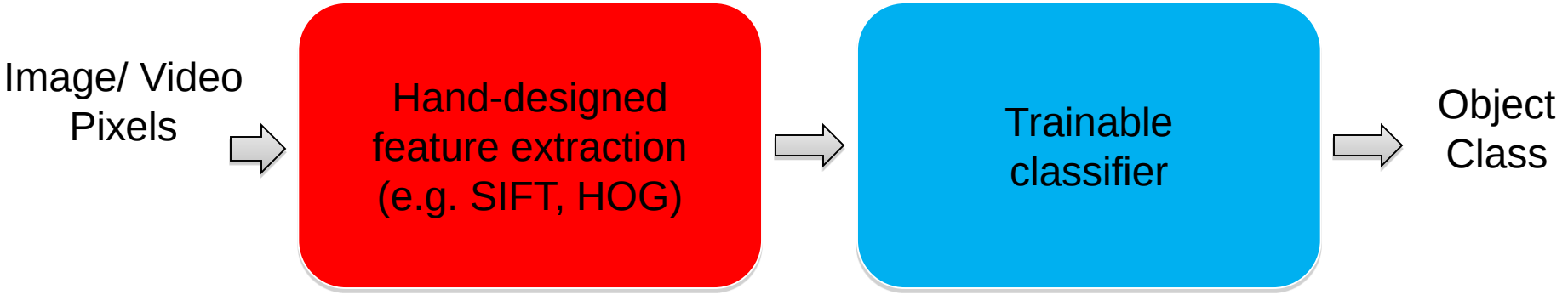


Figure from http://neuralnetworksanddeeplearning.com/chap5.html

Traditional Recognition Approach



- Features are key to recent progress in recognition, but research shows they're flawed…
- Where next?

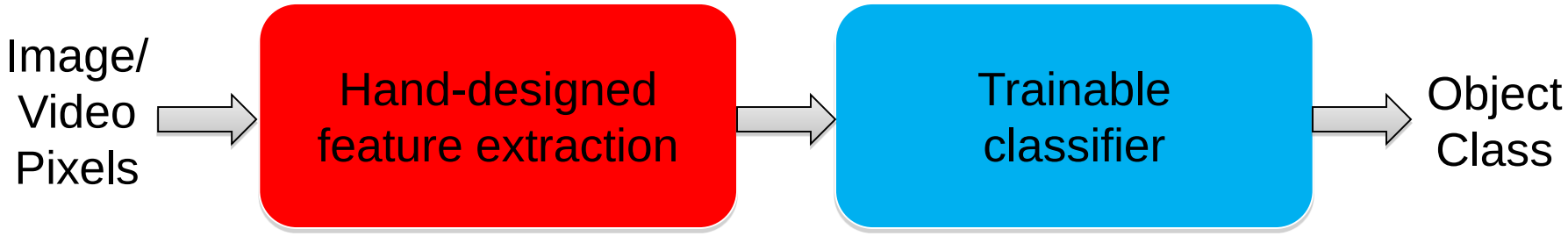
Adapted from Lana Lazebnik

What about learning the features?

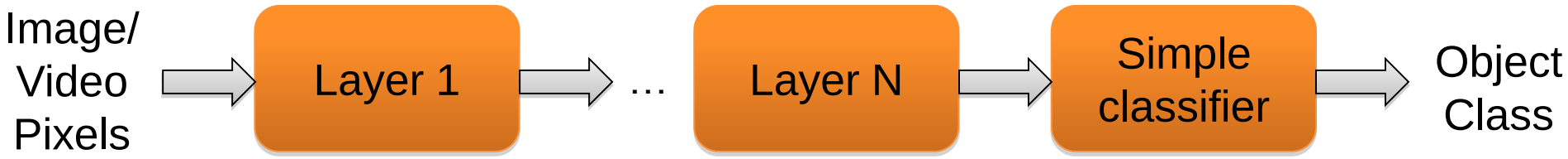
- Learn a *feature hierarchy* all the way from pixels to classifier
- Each layer extracts features from the output of previous layer
- Train all layers jointly

“Shallow” vs. “deep” architectures

Traditional recognition: “Shallow” architecture



Deep learning: “Deep” architecture



Neural network definition

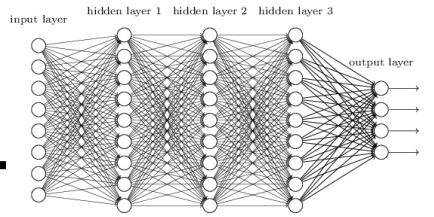
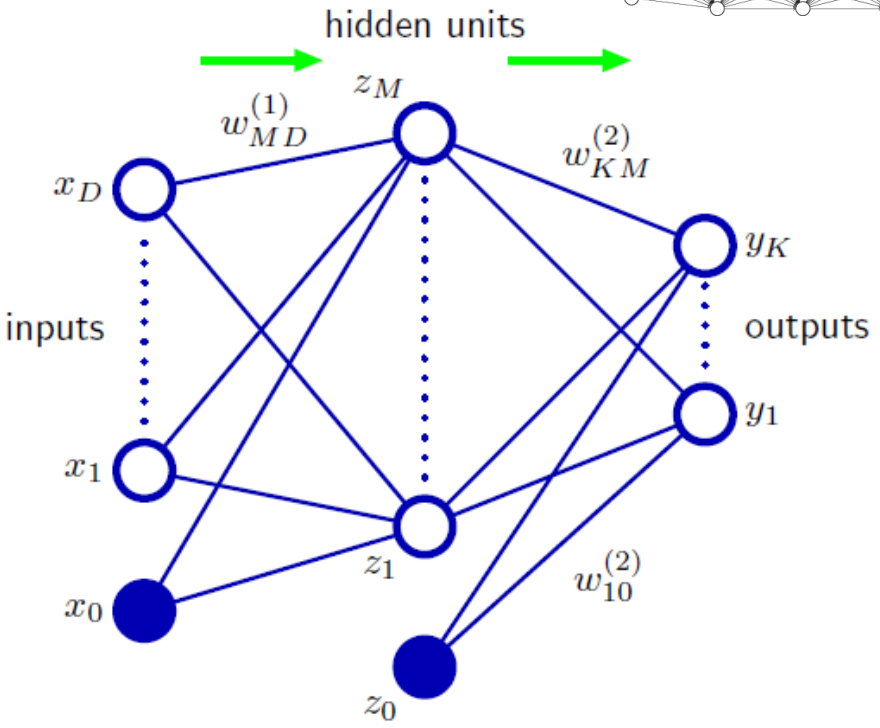


Figure 5.1 Network diagram for the two-layer neural network corresponding to (5.7). The input, hidden, and output variables are represented by nodes, and the weight parameters are represented by links between the nodes, in which the bias parameters are denoted by links coming from additional input and hidden variables x_0 and z_0. Arrows denote the direction of information flow through the network during forward propagation.



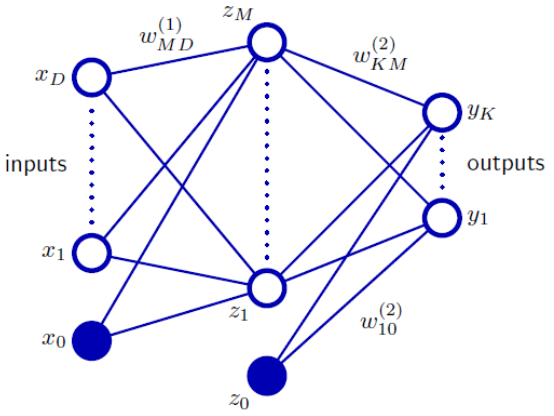
- Activations: $$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}$$

Recall SVM: $w^T x + b$

- Nonlinear activation function *h* (e.g. sigmoid, RELU): $$z_j = h(a_j)$$

Figure from Christopher Bishop

Neural network definition



- Layer 2

$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}$$

- Layer 3 (final)

$$a_k =$$

- Outputs (e.g. sigmoid/softmax)

(binary) $$y_k = \sigma(a_k) = \frac{1}{1 + \exp(-a_k)}$$

(multiclass) $$y_k = \frac{\exp(a_k)}{\sum_j \exp(a_j)}$$

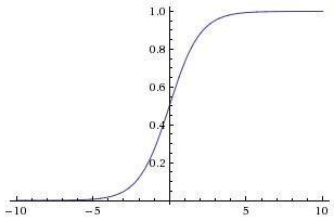
- Finally:

(binary)
$$y_k(\mathbf{x}, \mathbf{w}) = \sigma\left(\sum_{j=1}^{M} w_{kj}^{(2)} h\left(\sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)} \right) + w_{k0}^{(2)} \right)$$

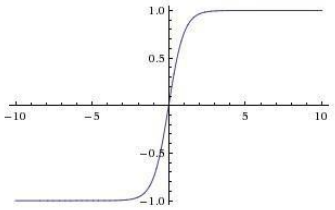
Activation functions

Sigmoid

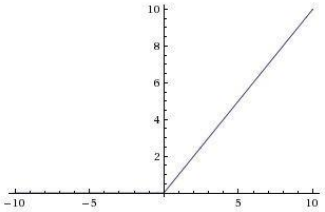
$$\sigma(x) = 1/(1+e^{-x})$$



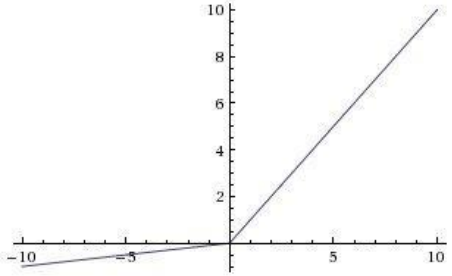
tanh tanh(x)



ReLU max(0,x)



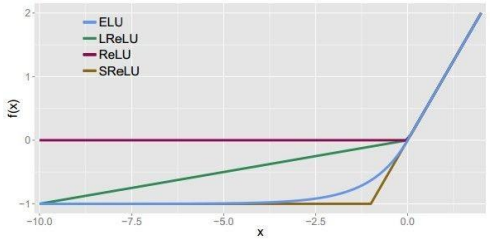
Leaky ReLU
max(0.1x, x)



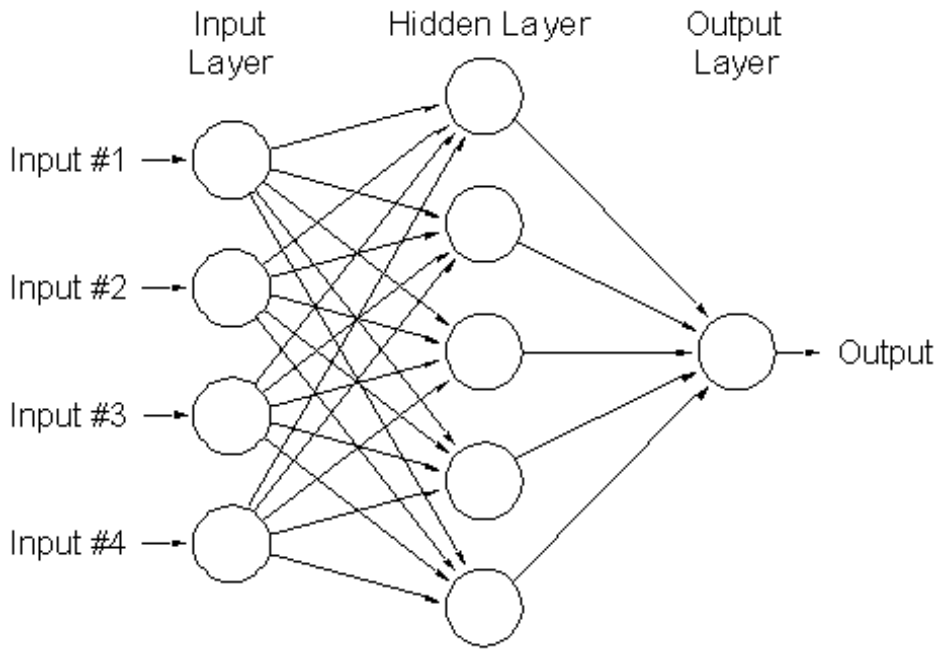
Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \leq 0 \end{cases}$$



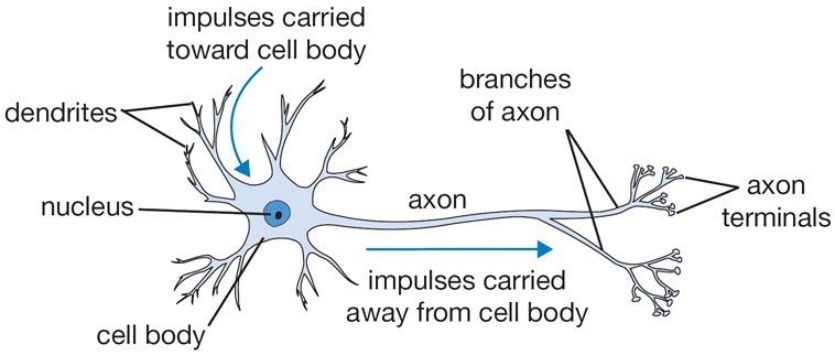
A multi-layer neural network

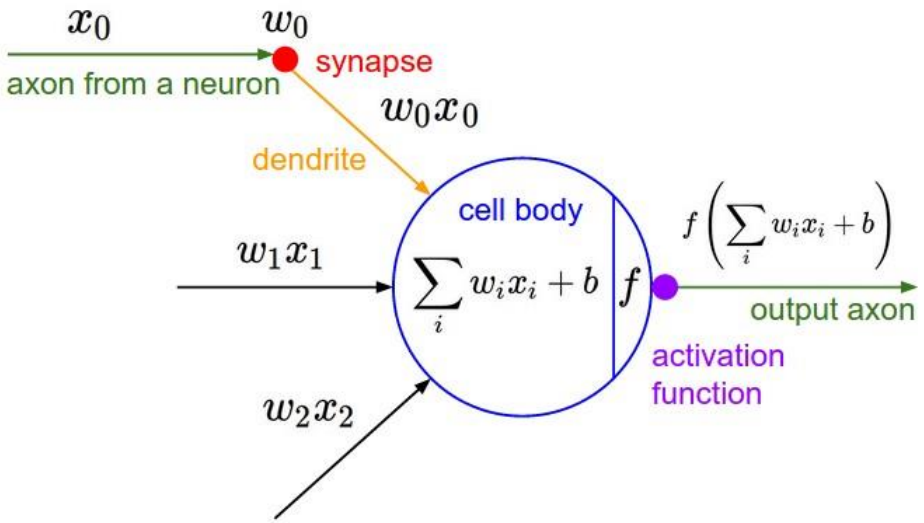


- *Nonlinear* classifier
- Can approximate any continuous function to arbitrary accuracy given sufficiently many hidden units

Inspiration: Neuron cells

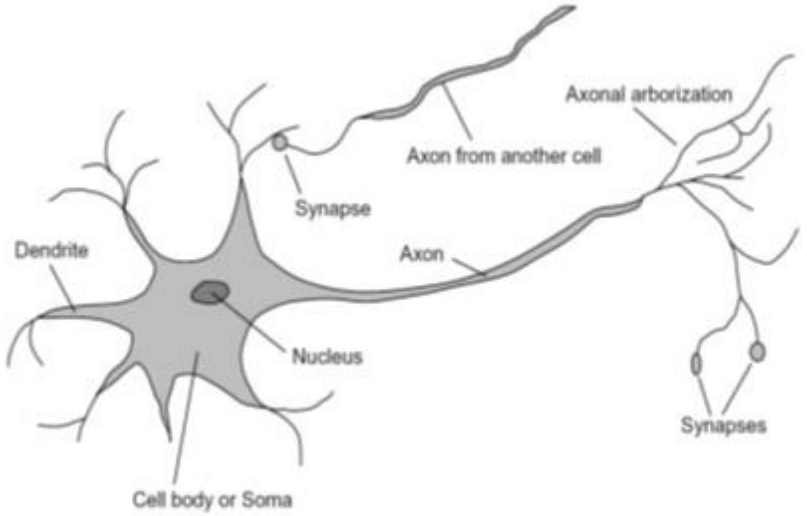
- Neurons
  - accept information from multiple inputs,
  - transmit information to other neurons.
- Multiply inputs by weights along edges
- Apply some function to the set of inputs at each node
- If output of function over threshold, neuron “fires”



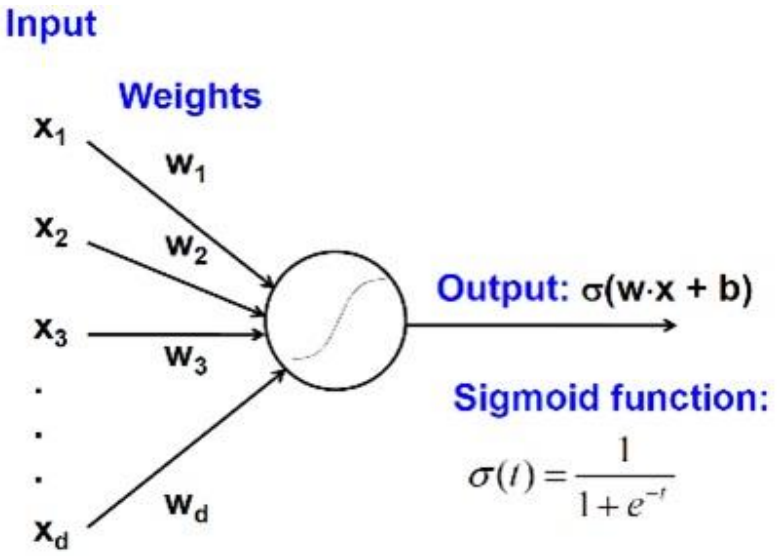


Text: HKUST, figures: Andrej Karpathy

Biological analog

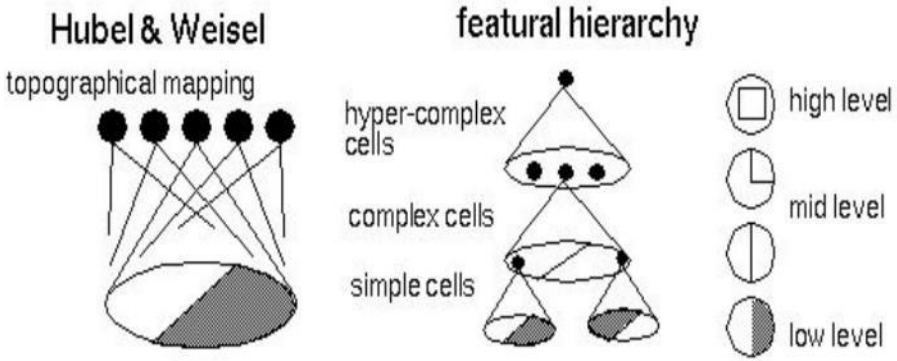


A biological neuron

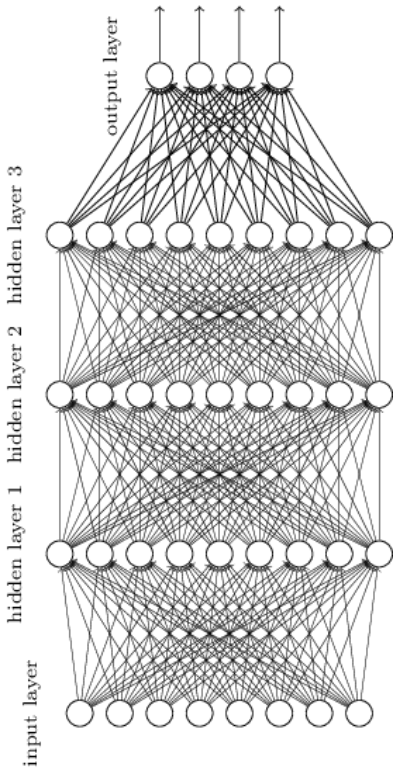


An artificial neuron

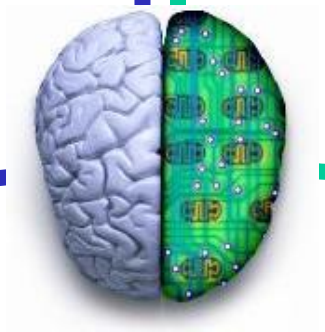
Biological analog



Hubel and Weisel's architecture



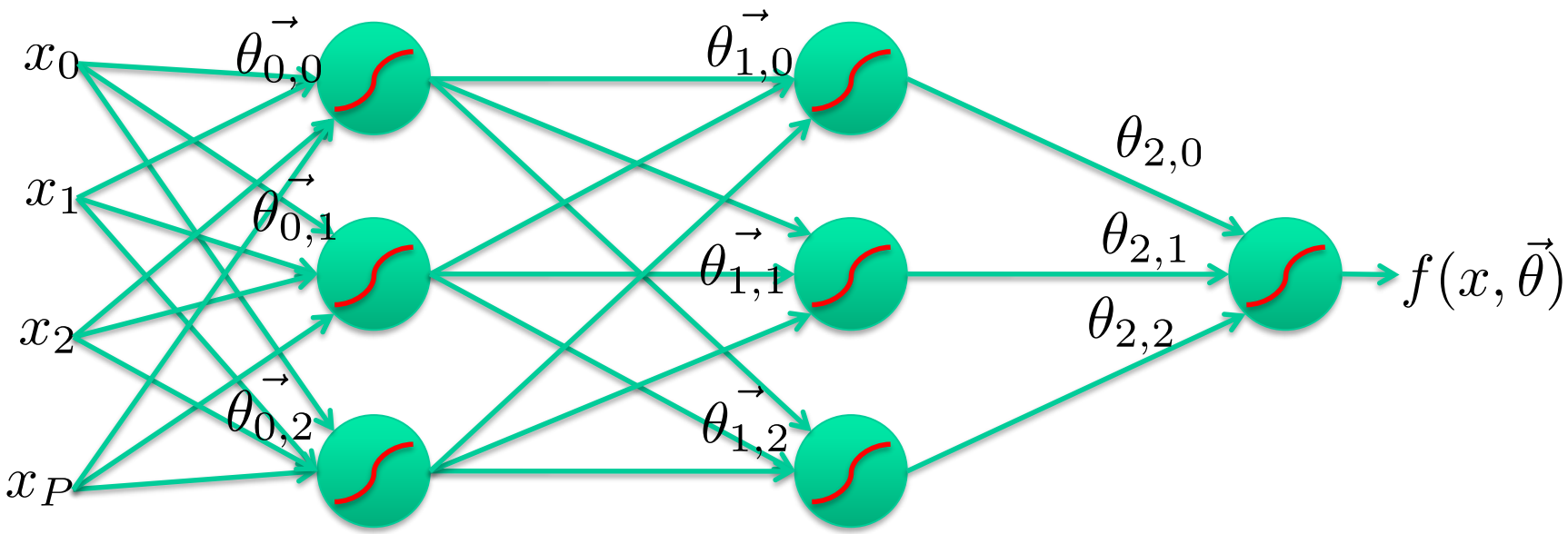
Multi-layer neural network



Adapted from Jia-bin Huang

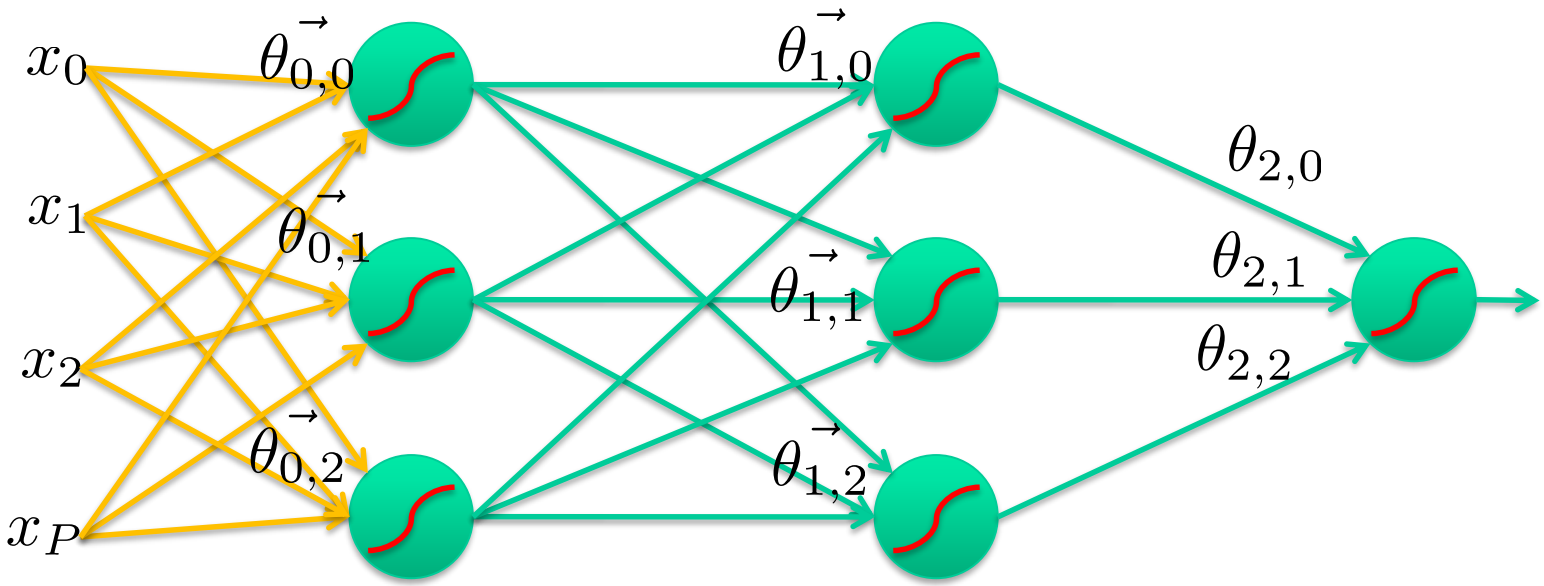
Multilayer networks

- Cascade neurons together
- Output from one layer is the input to the next
- Each layer has its own sets of weights



Feed-forward networks

- Predictions are fed forward through the network to classify



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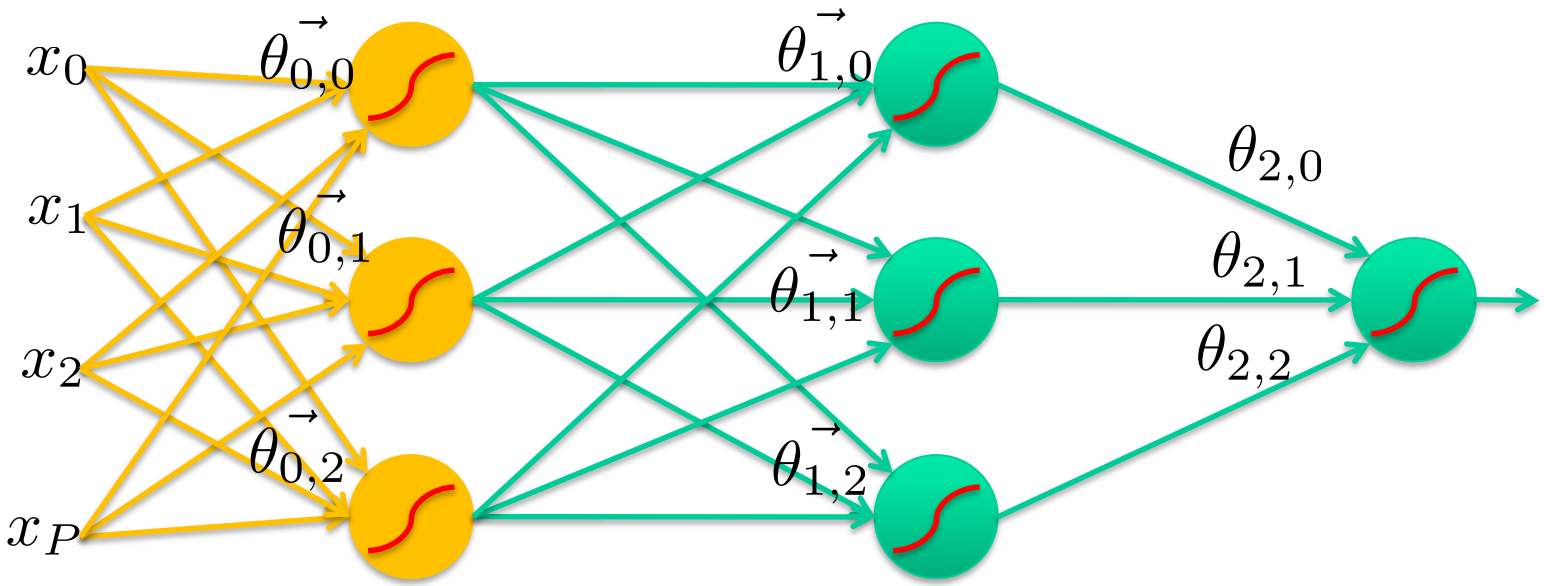

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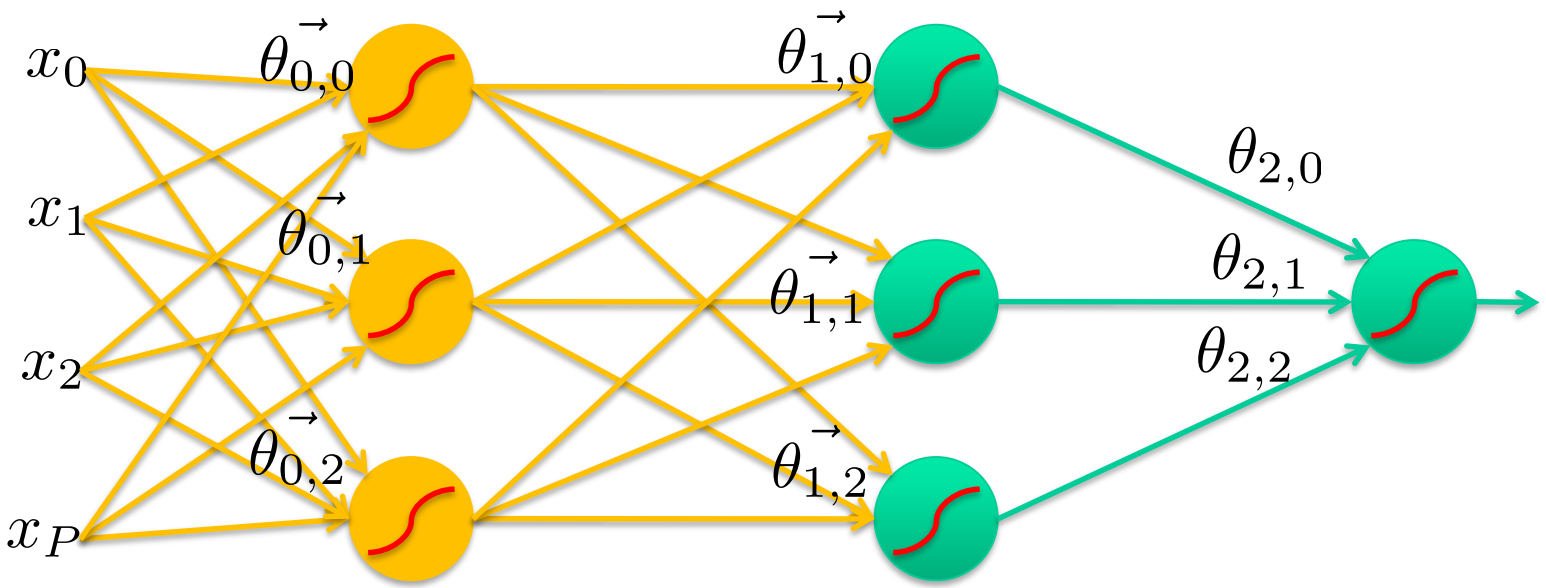

Feed-forward networks

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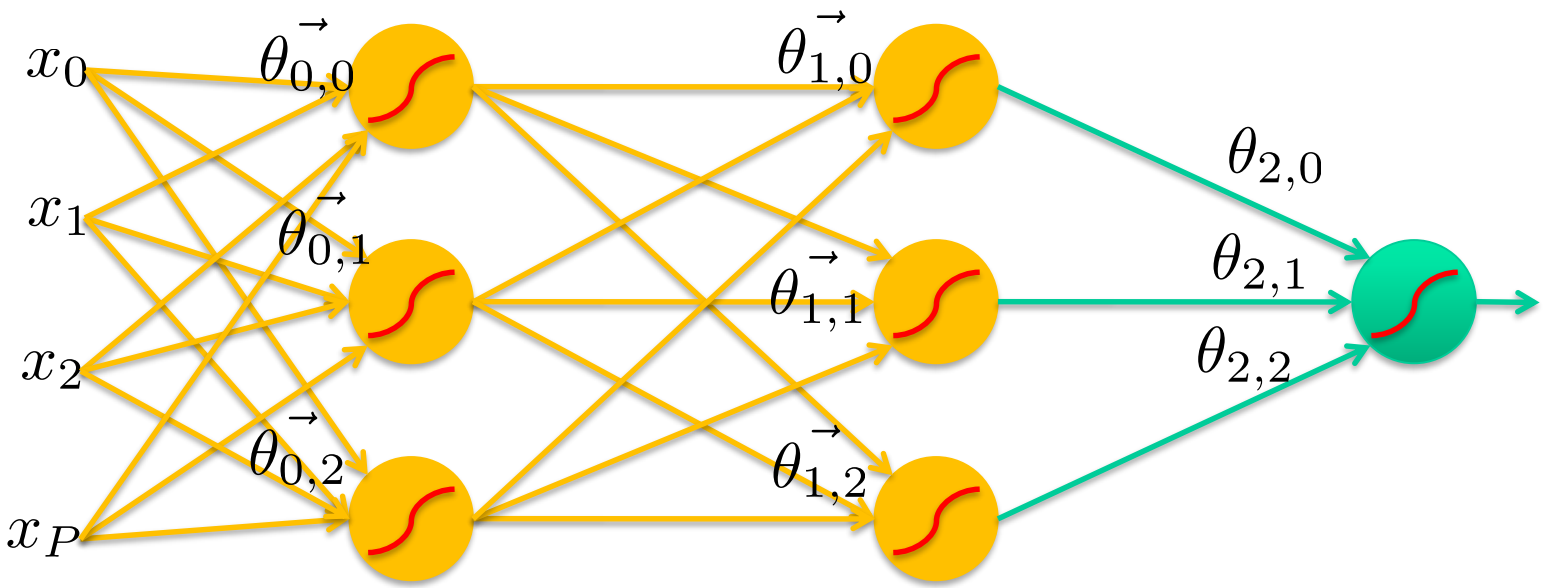

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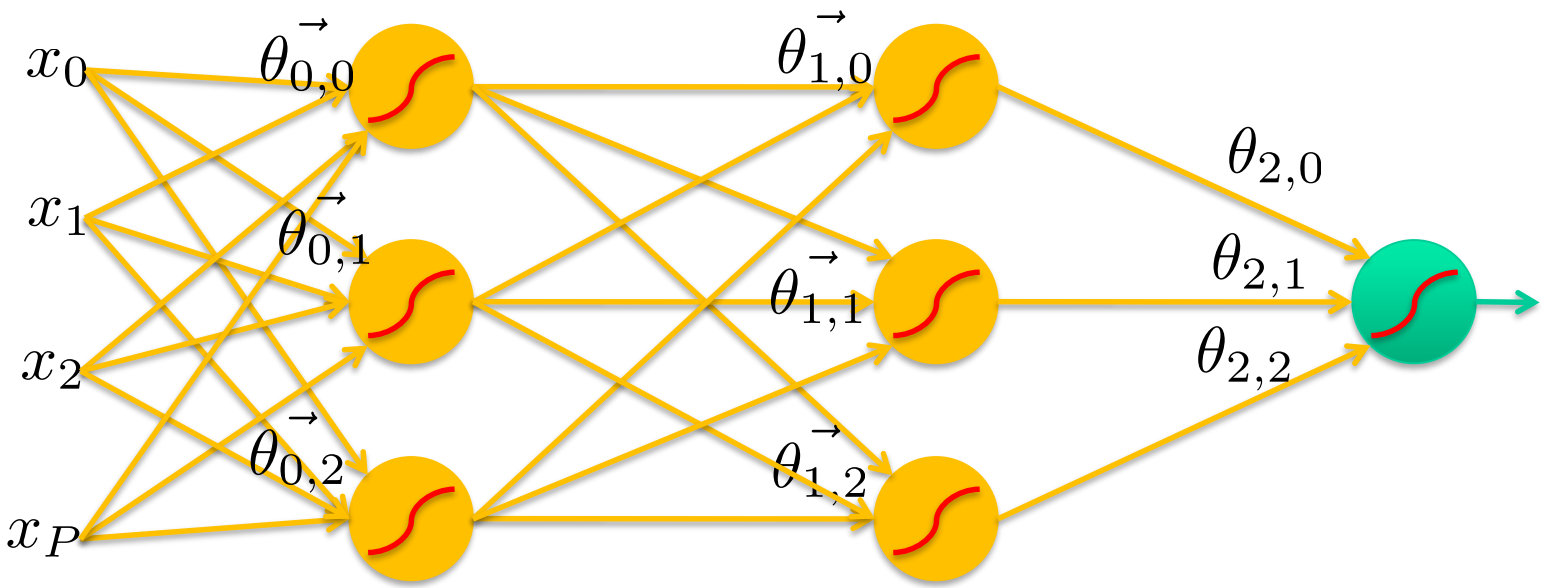

Feed-forward networks

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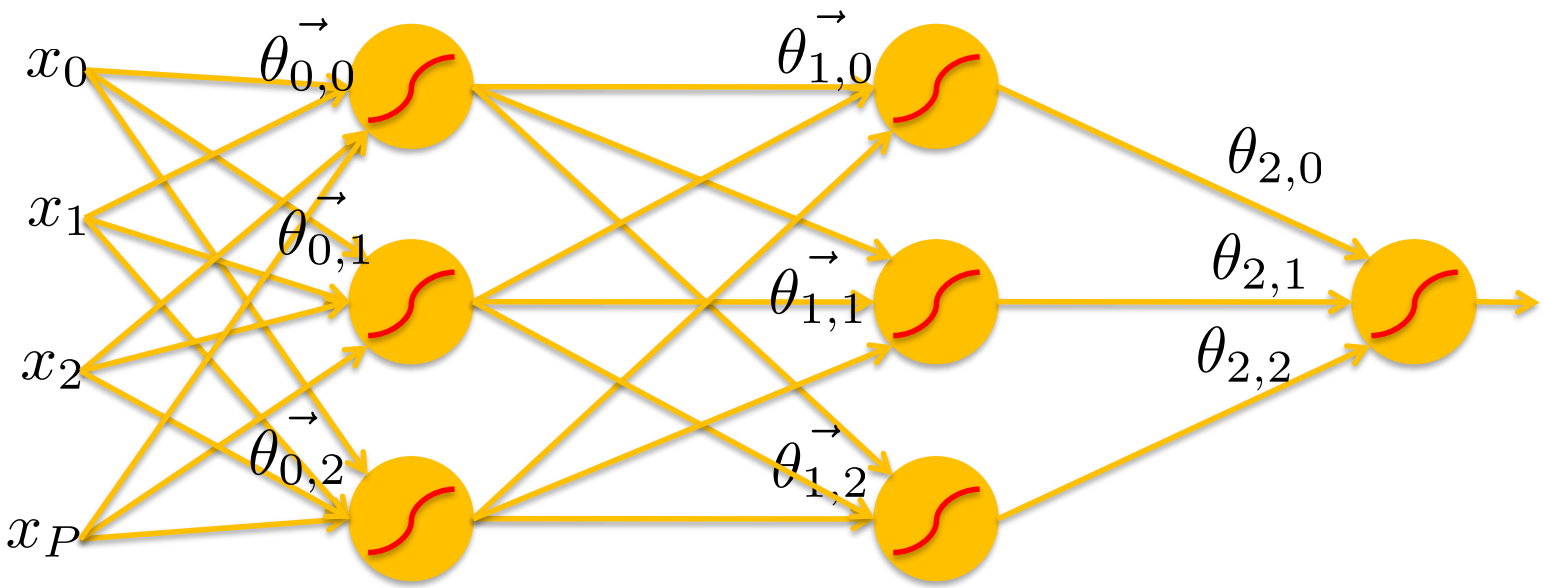


Deep neural networks

- Lots of hidden layers
- Depth = power (usually)

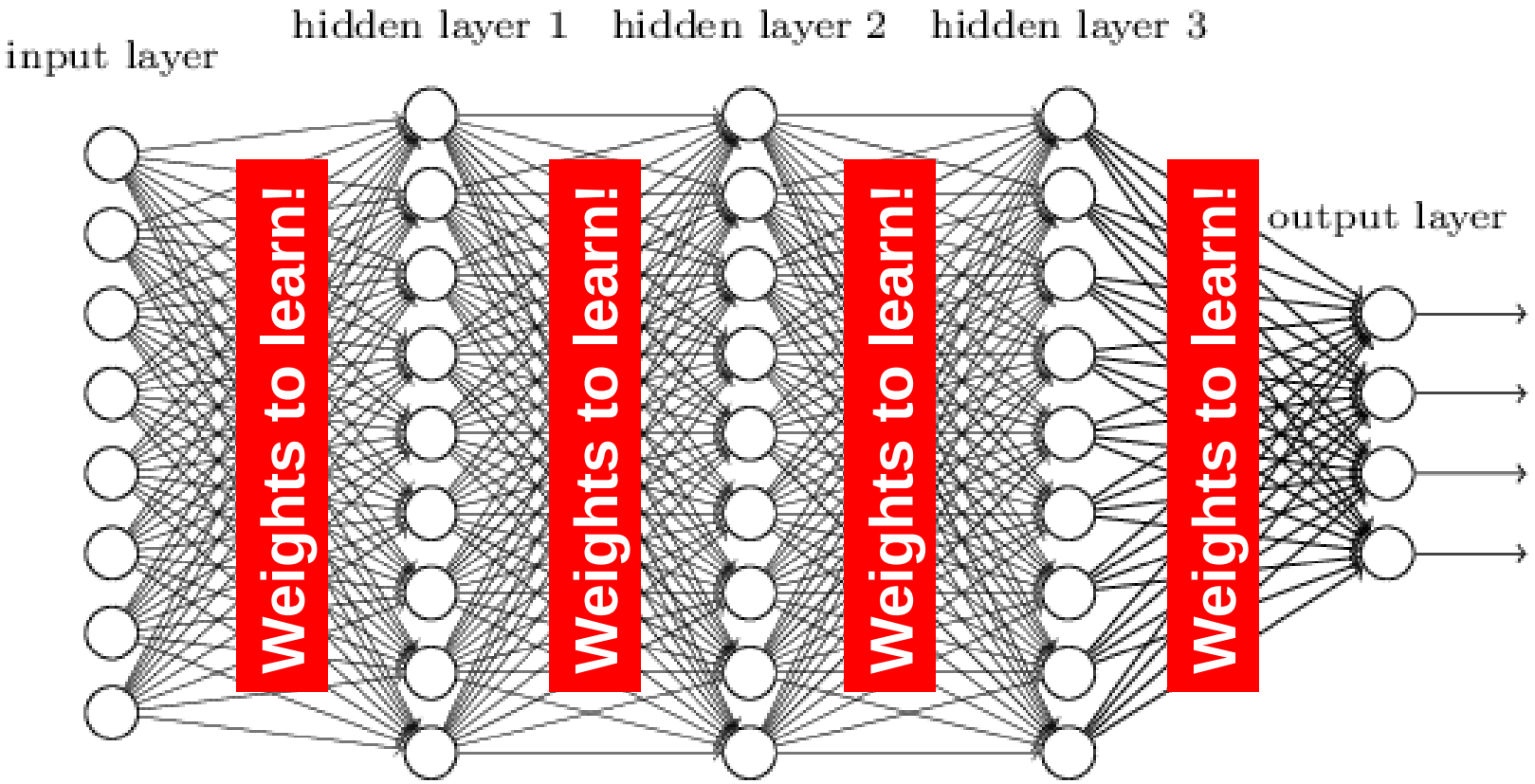
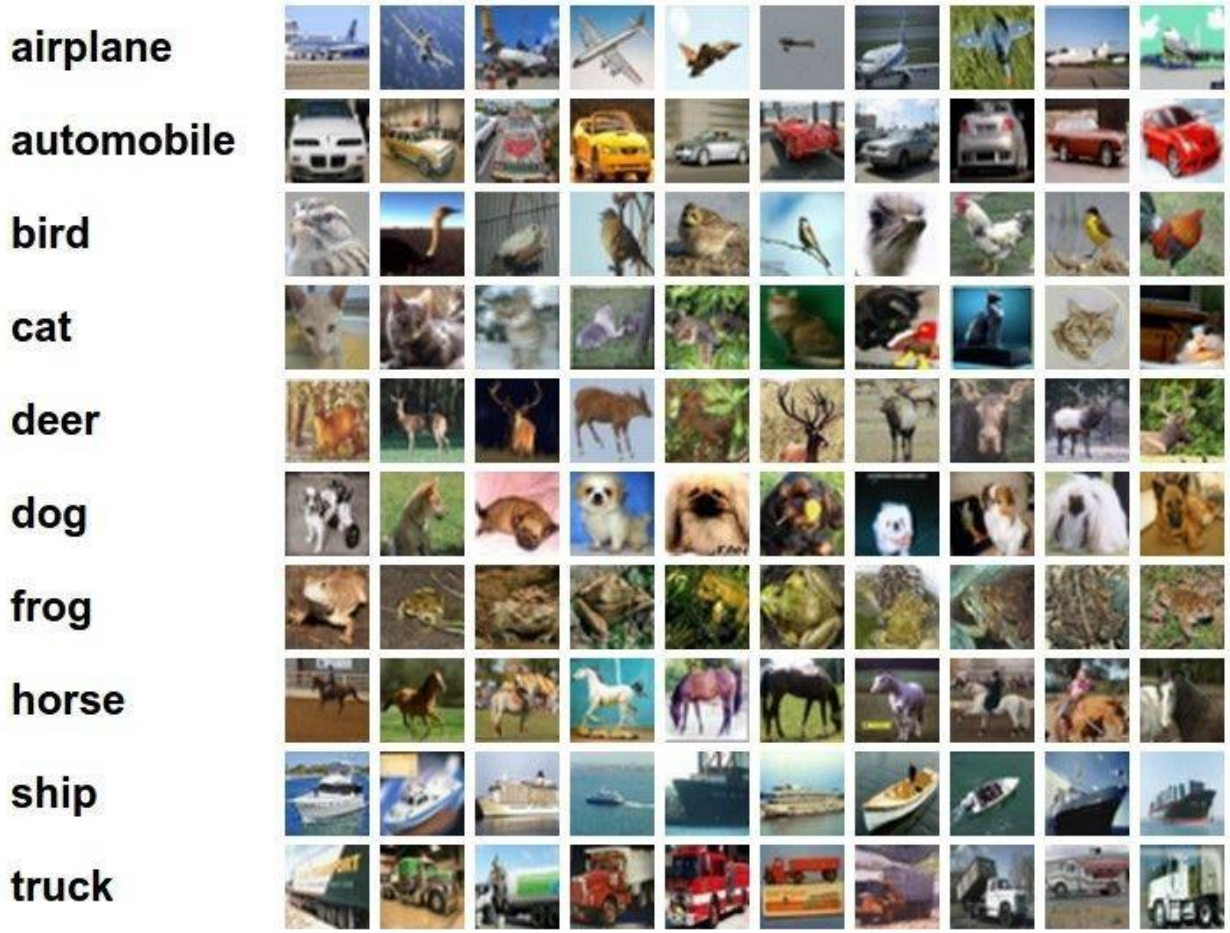


Figure from http://neuralnetworksanddeeplearning.com/chap5.html

How do we train them?

- The goal is to iteratively find such a set of weights that allow the activations/outputs to match the desired output
- We want to *minimize a* ***loss function***
- The loss function is a function of the weights in the network
- For now let’s simplify and assume there’s a single layer of weights in the network

Classification goal



Example dataset: **CIFAR-10**
10 labels
50,000 training images
each image is **32x32x3**
10,000 test images.

Classification scores

$$f(x, W) = Wx$$

f(**x**,**W**)

[32x32x3]
array of numbers 0...1
(3072 numbers total)

10 numbers, indicating class scores

Linear classifier

$$f(x, W) = Wx$$

10x1 (output)

10x3072 (W)

3072x1 (x)

(+b) 10x1

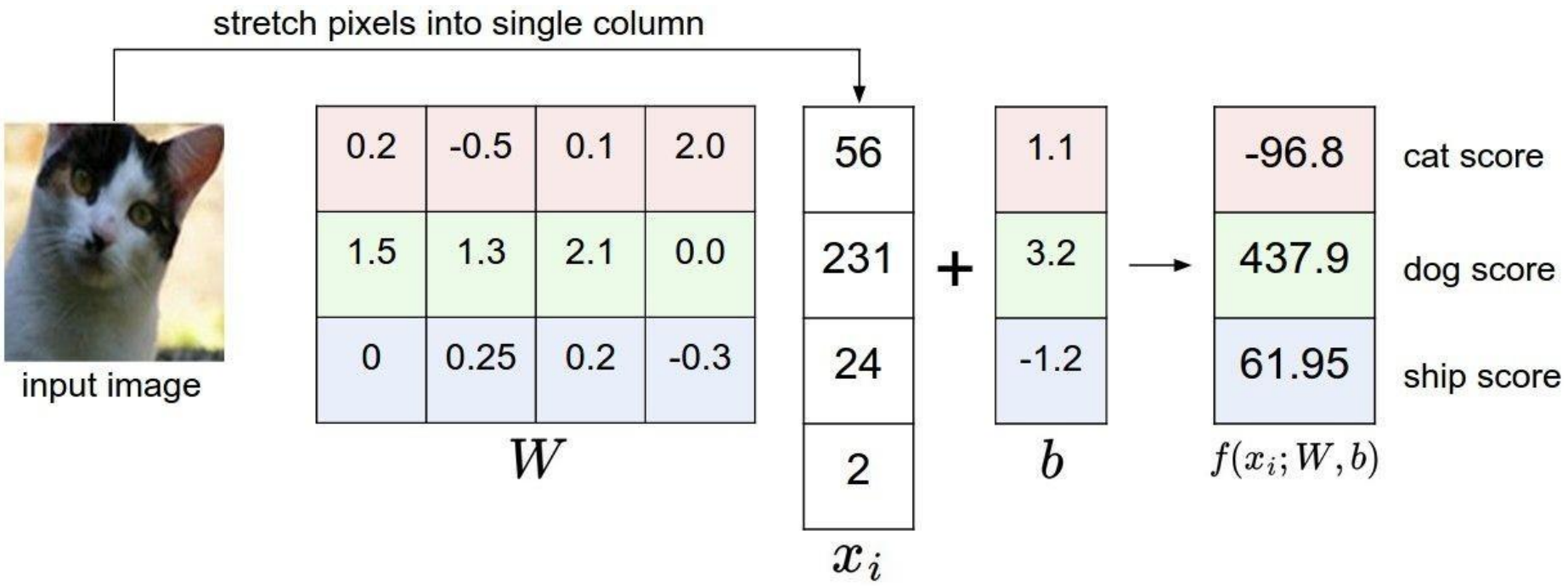
[32x32x3]
array of numbers 0...1

10 numbers, indicating class scores

parameters, or “weights”

Linear classifier

Example with an image with 4 pixels, and 3 classes (cat/dog/ship)



Linear classifier

Going forward: Loss function/Optimization



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

TODO:

1. Define a **loss function** that quantifies our unhappiness with the scores across the training data.

2. Come up with a way of efficiently finding the parameters that minimize the loss function. **(optimization)**

Linear classifier

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

Hinge loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

Want: $s_{y_i} >= s_j + 1$
i.e. $s_j - s_{y_i} + 1 <= 0$

If true, loss is 0
If false, loss is magnitude of violation

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9		

Hinge loss:

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the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

= max(0, 5.1 - 3.2 + 1)
+max(0, -1.7 - 3.2 + 1)
= max(0, 2.9) + max(0, -3.9)
= 2.9 + 0
= 2.9

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	

Hinge loss:

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where x_i is the image and
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and using the shorthand for the scores vector: $s = f(x_i, W)$

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

= max(0, 1.3 - 4.9 + 1)
+max(0, 2.0 - 4.9 + 1)
= max(0, -2.6) + max(0, -1.9)
= 0 + 0
= 0

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	12.9

Hinge loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

= max(0, 2.2 - (-3.1) + 1)
+max(0, 2.5 - (-3.1) + 1)
= max(0, 5.3 + 1)
+ max(0, 5.6 + 1)
= 6.3 + 6.6
= 12.9

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

Suppose: 3 training examples, 3 classes.
With some W the scores $f(x, W) = Wx$ are:



cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**
Losses:	2.9	0	12.9

Hinge loss:

Given an example (x_i, y_i)
where x_i is the image and
where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

and the full training loss is the mean over all examples in the training data:

$$L = \frac{1}{N} \sum_{i=1}^{N} L_i$$

L = (2.9 + 0 + 12.9)/3
= 15.8 / 3 = **5.3**

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

$$f(x, W) = Wx$$

$$L = \frac{1}{N} \sum_{i=1}^{N} \sum_{j \neq y_i} \max(0, f(x_i; W)_j - f(x_i; W)_{y_i} + 1)$$

Adapted from Andrej Karpathy

Linear classifier: Hinge loss

Weight Regularization

λ = regularization strength (hyperparameter)

$$L = \frac{1}{N}\sum_{i=1}^{N}\sum_{j\neq y_i}\max(0, f(x_i; W)_j - f(x_i; W)_{y_i} + 1) + \lambda R(W)$$

In common use:

L2 regularization

L1 regularization

Dropout (will see later)

$$R(W) = \sum_k \sum_l W_{k,l}^2$$

$$R(W) = \sum_k \sum_l |W_{k,l}|$$

Another loss: Softmax (cross-entropy)

cat **3.2**

car 5.1

frog -1.7

scores = unnormalized log probabilities of the classes.

$$P(Y = k|X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

where $s = f(x_i; W)$

Want to maximize the log likelihood, or (for a loss function) to minimize the negative log likelihood of the correct class:

$$L_i = -\log P(Y = y_i|X = x_i)$$

Another loss: Softmax (cross-entropy)

$$L_i = -\log\left(\frac{e^{sy_i}}{\sum_j e^{s_j}}\right)$$

unnormalized probabilities

	unnormalized log probabilities	exp	unnormalized probabilities	normalize	probabilities	
cat	**3.2**		**24.5**		**0.13**	L_i = -log(0.13) = **0.89**
car	5.1		164.0		0.87	
frog	-1.7		0.18		0.00	

Adapted from Andrej Karpathy

Other losses

- Triplet loss (Schroff, FaceNet)

$$\sum_{i}^{N} \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \right]_+$$

a denotes anchor
p denotes positive
n denotes negative

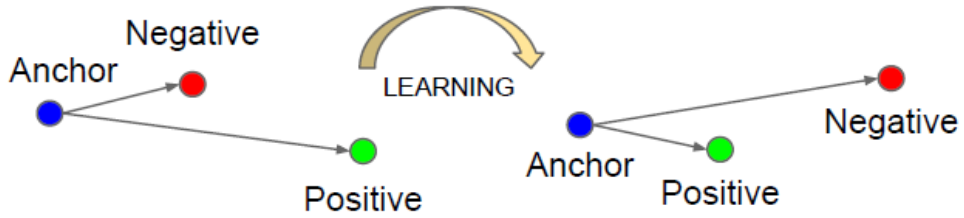


Figure 3. The **Triplet Loss** minimizes the distance between an *anchor* and a *positive*, both of which have the same identity, and maximizes the distance between the *anchor* and a *negative* of a different identity.

- Anything you want!

How to minimize the loss function?

How to minimize the loss function?

In 1-dimension, the derivative of a function:

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

In multiple dimensions, the **gradient** is the vector of (partial derivatives).

current W:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25347

gradient dW:

[?,
?,
?,
?,
?,
?,
?,
?,
?,…]

current W:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25347

W + h (first dim)**:**

[0.34 + **0.0001**,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25322

gradient dW:

[?,
?,
?,
?,
?,
?,
?,
?,
?,…]

current W:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25347

W + h (first dim)**:**

[0.34 + **0.0001**,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25322

gradient dW:

[**-2.5**,
?,
?,

(1.25322 - 1.25347)/0.0001
= -2.5

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

?,
?,…]

current W:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25347

W + h (second dim)**:**

[0.34,
-1.11 + **0.0001**,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25353

gradient dW:

[-2.5,
?,
?,
?,
?,
?,
?,
?,
?,…]

current W:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25347

W + h (second dim)**:**

[0.34,
-1.11 + **0.0001**,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25353

gradient dW:

[-2.5,
0.6,
?,
?,

(1.25353 - 1.25347)/0.0001
= 0.6

$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

?,…]

current W:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25347

W + h (third dim)**:**

[0.34,
-1.11,
0.78 + **0.0001**,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25347

gradient dW:

[-2.5,
0.6,
?,
?,
?,
?,
?,
?,
?,…]

This is silly. The loss is just a function of W:

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i + \sum_k W_k^2$$

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

$$s = f(x; W) = Wx$$

want $\nabla_W L$

This is silly. The loss is just a function of W:

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i + \sum_k W_k^2$$

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

$$s = f(x; W) = Wx$$

want $\nabla_W L$

Calculus

$\nabla_W L$ = ...

current W:

[0.34,
-1.11,
0.78,
0.12,
0.55,
2.81,
-3.1,
-1.5,
0.33,…]

loss 1.25347

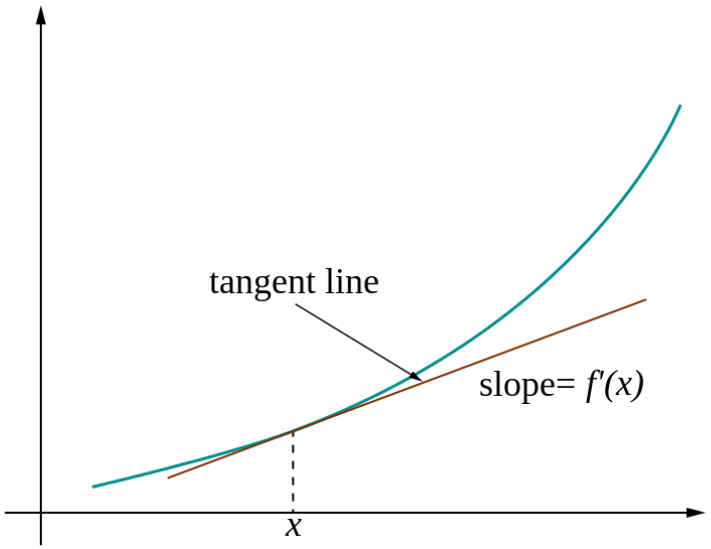
dW = ...
(some function
data and W)

gradient dW:

[-2.5,
0.6,
0,
0.2,
0.7,
-0.5,
1.1,
1.3,
-2.1,…]

Loss gradients

- Denoted as (diff notations): $\frac{\partial E}{\partial w_{ji}^{(1)}}$ $\nabla_W L$
- i.e. how does the loss change as a function of the weights
- We want to change the weights in such a way that makes the loss decrease as fast as possible



Gradient descent

- We'll update weights
- Move in direction opposite to gradient:

$$\mathbf{w}^{(\tau+1)} = \mathbf{w}^{(\tau)} - \eta \nabla E(\mathbf{w}^{(\tau)})$$

Time

Learning rate

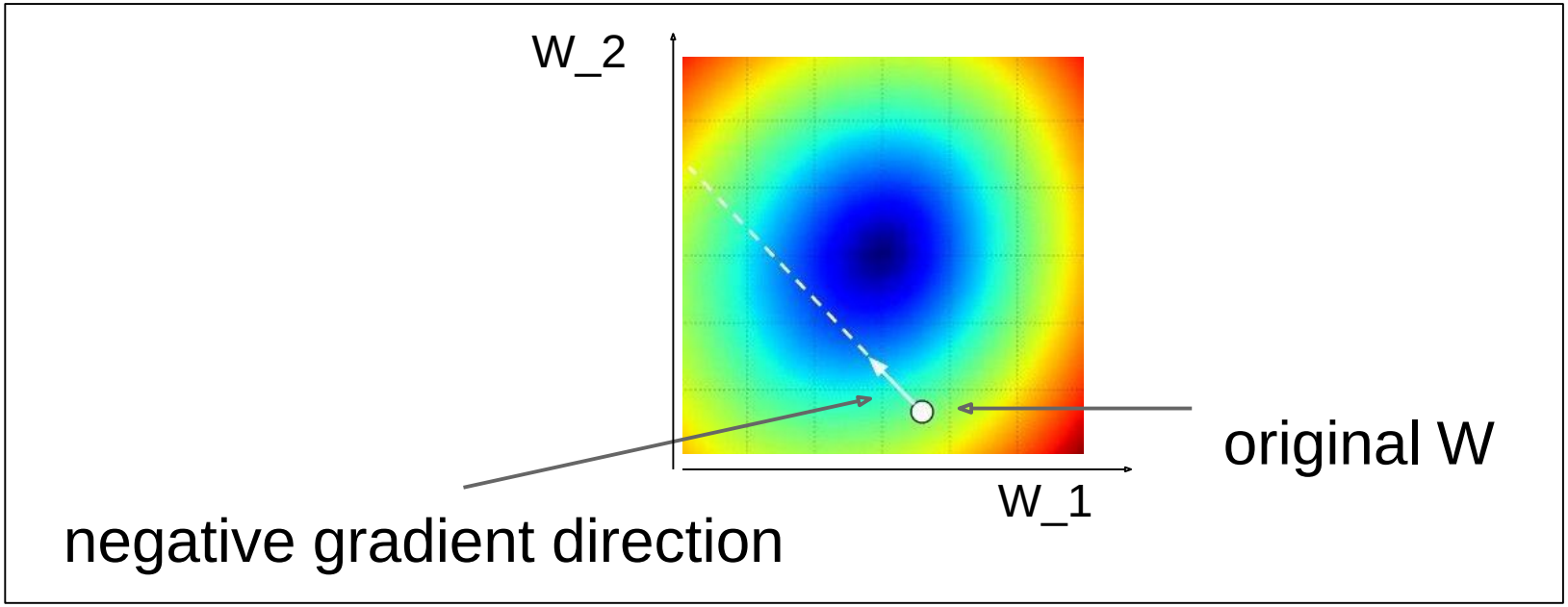


Figure from Andrej Karpathy

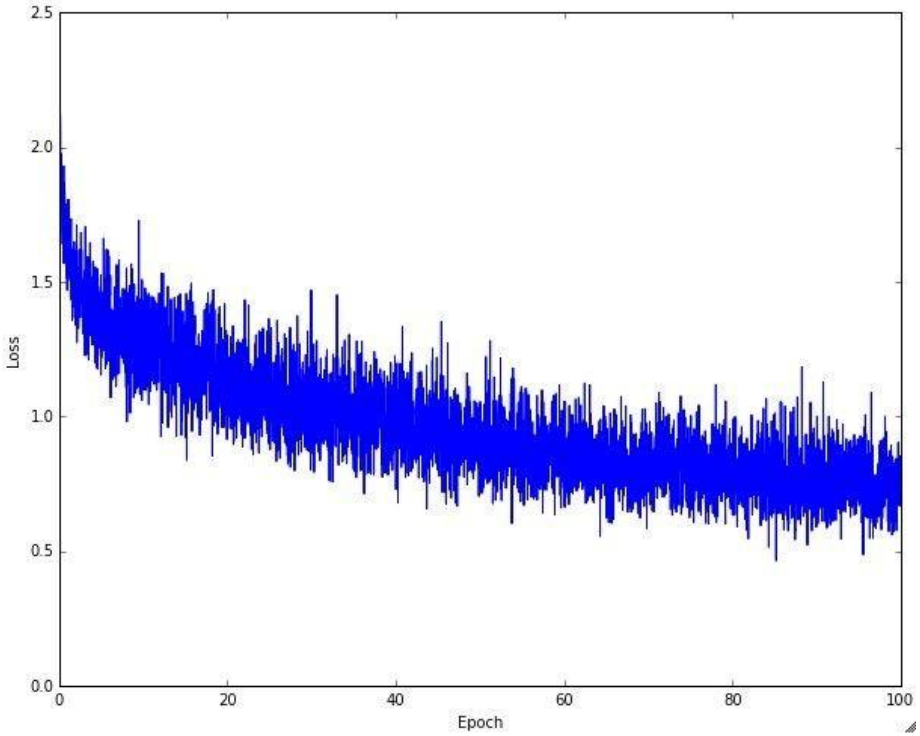
Gradient descent

- Iteratively *subtract* the gradient with respect to the model parameters (w)
- I.e. we're moving in a direction opposite to the gradient of the loss
- I.e. we're moving towards *smaller* loss

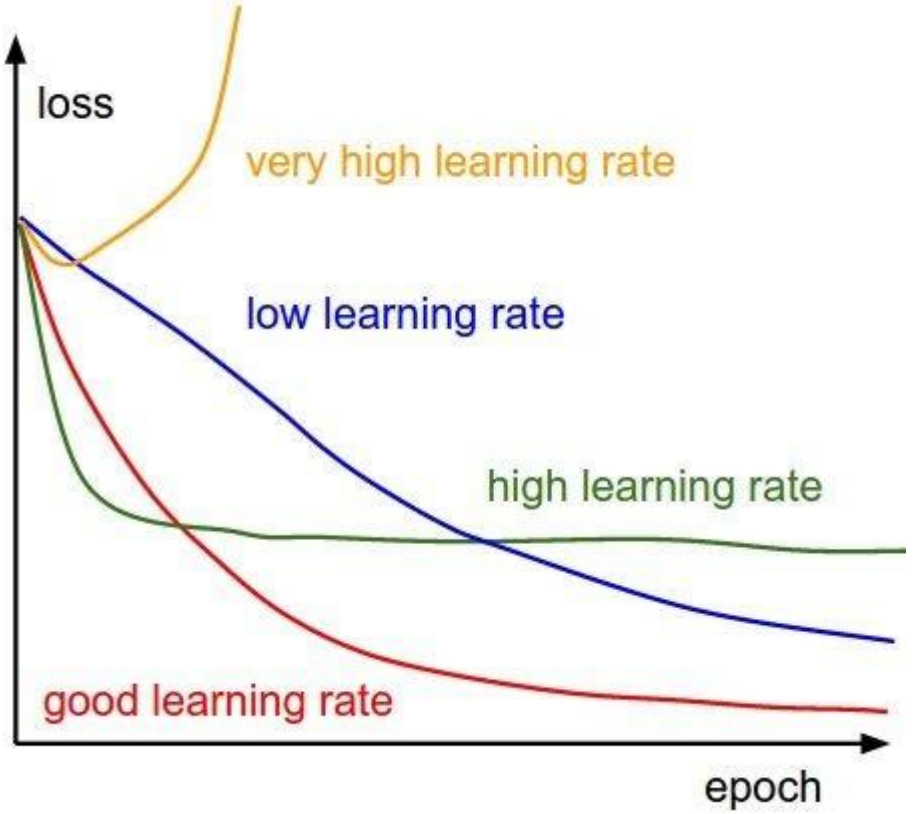
Mini-batch gradient descent

- In classic gradient descent, we compute the gradient from the loss for all training examples
- Could also only use *some* of the data for each gradient update
- We cycle through all the training examples multiple times
- Each time we've cycled through all of them once is called an 'epoch'
- Allows faster training (e.g. on GPUs), parallelization

Learning rate selection



The effects of step size (or “learning rate”)



Gradient descent in multi-layer nets

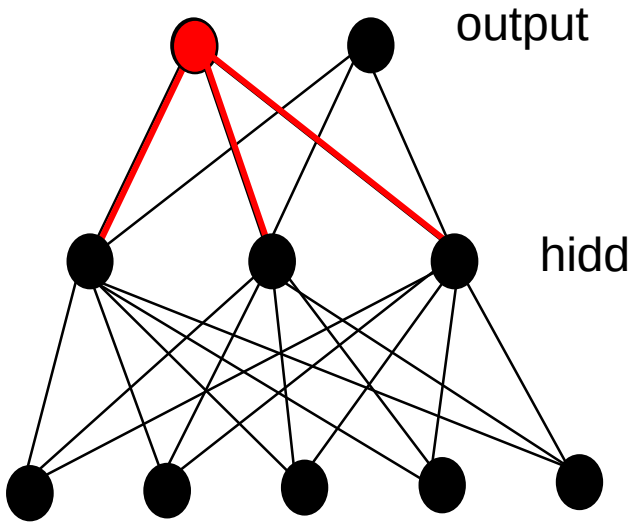
- We'll update weights
- Move in direction opposite to gradient:

$$\mathbf{w}^{(\tau+1)} = \mathbf{w}^{(\tau)} - \eta \nabla E(\mathbf{w}^{(\tau)})$$

- How to update the weights at all layers?
- Answer: backpropagation of error from higher layers to lower layers

Backpropagation: Graphic example

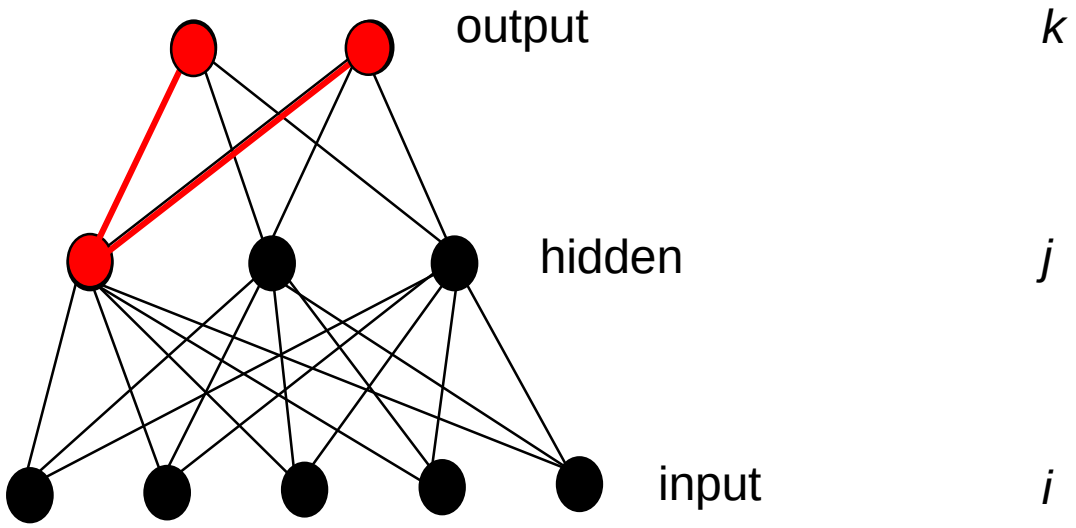
First calculate error of output units and use this to change the top layer of weights.



Adapted from Ray Mooney, equations from Chris Bishop

Backpropagation: Graphic example

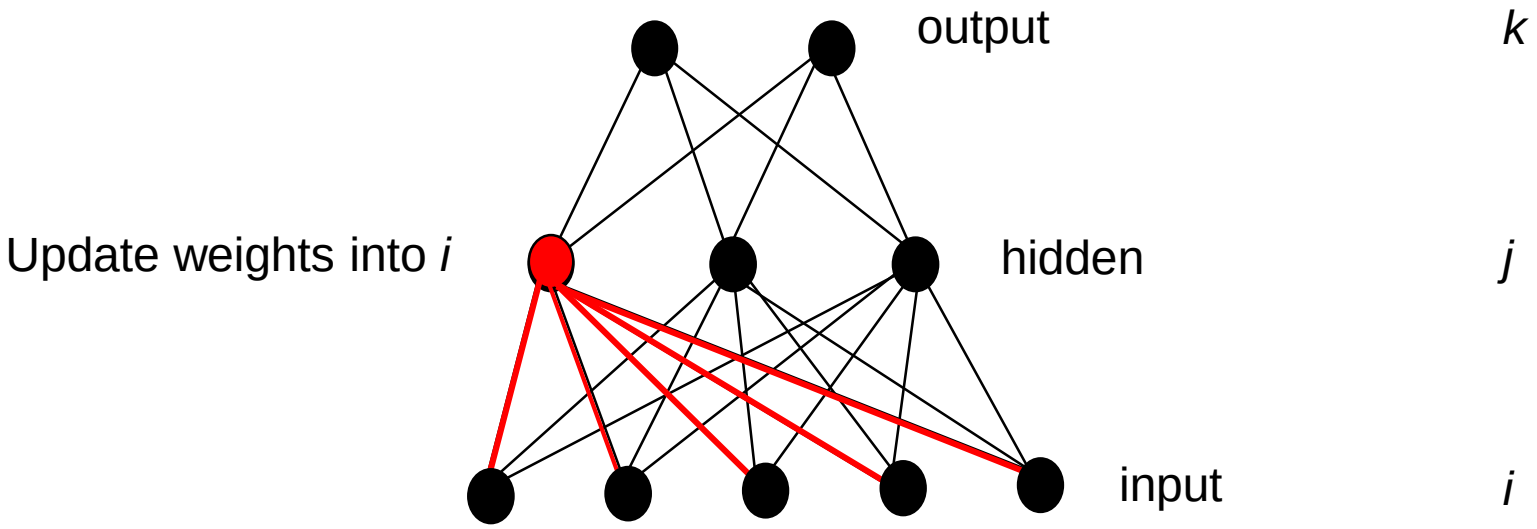
Next calculate error for hidden units based on errors on the output units it feeds into.



Adapted from Ray Mooney, equations from Chris Bishop

Backpropagation: Graphic example

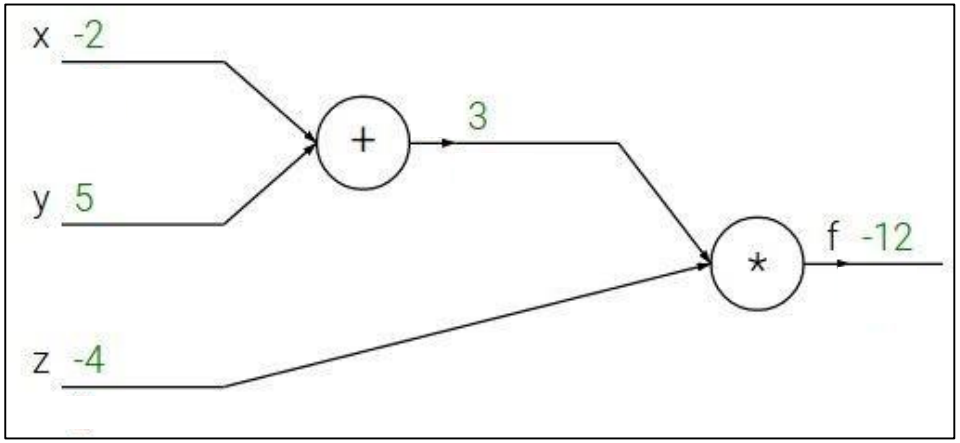
Finally update bottom layer of weights based on errors calculated for hidden units.



Adapted from Ray Mooney, equations from Chris Bishop

$$f(x, y, z) = (x + y)z$$

e.g. x = -2, y = 5, z = -4



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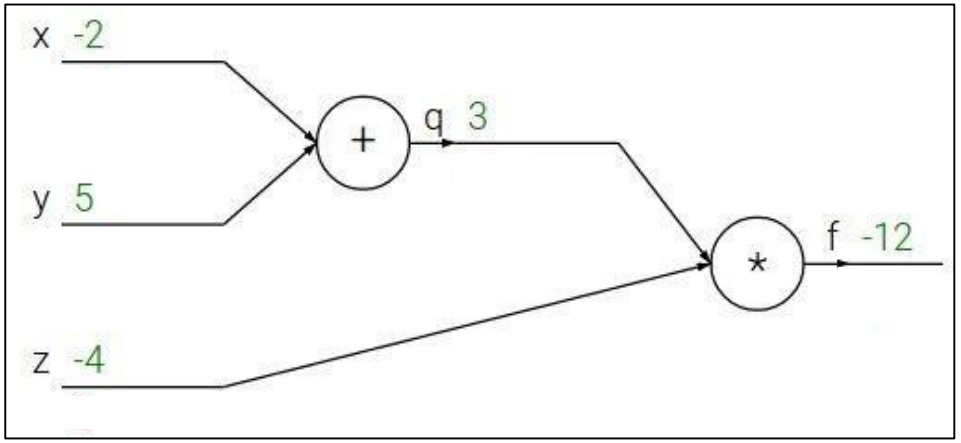

$$q = x + y \qquad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \qquad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

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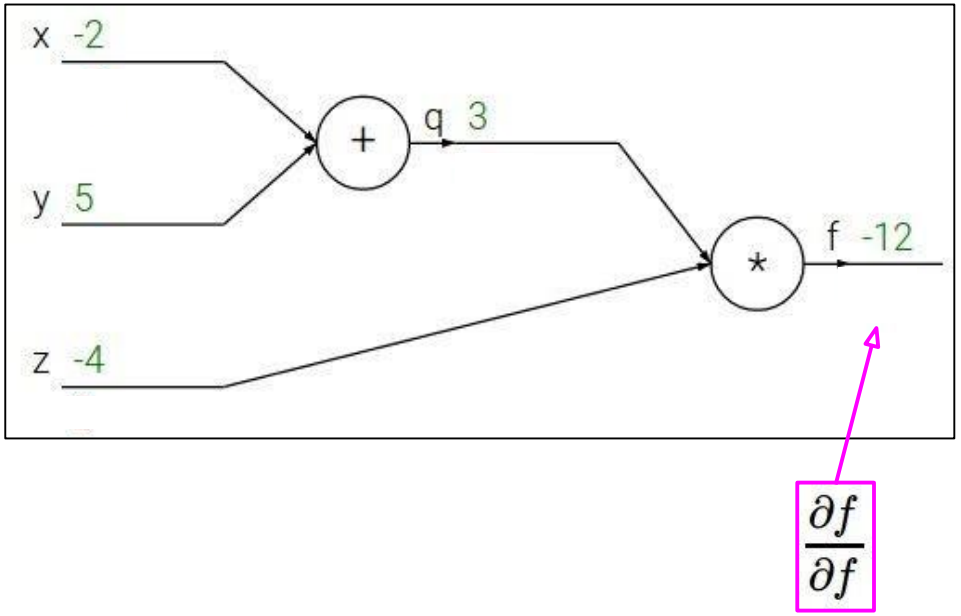
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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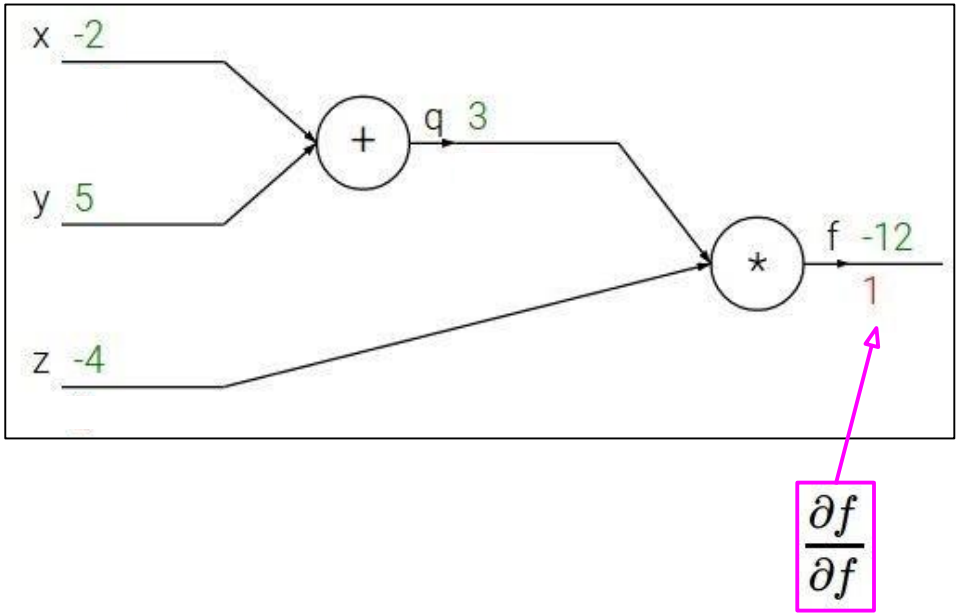
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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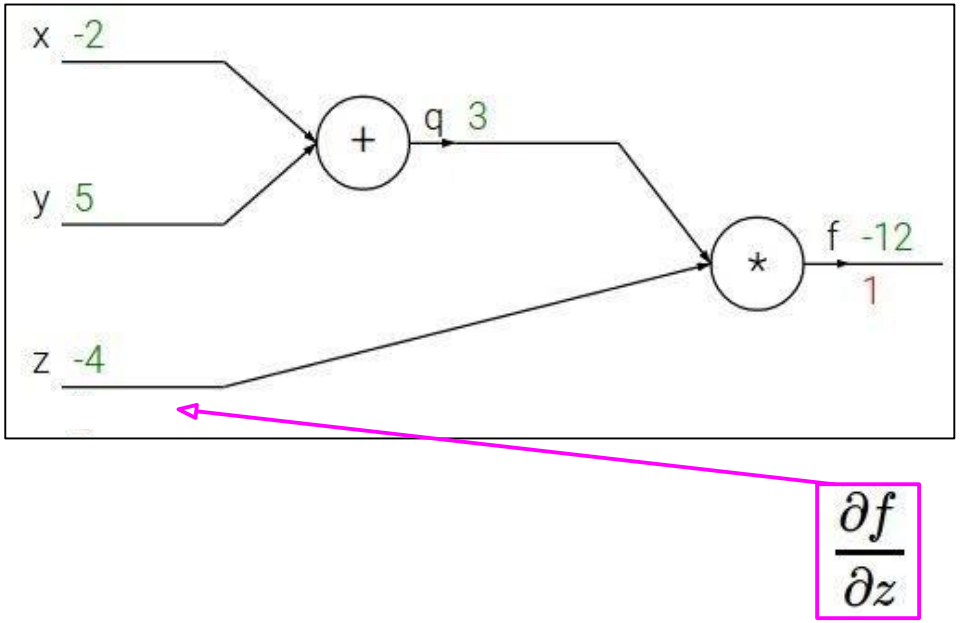

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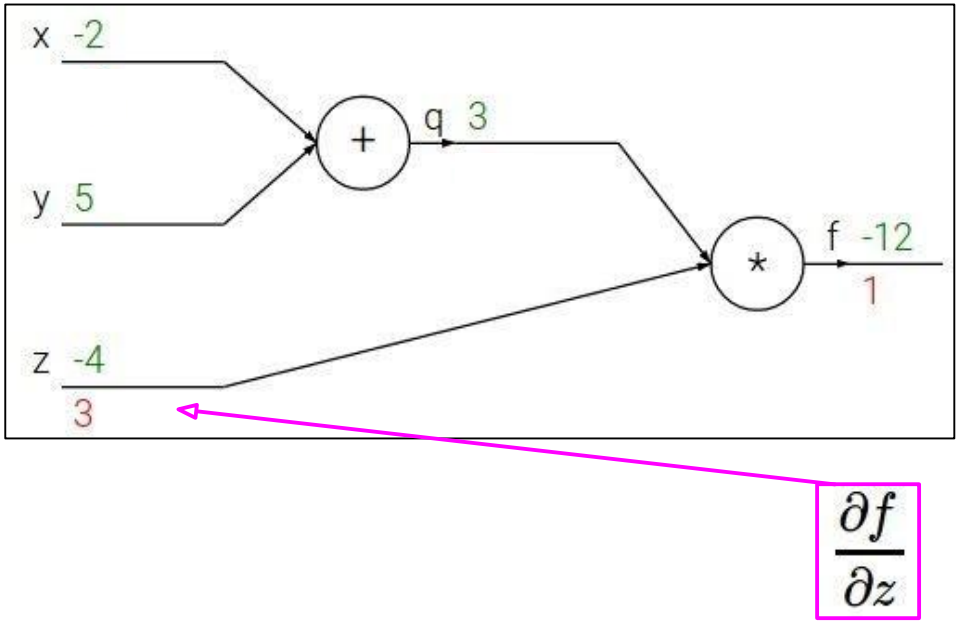
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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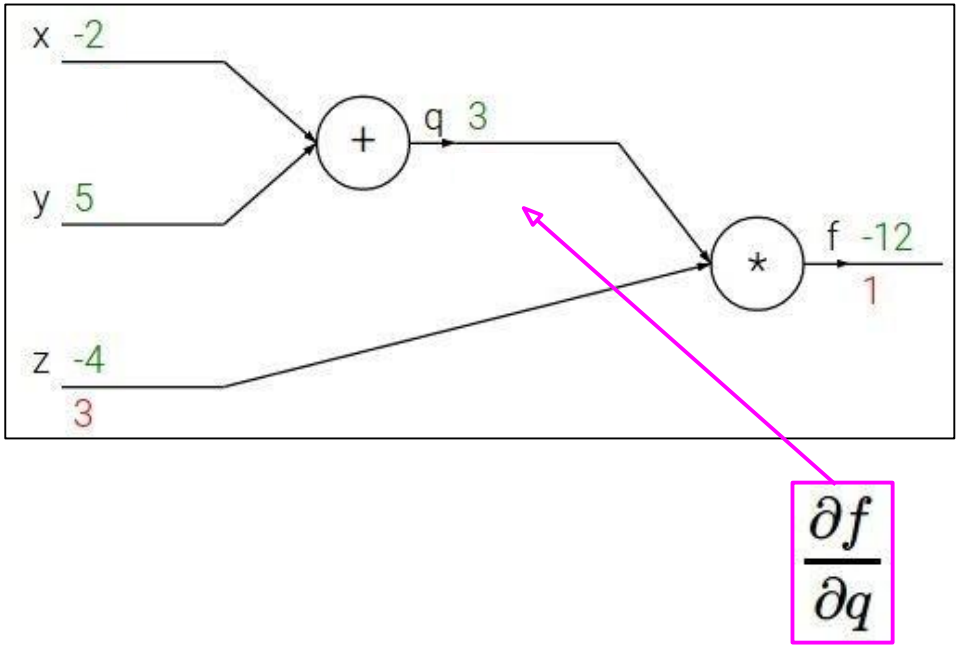
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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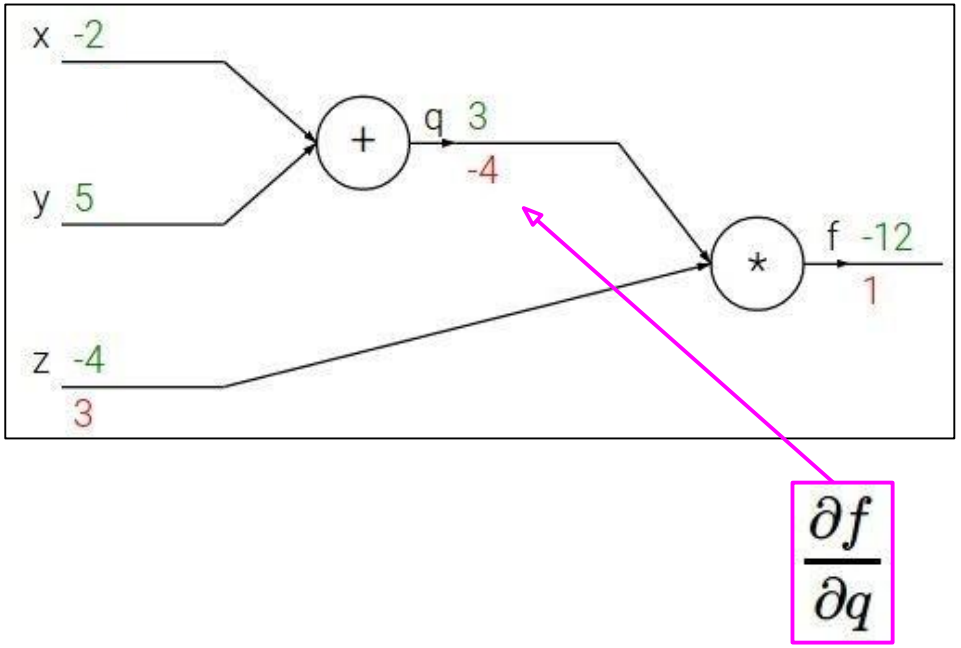
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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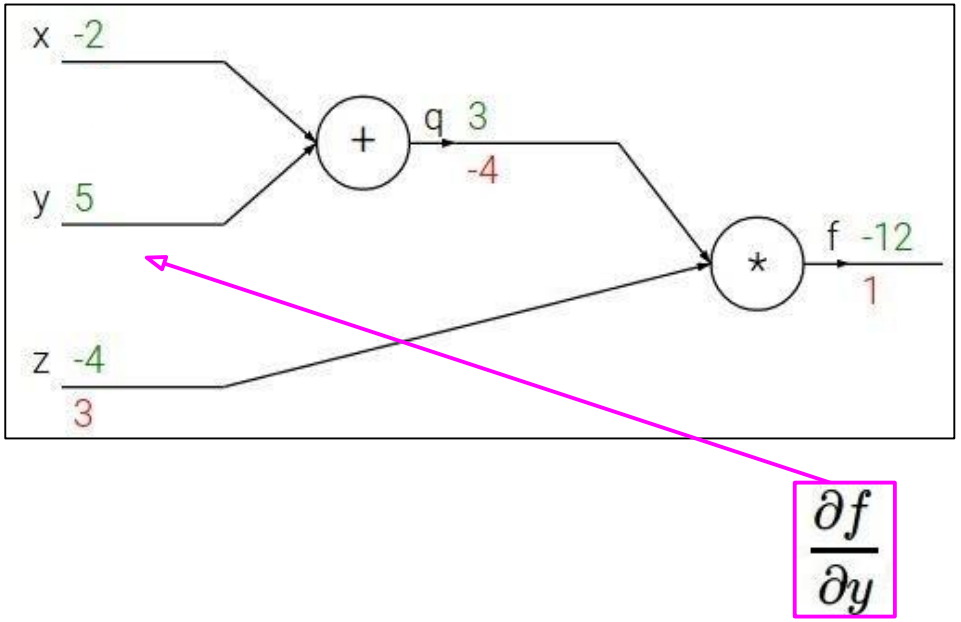
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



$$f(x, y, z) = (x + y)z$$

e.g. x = -2, y = 5, z = -4

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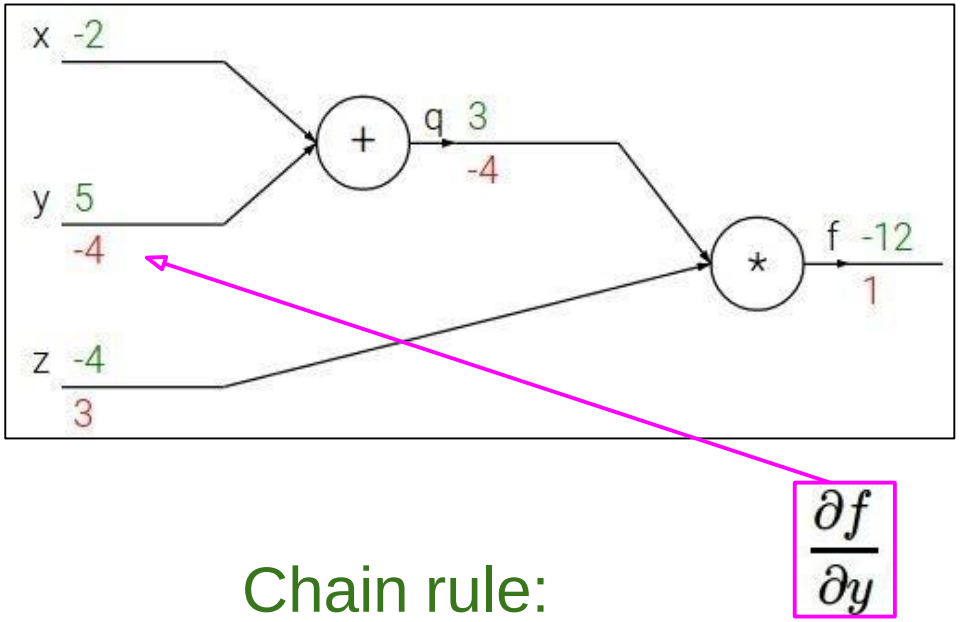
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



Chain rule:

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y}$$

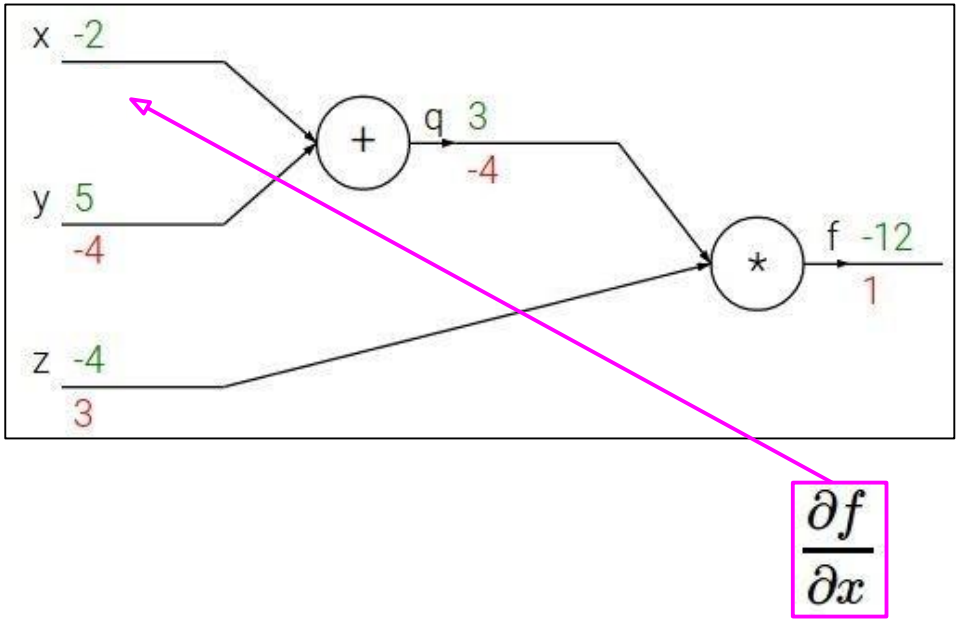
$$f(x, y, z) = (x + y)z$$

e.g. x = -2, y = 5, z = -4

$$q = x + y \qquad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \qquad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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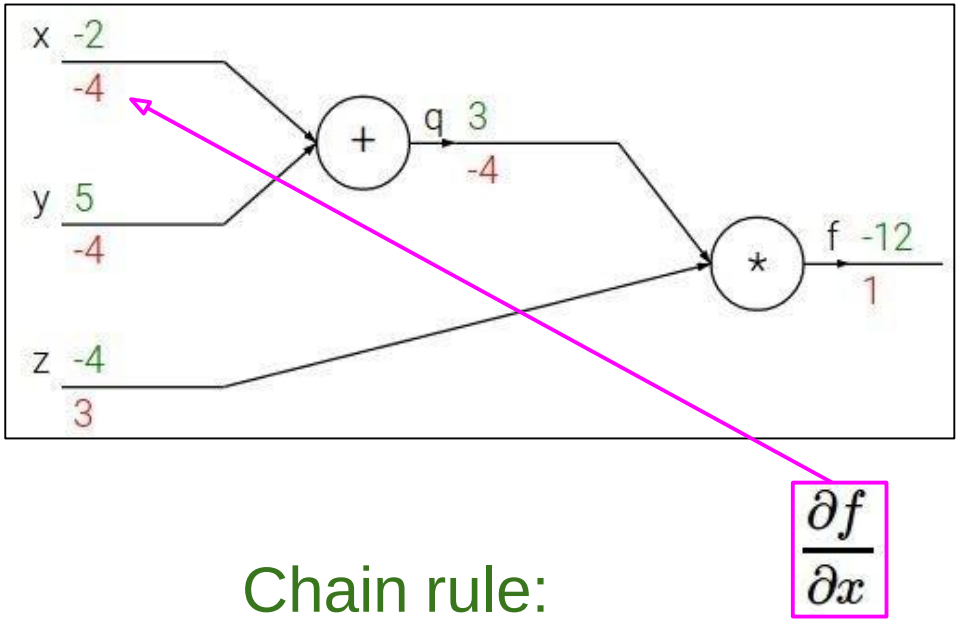

Chain rule:

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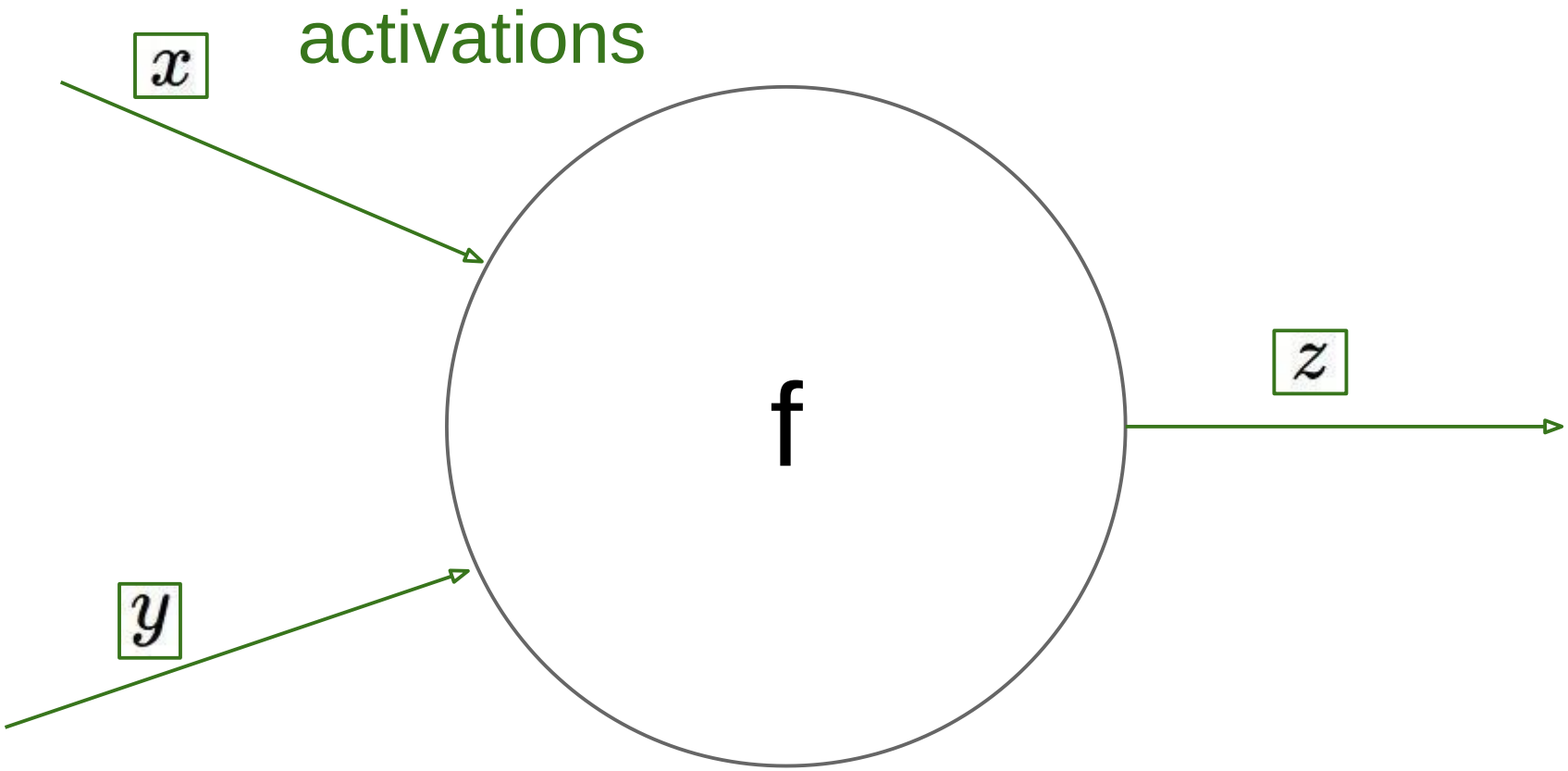
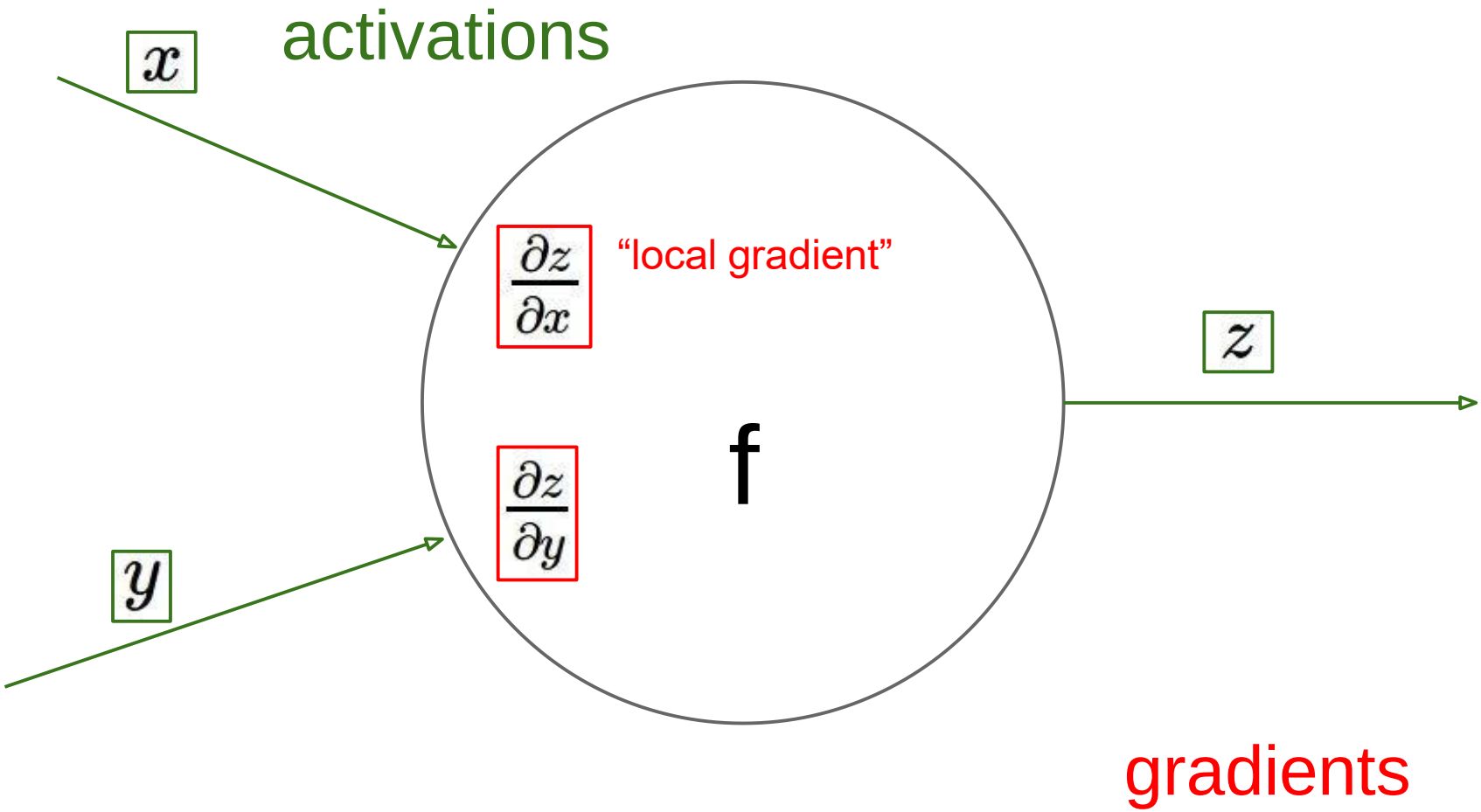
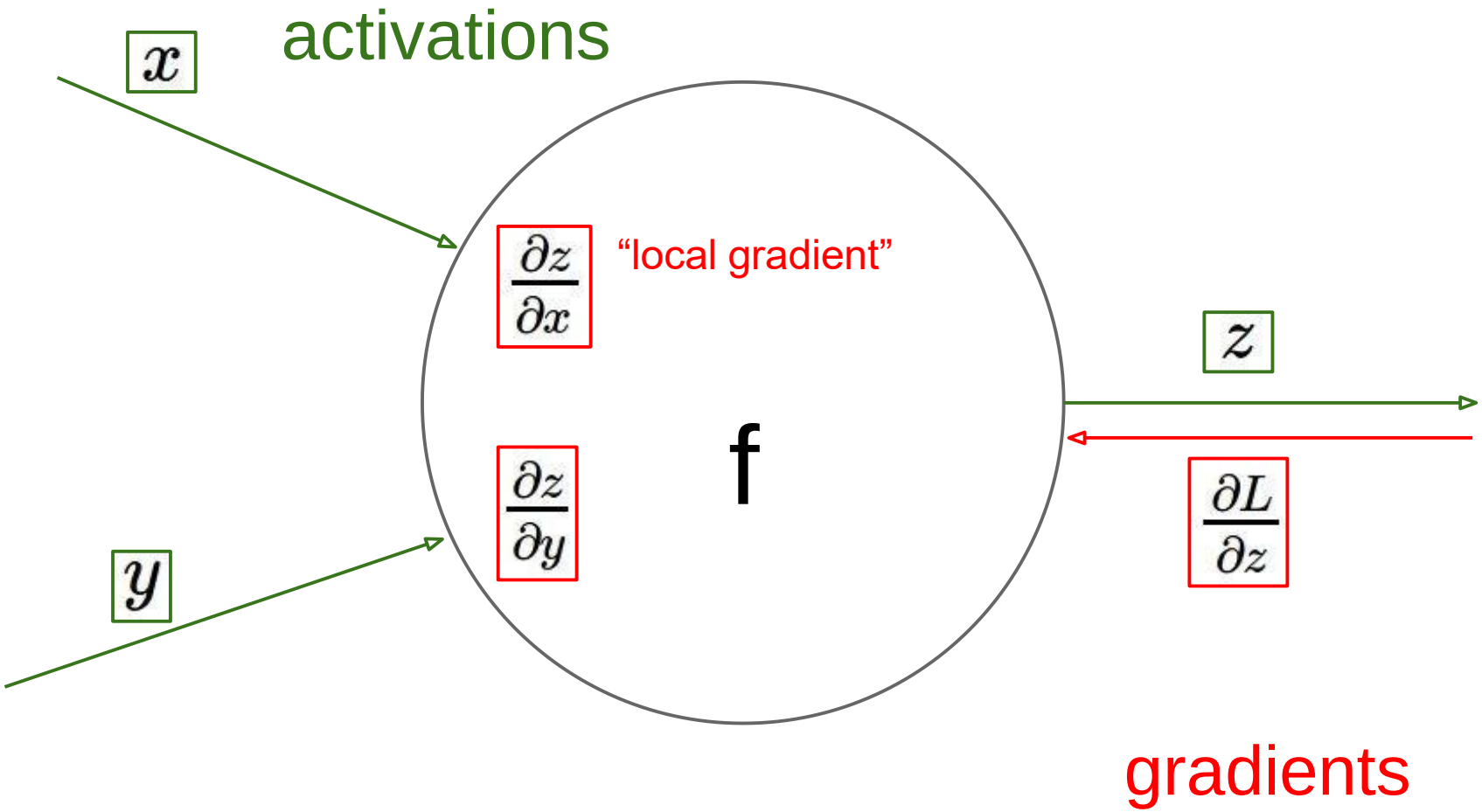
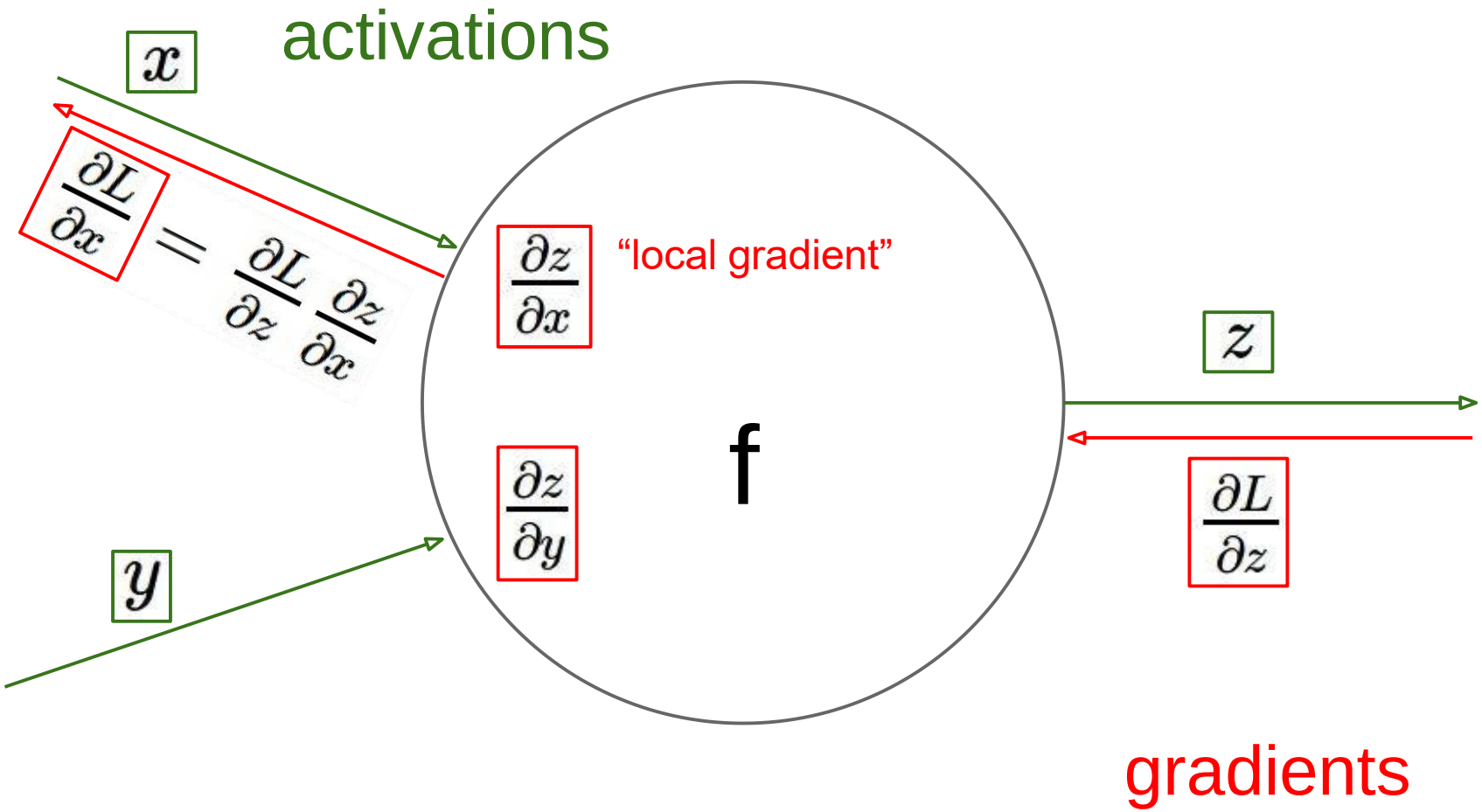
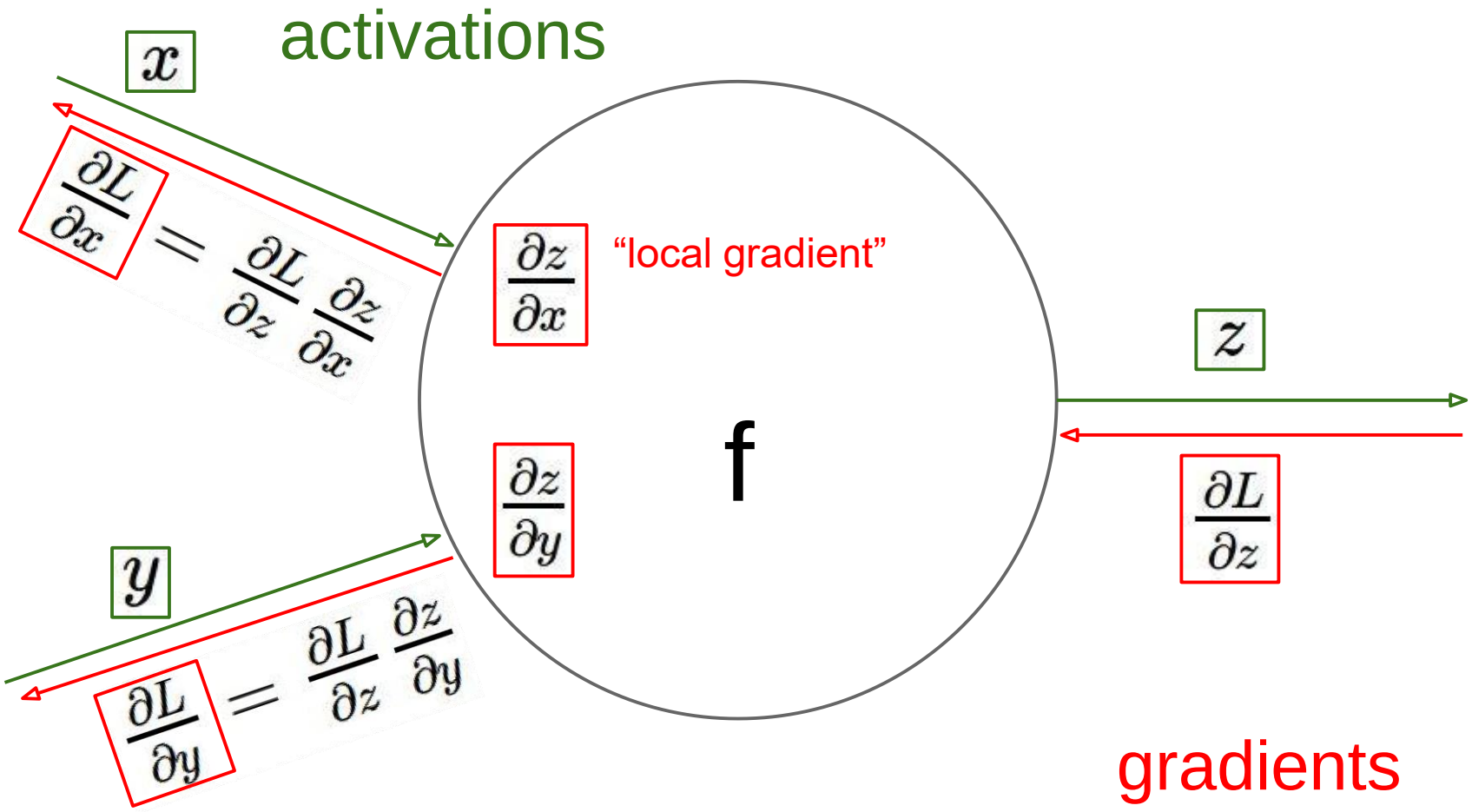

activations
x
f
z
y


activations
x
$\frac{\partial z}{\partial x}$
"local gradient"
z
f
$\frac{\partial z}{\partial y}$
y
gradients


activations
x
y
$\frac{\partial z}{\partial x}$
"local gradient"
$\frac{\partial z}{\partial y}$
f
z
$\frac{\partial L}{\partial z}$
gradients

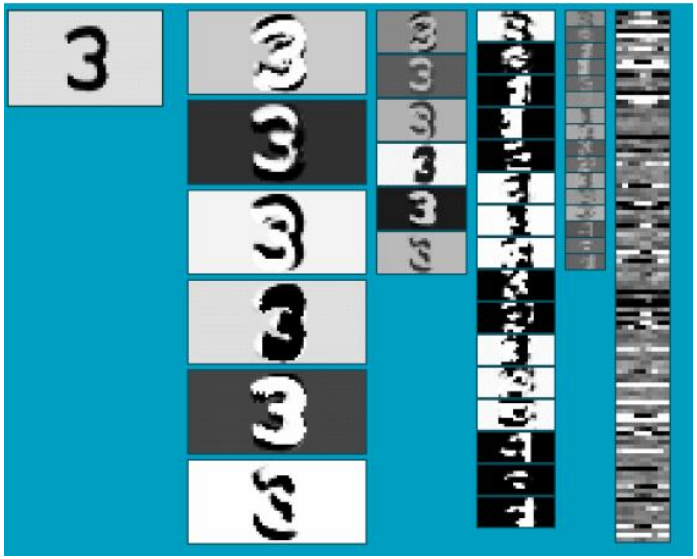

activations
x
$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial x}$
$\frac{\partial z}{\partial x}$
"local gradient"
z
f
$\frac{\partial z}{\partial y}$
$\frac{\partial L}{\partial z}$
y
gradients

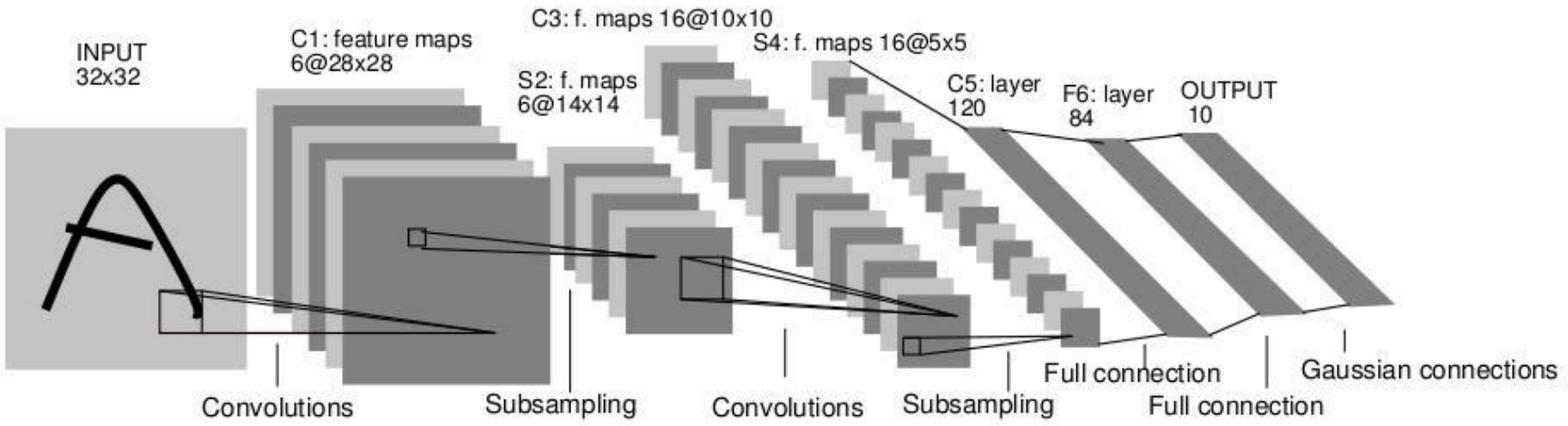

activations
x
$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial x}$
$\frac{\partial z}{\partial x}$
"local gradient"
z
f
$\frac{\partial z}{\partial y}$
$\frac{\partial L}{\partial z}$
y
$\frac{\partial L}{\partial y} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial y}$
gradients

Convolutional neural networks

Convolutional Neural Networks (CNN)

- Neural network with specialized connectivity structure
- Stack multiple stages of feature extractors
- Higher stages compute more global, more invariant, *more abstract* features
- Classification layer at the end





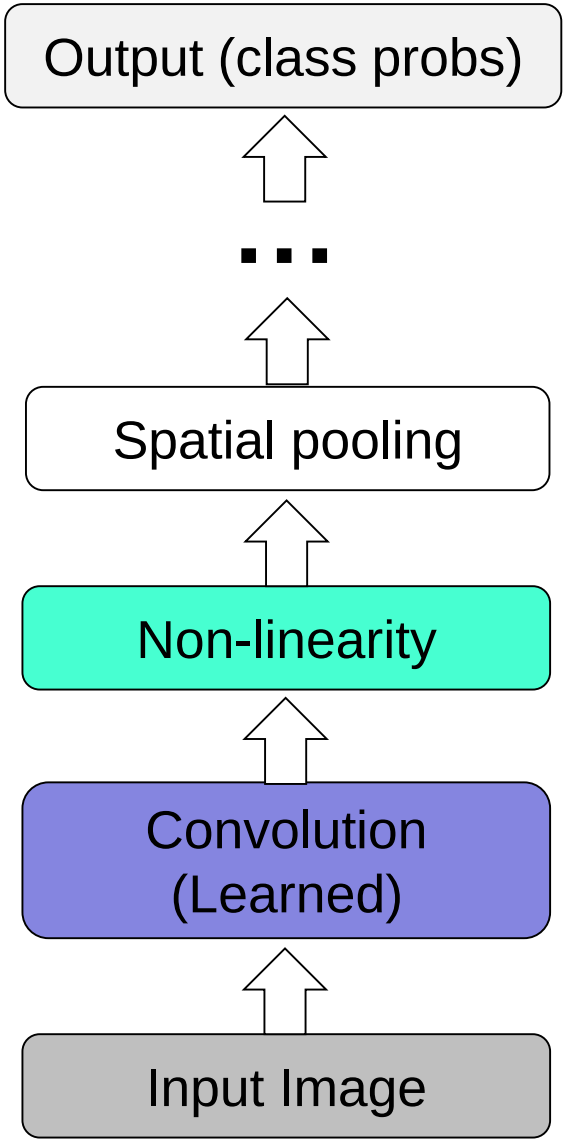
Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Adapted from Rob Fergus

Convolutional Neural Networks (CNN)

- Feed-forward feature extraction:
  1. Convolve input with learned filters
  2. Apply non-linearity
  3. **Spatial pooling (downsample)**

- Supervised training of convolutional filters by back-propagating classification error



Adapted from Lana Lazebnik

1. Convolution

- Apply learned filter weights
- One feature map per filter
- Stride can be greater than 1 (faster, less memory)

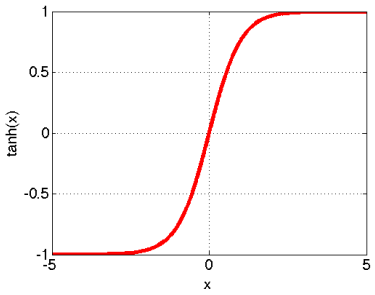
Input

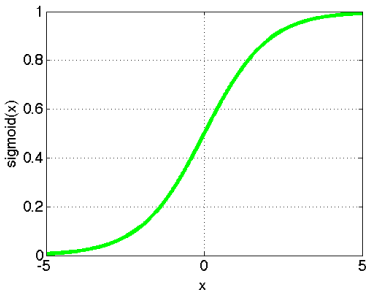
Feature Map

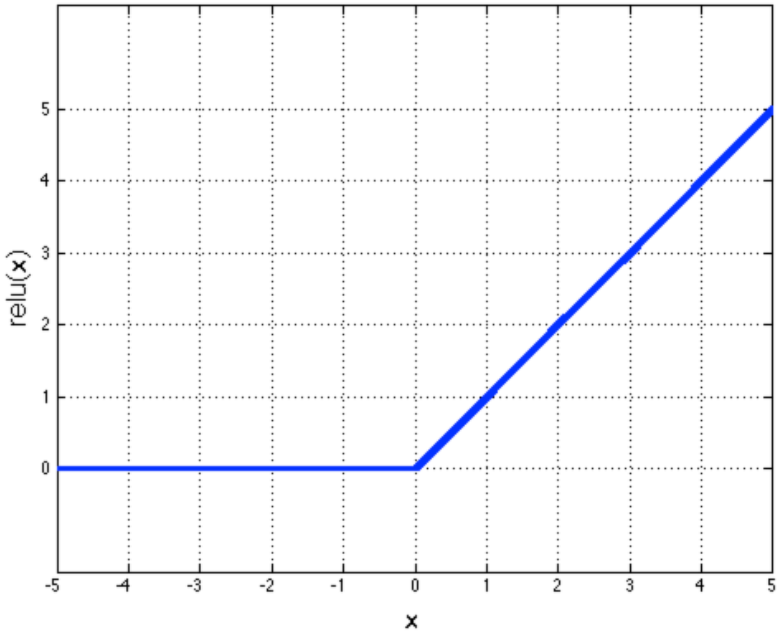
Adapted from Rob Fergus

2. Non-Linearity

- Per-element (independent)
- Some options:
  - Tanh
  - Sigmoid: 1/(1+exp(-x))
  - Rectified linear unit (ReLU)
    - Avoids saturation issues



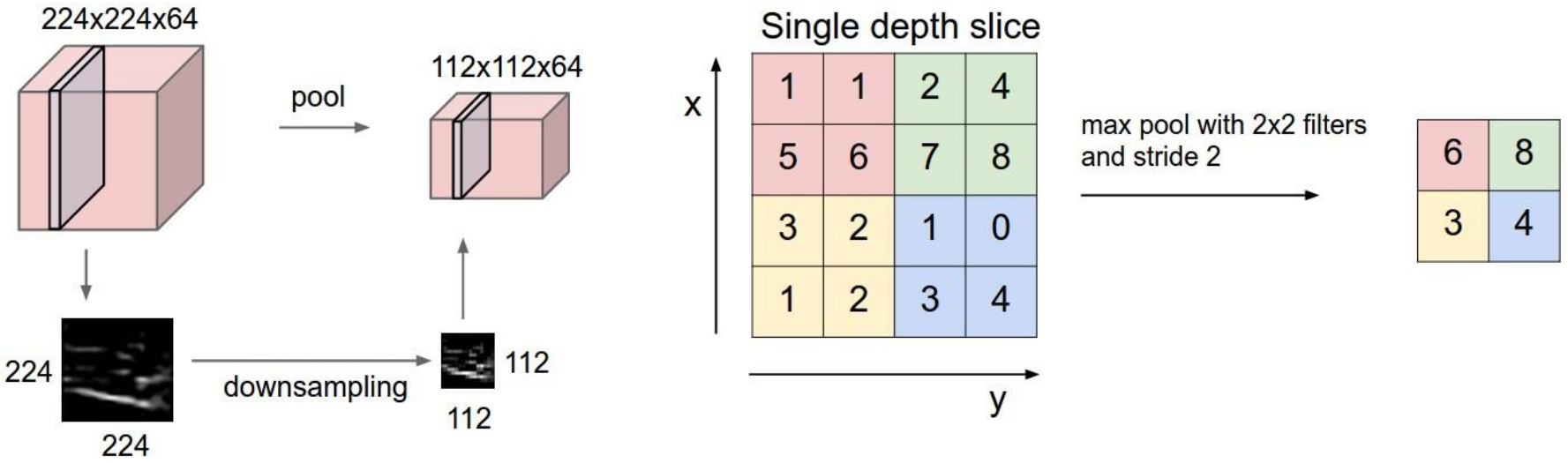




Adapted from Rob Fergus

3. Spatial Pooling

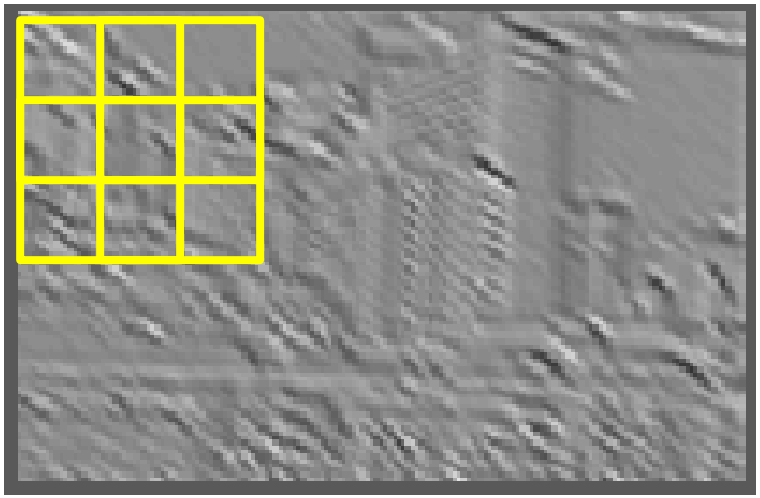
- Sum or max over non-overlapping / overlapping regions



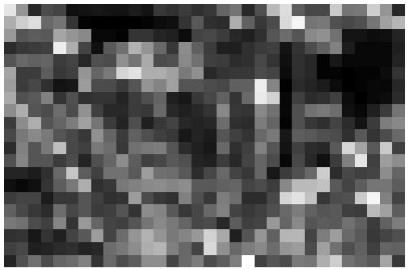
Rob Fergus, figure from Andrej Karpathy

3. Spatial Pooling

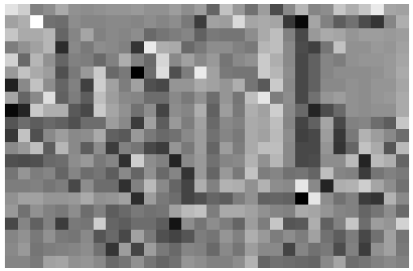
- Sum or max over non-overlapping / overlapping regions
- Role of pooling:
  - Invariance to small transformations
  - Larger receptive fields (neurons see more of input)



Max

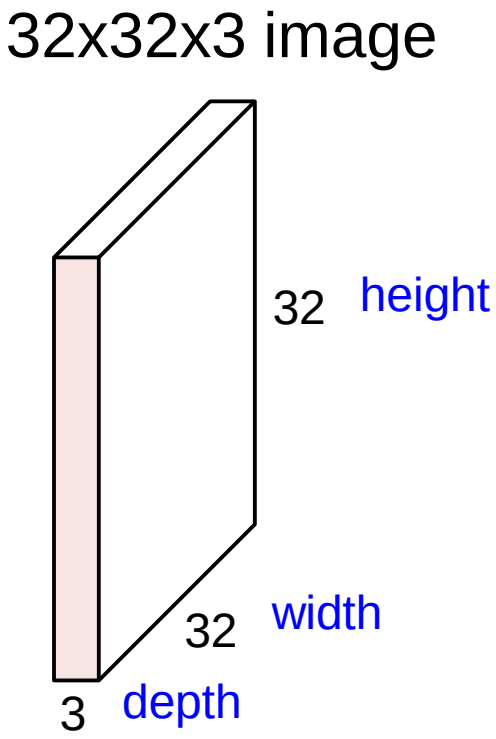


Sum



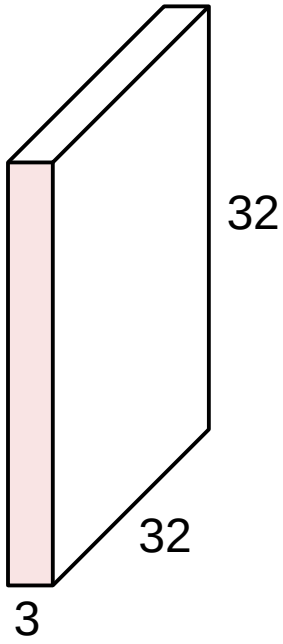
Adapted from Rob Fergus

Convolutions: More detail

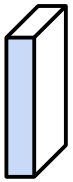


Convolutions: More detail

32x32x3 image



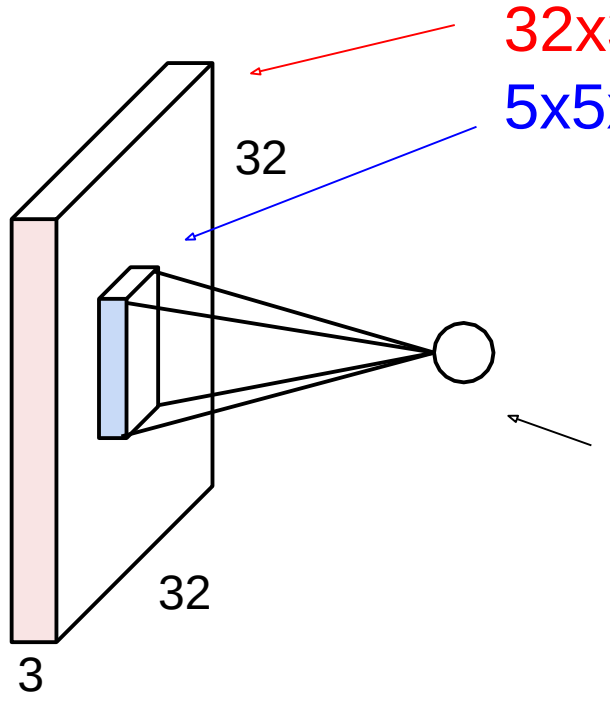
5x5x3 filter



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

Convolutions: More detail

Convolution Layer

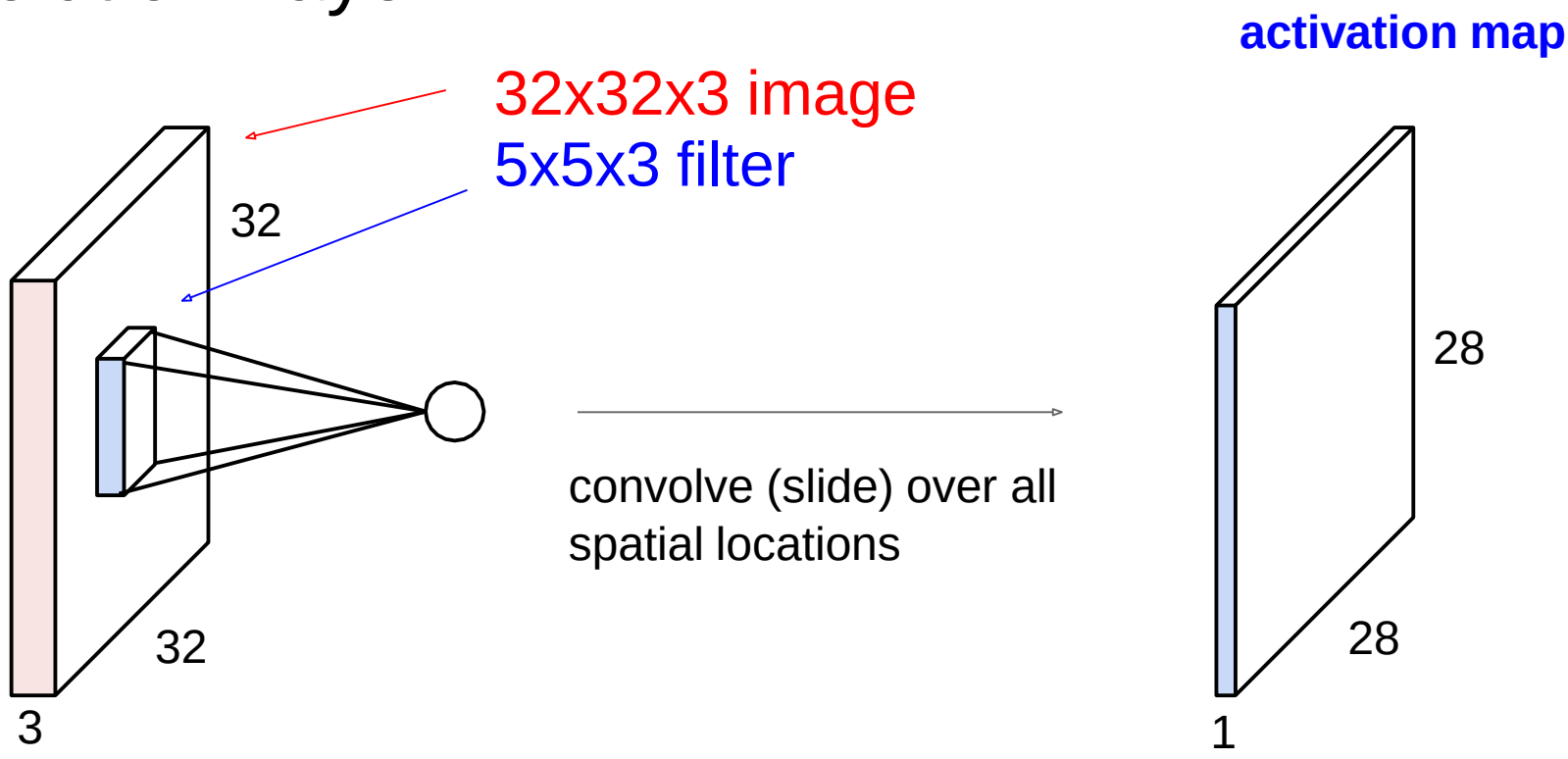


1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Convolutions: More detail

Convolution Layer



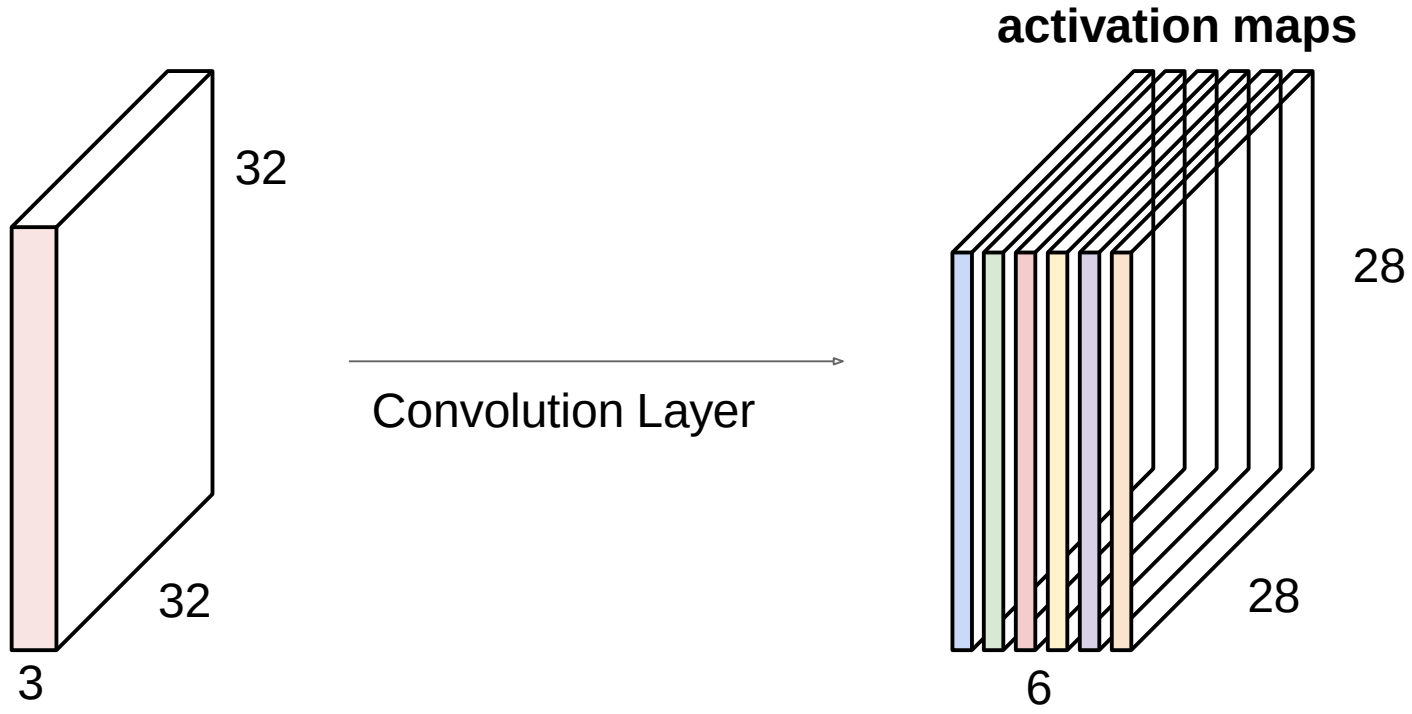
Convolutions: More detail

Convolution Layer

consider a second, green filter

Convolutions: More detail

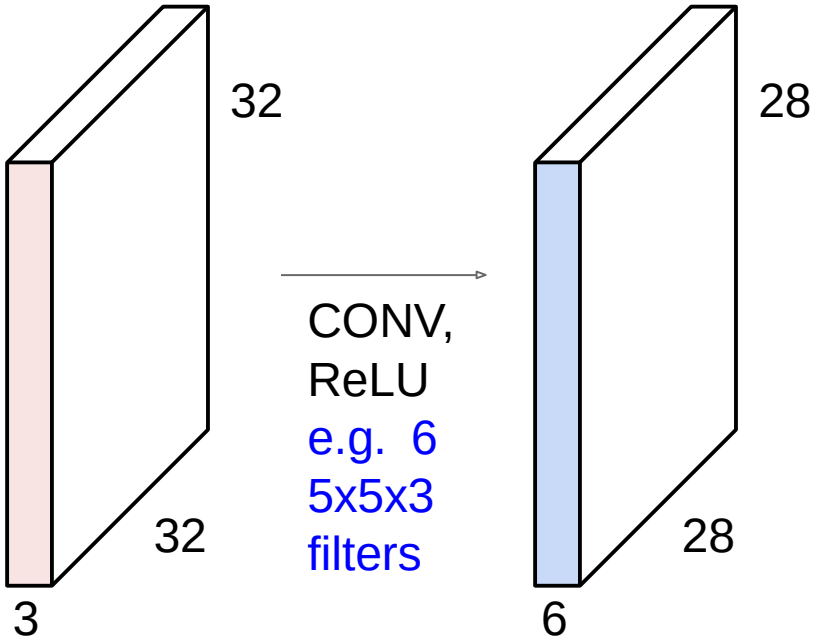
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



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

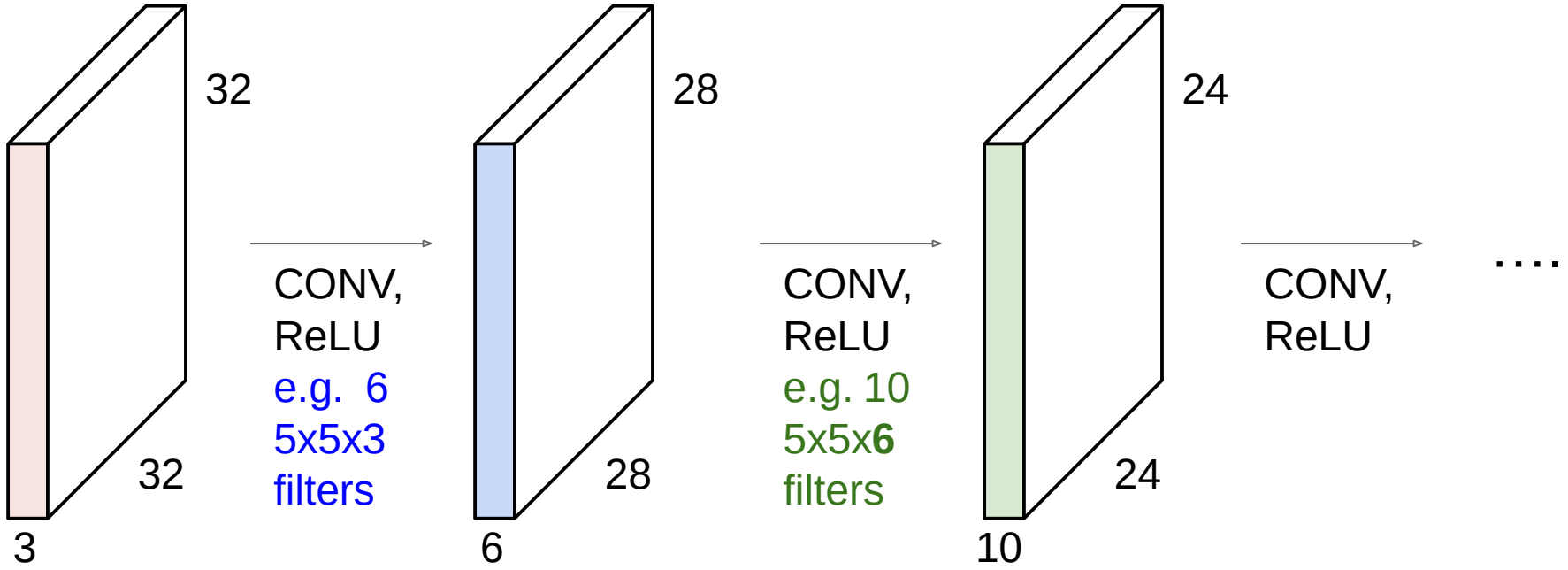
Convolutions: More detail

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



Convolutions: More detail

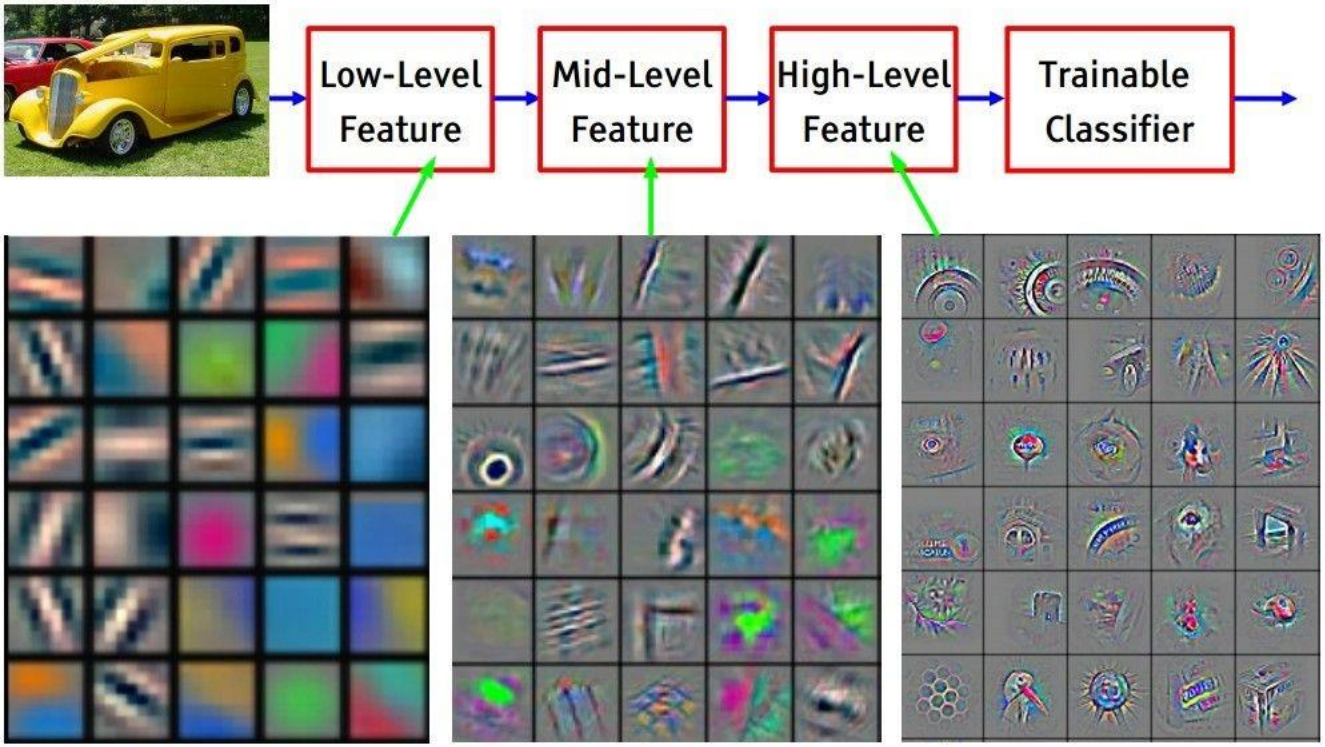
Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



Convolutions: More detail

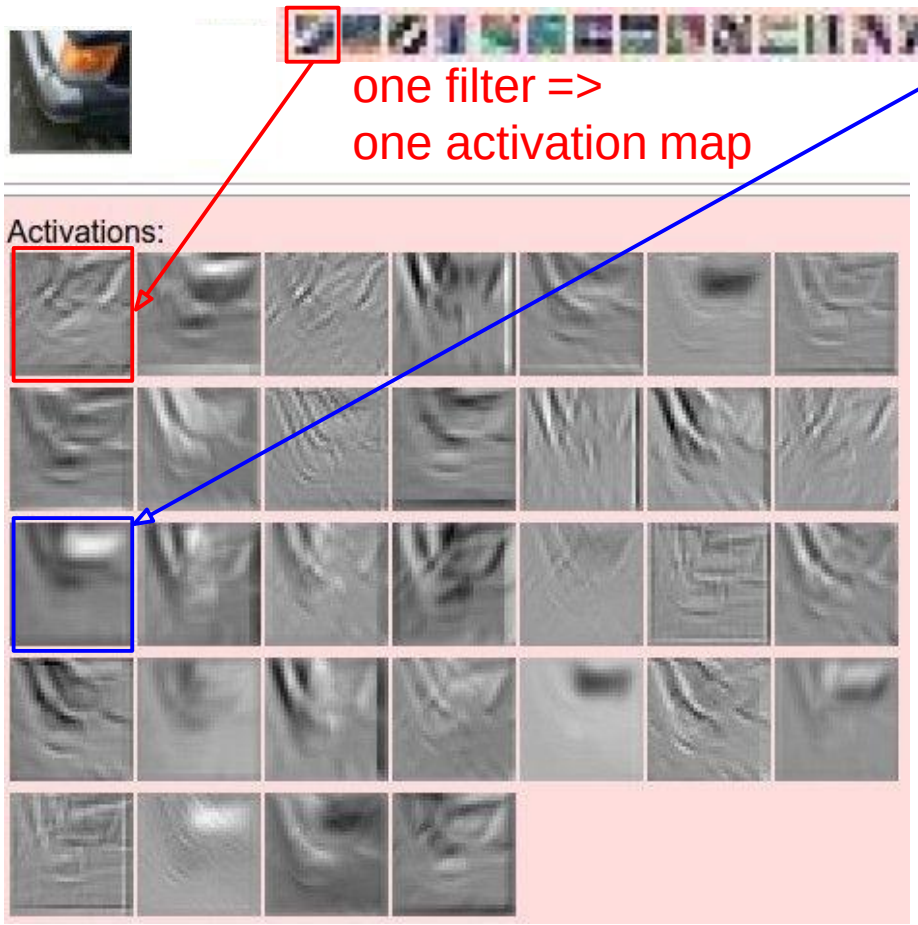
Preview

[From recent Yann LeCun slides]



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

Convolutions: More detail



example 5x5 filters
(32 total)

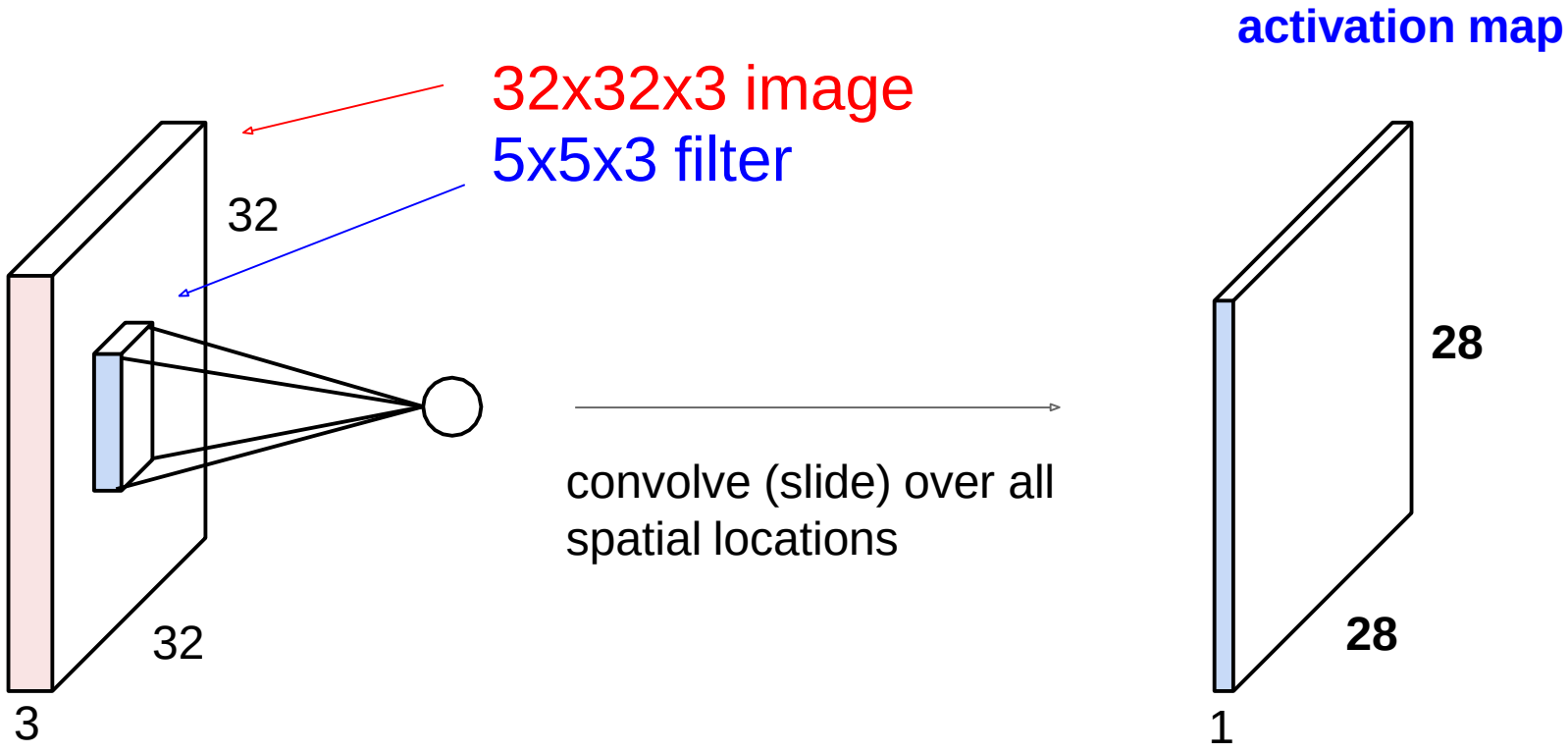
We call the layer convolutional because it is related to convolution of two signals:

$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v]F[i+u,j+v]$$

Element-wise multiplication and sum of a filter and the signal (image)

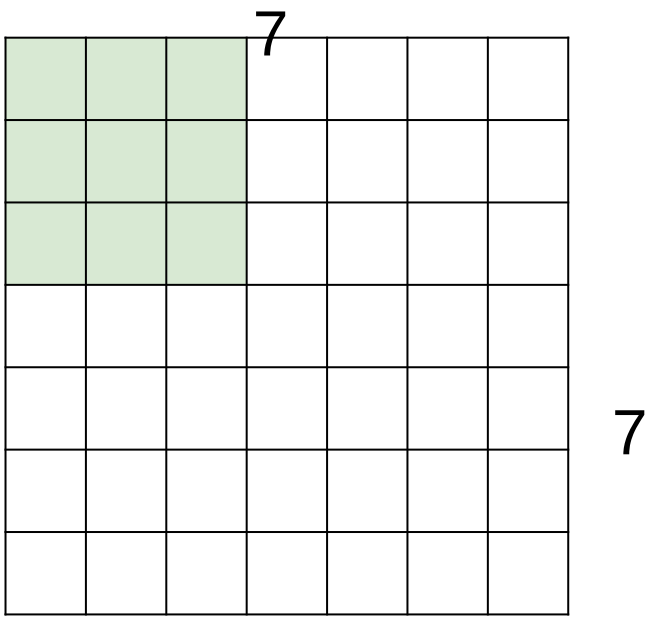
Convolutions: More detail

A closer look at spatial dimensions:



Convolutions: More detail

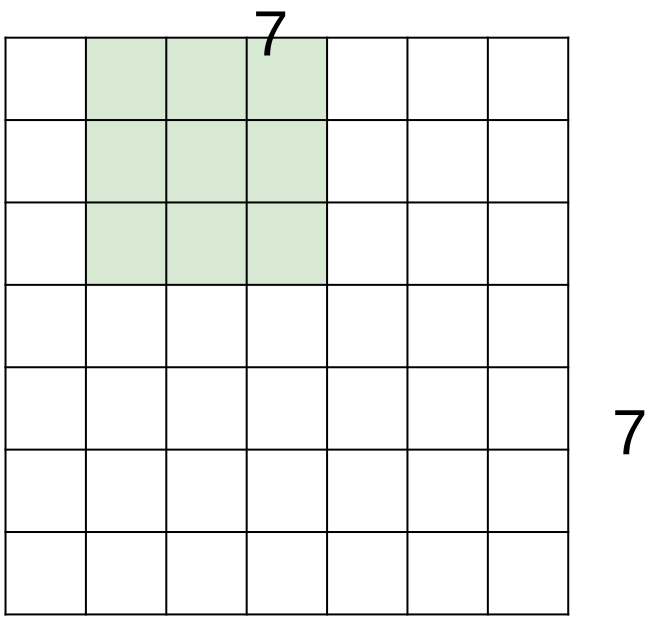
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

Convolutions: More detail

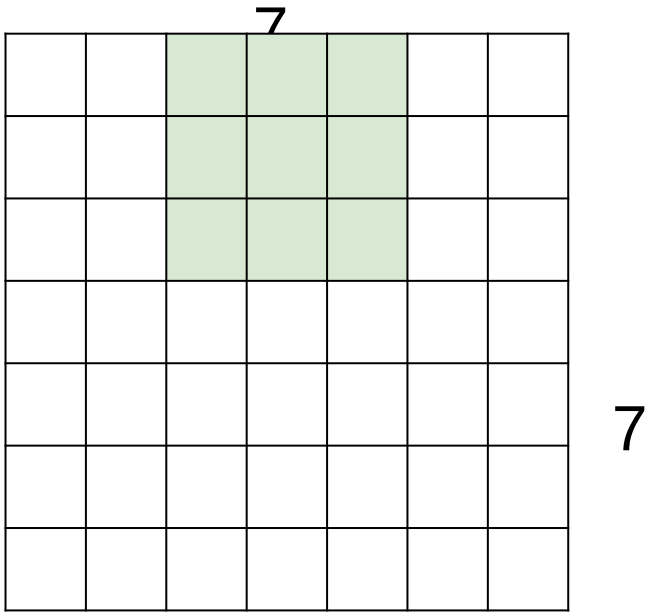
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

Convolutions: More detail

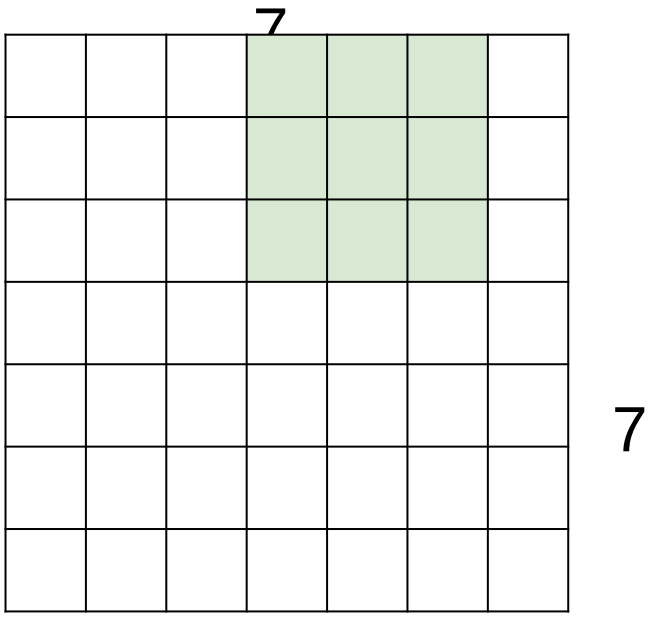
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

Convolutions: More detail

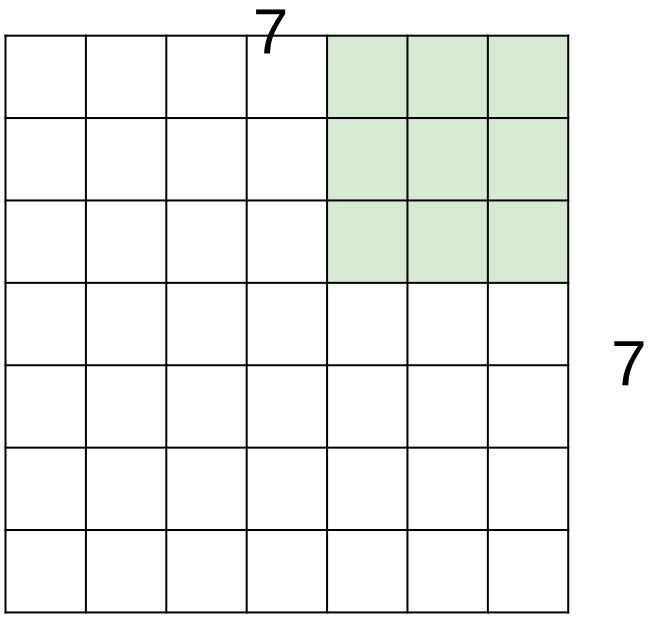
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

Convolutions: More detail

A closer look at spatial dimensions:

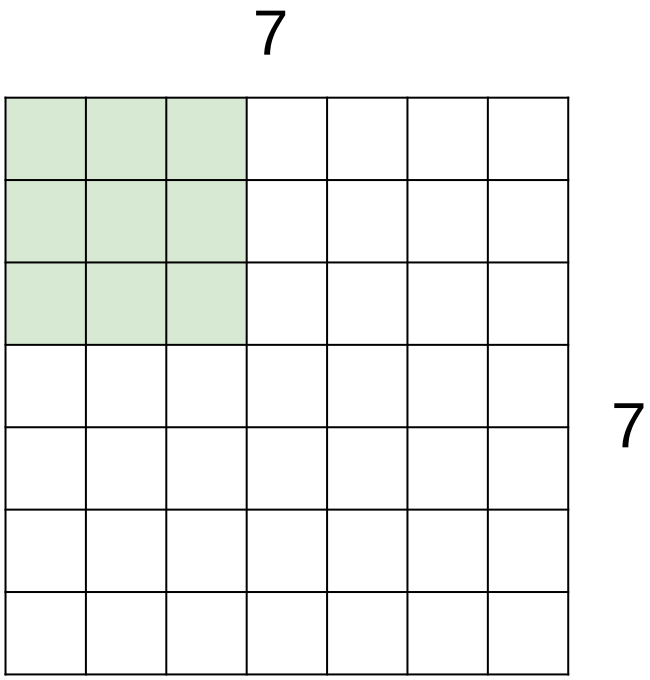


7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

Convolutions: More detail

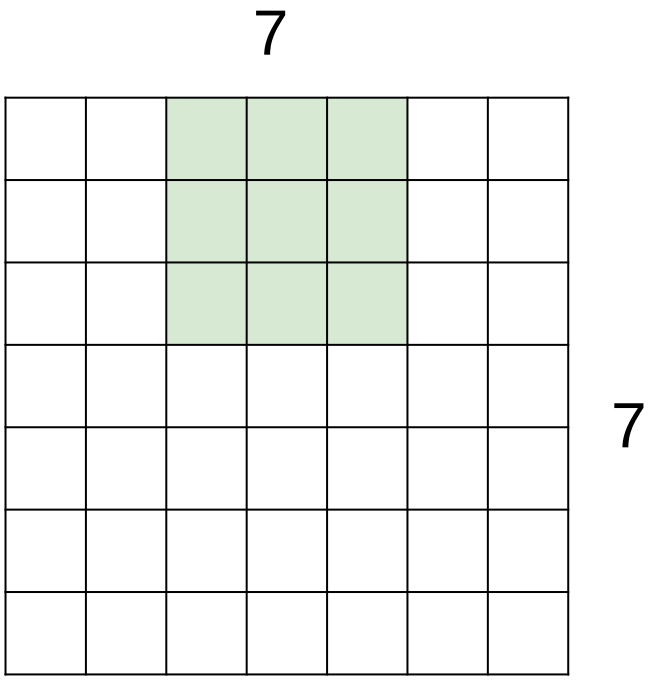
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

Convolutions: More detail

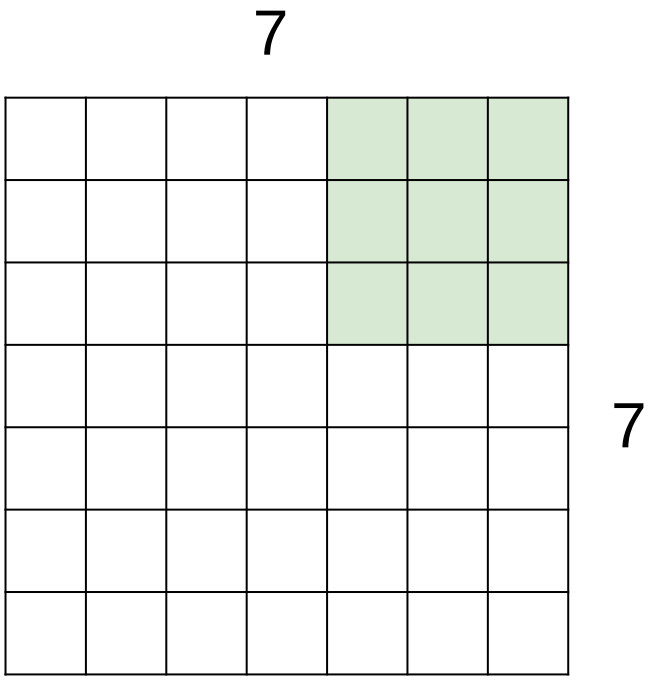
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

Convolutions: More detail

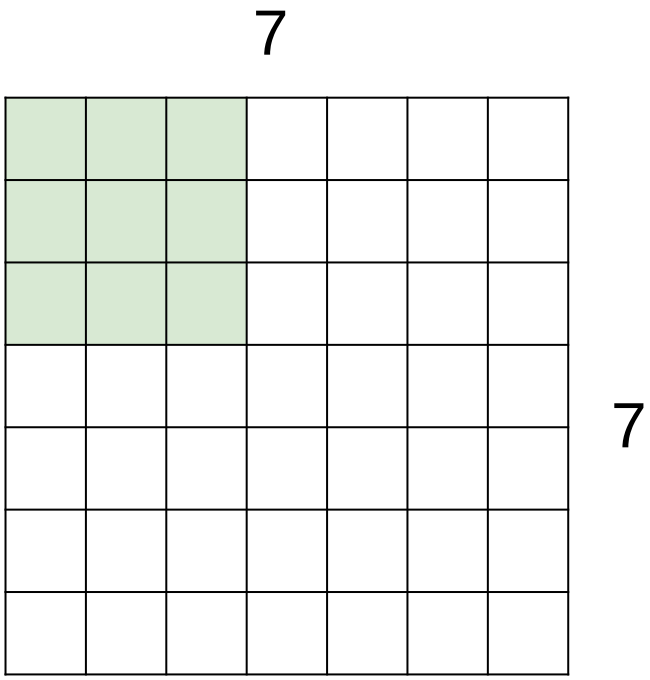
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

Convolutions: More detail

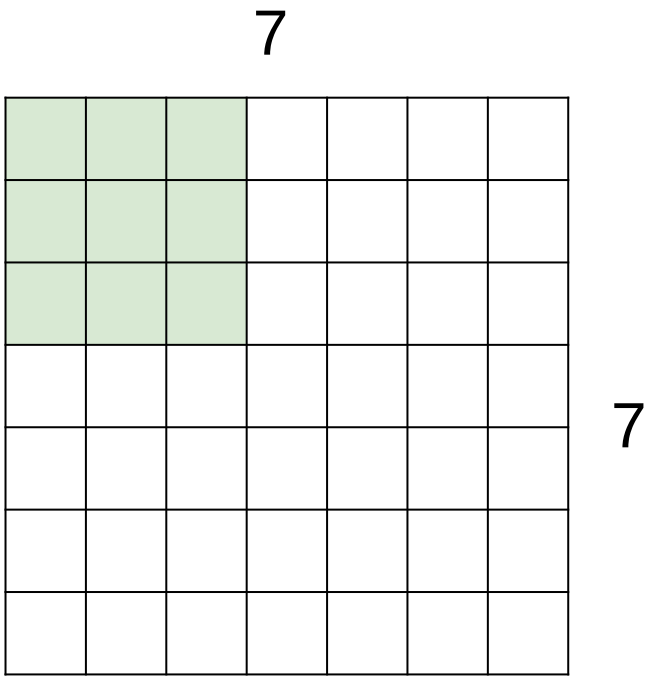
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

Convolutions: More detail

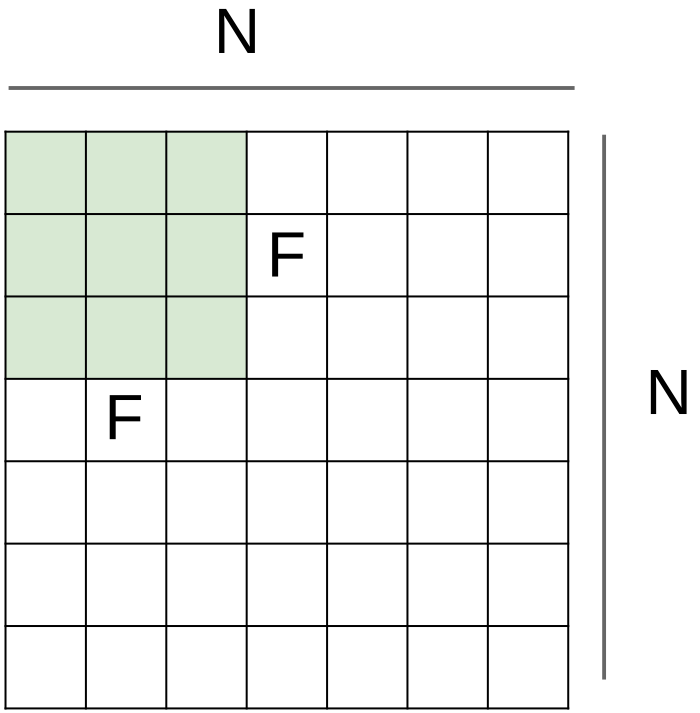
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.

Convolutions: More detail

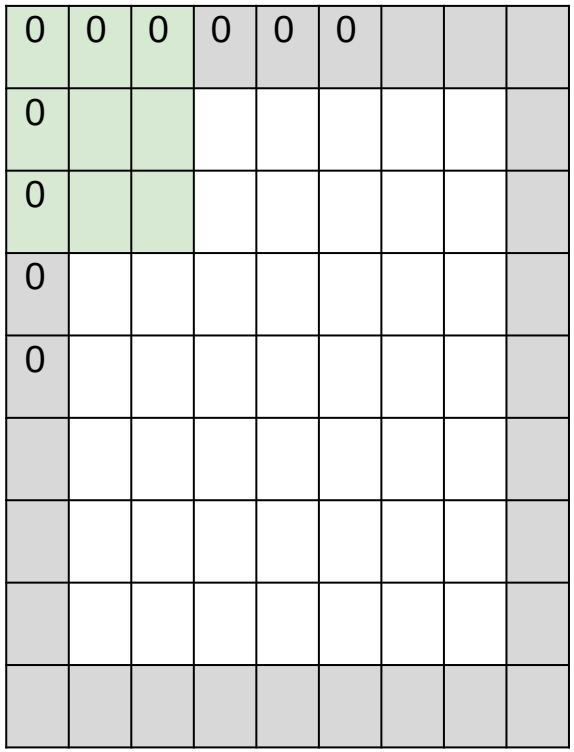


Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

Convolutions: More detail

In practice: Common to zero pad the border

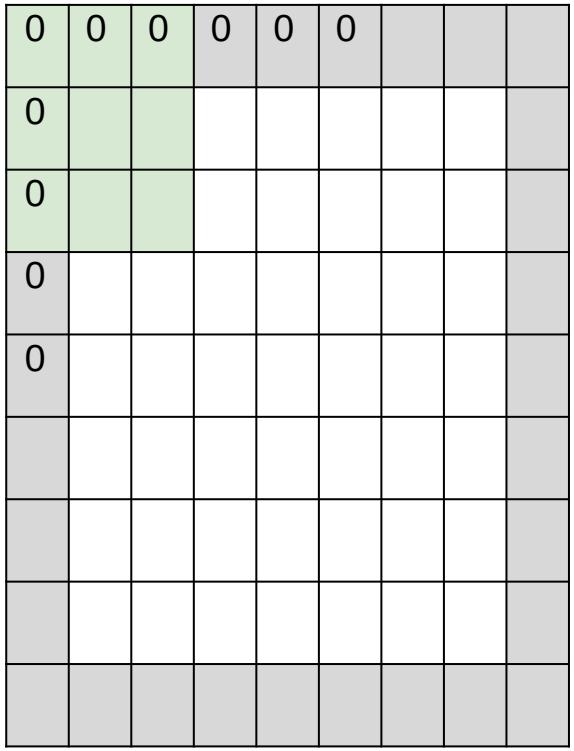


e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

Convolutions: More detail

In practice: Common to zero pad the border

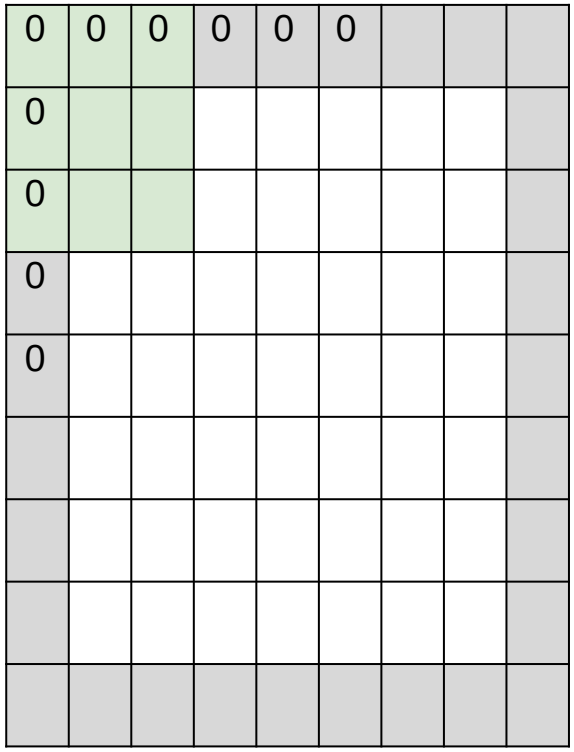


e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!

Convolutions: More detail

In practice: Common to zero pad the border



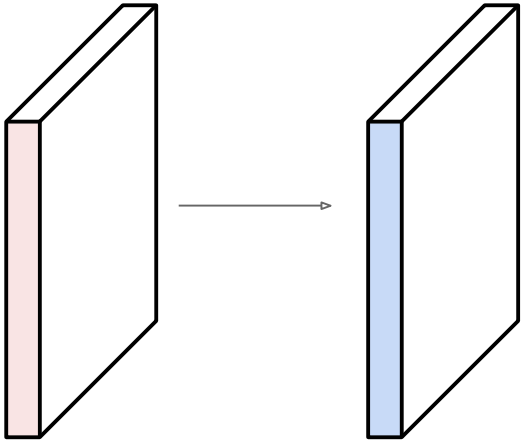
e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

(N + 2*padding - F) / stride + 1

Convolutions: More detail

Examples time:

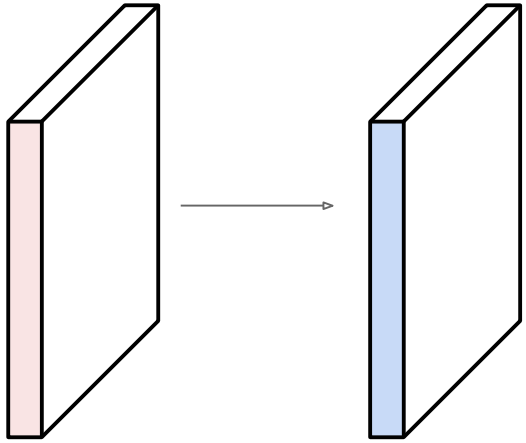


Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Output volume size: ?

Convolutions: More detail

Examples time:

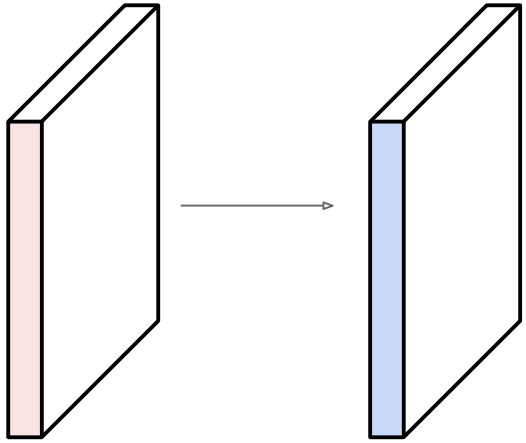


Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Output volume size:
(32+2*2-5)/1+1 = 32 spatially, so
32x32x10

Convolutions: More detail

Examples time:

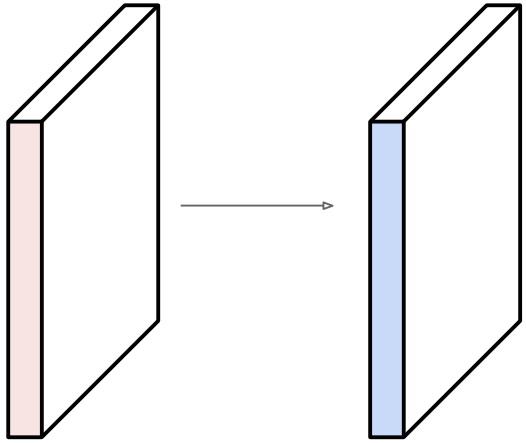


Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?

Convolutions: More detail

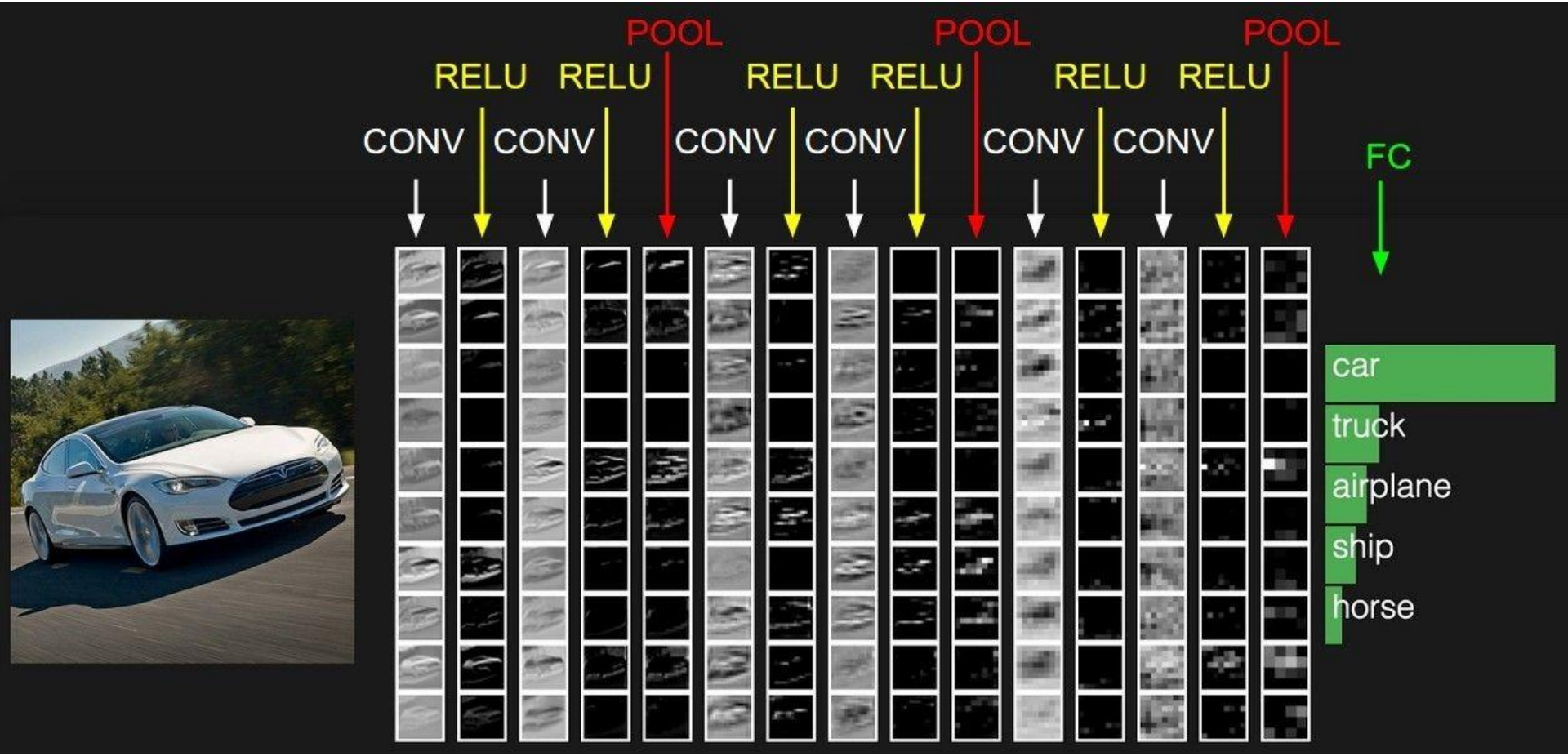
Examples time:



Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?
each filter has 5*5*3 + 1 = 76 params (+1 for bias)
=> 76*10 = **760**

Putting it all together



A Common Architecture: AlexNet

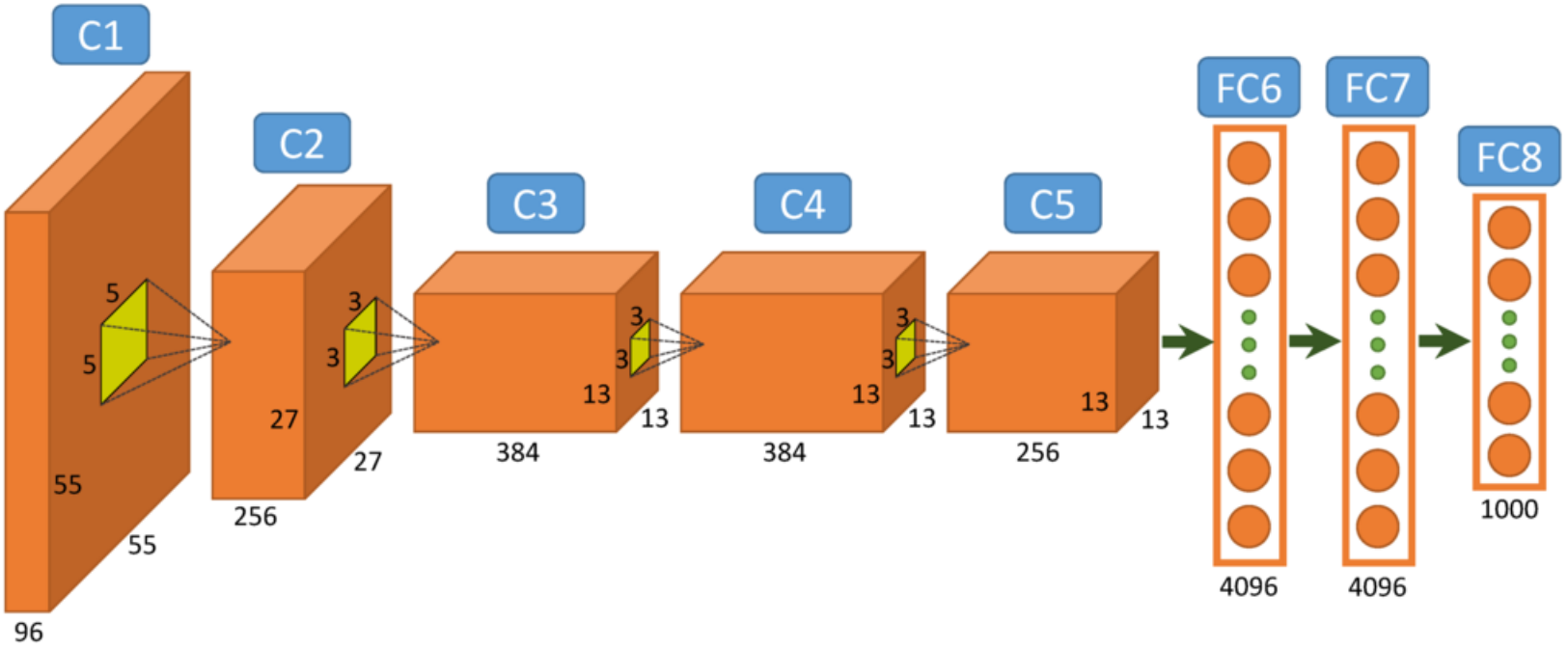


Figure from http://www.mdpi.com/2072-4292/7/11/14680/htm

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

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

best model

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

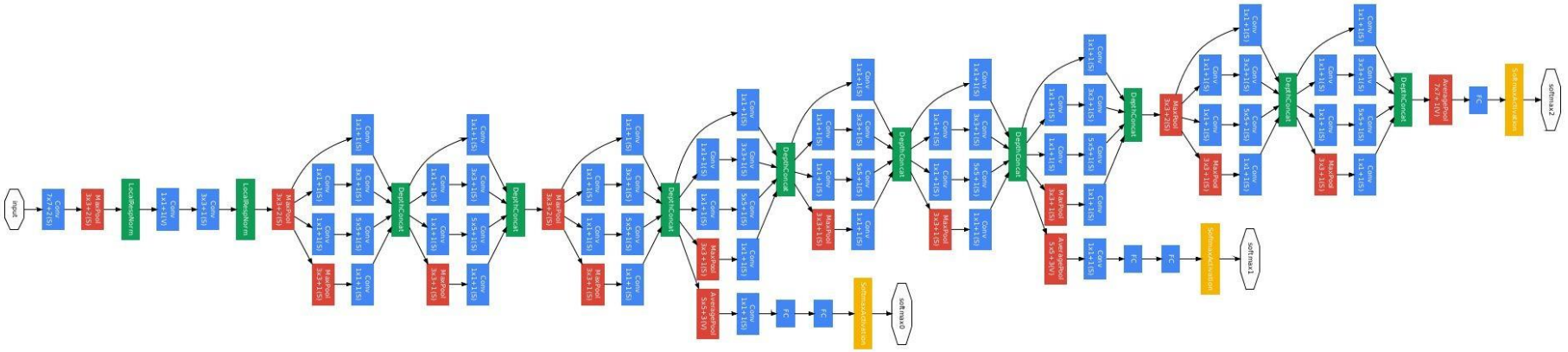
ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

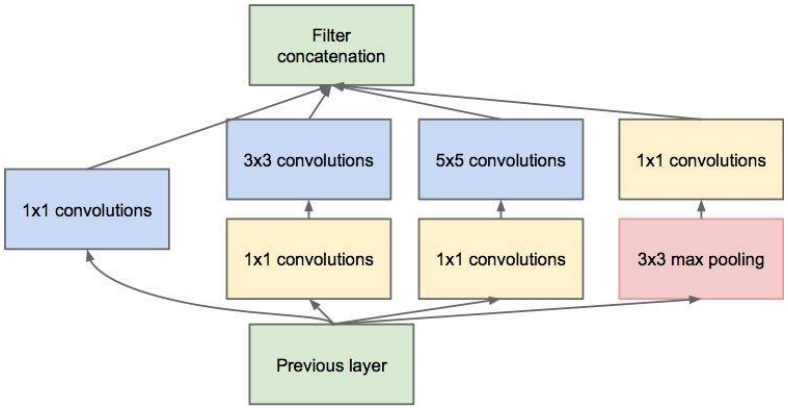
Table 2: **Number of parameters** (in millions).

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

Case Study: GoogLeNet

[Szegedy et al., 2014]





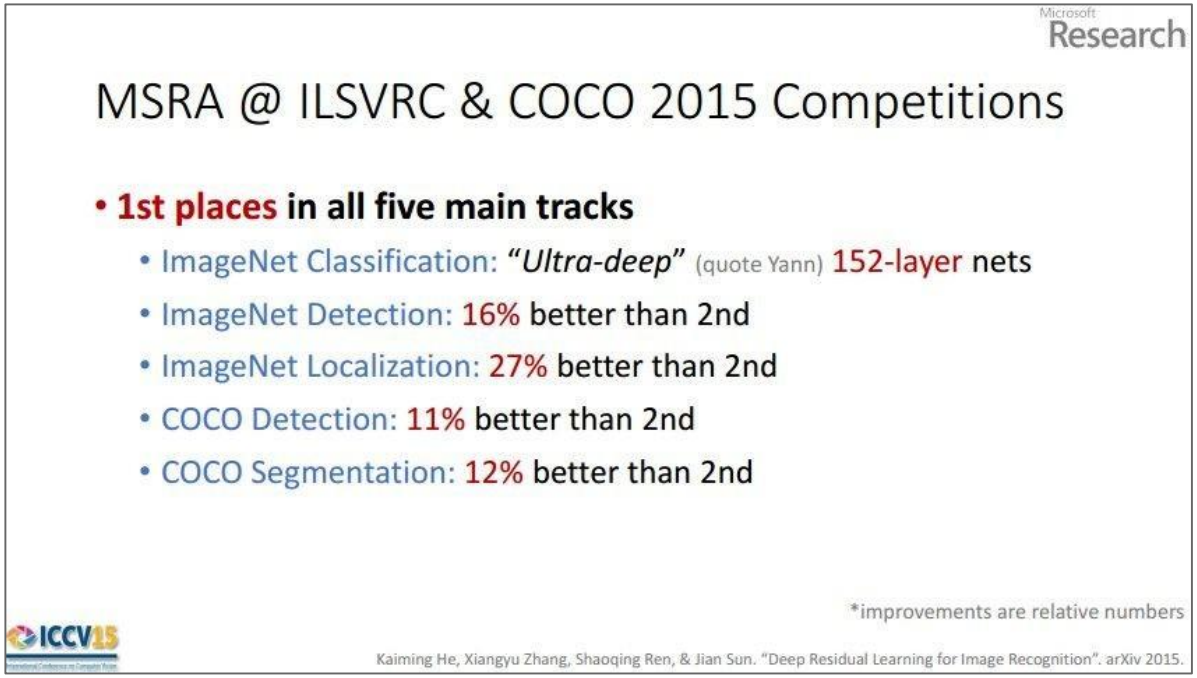
Inception module

ILSVRC 2014 winner (6.7% top 5 error)

Case Study: ResNet

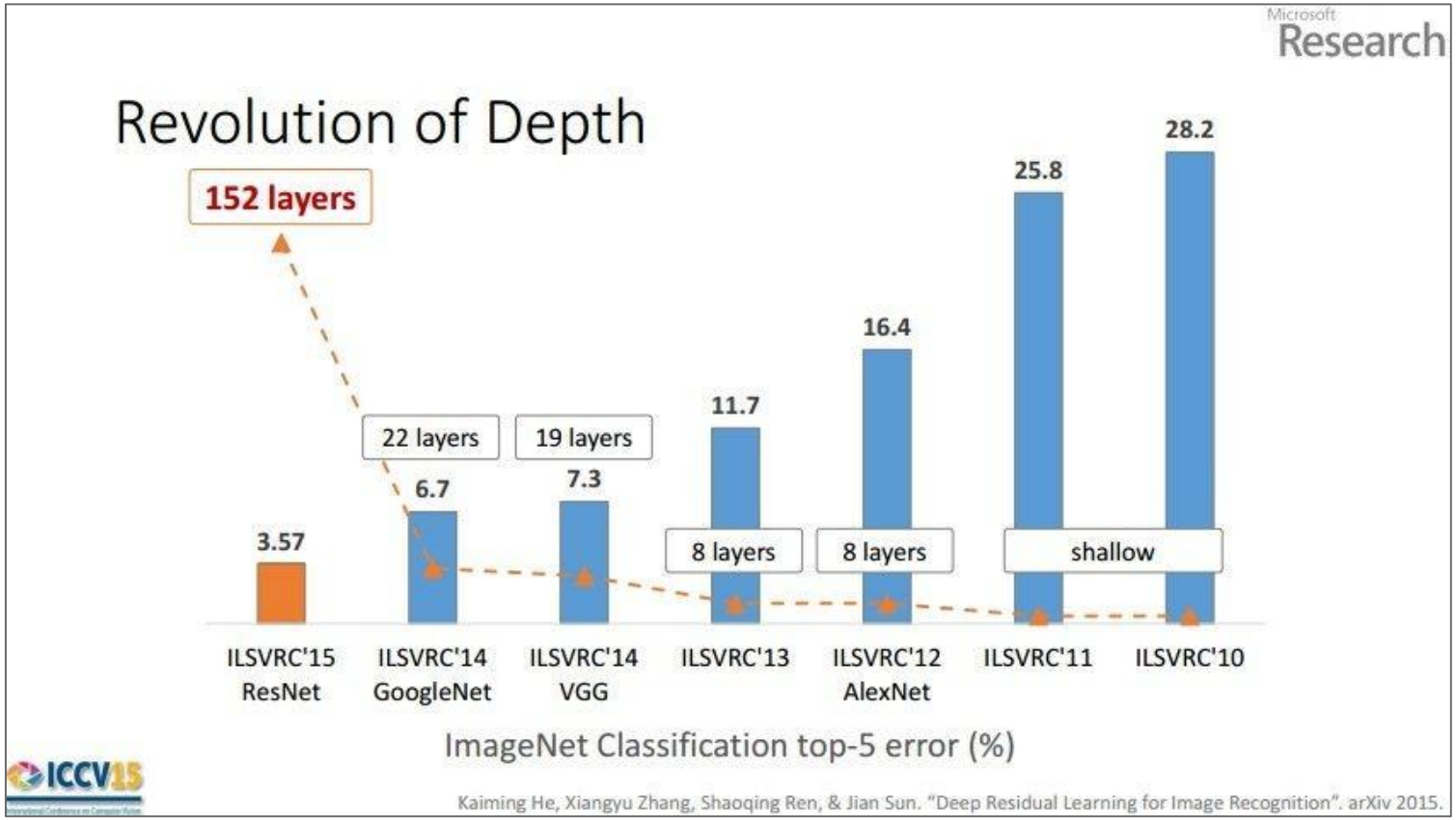
[He et al., 2015]

ILSVRC 2015 winner (3.6% top 5 error)



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

Case Study: ResNet



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Case Study: ResNet

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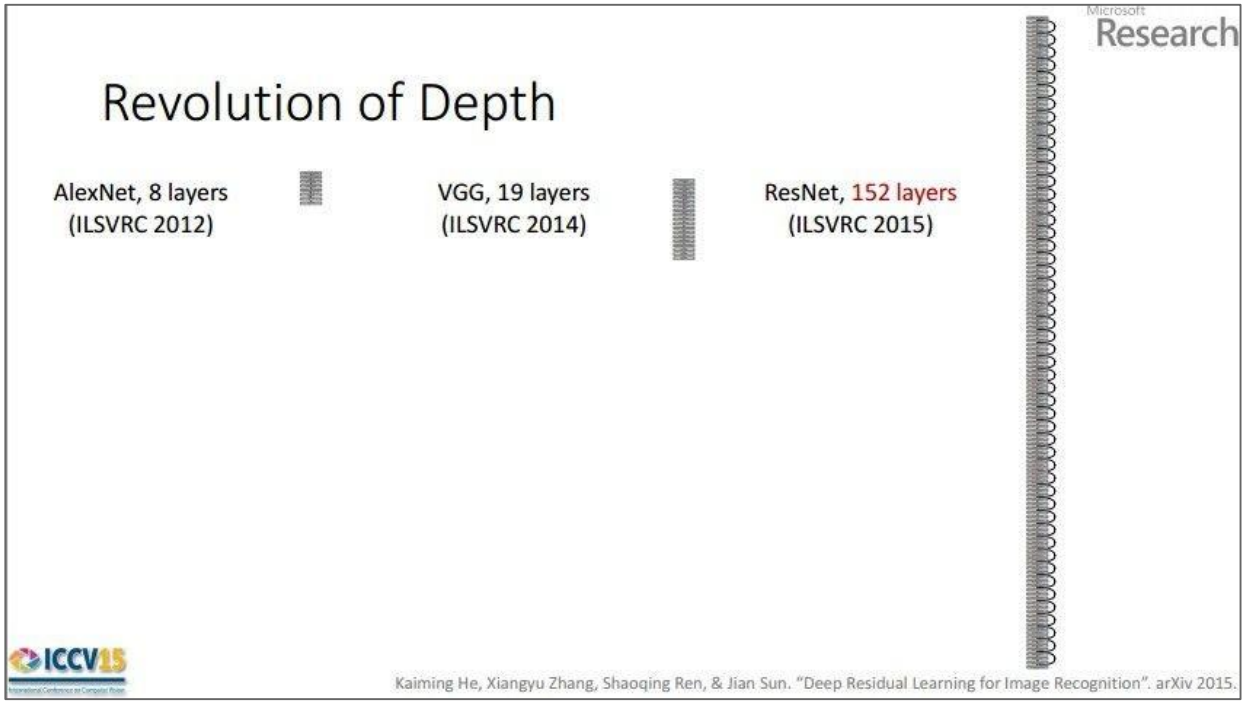


(slide from Kaiming He's recent presentation)

2-3 weeks of training on 8 GPU machine

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

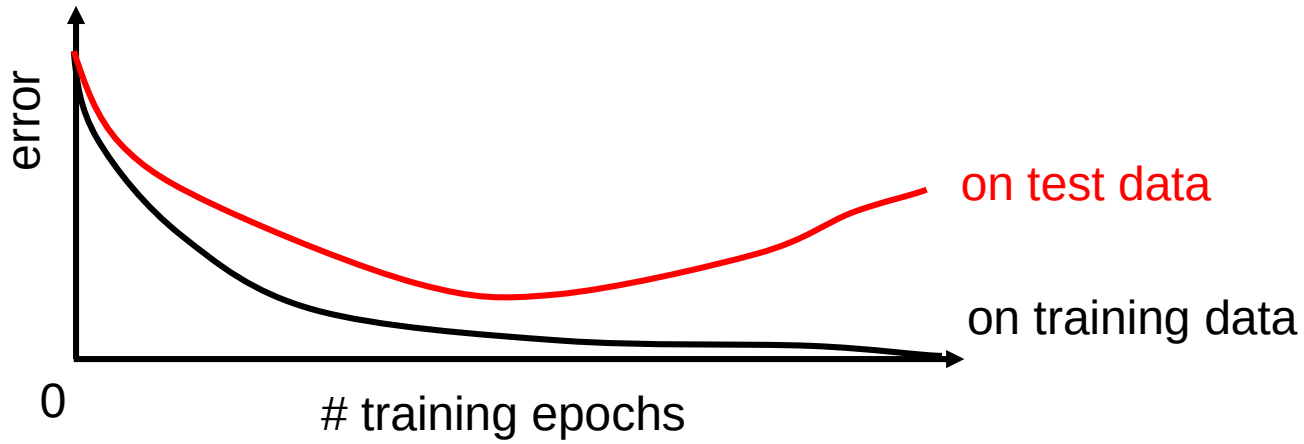
Practical matters

Comments on training algorithm

- Not guaranteed to converge to zero training error, may converge to local optima or oscillate indefinitely.
- However, in practice, does converge to low error for many large networks on real data, with good choice of hyperparameters (e.g. learning rate).
- Thousands of epochs (epoch = network sees all training data once) may be required, hours or days to train.
- To avoid local-minima problems, run several trials starting with different random weights (*random restarts*), and take results of trial with lowest training set error.
- May be hard to set learning rate and to select number of hidden units and layers.
- Neural networks had fallen out of fashion in 90s, early 2000s; back with a new name and improved performance (deep networks trained with dropout and lots of data).

Over-training prevention

- Running too many epochs can result in over-fitting.



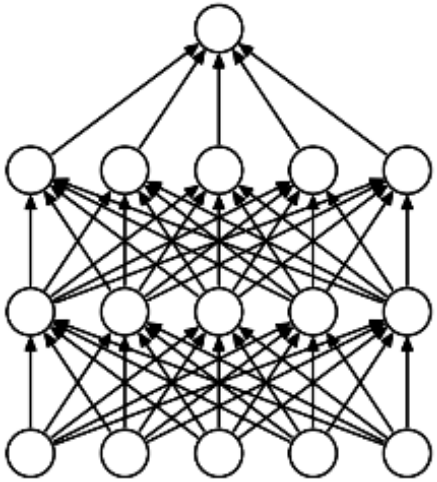
- Keep a hold-out validation set and test accuracy on it after every epoch. Stop training when additional epochs actually increase validation error.

Adapted from Ray Mooney

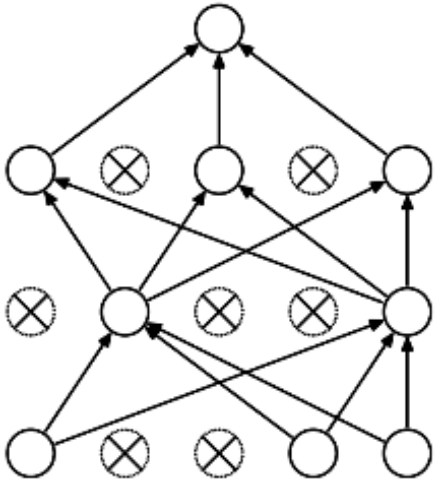
Training: Best practices

- Use regularization
- To initialize weights, use “Xavier initialization”
- Use RELU or leaky RELU or ELU, don’t use sigmoid
- Use data augmentation
- Use mini-batch
- Center (subtract mean from) your data
- Use cross-validation for your parameters
- Learning rate: too high? Too low?

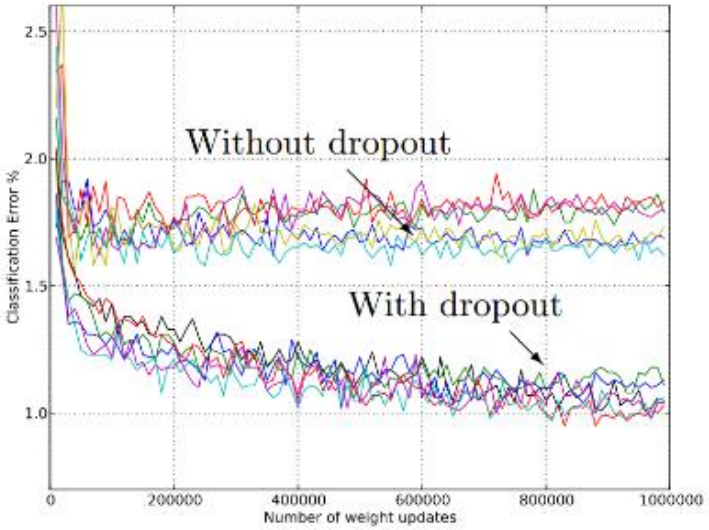
Regularization: Dropout



(a) Standard Neural Net



(b) After applying dropout.



- Randomly turn off some neurons
- Allows individual neurons to independently be responsible for performance

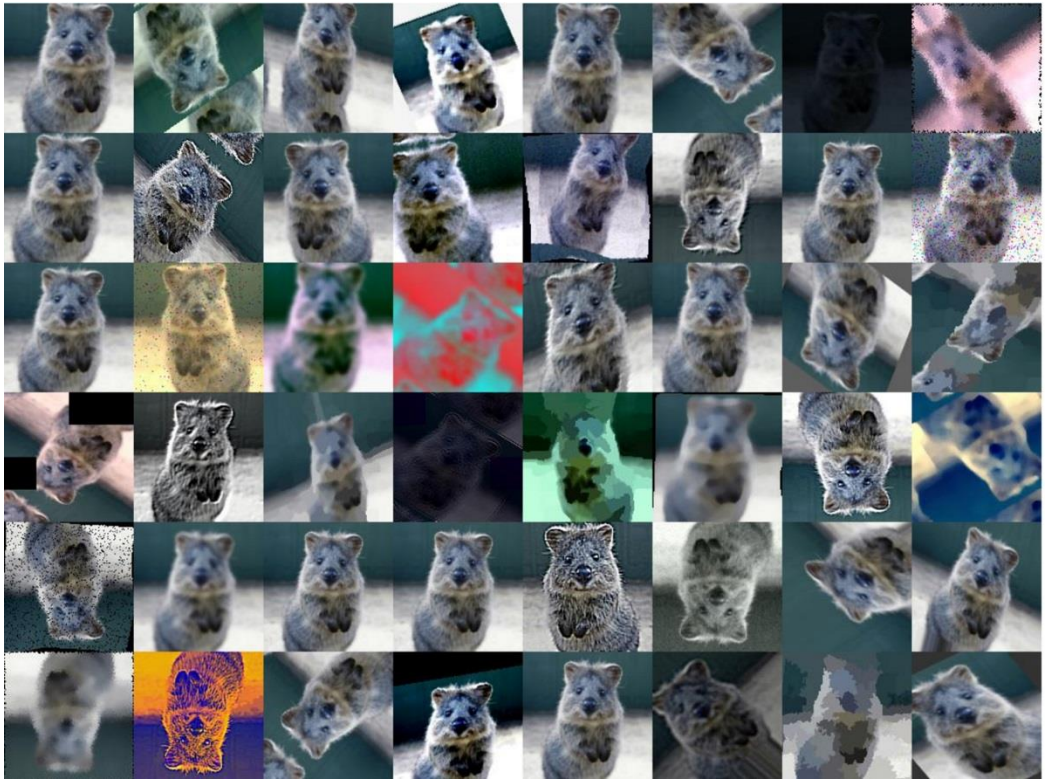
Dropout: A simple way to prevent neural networks from overfitting [Srivastava JMLR 2014]

Adapted from Jia-bin Huang

Data Augmentation (Jittering)

Create *virtual* training samples

- Horizontal flip
- Random crop
- Color casting
- Geometric distortion



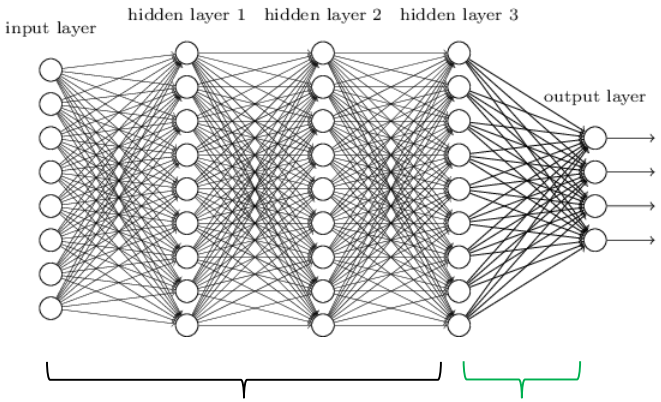
Jia-bin Huang, Image: https://github.com/aleju/imgaug

Transfer Learning

"You need a lot of data if you want to train/use CNNs"

Transfer Learning with CNNs

- The more weights you need to learn, the more data you need
- That's why with a deeper network, you need more data for training than for a shallower network
- One possible solution:



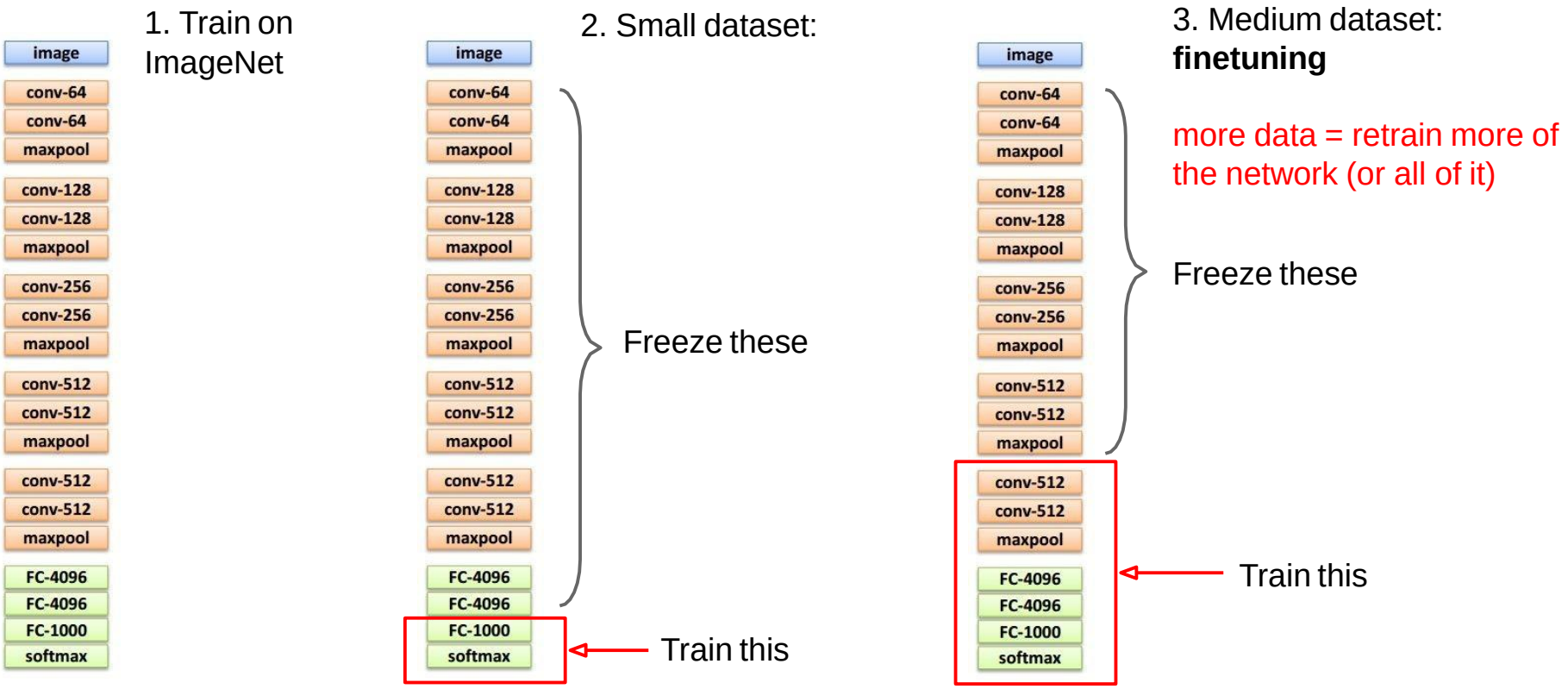
Set these to the already learned weights from another network

Learn these on your own task

Transfer Learning with CNNs

Source: classification on ImageNet

Target: some other task/data



Another option: use network as feature extractor, train SVM on extracted features for target task

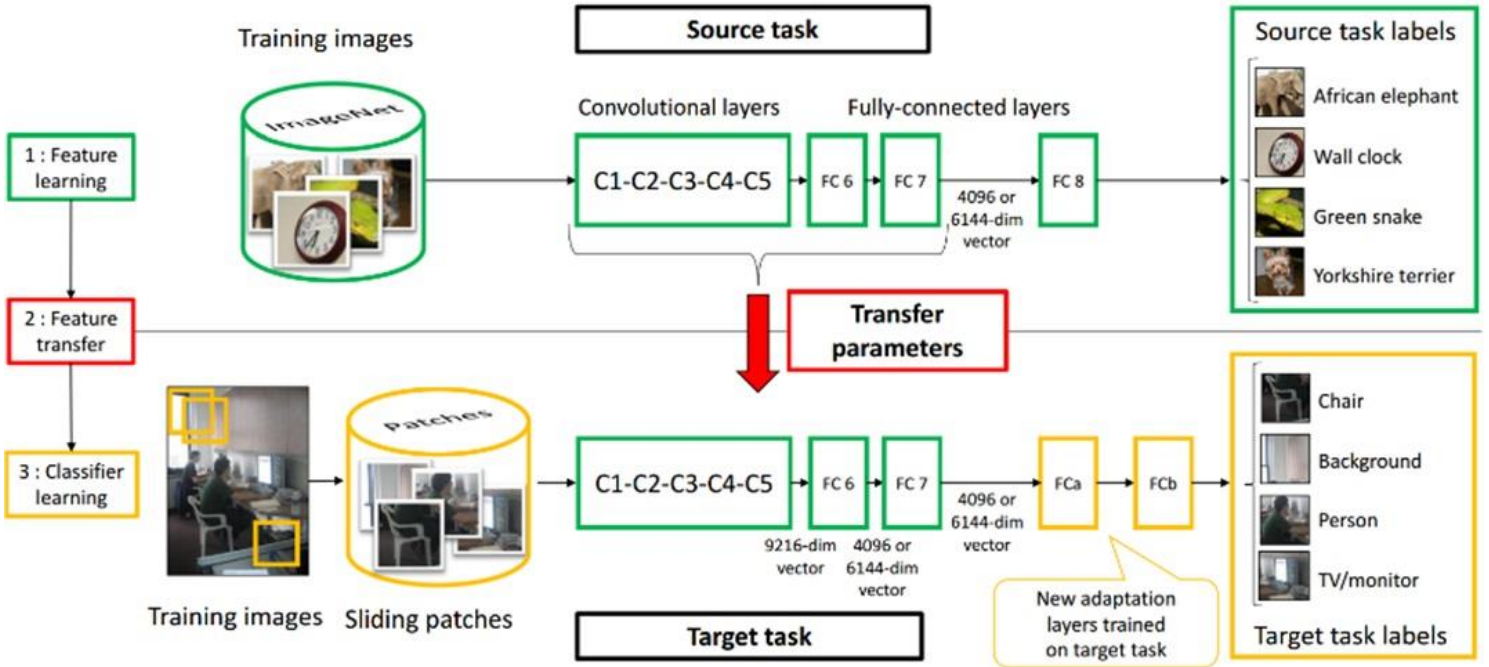
Adapted from Andrej Karpathy

Transfer Learning with CNNs

	very similar dataset	**very different dataset**
very little data	Use linear classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

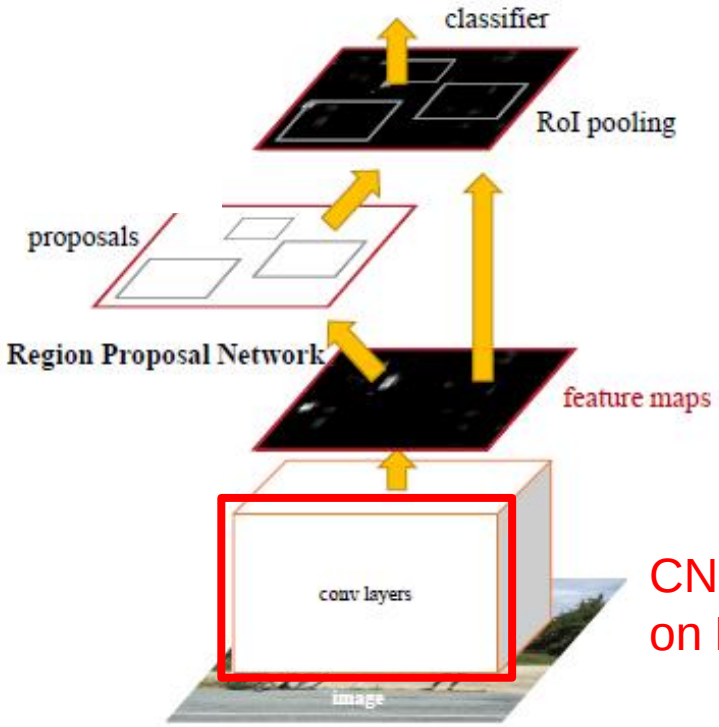
Pre-training on ImageNet

- Have a source domain and target domain
- Train a network to classify ImageNet classes
  - Coarse classes and ones with fine distinctions (dog breeds)
- Remove last layers and train layers to replace them, that predict target classes



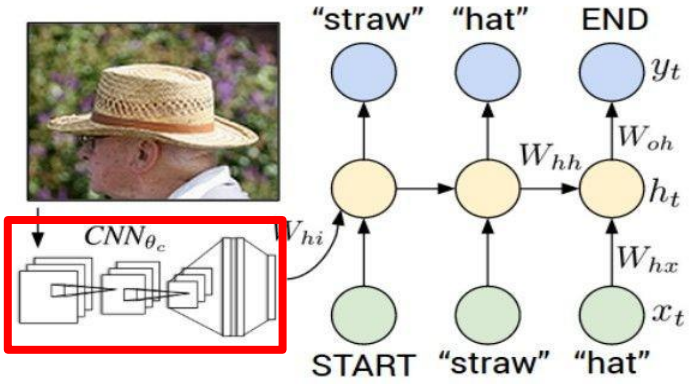
Oquab et al., "Learning and Transferring Mid-Level Image Representations…", CVPR 2014

Transfer learning with CNNs is pervasive…



CNN pretrained on ImageNet

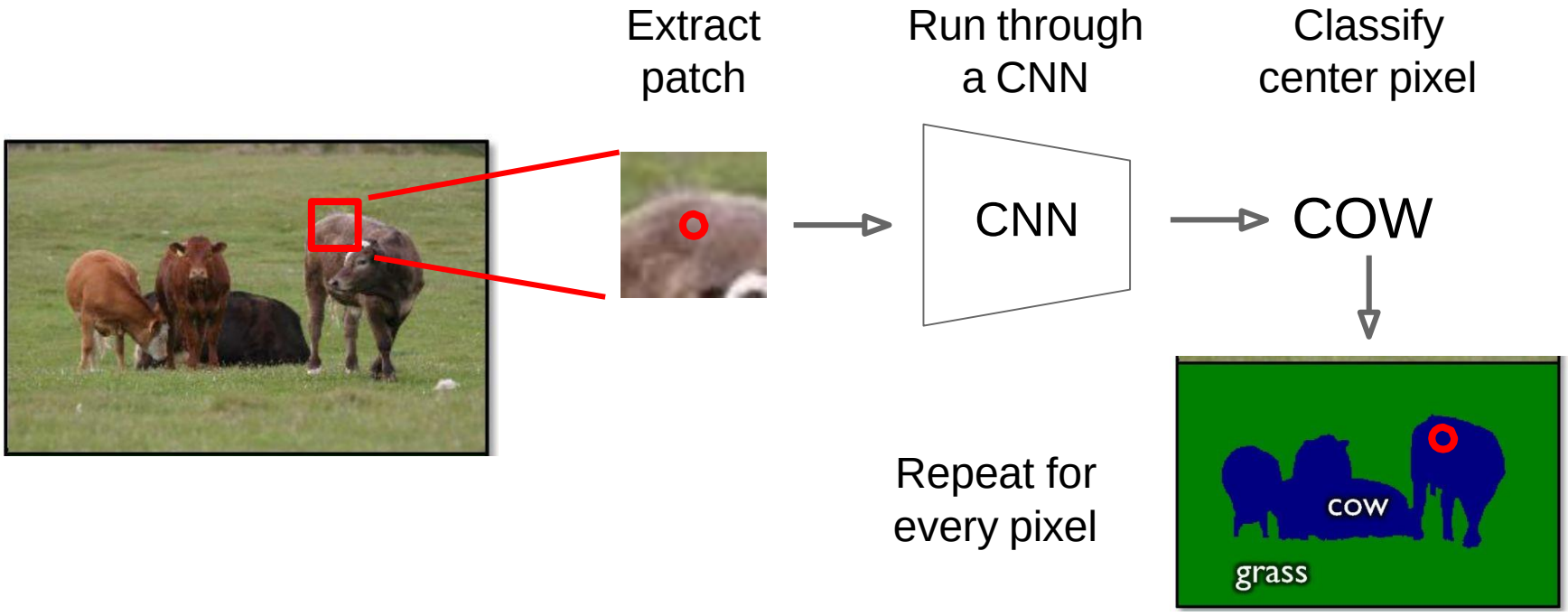
Image Captioning
Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015



Object Detection
Ren et al., "Faster R-CNN", NIPS 2015

Adapted from Andrej Karpathy

Semantic segmentation



Photographer identification

Who took this photograph?

- Deep net features achieve 74% accuracy
  - Chance is less than 3%, human performance is 47%
- Method learns what proto-objects + scenes authors shoot

Thomas and Kovashka, CVPR 2016

Analysis of pre-training on ImageNet

- Source:
  - distinguish 1000 ImageNet categories (incl. many dog breeds)
- Target tasks:
  - object detection and action recognition on PASCAL
  - scene recognition on SUN
- Pre-training with 500 images per class is about as good as pre-training with 1000
- Pre-training with 127 classes is about as good as pre-training with 1000
- Pre-training with (fewer classes, more images per class) > (more classes, fewer images)
- Small drop in if classes with fine-grained distinctions removed from pre-training set

Huh et al., "What makes ImageNet good for transfer learning?", arxiv 2016

Packages

TensorFlow

Torch / PyTorch

Keras

Caffe and Caffe Model Zoo

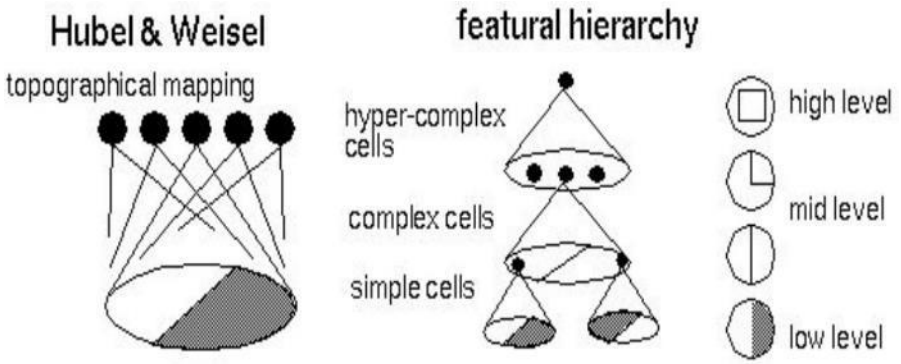
Some Learning Resources

http://deeplearning.net/

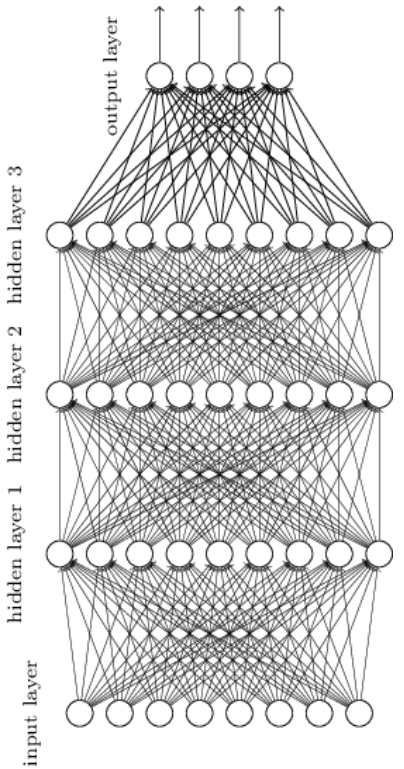
http://cs231n.stanford.edu

Understanding CNNs

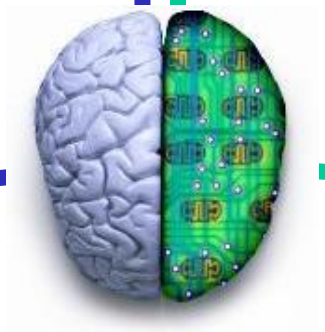
Recall: Biological analog



Hubel and Weisel's architecture

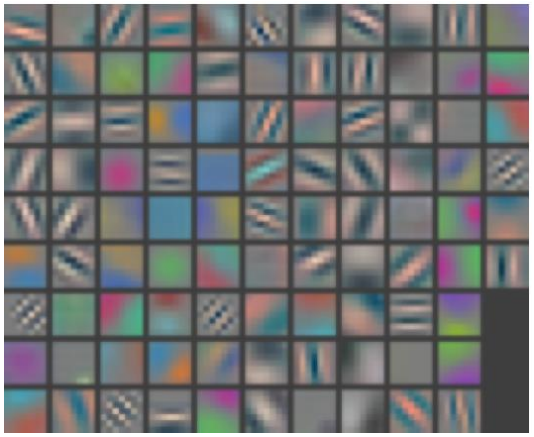


Multi-layer neural network



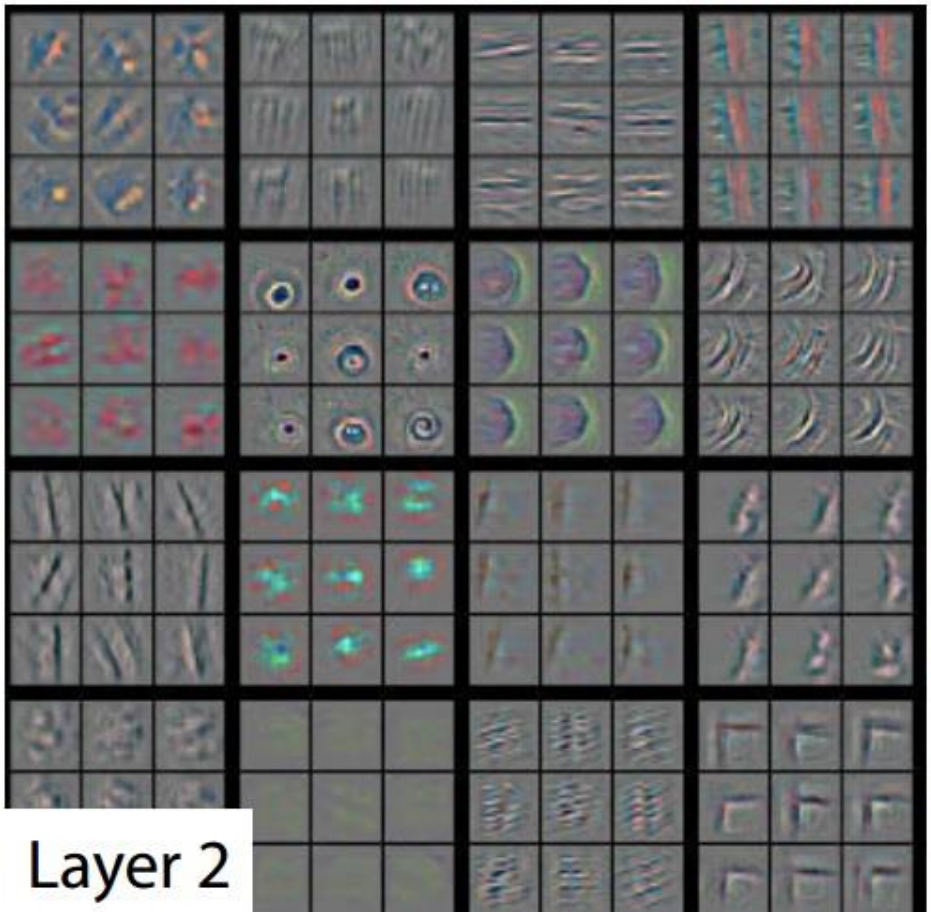
Adapted from Jia-bin Huang

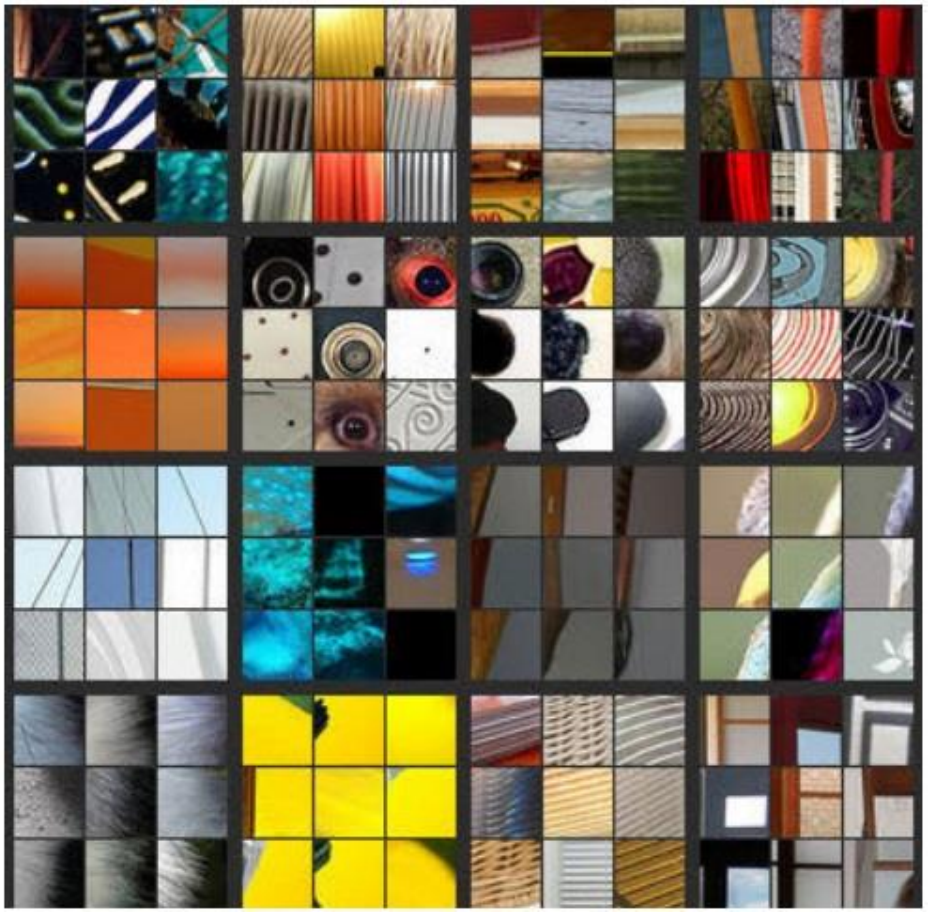
Layer 1



Visualizing and Understanding Convolutional Networks [Zeiler and Fergus, ECCV 2014]

Layer 2

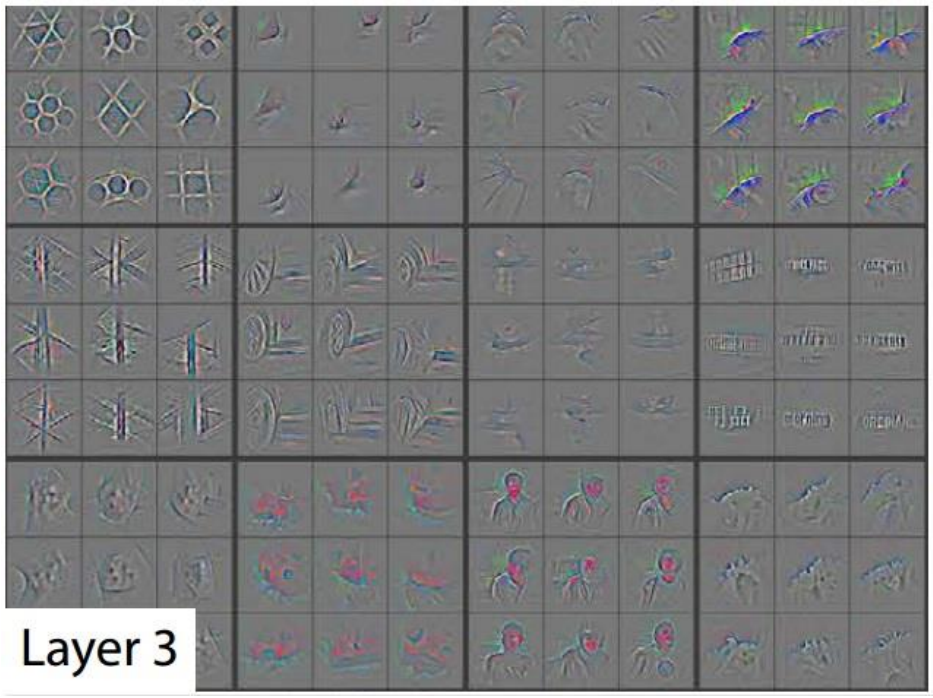




- Activations projected down to pixel level via decovolution
- Patches from validation images that give maximal activation of a given feature map

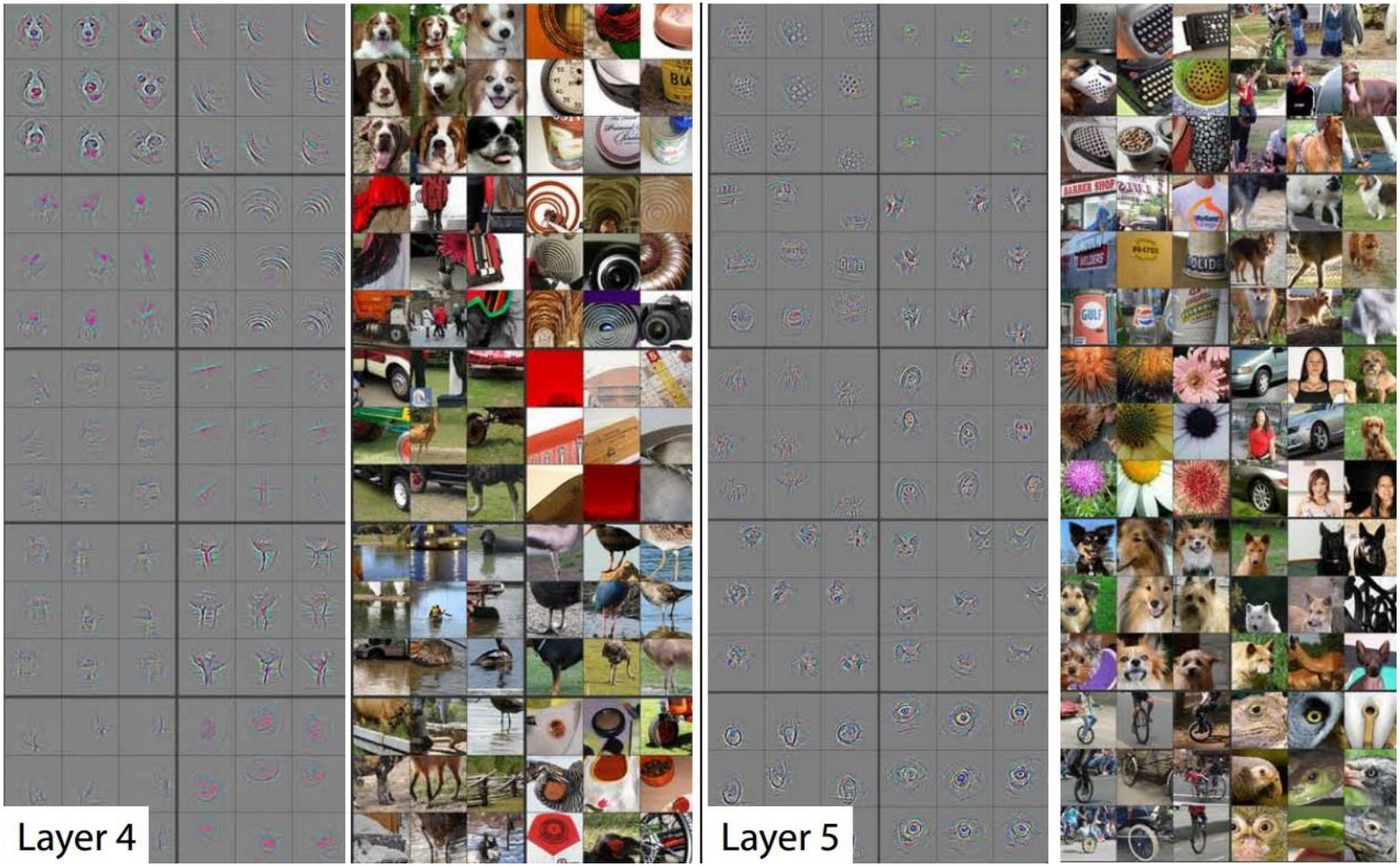
Visualizing and Understanding Convolutional Networks [Zeiler and Fergus, ECCV 2014]

Layer 3



Visualizing and Understanding Convolutional Networks [Zeiler and Fergus, ECCV 2014]

Layer 4 and 5



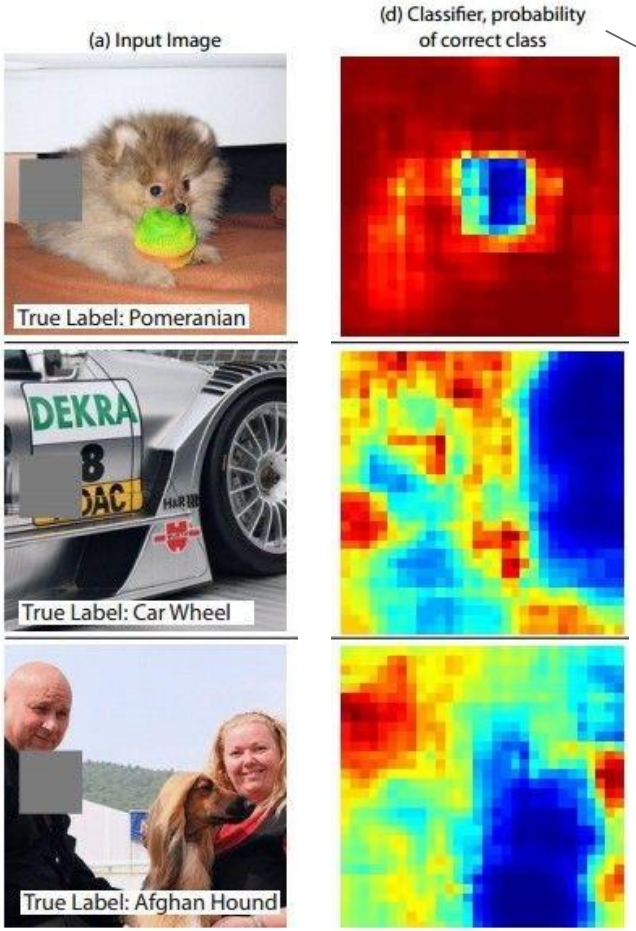
Visualizing and Understanding Convolutional Networks [Zeiler and Fergus, ECCV 2014]

Occlusion experiments

(as a function of the position of the square of zeros in the original image)

[Zeiler & Fergus 2014]

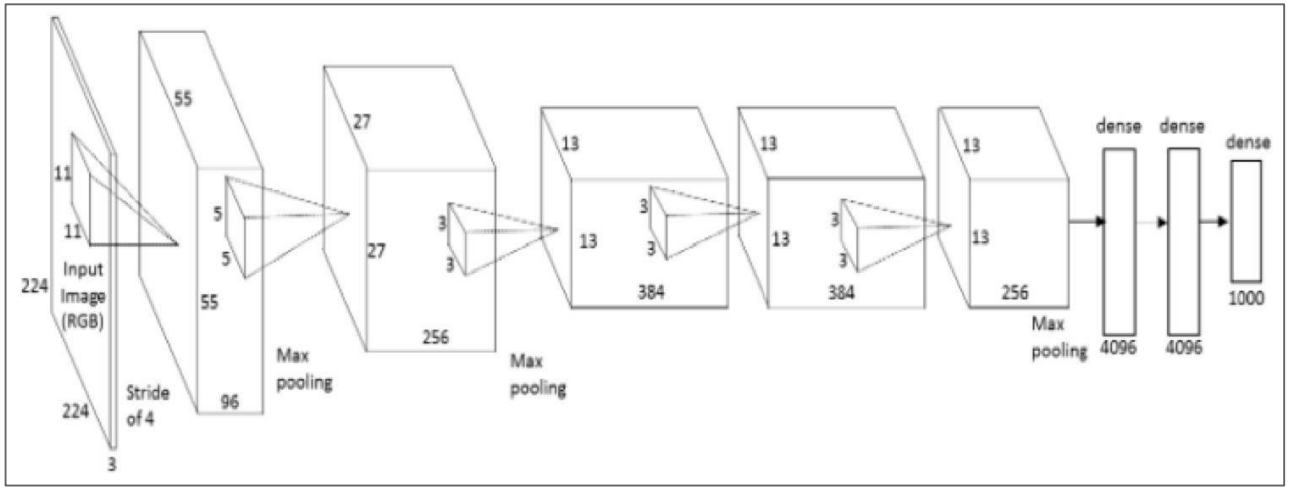
Occlusion experiments



(as a function of the position of the square of zeros in the original image)

[Zeiler & Fergus 2014]

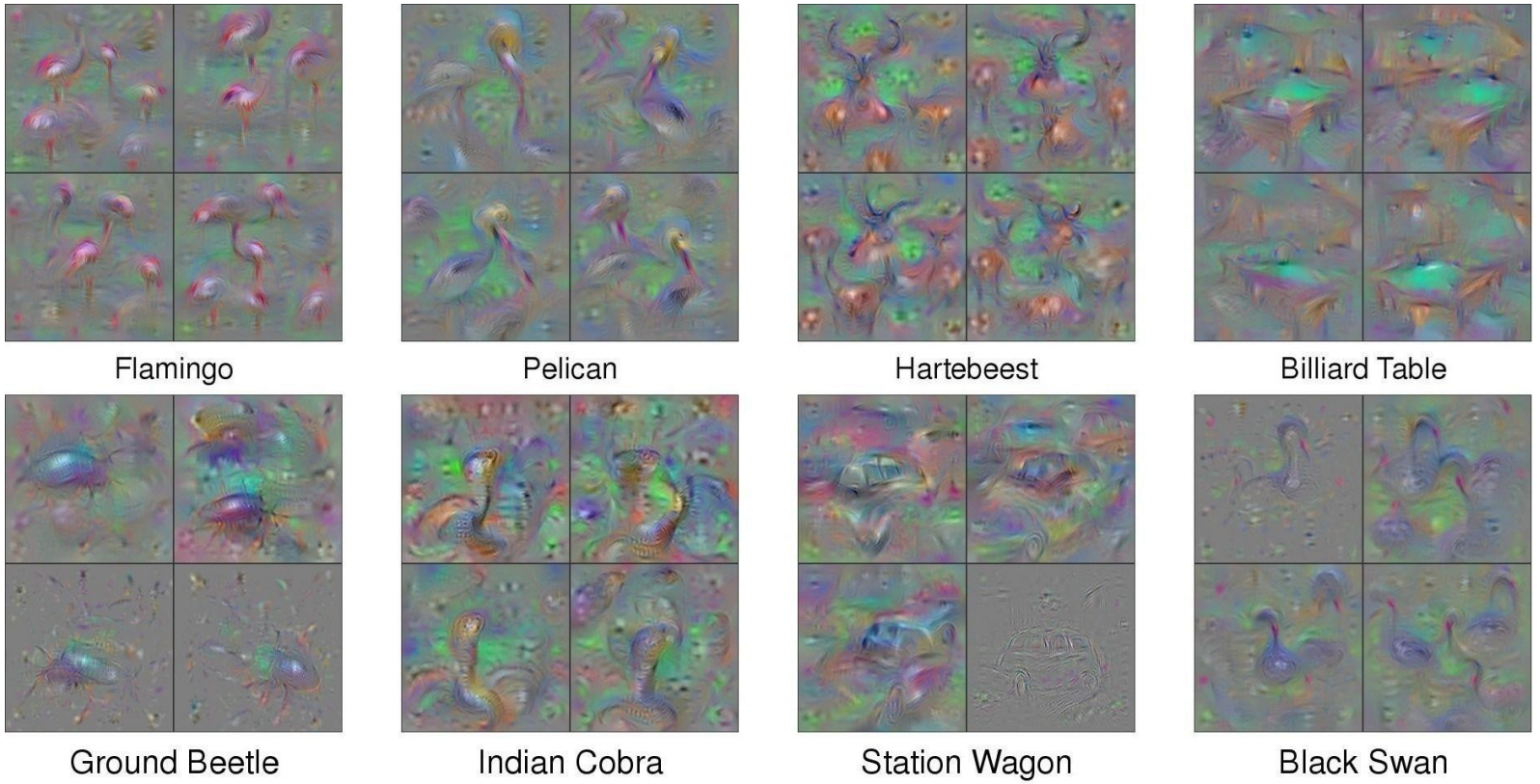
What image maximizes a class score?



Repeat:

1. Forward an image
2. Set activations in layer of interest to all zero, except for a 1.0 for a neuron of interest
3. Backprop to image
4. Do an “image update”

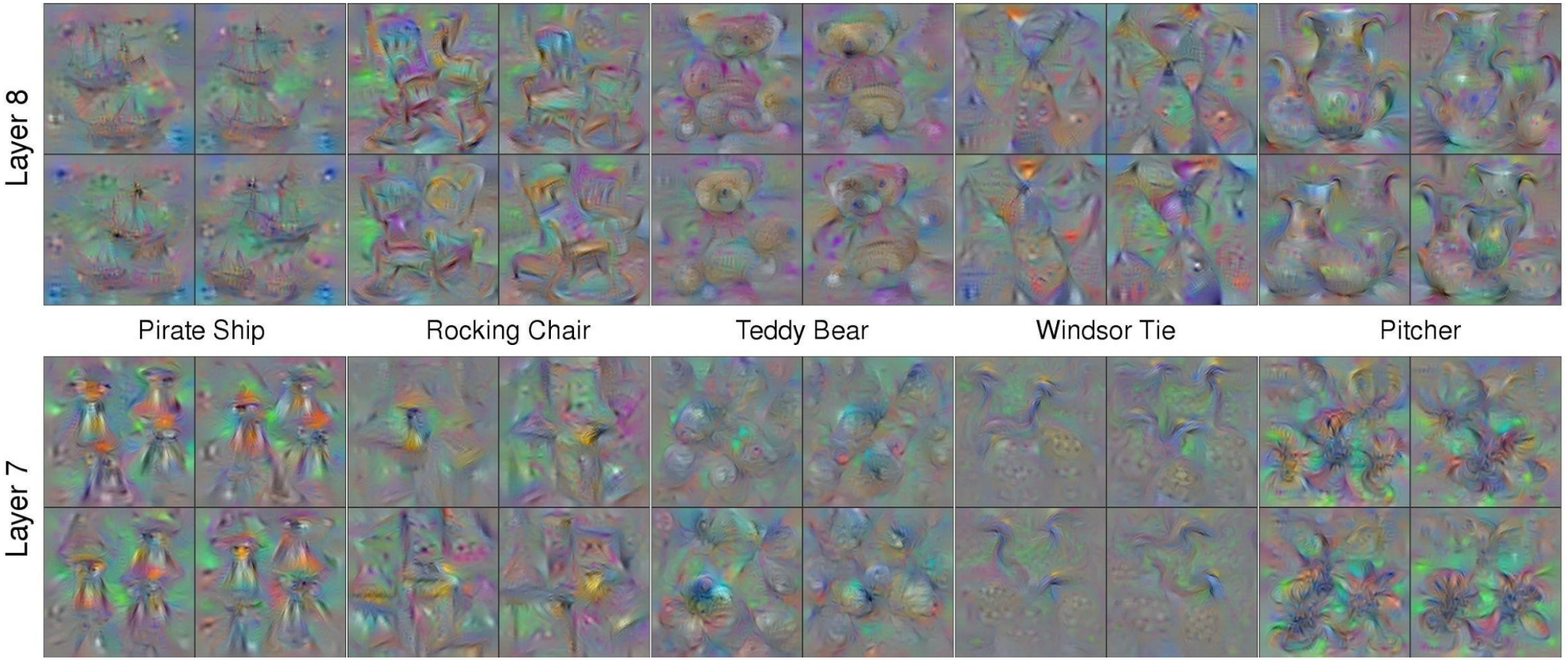
What image maximizes a class score?



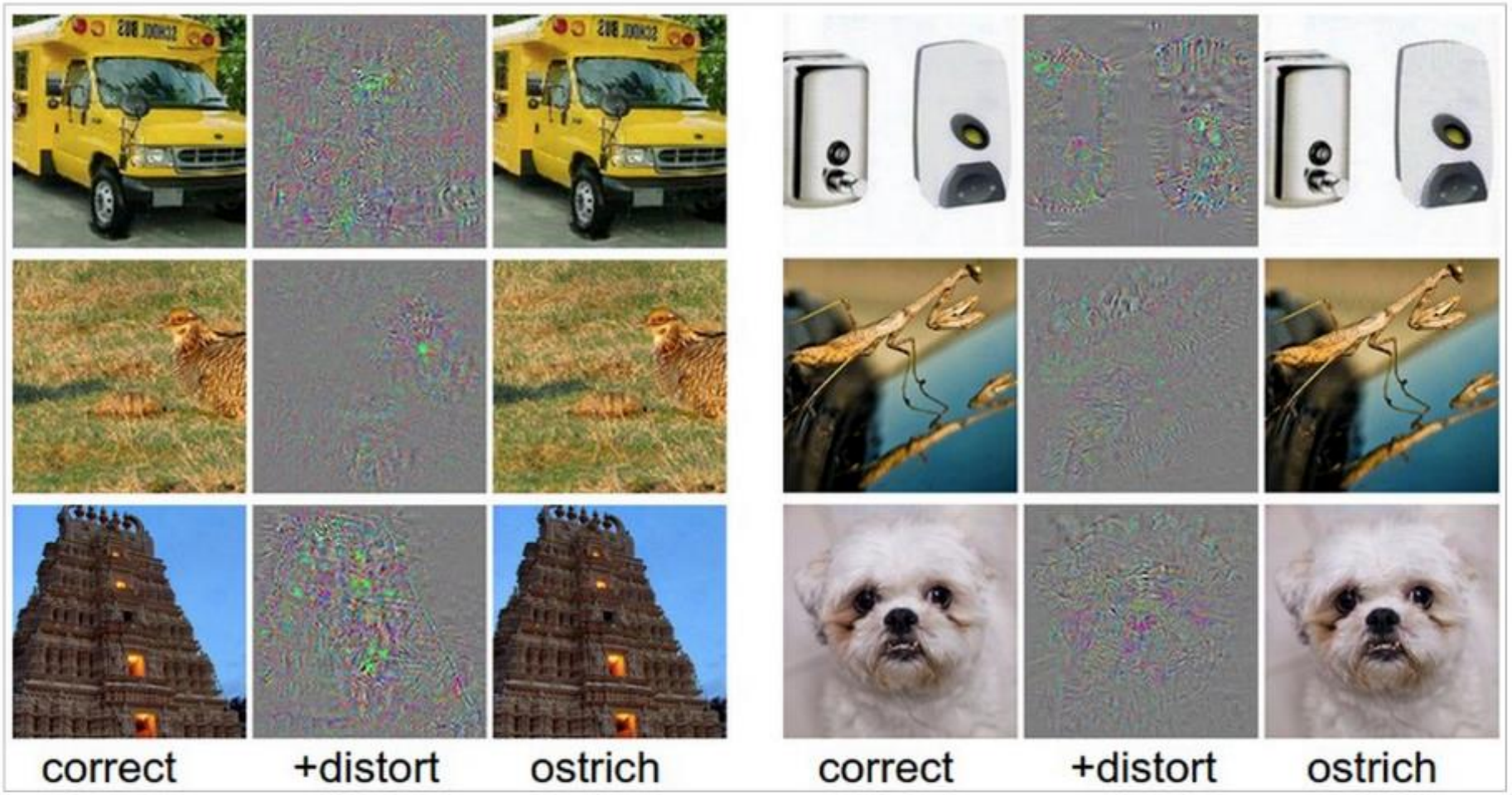
[Understanding Neural Networks Through Deep Visualization, Yosinski et al. , 2015]

http://yosinski.com/deepvis

What image maximizes a class score?



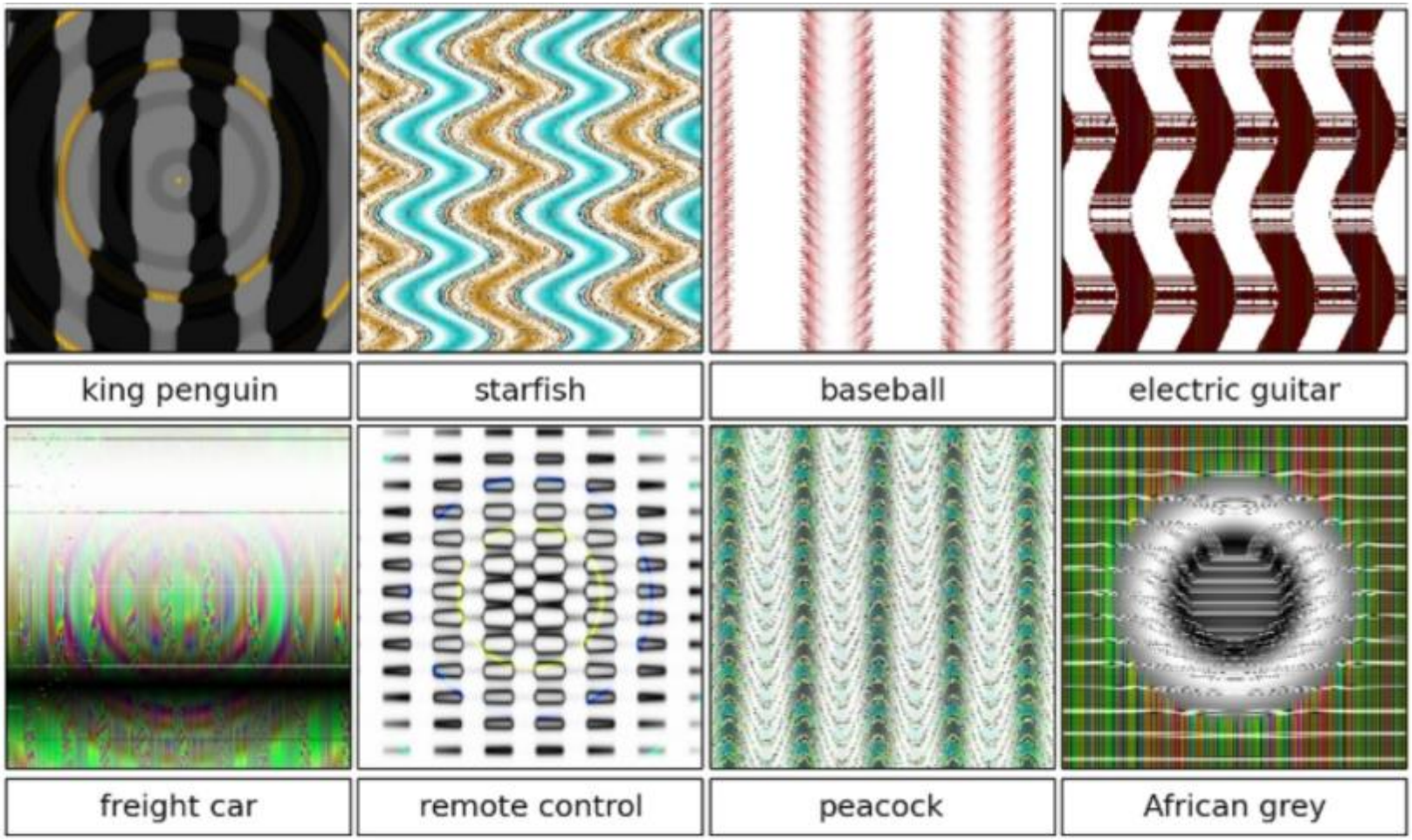
Breaking CNNs



Take a correctly classified image (left image in both columns), and add a tiny distortion (middle) to fool the ConvNet with the resulting image (right).

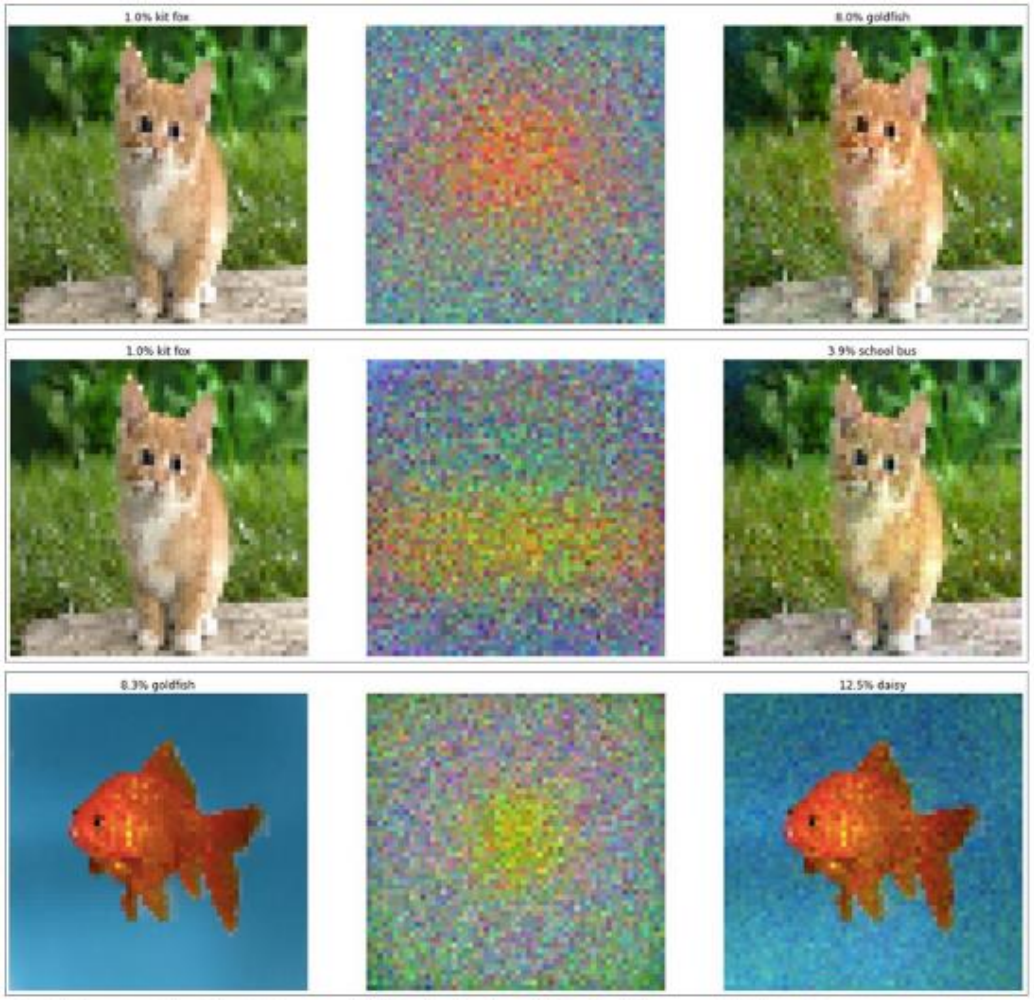
Intriguing properties of neural networks [Szegedy ICLR 2014]

Breaking CNNs



Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images [Nguyen et al. CVPR 2015]

Fooling a linear classifier



Fooled linear classifier: The starting image (left) is classified as a kit fox. That's incorrect, but then what can you expect from a linear classifier? However, if we add a small amount "goldfish" weights to the image (top row, middle), suddenly the classifier is convinced that it's looking at one with high confidence. We can distort it with the school bus template instead if we wanted to.

To fool a linear classifier, add a small multiple of the weight vector to the training example:

$\mathbf{x} \leftarrow \mathbf{x} + \alpha \mathbf{w}$

http://karpathy.github.io/2015/03/30/breaking-convnets/

Summary

- We use deep neural networks because of their strong performance in practice
- Convolutional neural network (CNN)
  - Convolution, nonlinearity, max pooling
- Training deep neural nets
  - We need an objective function that measures and guides us towards good performance
  - We need a way to minimize the loss function: stochastic gradient descent
  - We need backpropagation to propagate error towards all layers and change weights at those layers
- Practices for preventing overfitting
  - Dropout; data augmentation; transfer learning