Convolutional neural networks III

October 2nd, 2019

Yong Jae Lee
UC Davis

Many slides from Rob Fergus, Svetlana Lazebnik, Jia-Bin Huang, Derek Hoiem, Adriana Kovashka, Andrej Karpathy

Announcements

- Sign-up for paper presentations
- First paper review due Thurs 11:59 PM

Gradient descent

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

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

Time

Learning rate

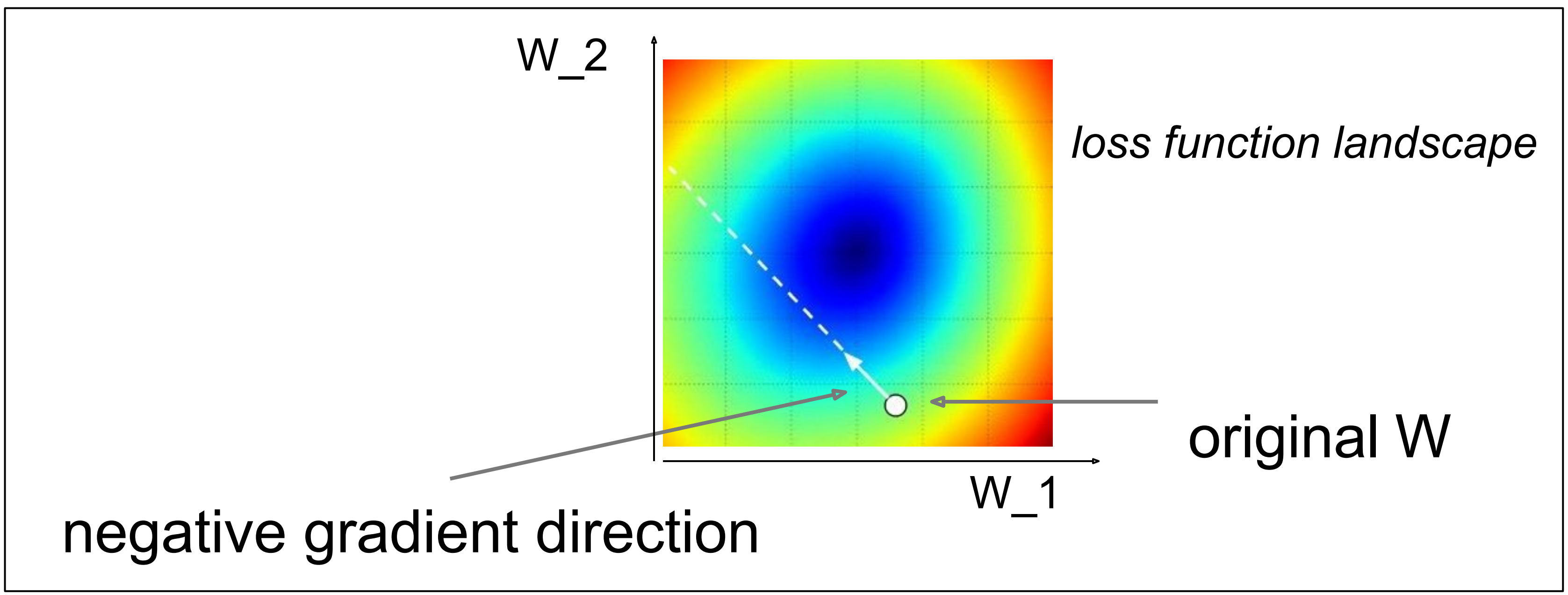


Figure from Andrej Karpathy

Gradient descent in multi-layer nets

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

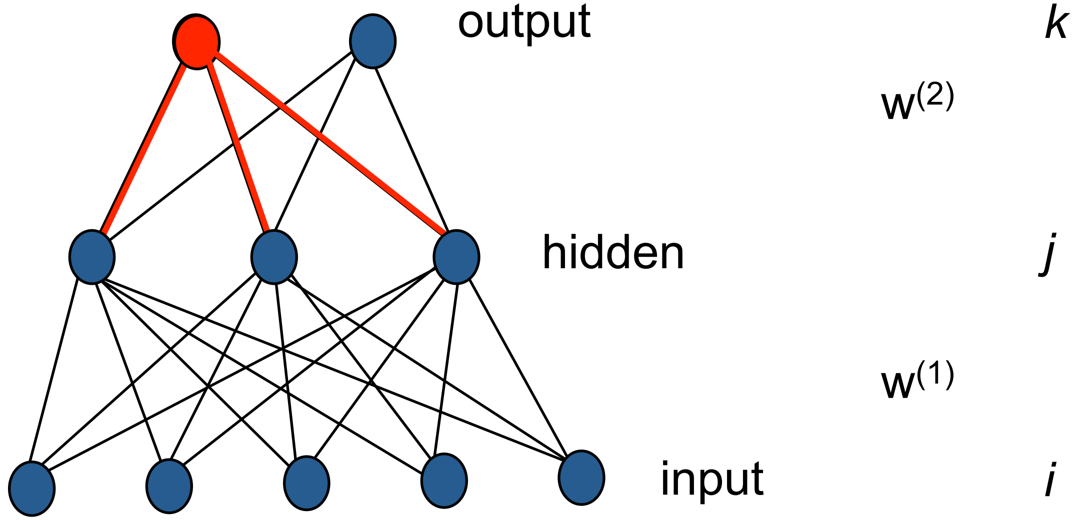
$$\mathbf{w}^{(\tau+1)} = \mathbf{w}^{(\tau)} - \eta \nabla E(\mathbf{w}^{(\tau)})$$

- How to update the weights at all layers?
- Answer: *backpropagation* of loss 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.

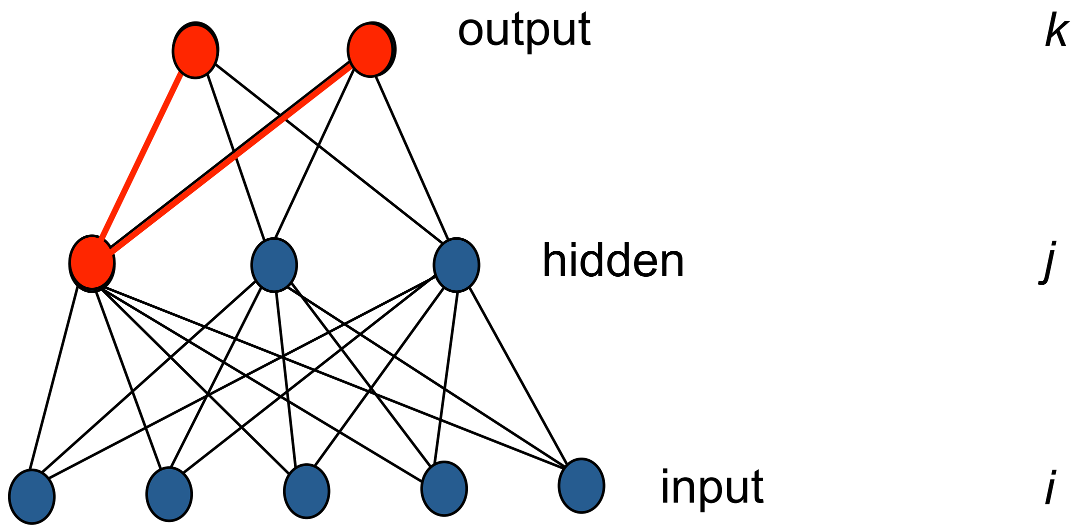
Update weights into *j*



Adapted from Ray Mooney

Backpropagation: Graphic example

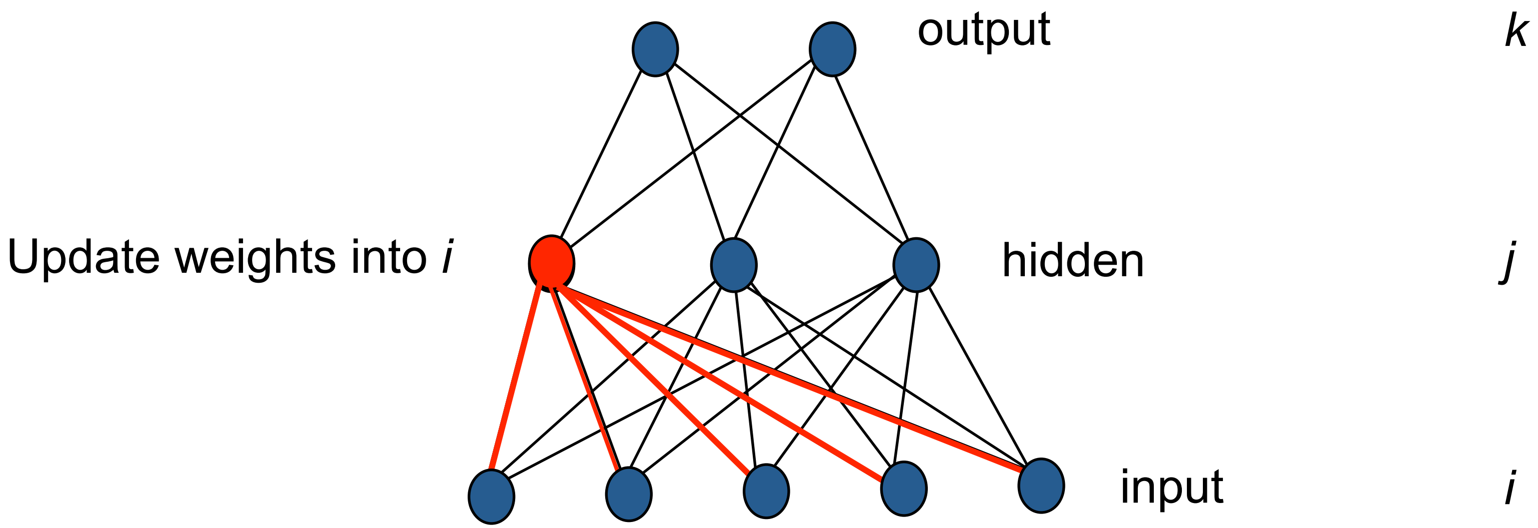
- Next calculate error for hidden units based on errors on the output units it feeds into.



Adapted from Ray Mooney

Backpropagation: Graphic example

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



Adapted from Ray Mooney

Backpropagation

- Easier if we use *computational graphs,* especially when we have complicated functions typical in deep neural networks

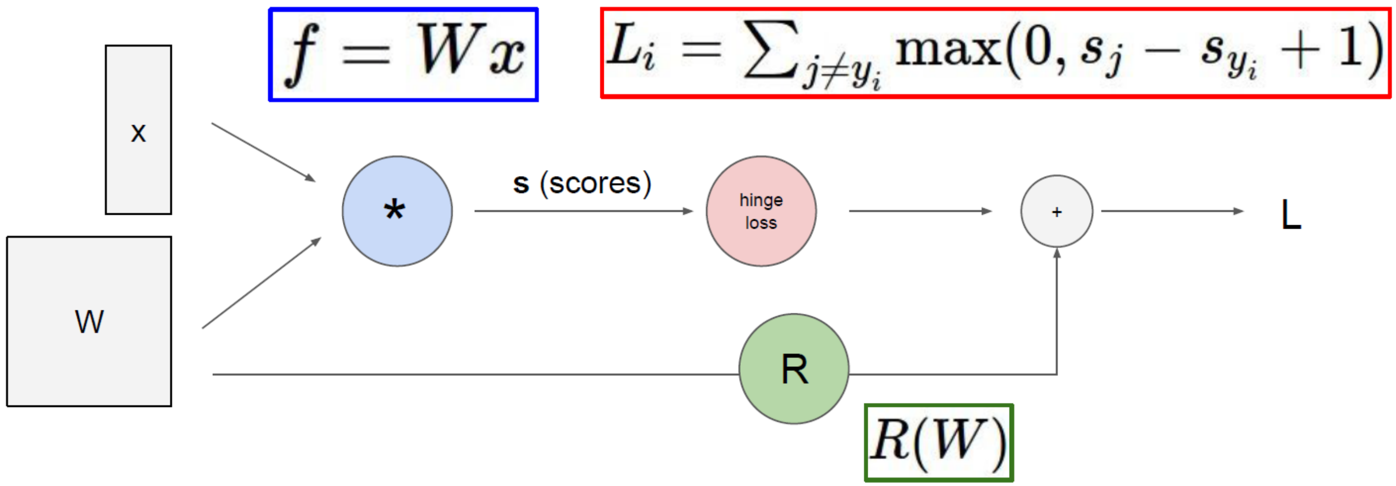
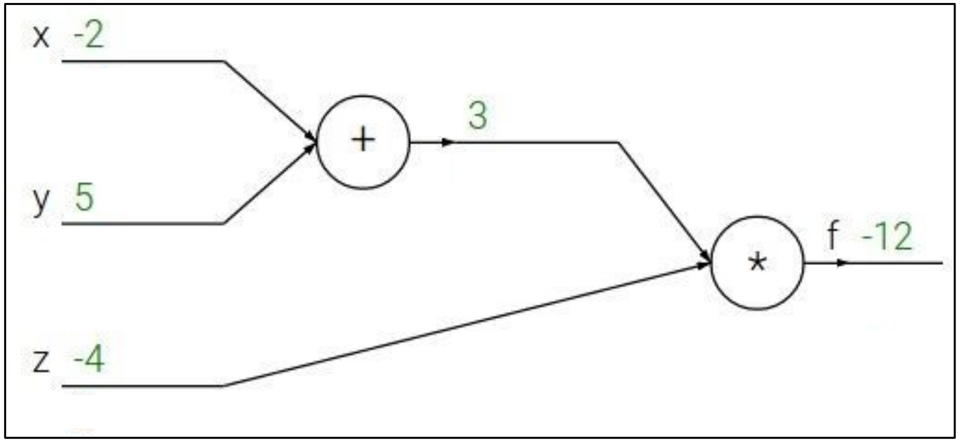


Figure from Karpathy

Backpropagation: a simple example

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

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



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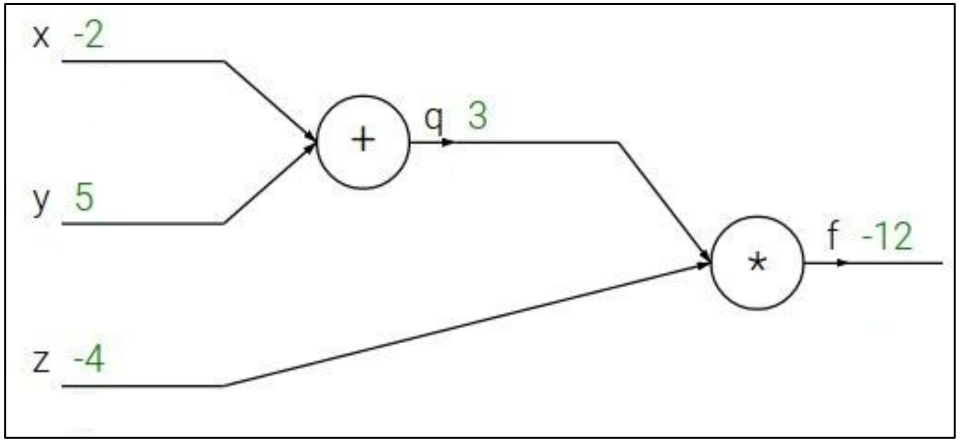
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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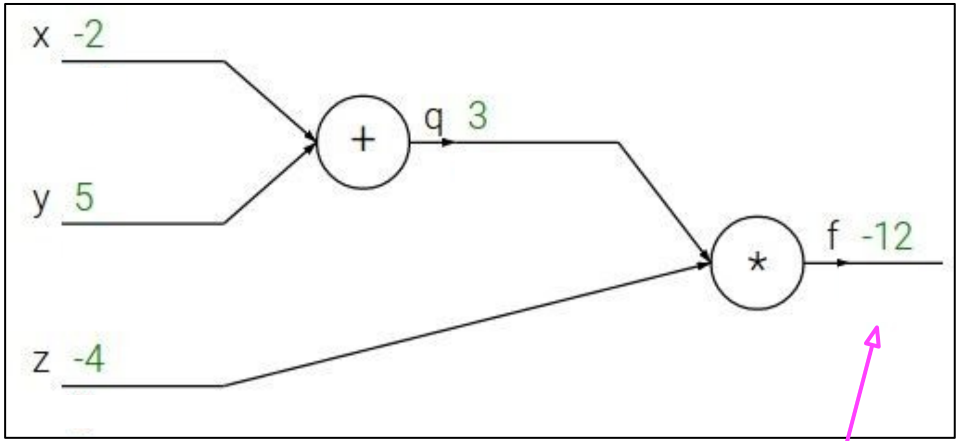

$$\frac{\partial f}{\partial f}$$

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

Backpropagation: a simple example

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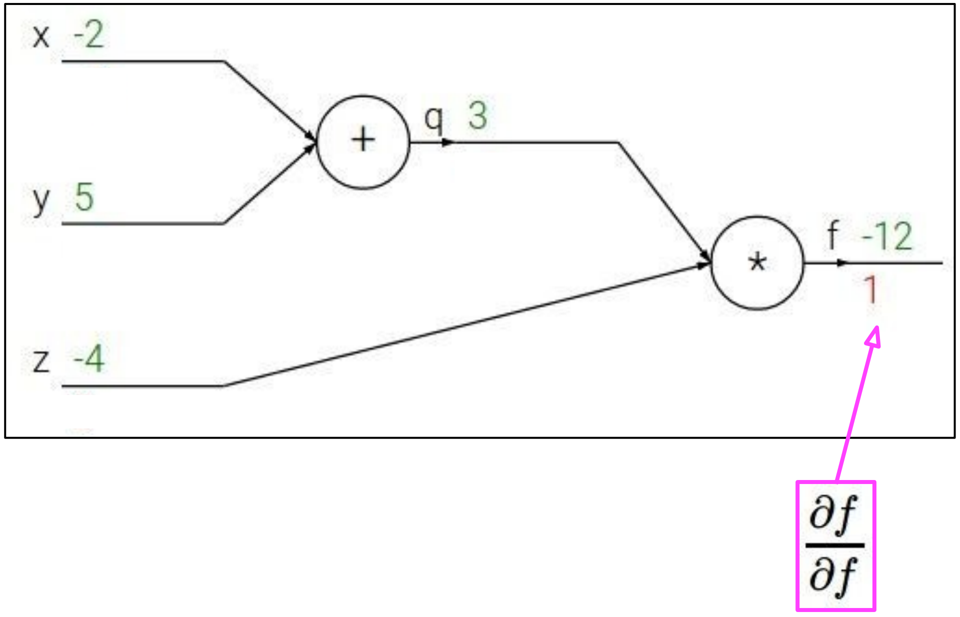

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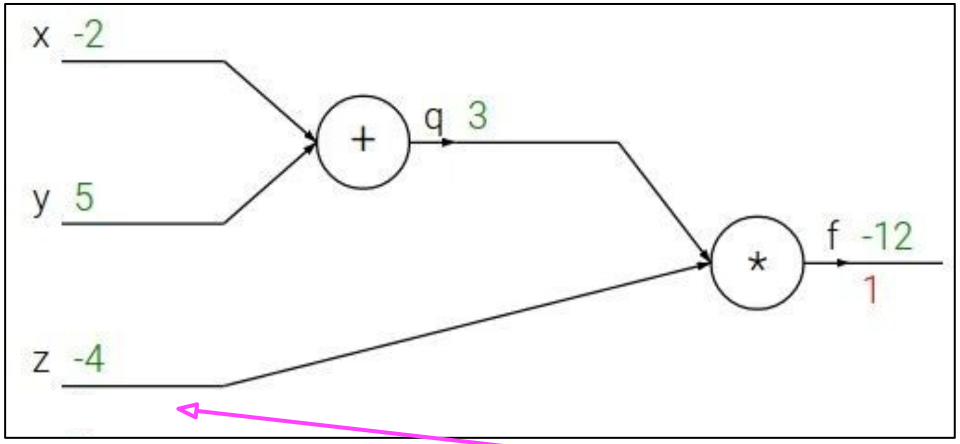

$$\frac{\partial f}{\partial z}$$

Backpropagation: a simple example

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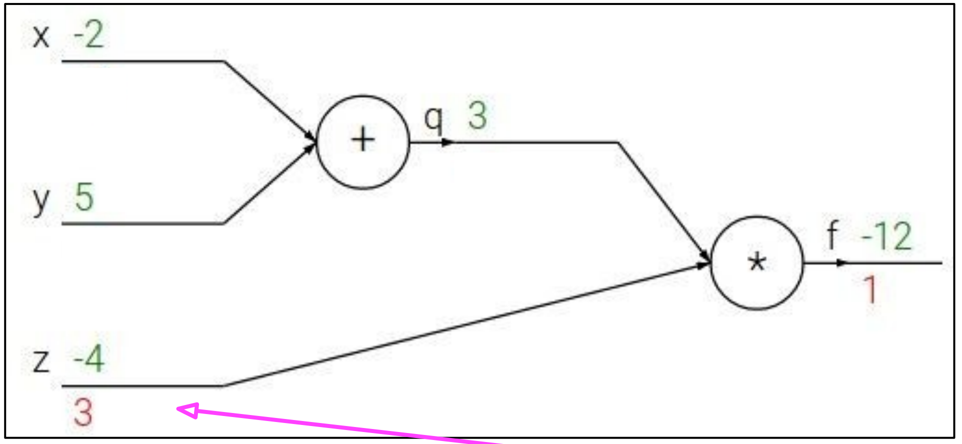

$\boxed{\dfrac{\partial f}{\partial z}}$

Andrej Karpathy

Backpropagation: a simple example

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

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

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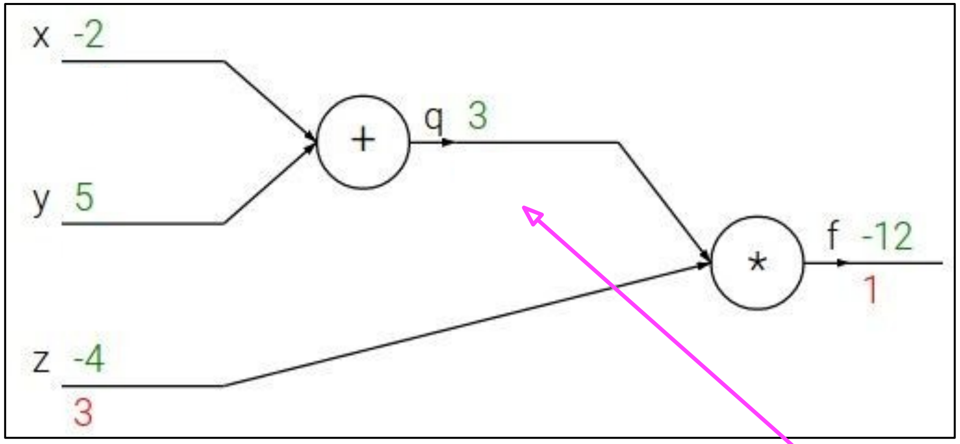

$$\frac{\partial f}{\partial q}$$

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

Backpropagation: a simple example

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

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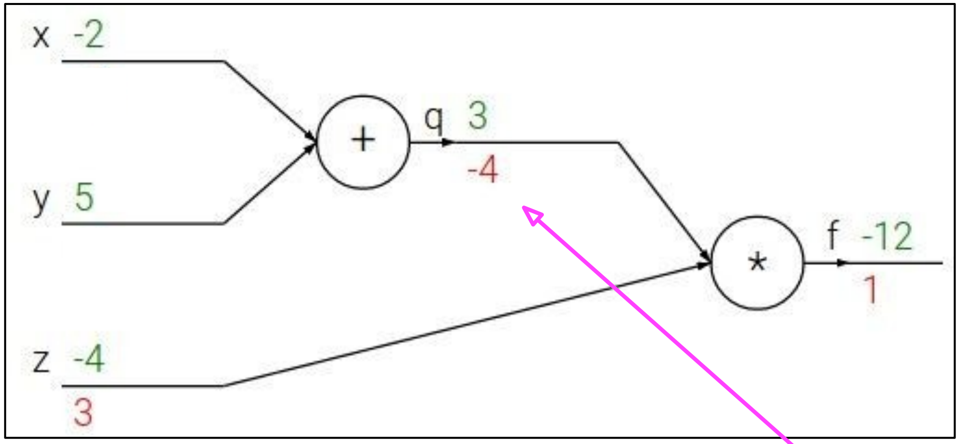

$$\frac{\partial f}{\partial q}$$

Backpropagation: a simple example

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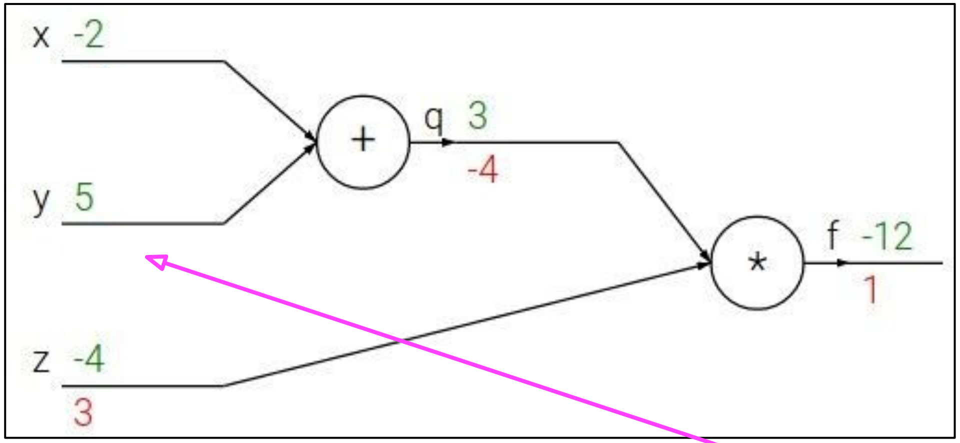
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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

Backpropagation: a simple example

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

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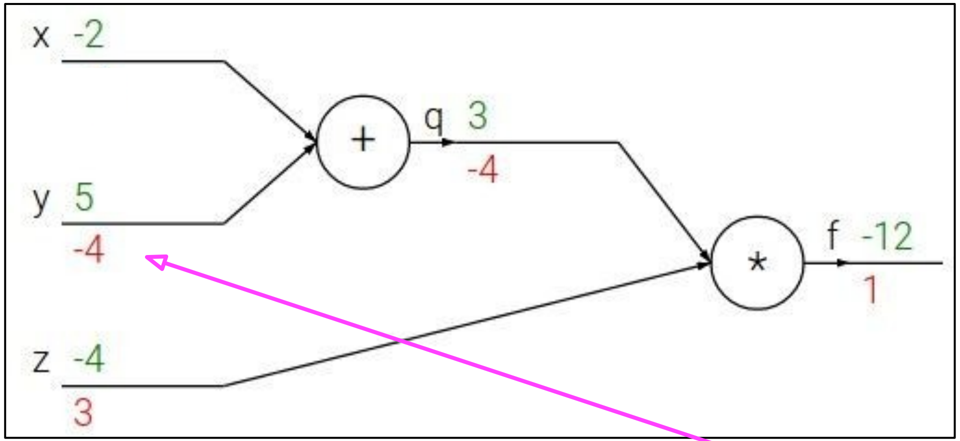

$$\frac{\partial f}{\partial y}$$

Chain rule:

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

Upstream gradient

Local gradient

Andrej Karpathy

Backpropagation: a simple example

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

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

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

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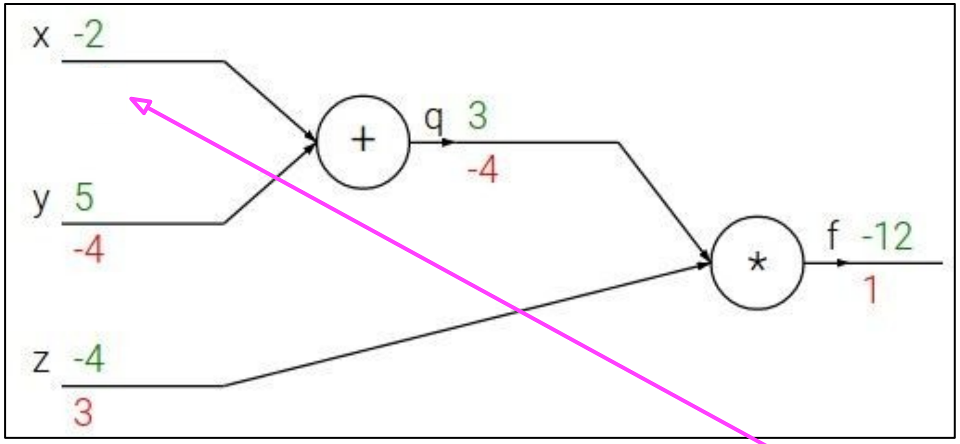

$$\boxed{\frac{\partial f}{\partial x}}$$

Backpropagation: a simple example

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

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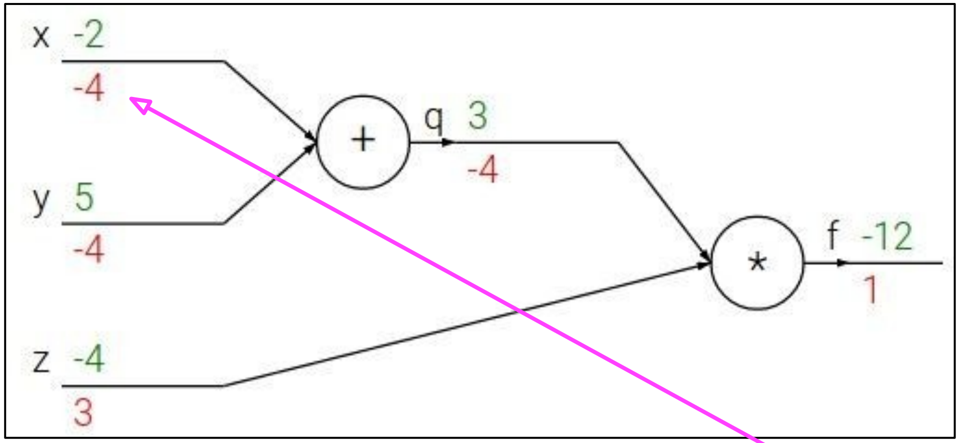
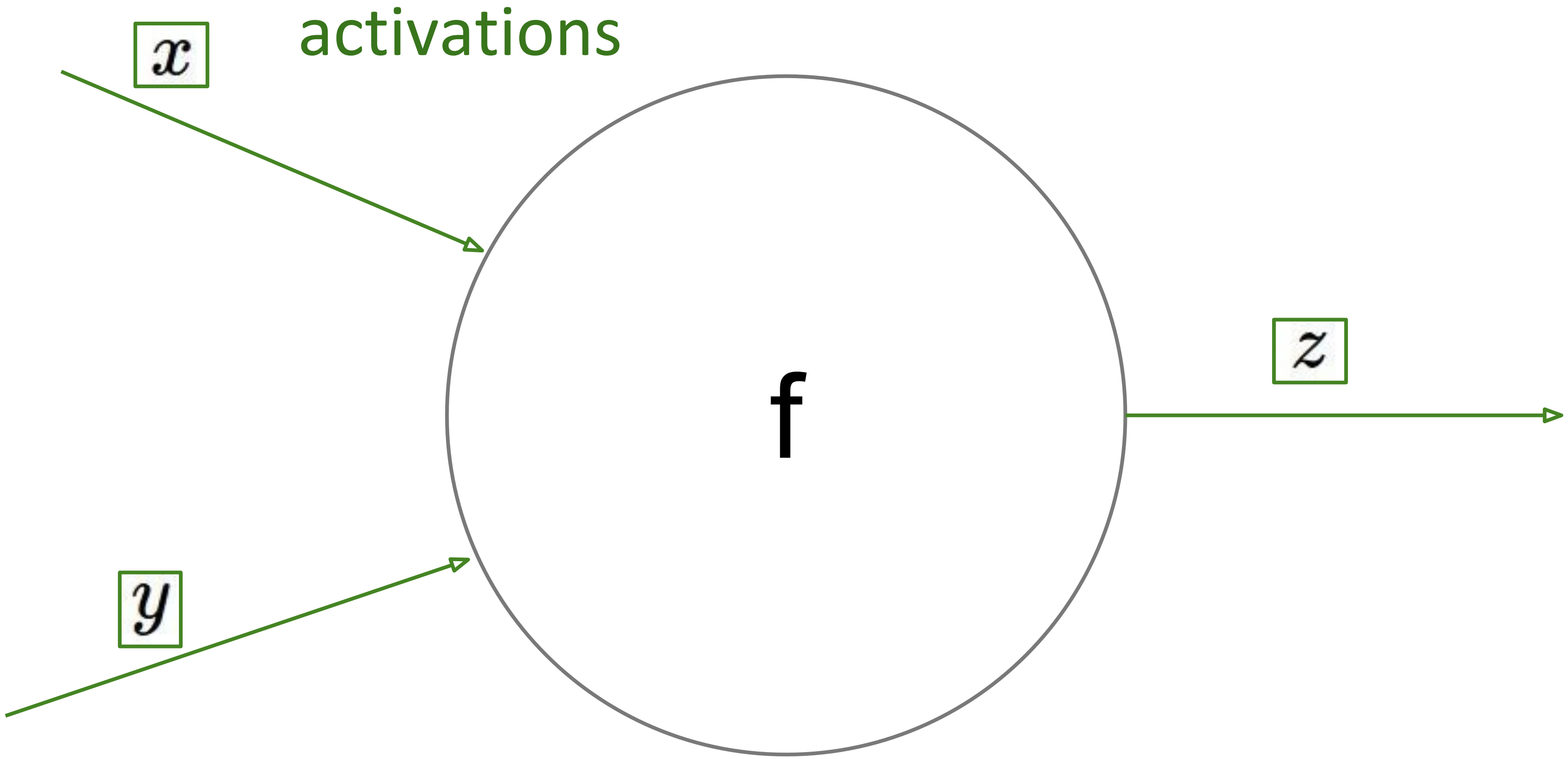


$$\frac{\partial f}{\partial x}$$

Chain rule:

$$\boxed{\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x}}$$



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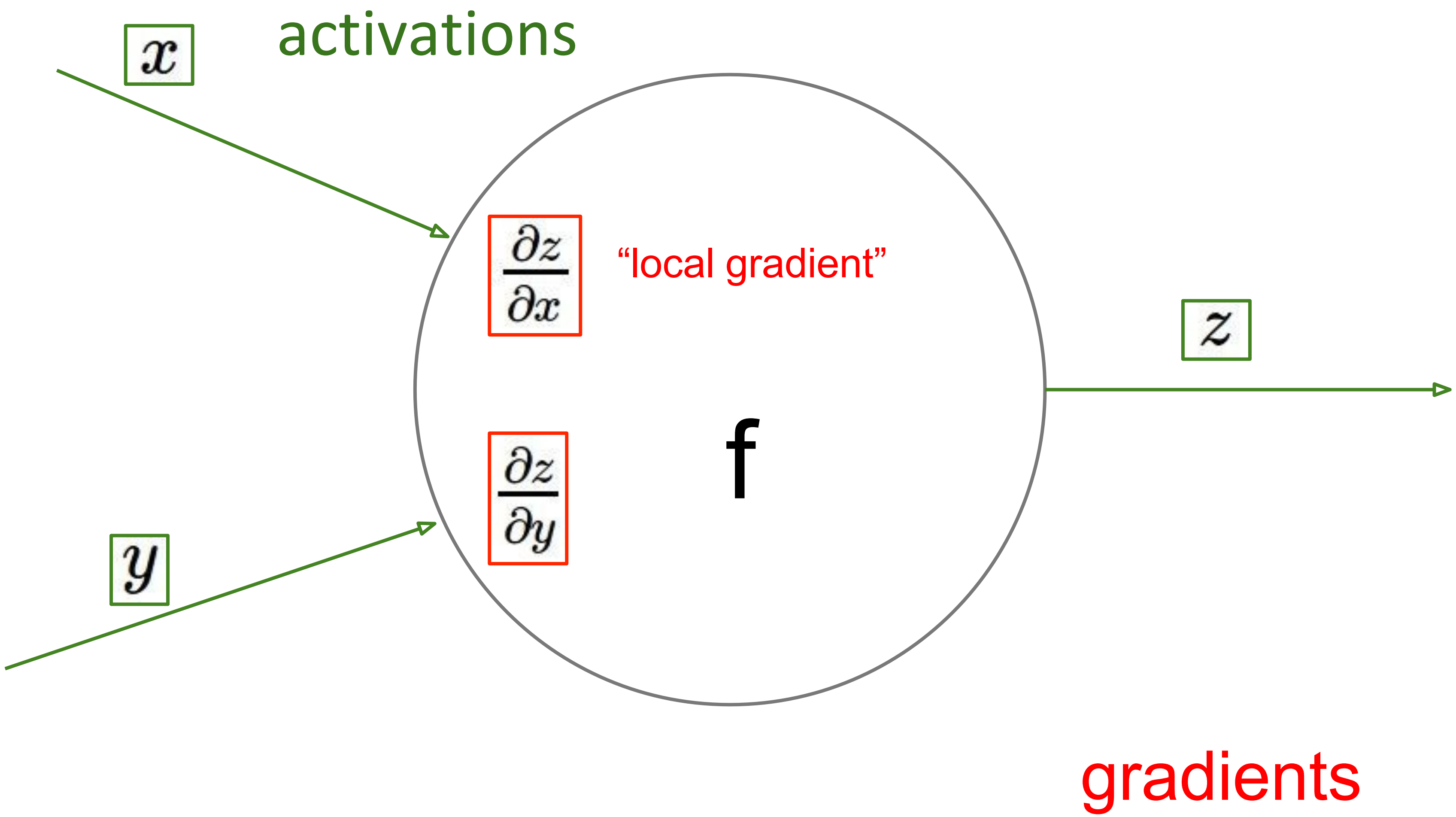

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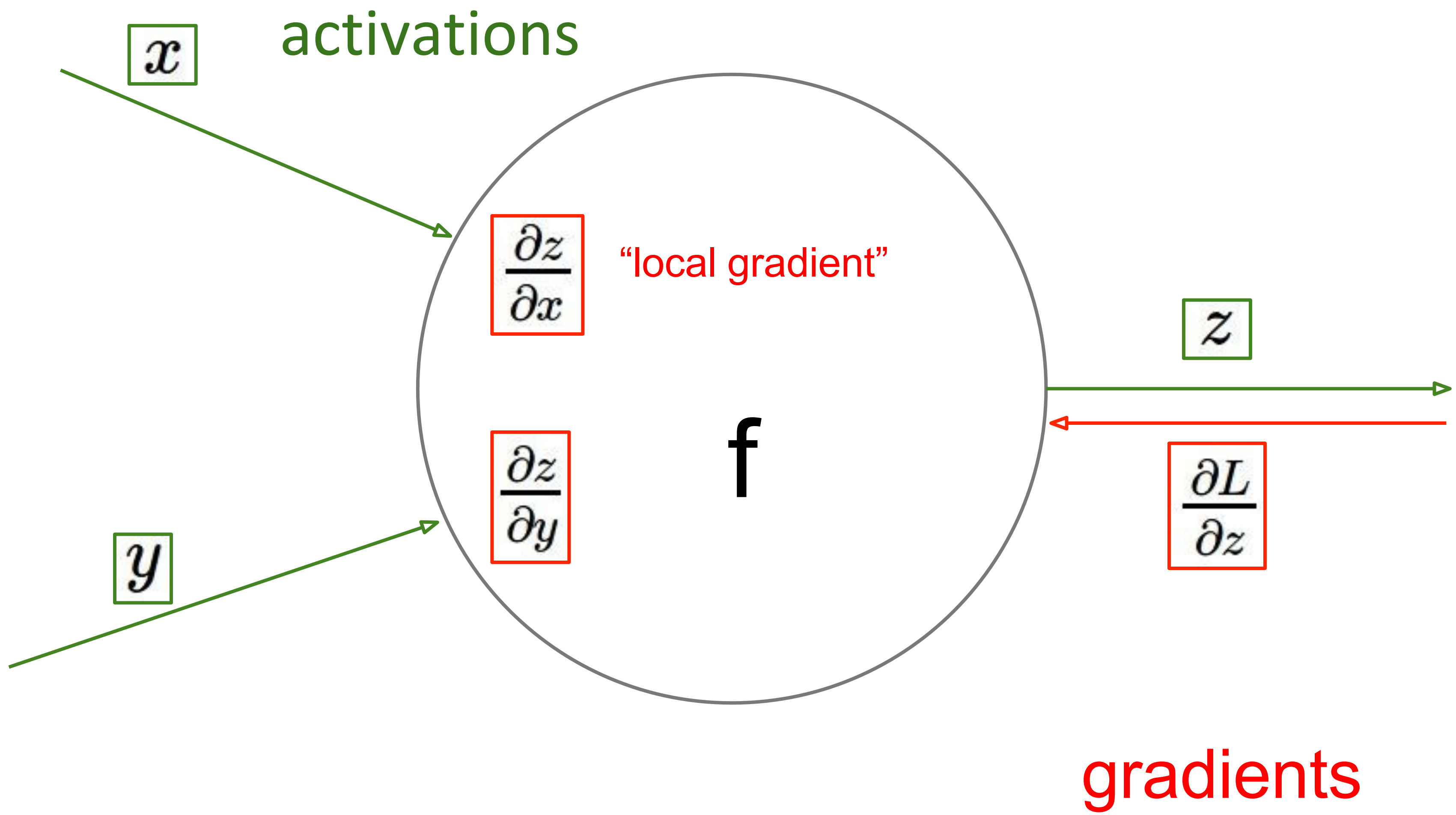

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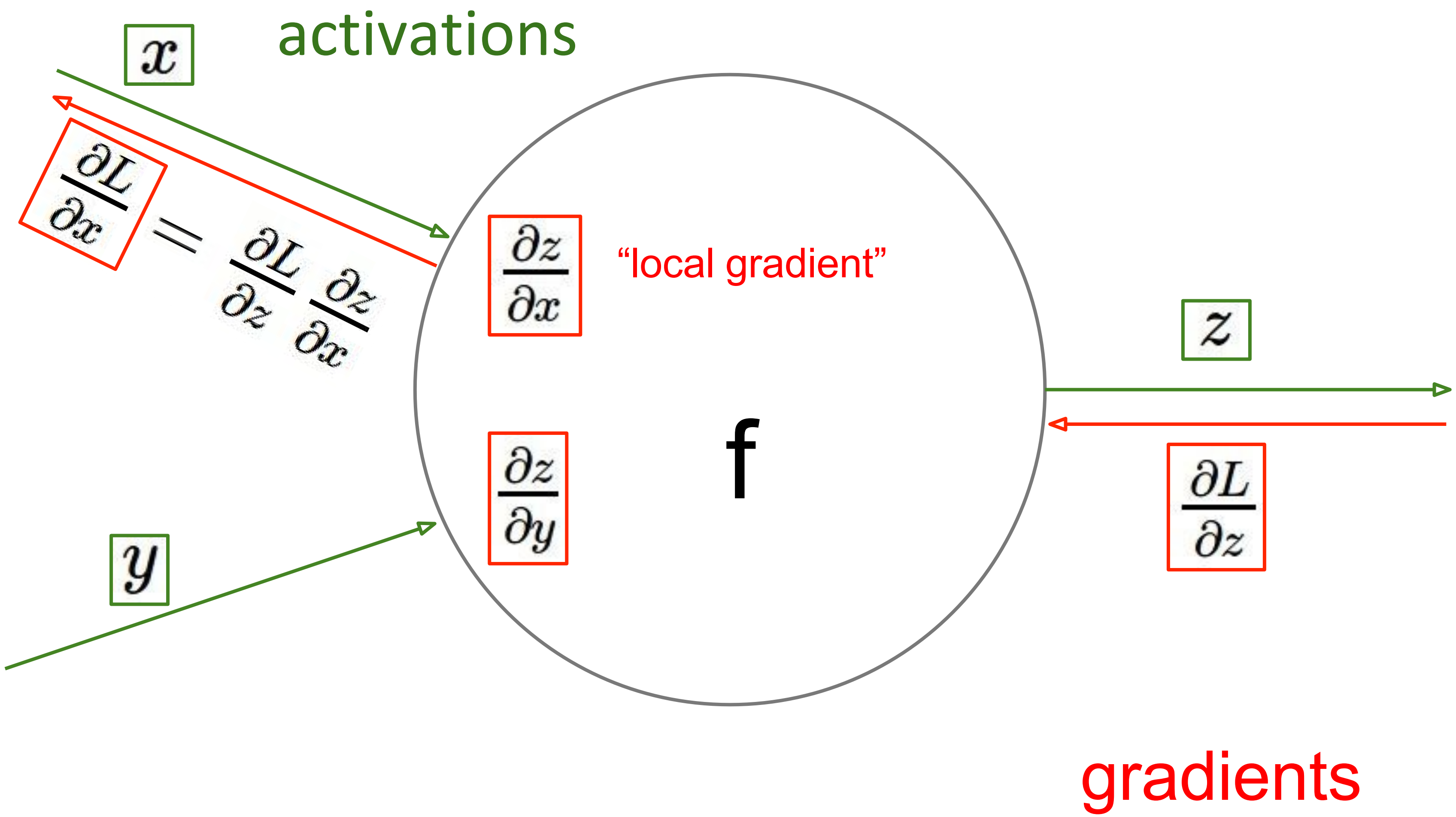

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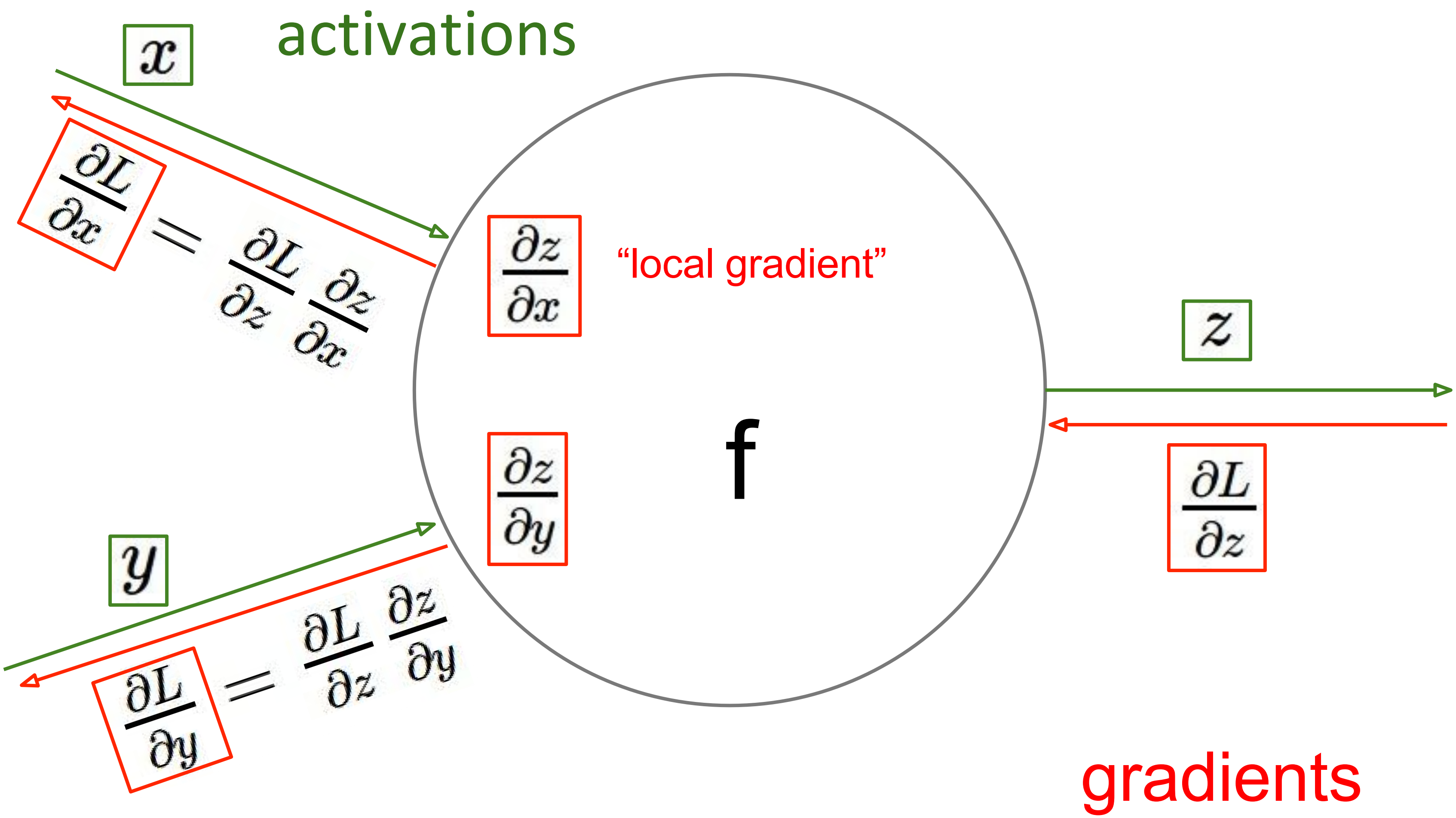
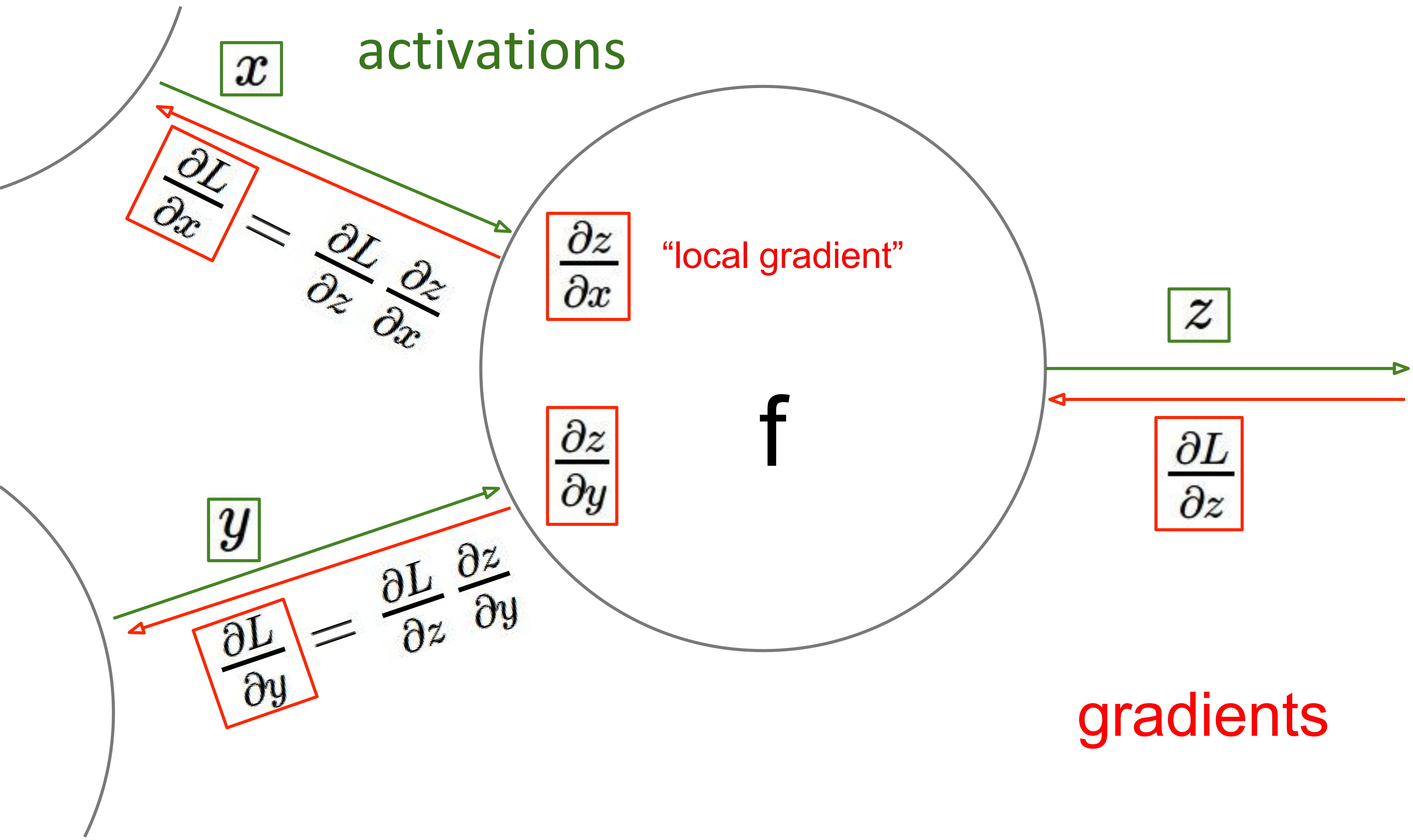


Andrej Karpathy



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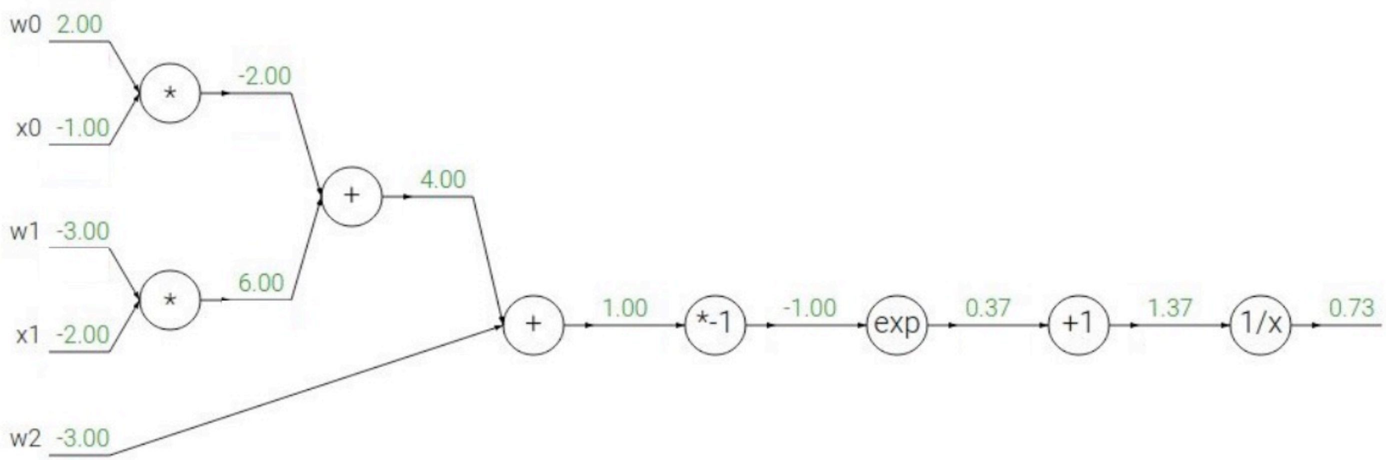
Backpropagation: another example

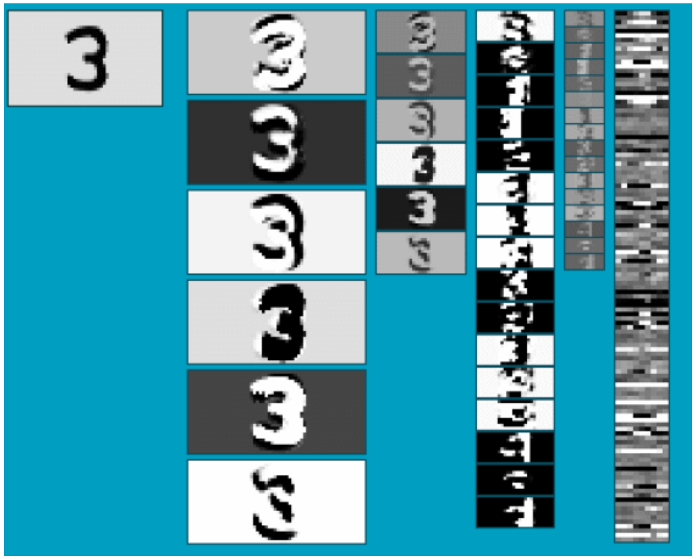
$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

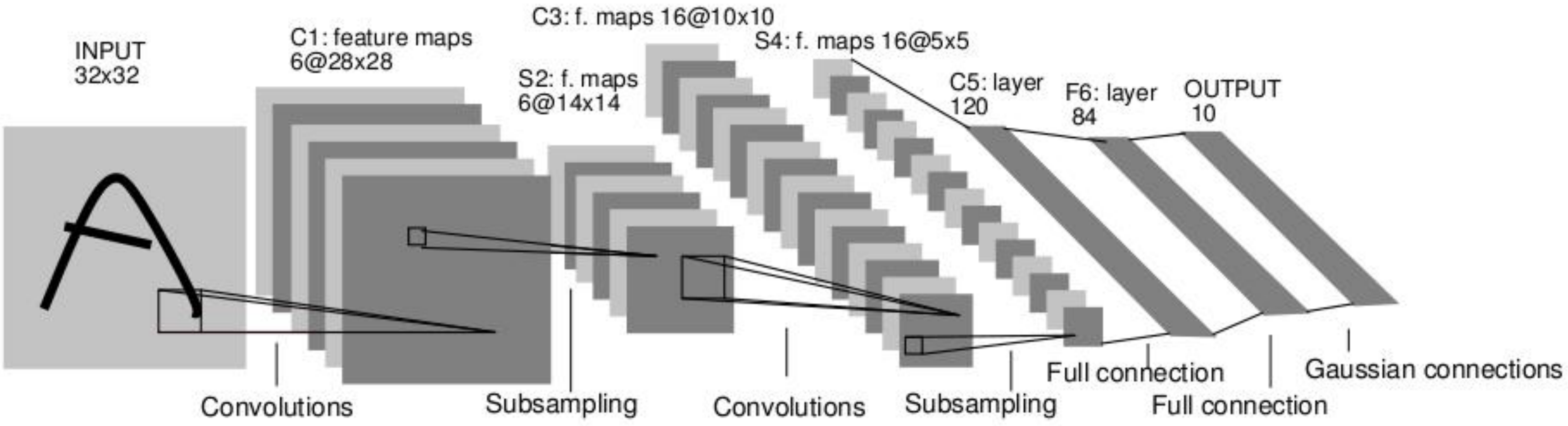


$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x$		$f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$	
$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a$		$f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$	

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



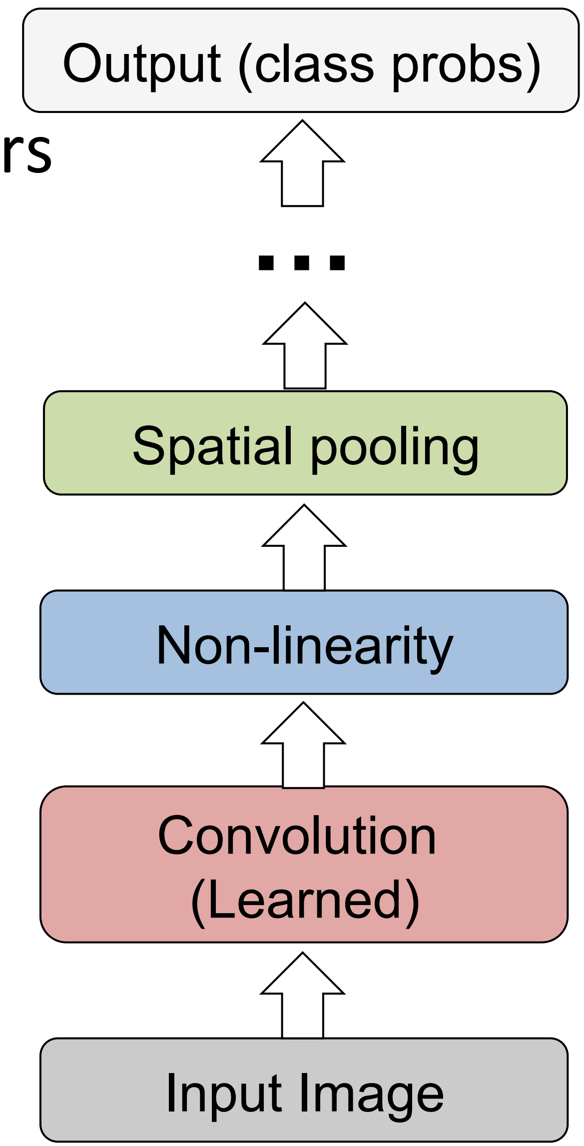


Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998

Adapted from Rob Fergus

Convolutional Neural Networks (CNN)

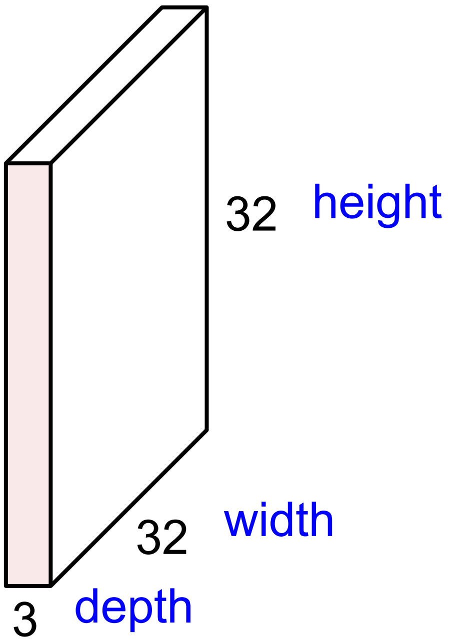
- Feed-forward feature extraction:
  1. Convolve input with learned filters
  2. Apply non-linearity
  3. Spatial pooling (downsample)
- Supervised training of convolutional filters by back-propagating classification error



Adapted from Lana Lazebnik

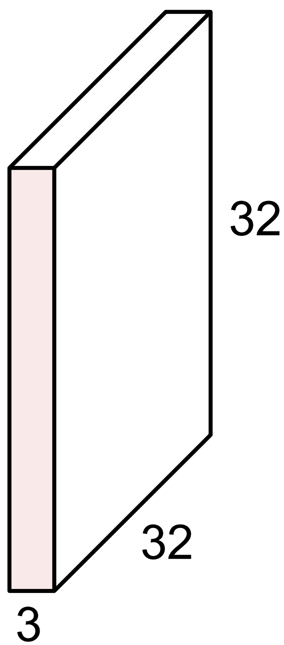
Convolutions: More detail

32x32x3 image

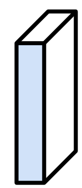


Convolutions: More detail

32x32x3 image



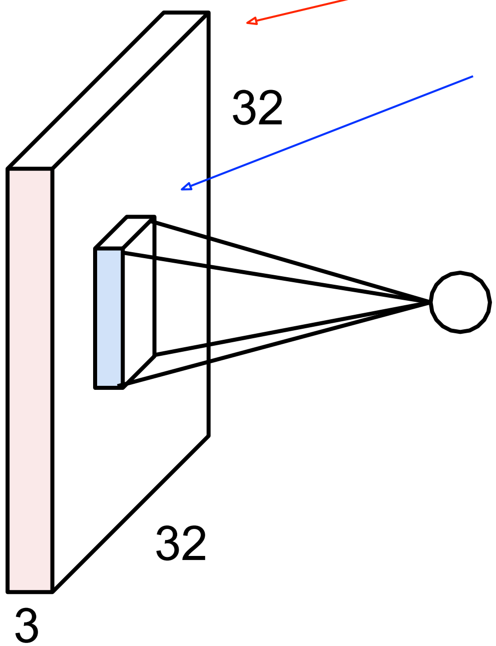
5x5x3 filter



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

Convolutions: More detail

Convolution Layer



32x32x3 image

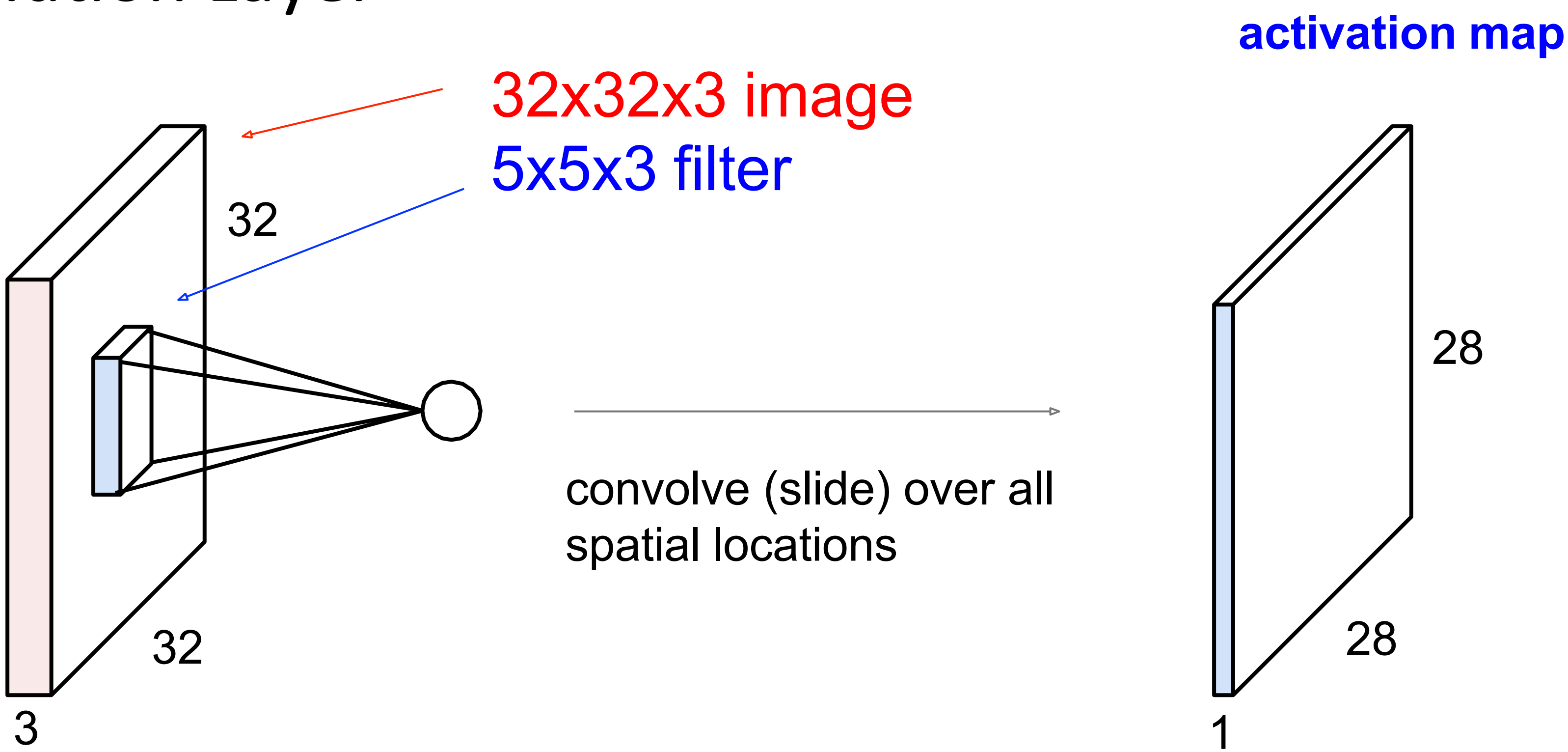
5x5x3 filter w

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)

$$w^T x + b$$

Convolutions: More detail

Convolution Layer



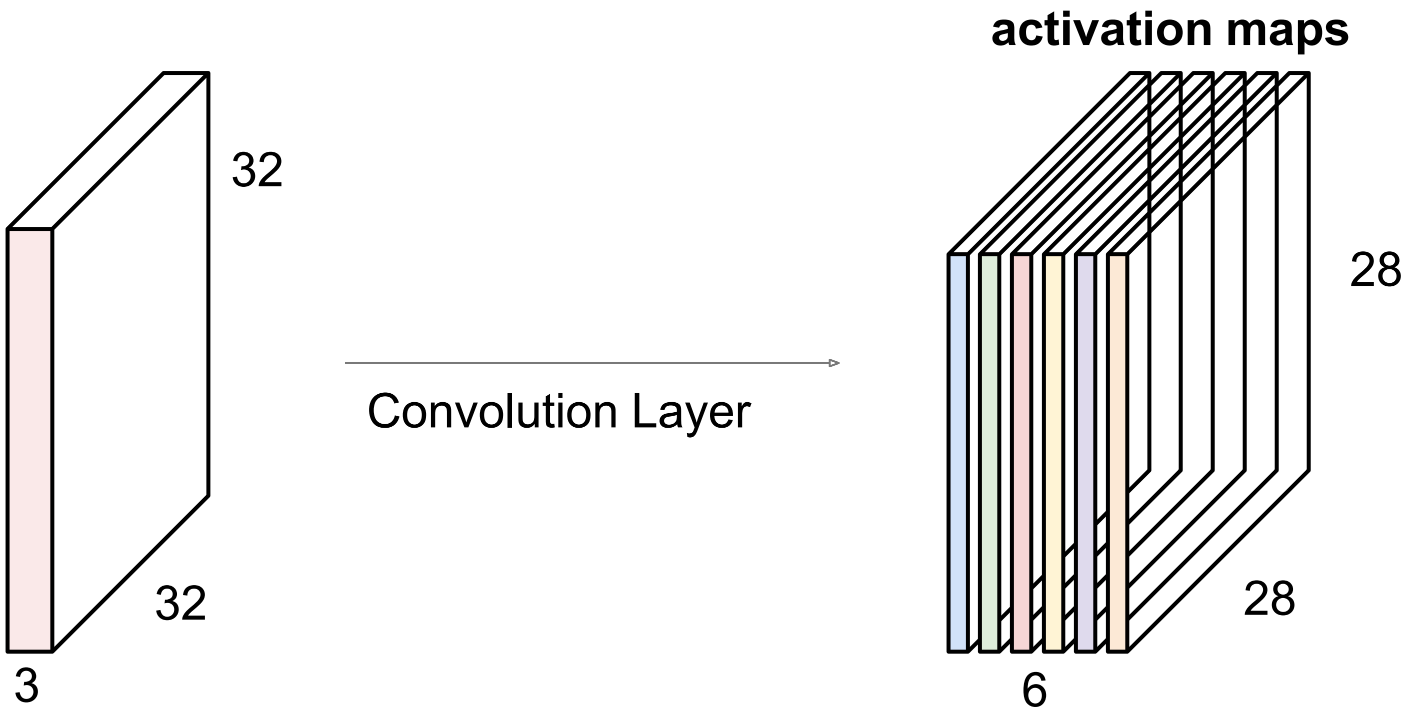
Convolutions: More detail

Convolution Layer

consider a second, green filter

Convolutions: More detail

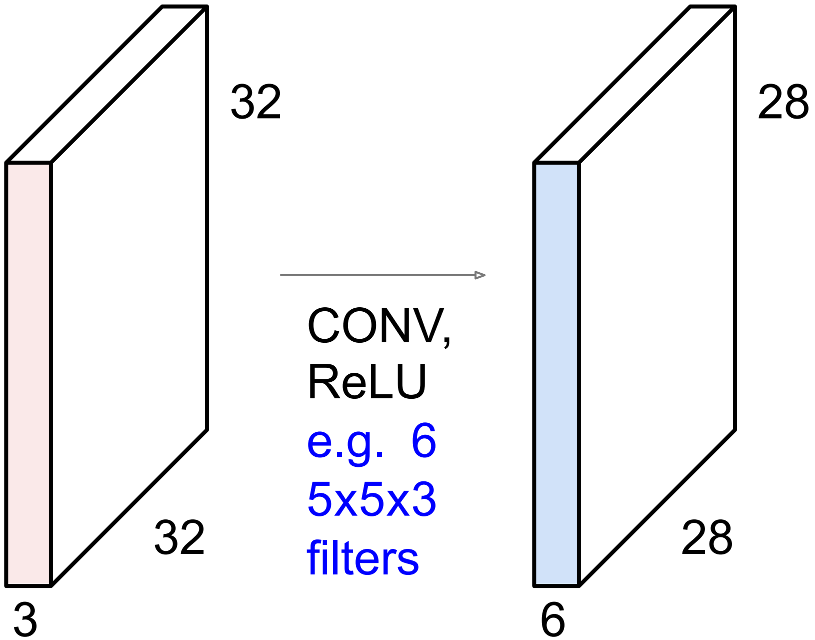
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



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



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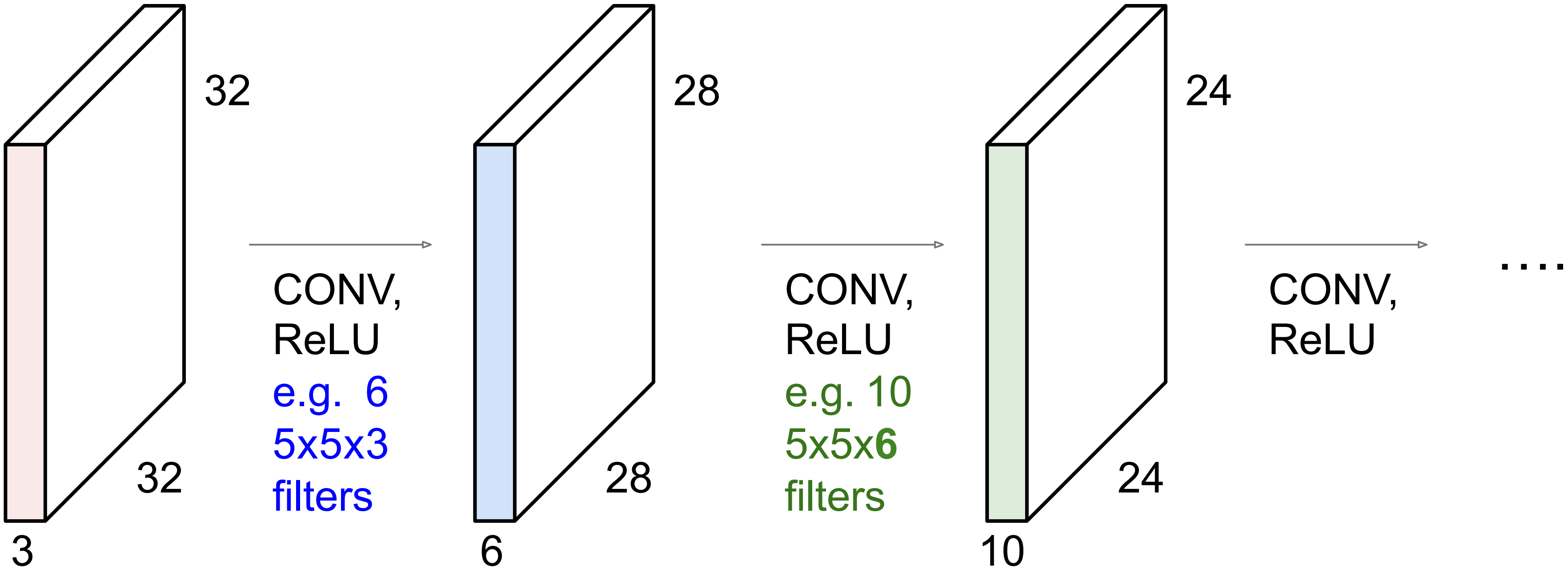
Convolutions: More detail

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



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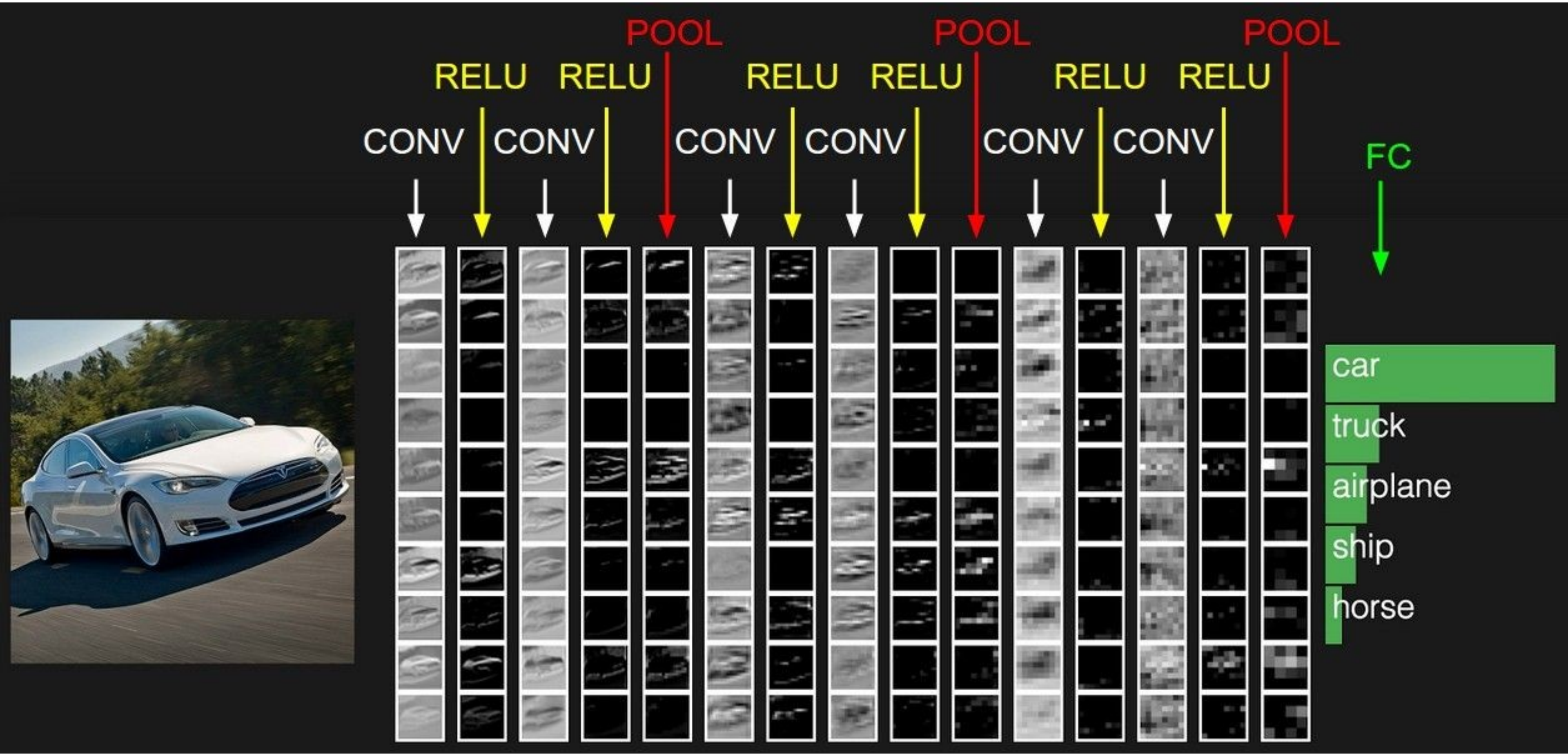
Convolutions: More detail

preview:



A Common Architecture: AlexNet

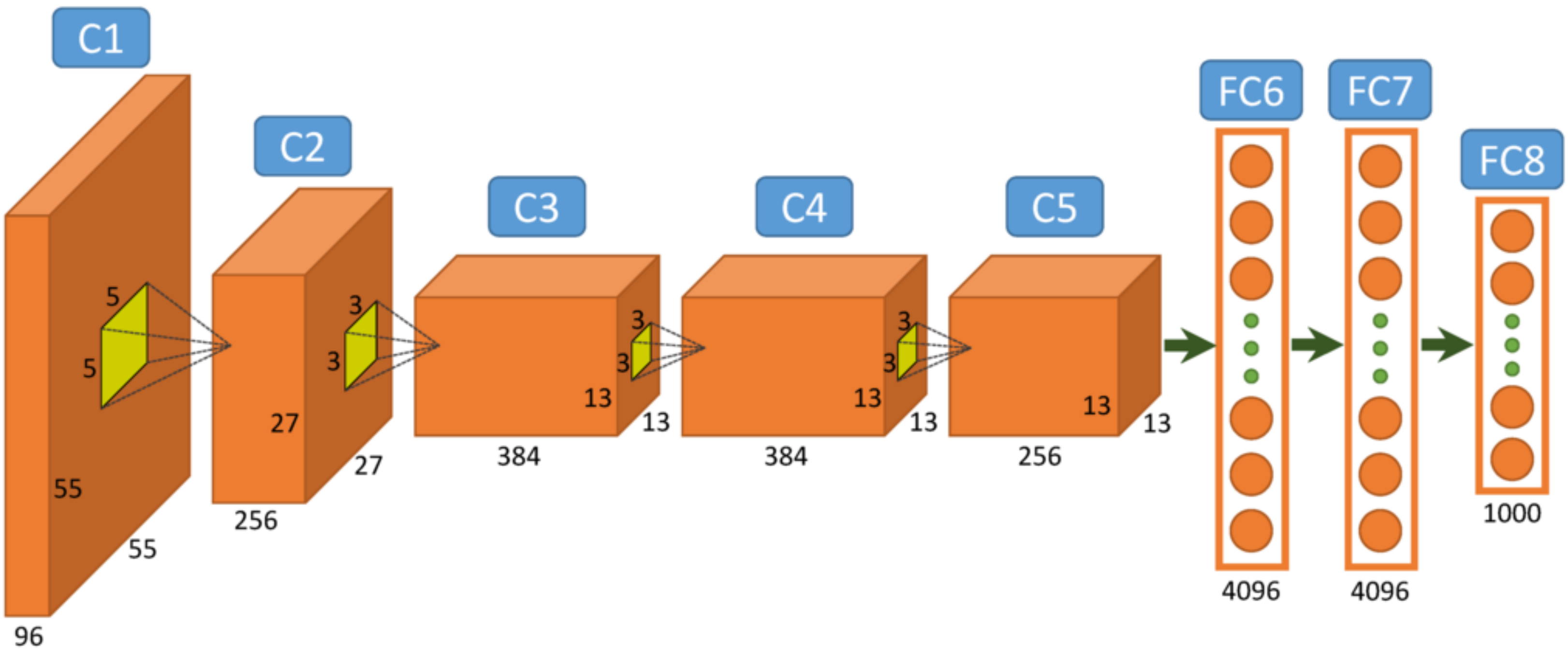


Figure from http://www.mdpi.com/2072-4292/7/11/14680/htm

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

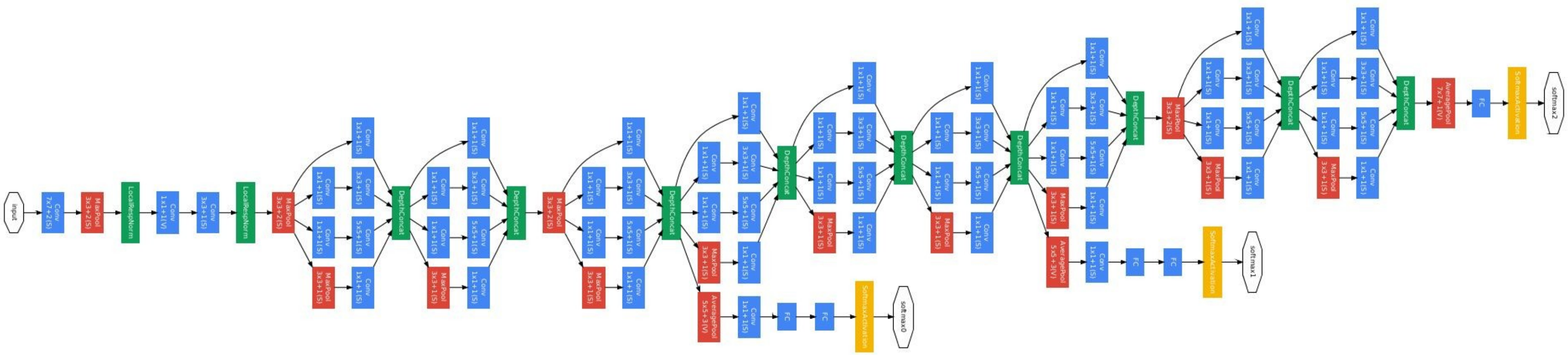
ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	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 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					

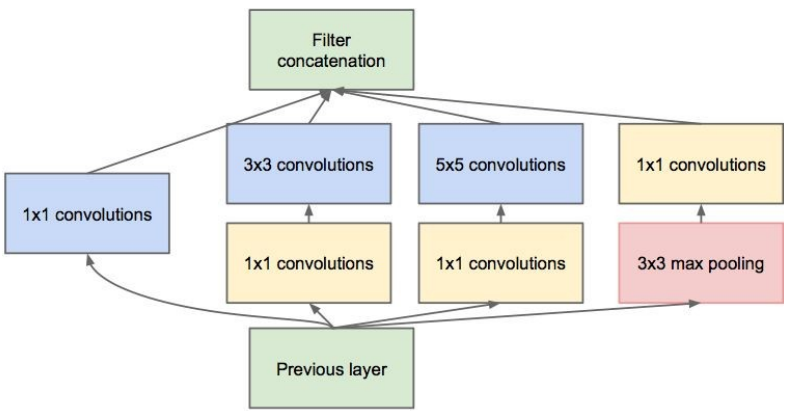
Table 2: **Number of parameters** (in millions).

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

Case Study: GoogLeNet

[Szegedy et al., 2014]





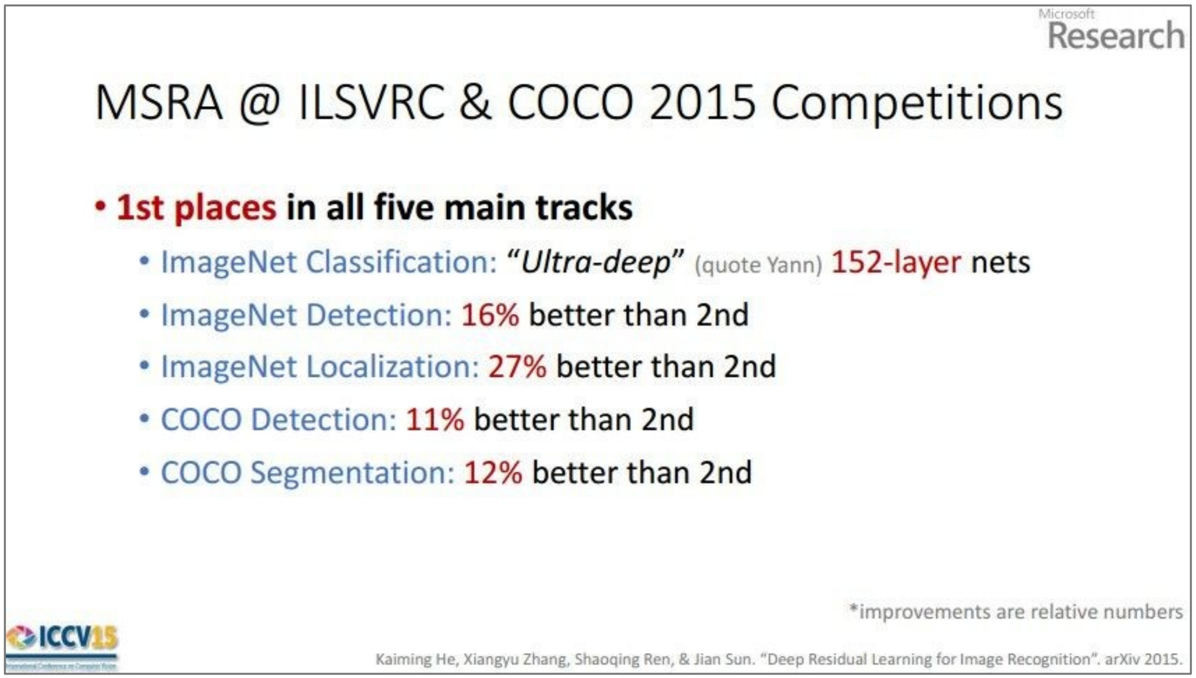
Inception module

ILSVRC 2014 winner (6.7% top 5 error)

Case Study: ResNet

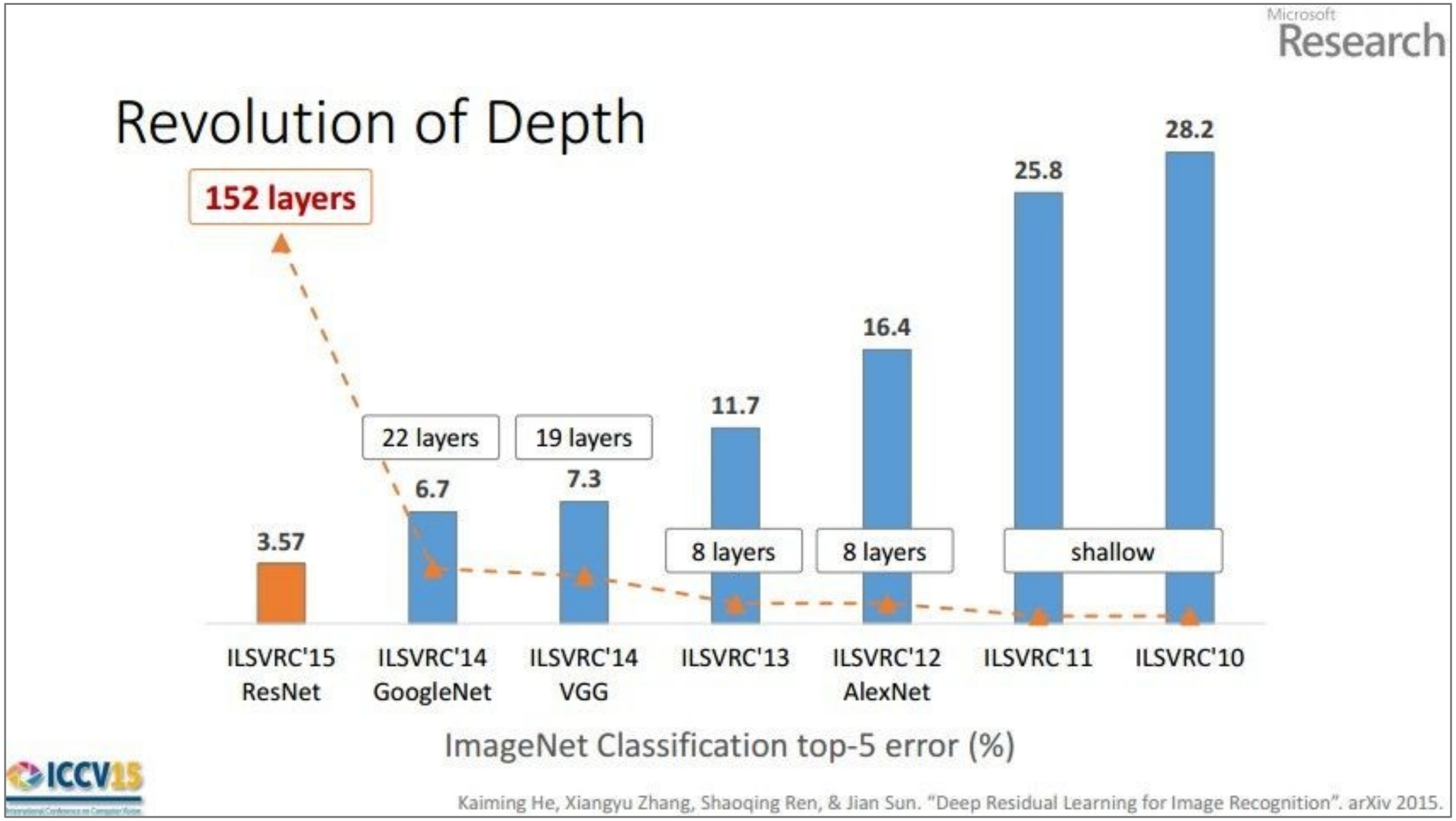
[He et al., 2015]

ILSVRC 2015 winner (3.6% top 5 error)



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

Case Study: ResNet

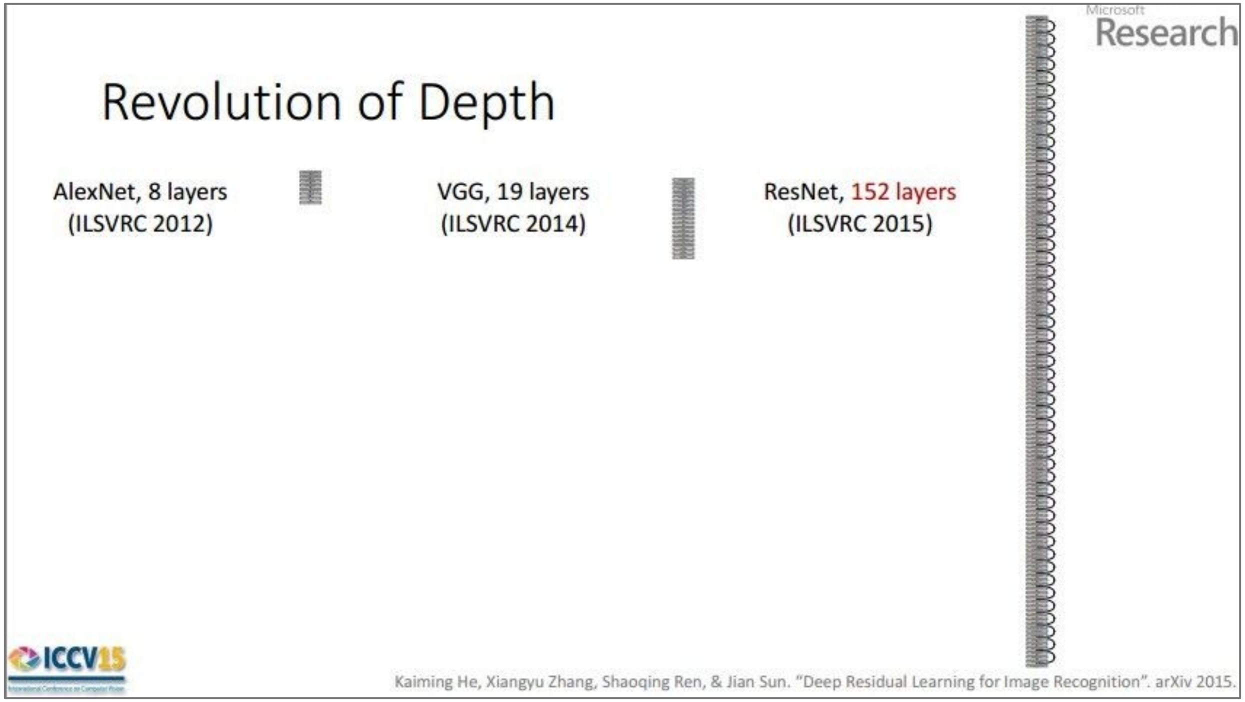


(slide from Kaiming He's presentation)

Case Study: ResNet

[He et al., 2015]

ILSVRC 2015 winner (3.6% top 5 error)



(slide from Kaiming He's presentation)

2-3 weeks of training on 8 GPU machine

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

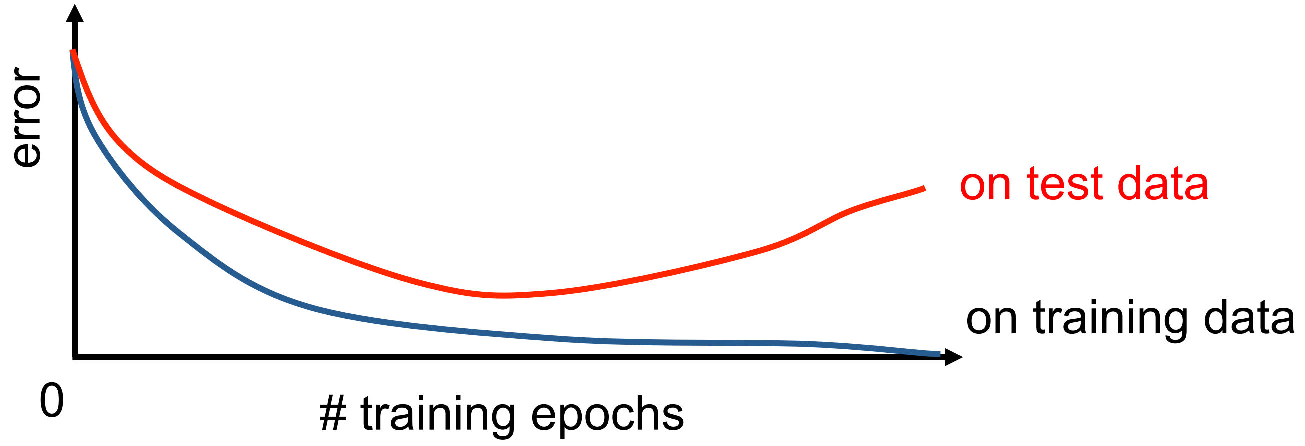
Practical matters

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.
- 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 significantly improved performance (deep networks trained with dropout and lots of data).

Over-training prevention

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



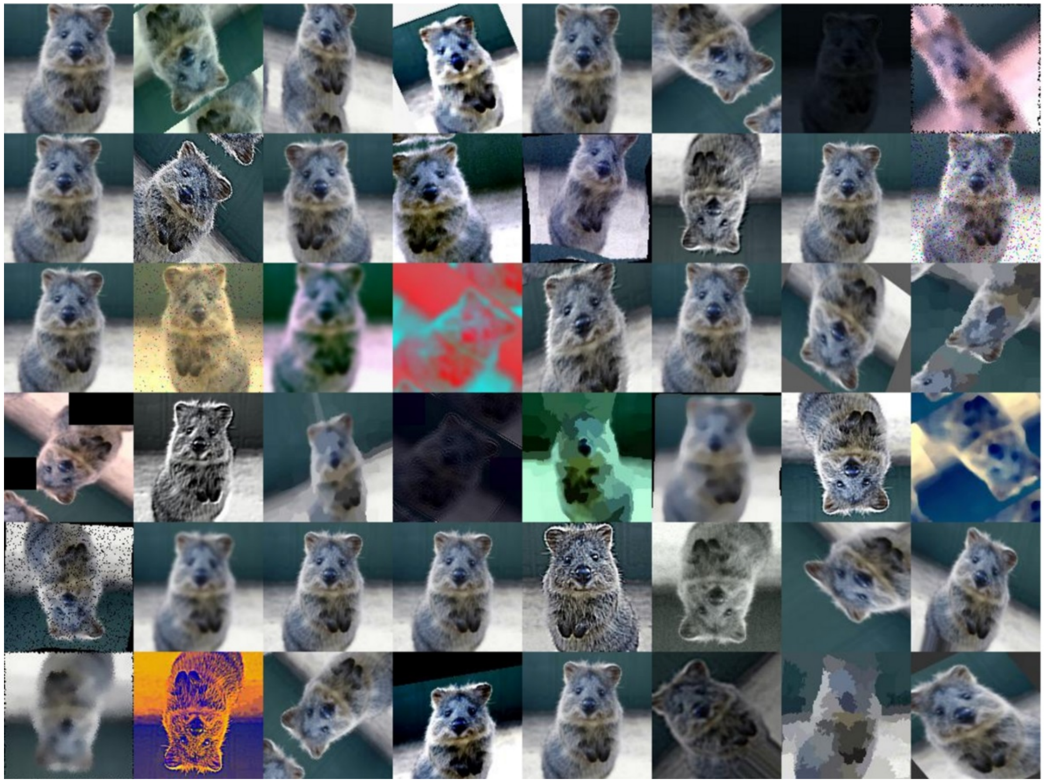
- Keep a hold-out validation set and test accuracy on it after every epoch. Stop training when additional epochs actually increase validation error.

Training: Best practices

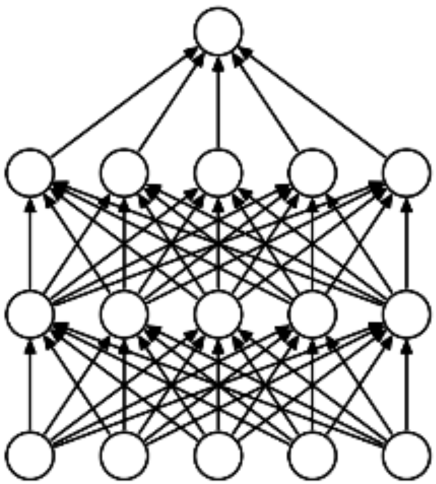
- Use mini-batch
- Use regularization
- Use cross-validation for your parameters
- Use RELU or leaky RELU, don’t use sigmoid
- Center (subtract mean from) your data
- Learning rate: too high? too low?
- Use BatchNorm

Data Augmentation (Jittering)

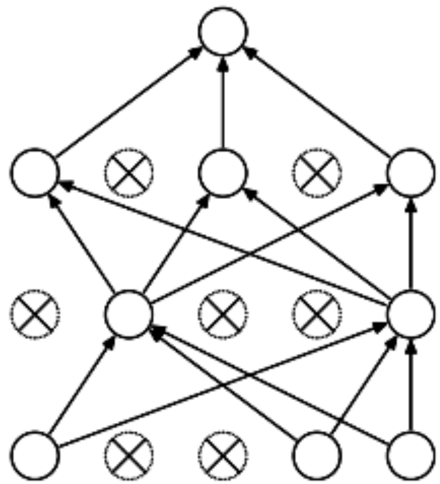
- Create *virtual* training samples
  - Horizontal flip
  - Random crop
  - Color casting
  - Geometric distortion



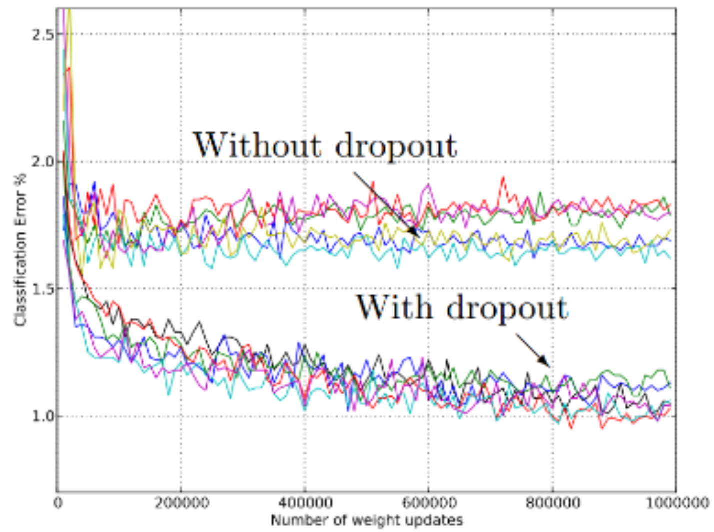
Regularization: Dropout



(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

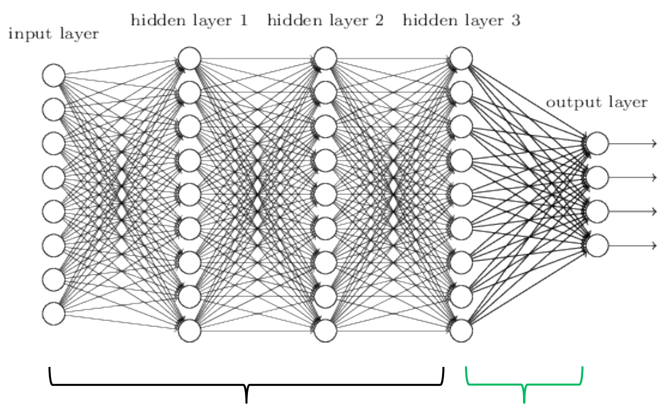
Transfer Learning

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

BUSTED

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:



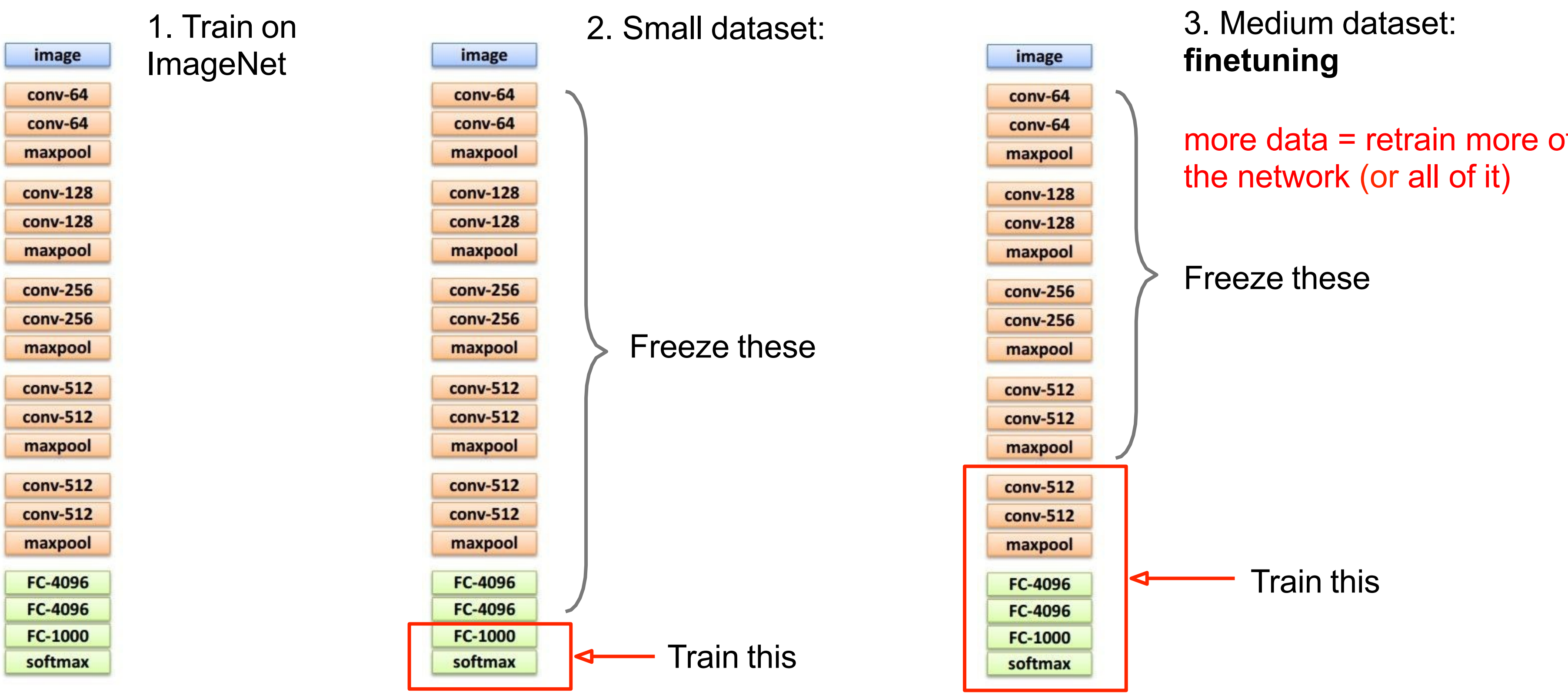
Set these to the already learned weights from another network

Learn these on your own task

Transfer Learning with CNNs

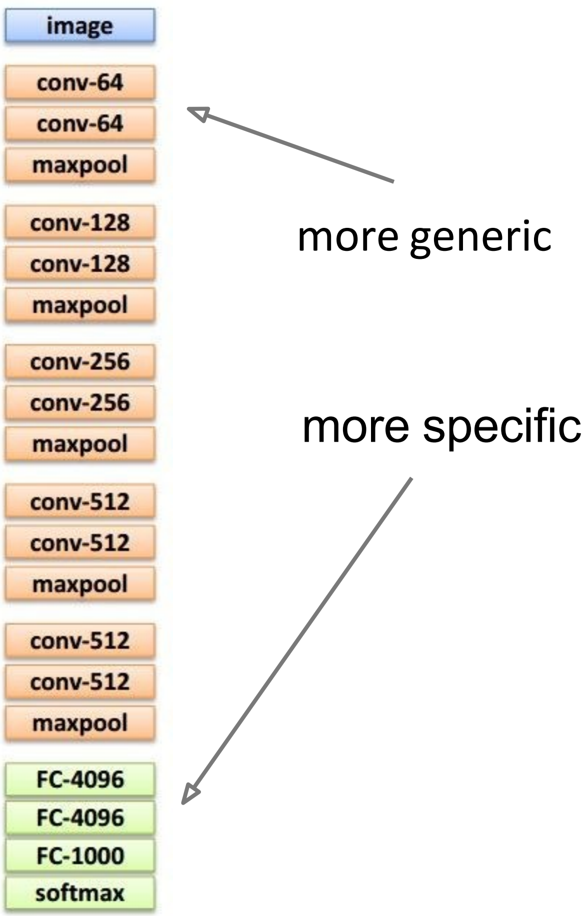
Source: classification on ImageNet

Target: some other task/data



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

Andrej Karpathy

Summary

- We use deep neural networks because of their strong performance in practice
- Convolutional neural networks (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 through all layers and change their weights
- Practices for preventing overfitting
  - Dropout; BatchNorm; data augmentation; transfer learning

Questions?

See you Friday!