Lecture 19
Intro to Deep Learning

COS 429: Computer Vision

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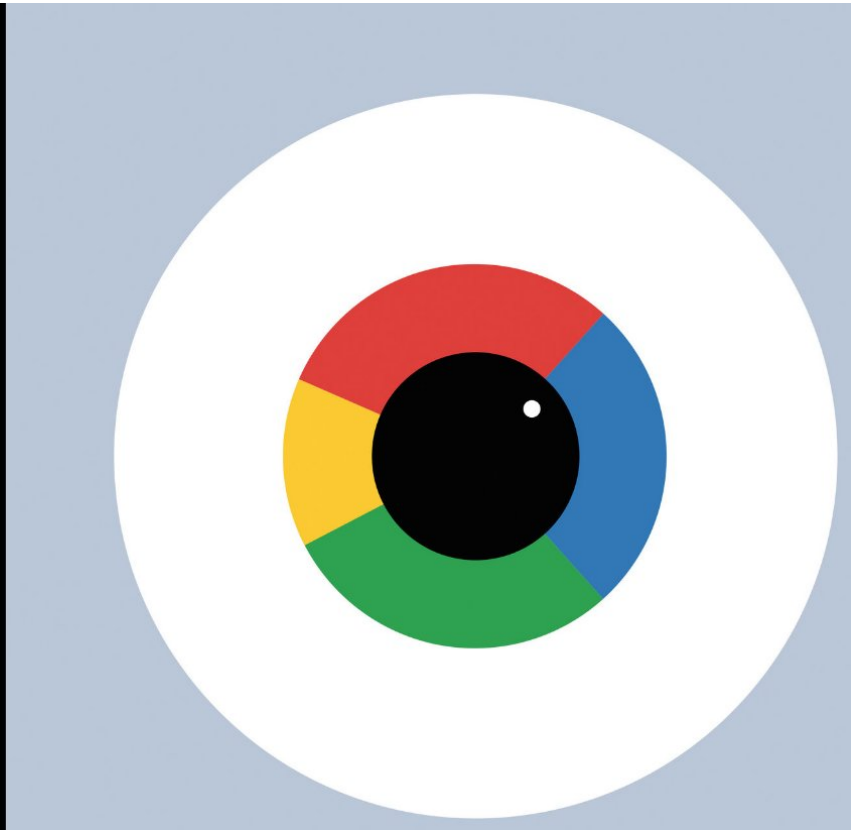
The Great A.I. Awakening

How Google used artificial intelligence to transform Google Translate, one of its more popular services — and how machine learning is poised to reinvent computing itself.

BY GIDEON LEWIS-KRAUS DEC. 14, 2016



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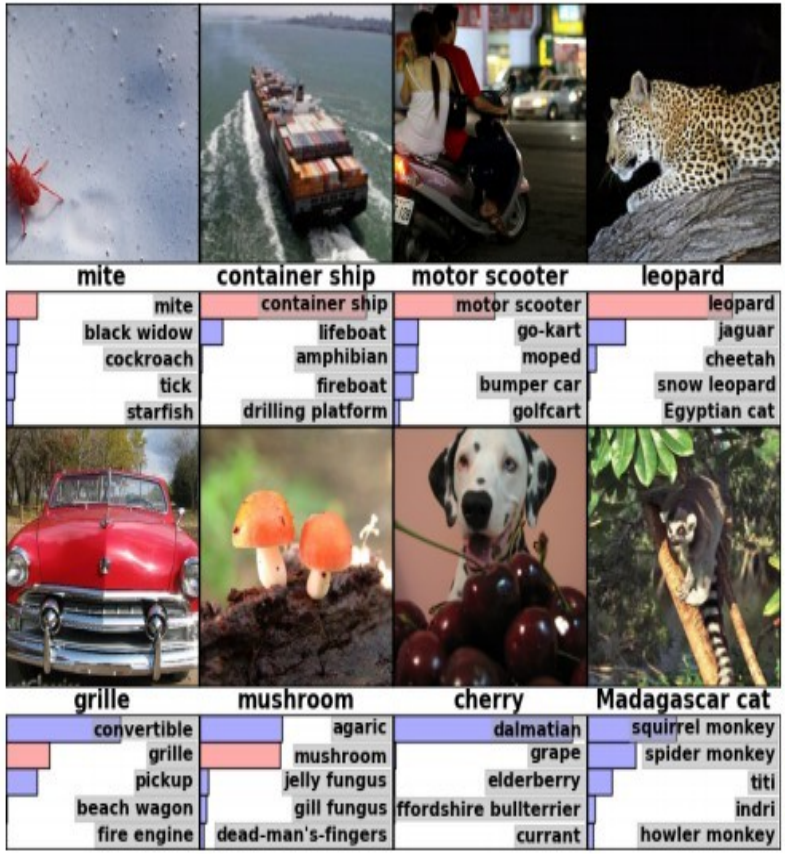
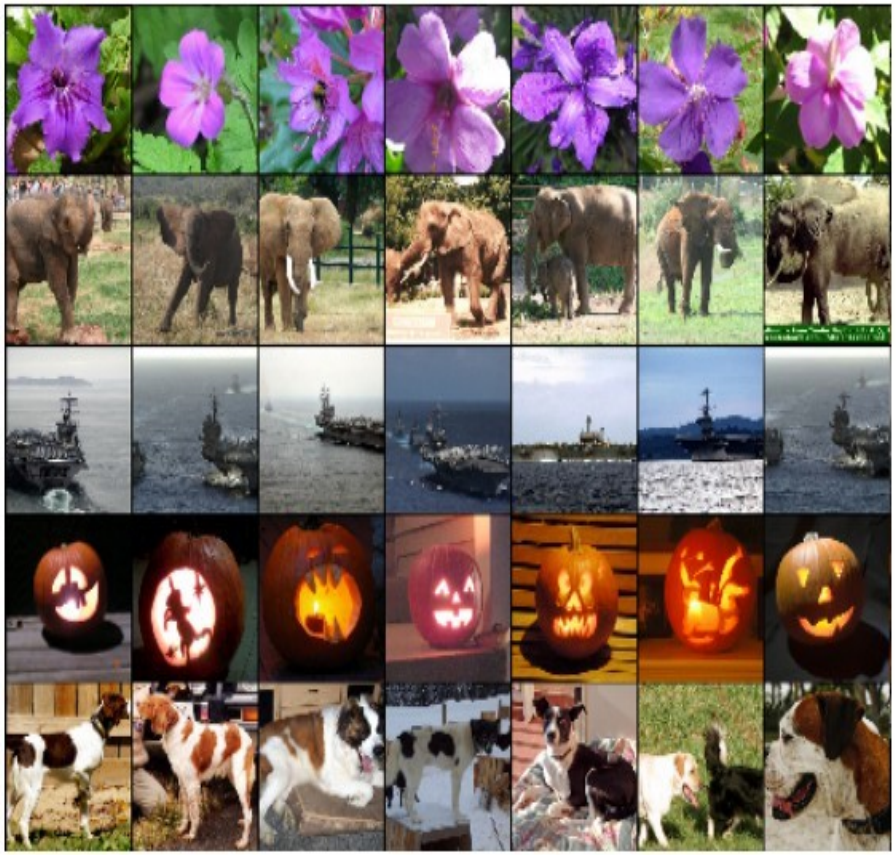
DL Applications – Image Classification and Retrival

Classification

Retrieval



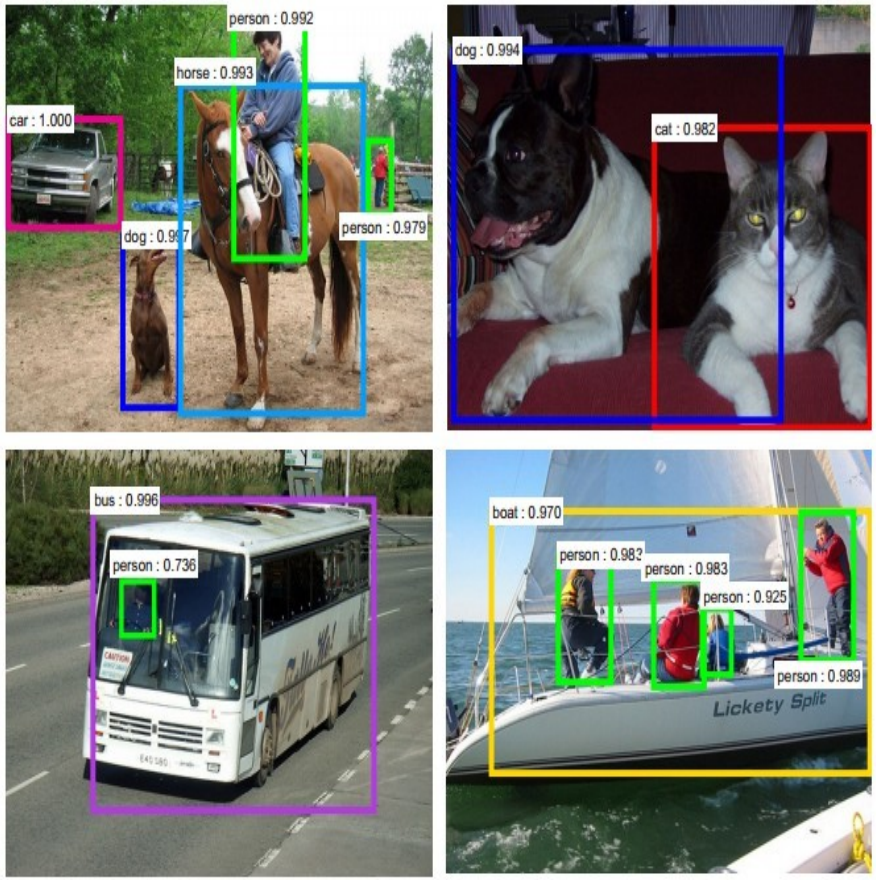


[Krizhevsky 2012]

Slide Credit:

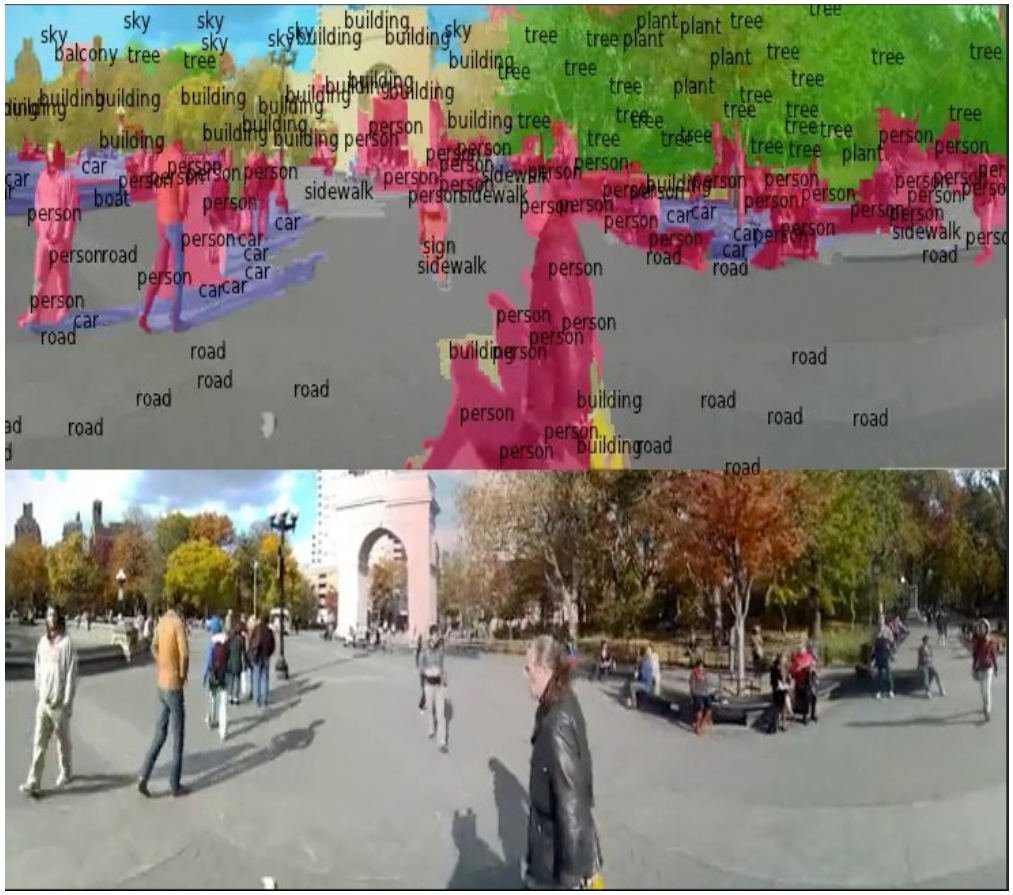
DL Applications – Object detection and Segmentation

Detection



[Faster R-CNN: Ren, He, Girshick, Sun 2015]

Segmentation

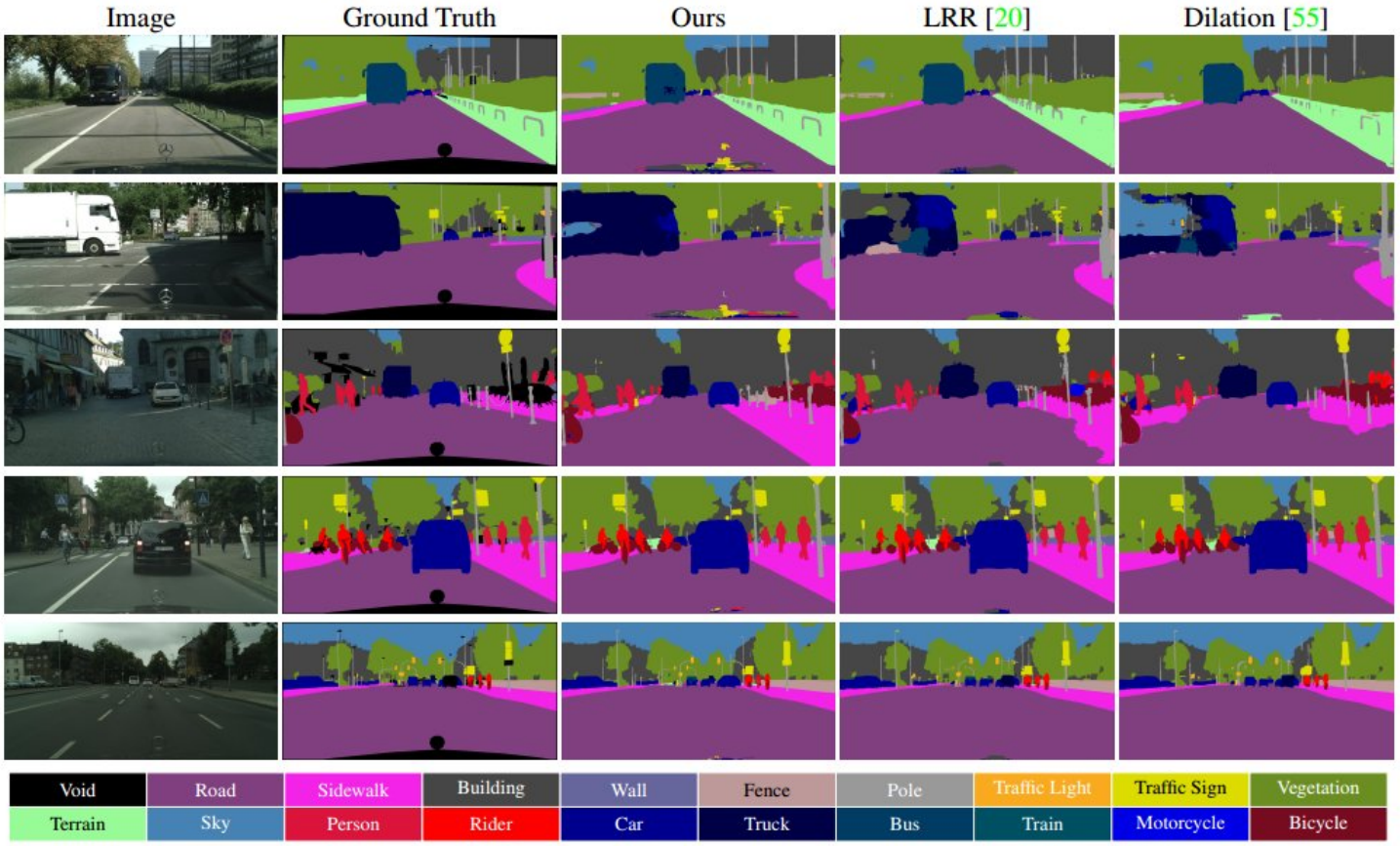


[Farabet et al., 2012]

Slide Credit:

Applications – Semantic Image Segmentation

Full-Resolution Residual Networks (FRRNs) for Semantic Image Segmentation in Street Scenes



https://www.youtube.com/watch?v=PNzQ4PNZSzc

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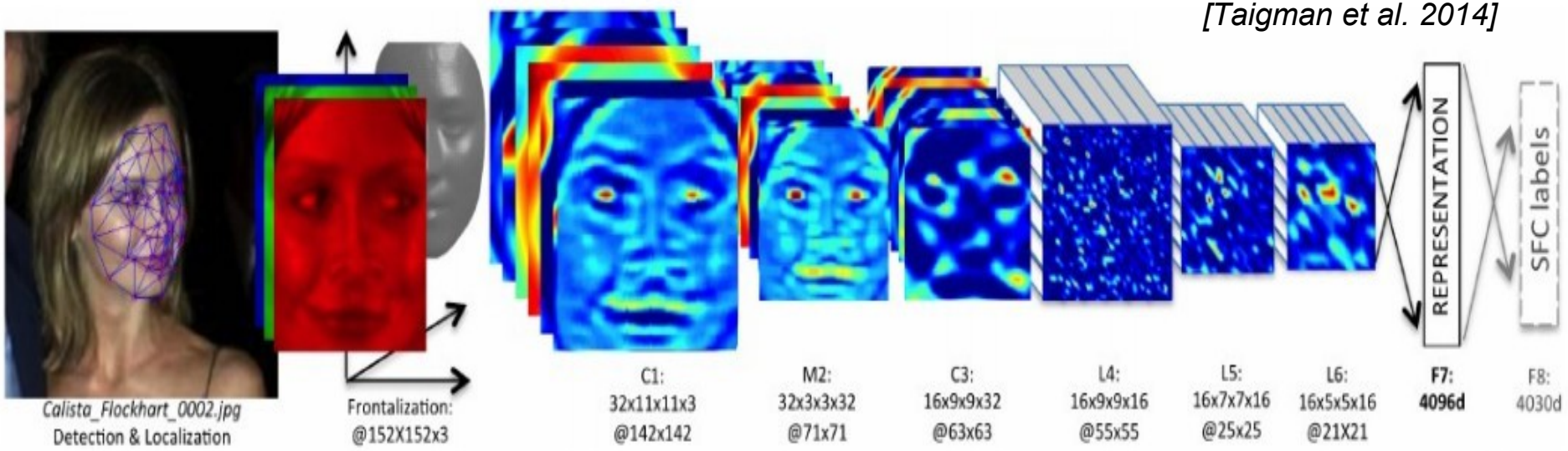
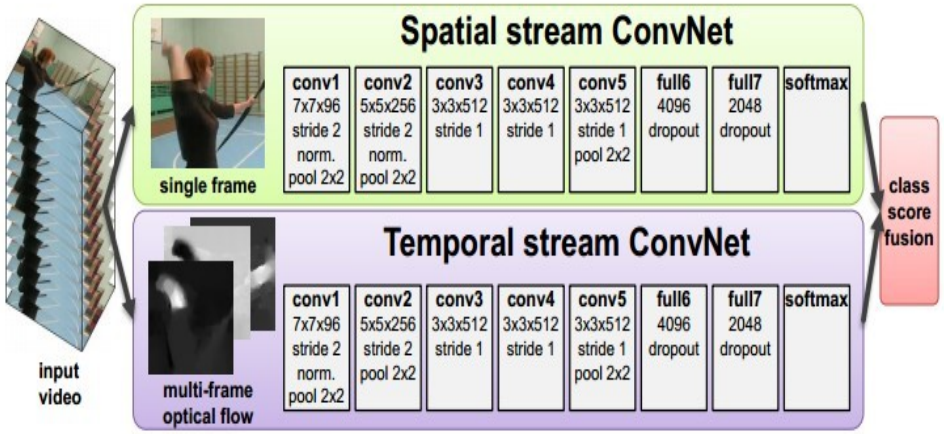
Applications – Face and Video Recognition

[Taigman et al. 2014]





[Simonyan et al. 2014]

Slide Credit:

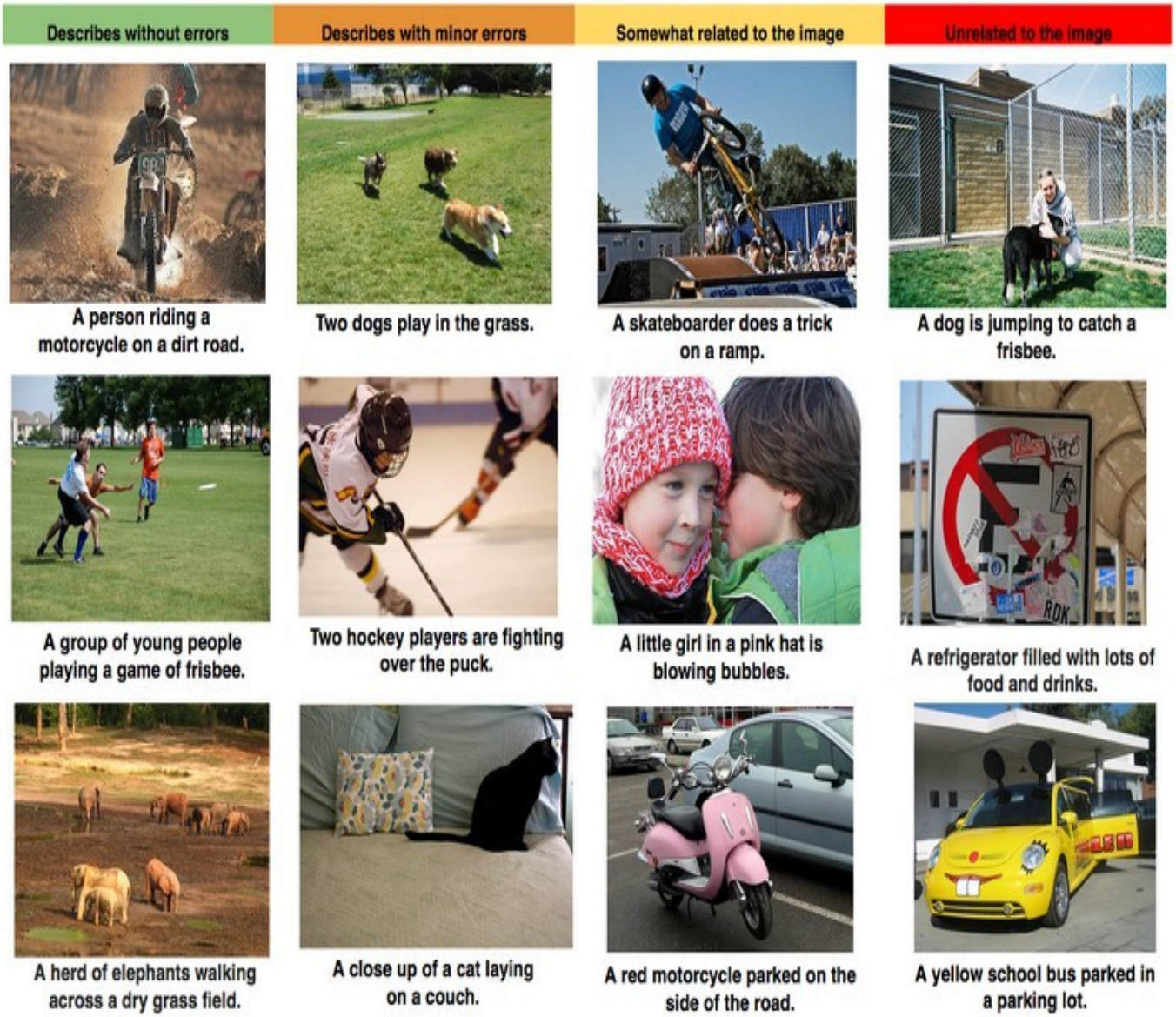
Applications – Human Pose Estimation

Figure 10: Qualitative results of our method on the MPII, LSP and FLIC datasets respectively. We see that the method is able to handle non-standard poses and resolve ambiguities between symmetric parts for a variety of different relative camera views.

[Convolutional Pose Machines. Shih-En Wei, Varun Ramakrishna, Takeo Kanade, Yaser Sheikh]

Slide Credit:

Applications - Image Captioning



[Vinyals et al., 2015]

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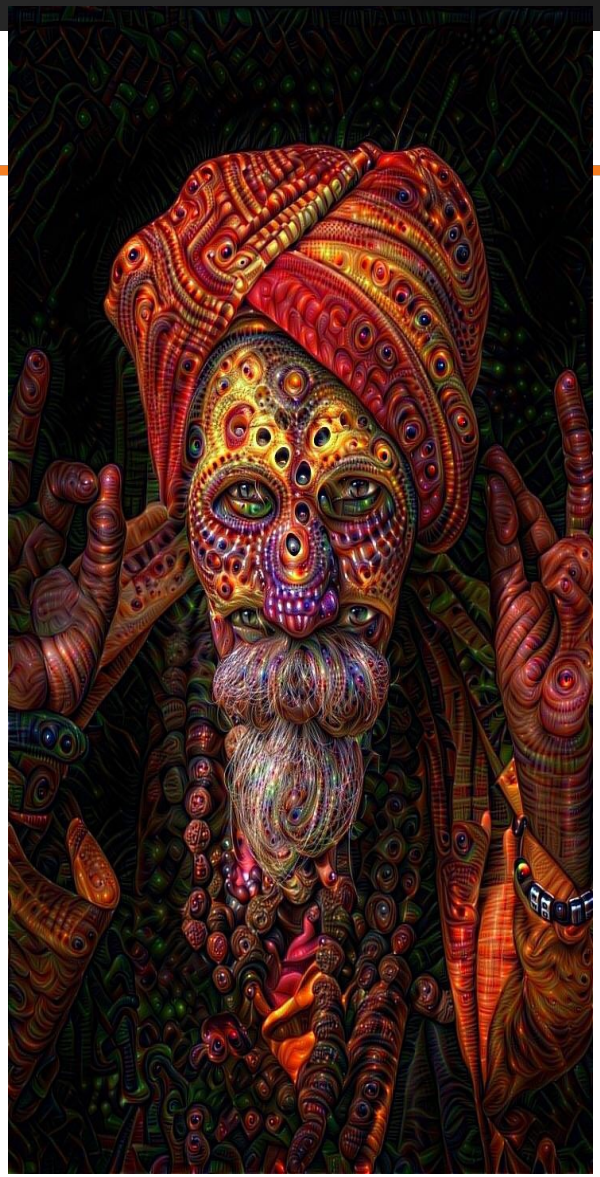

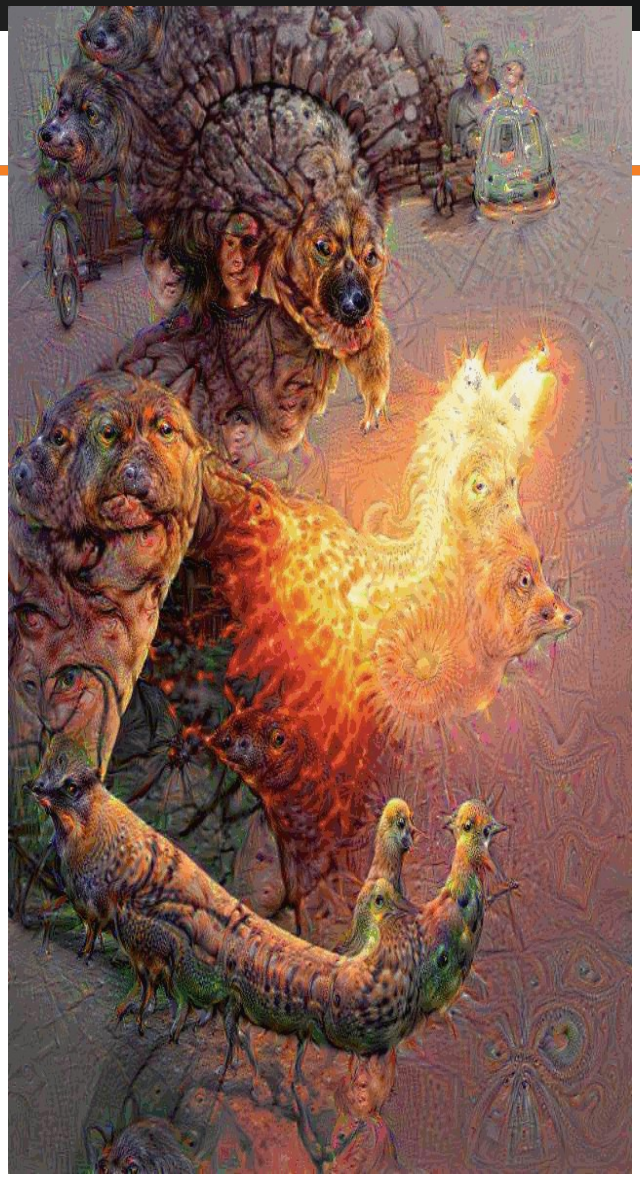

reddit.com/r/deepdream

Slide Credit:

DeepArt

Slide Credit:

Applications

Google's DeepMind AI has been secretly schooling online Go players

AlphaGo spent the past few days playing anonymous matches on public servers.

Andrew Dalton, @dolftown
01.04.17 in Robots

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Next The Official Microsoft Blog The Fire Hose Microsoft On the Issues Transform

Historic Achievement: Microsoft researchers reach human parity in conversational speech recognition

Slide Credit:

Applications

APRIL 3, 2017

Stanford researchers create deep learning algorithm that could boost drug development

Combining computer science and chemistry, researchers show how an advanced form of machine learning that works off small amounts of data can be used to solve problems in drug discovery.

amazingly subtle information, enabling them
nedical images as well as a doctor. But in
training that involves thousands to trillions
't work all that well in situations where there

Stanford MEDICINE | News Center

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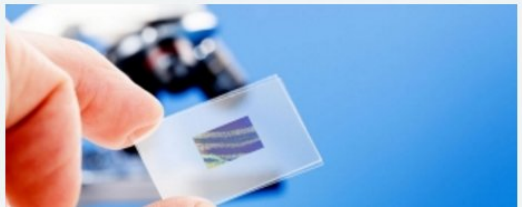
Computers trounce pathologists in predicting lung cancer type, severity

Automating the analysis of slides of lung cancer tissue samples increases the accuracy of tumor classification and patient prognoses, according to a new study.

AUG 16
2016

Computers can be trained to be more accurate than pathologists in assessing slides of lung cancer tissues, according to a new study by researchers at the Stanford University School of Medicine.



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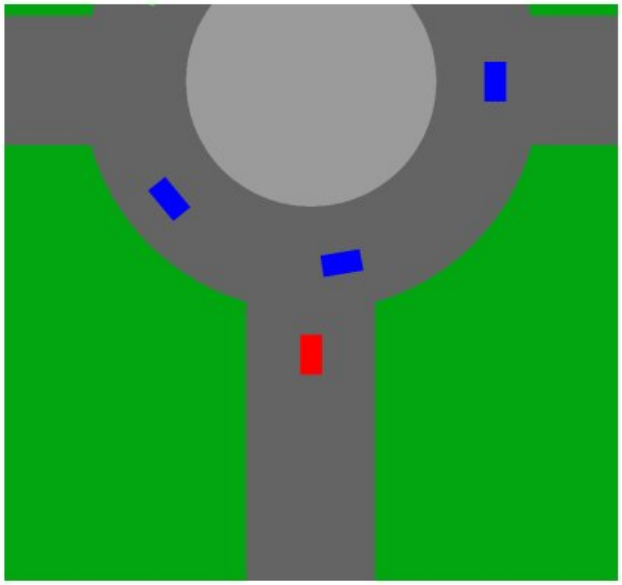
Applications – Reinforcement learning

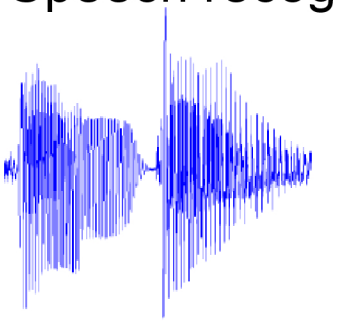
[Mnih 2013]



[Deep Reinforcement Learning for Driving Policy. Shwartz 2016]

Classical Recognition

Speech recognition (early 90's – 2011)



MFCC → Mix of Gaussians → Classifier

Low level features — fixed — MFCC

Mix of Gaussians — unsupervised — Mid level features

Classifier — supervised

Object recognition (2006 – 2012)

SIFT HoG → K-means Sparse Coding → Pooling → Classifier

Low level features — fixed — SIFT HoG

K-means Sparse Coding — unsupervised — Mid level features

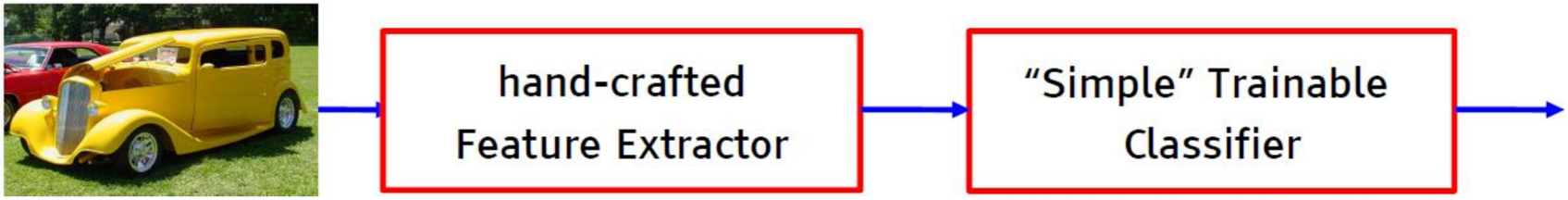
Classifier — supervised

Slide Credit: LeCun

End-to-End?

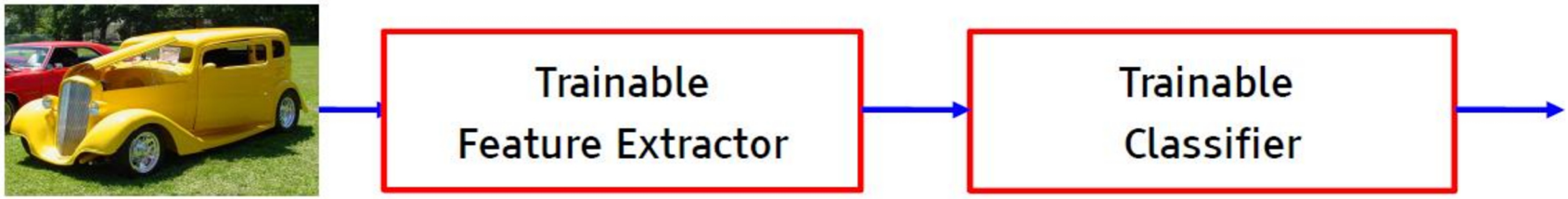
Deep learning can be summarized as learning both the representation and the classifier out of it

- Fixed engineered features (or kernels) + trainable classifier



VS.

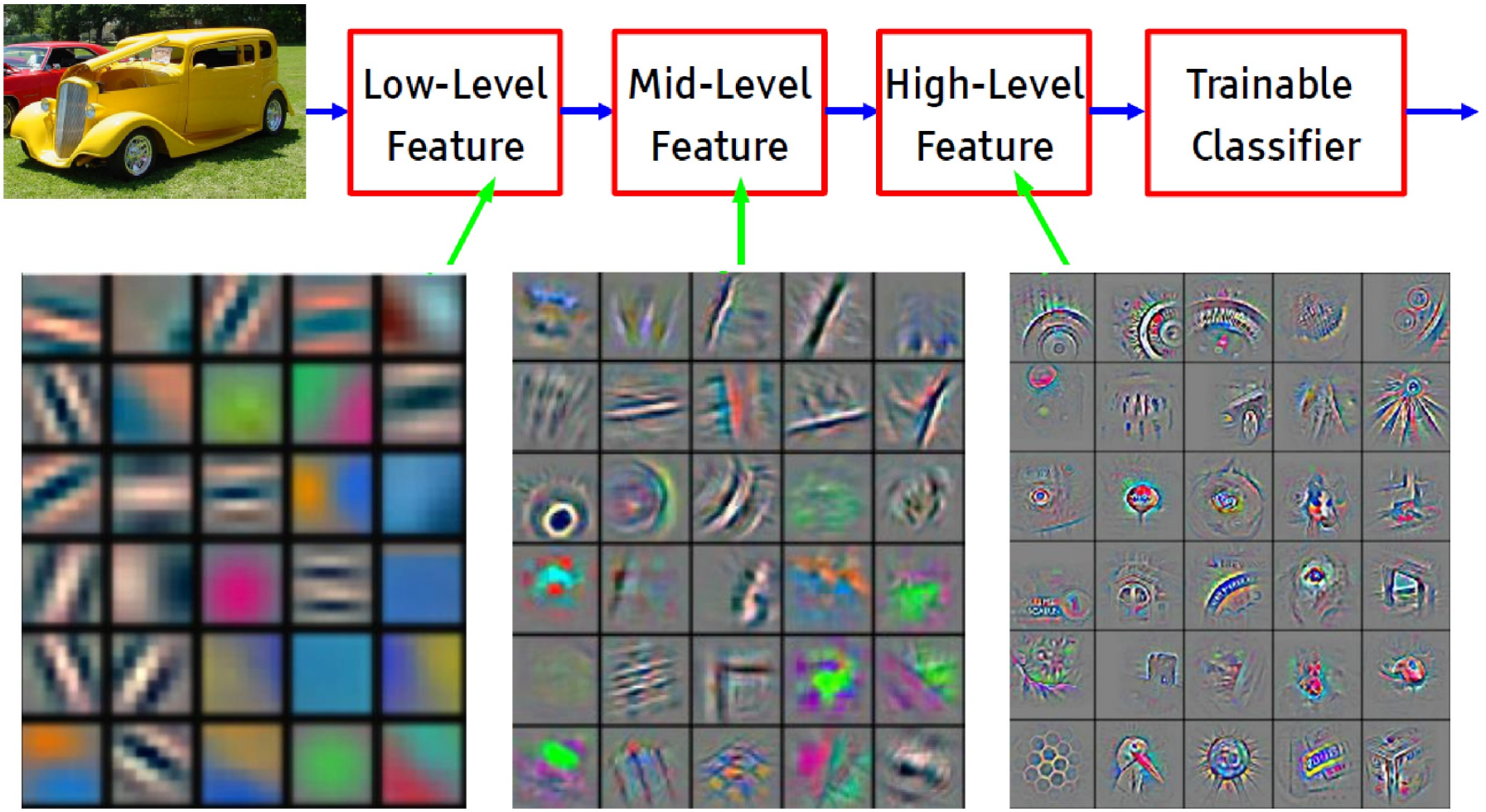
- End-to-end learning / feature learning / deep learning



Slide Credit: LeCun

End-to-End?

In deep learning we have multiple stages of non linear feature transformation



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

Slide Credit: LeCun

Learning Representations

Learning the representation is a challenging problem for ML, CV, AI, Neuroscience, Cognitive Science, ...

Cognitive perspective

- How can a perceptual system build itself by looking at the external world?
- How much prior structure is necessary?

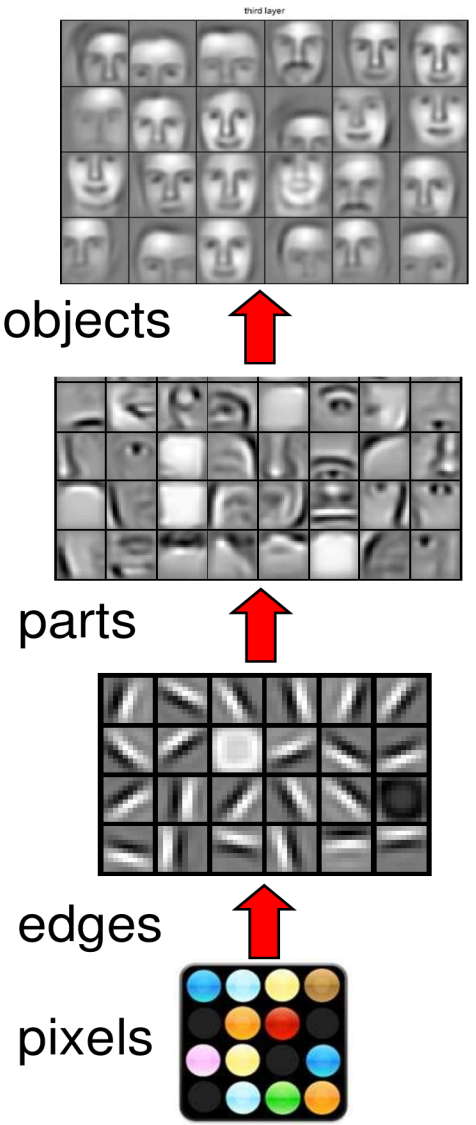
Neuroscience

- Does the cortex «run» a single, general learning algorithm? Or multiple simpler ones?

ML/AI Perspective

- What is the fundamental principle?
- What is the learning algorithm?
- What is the architecture?

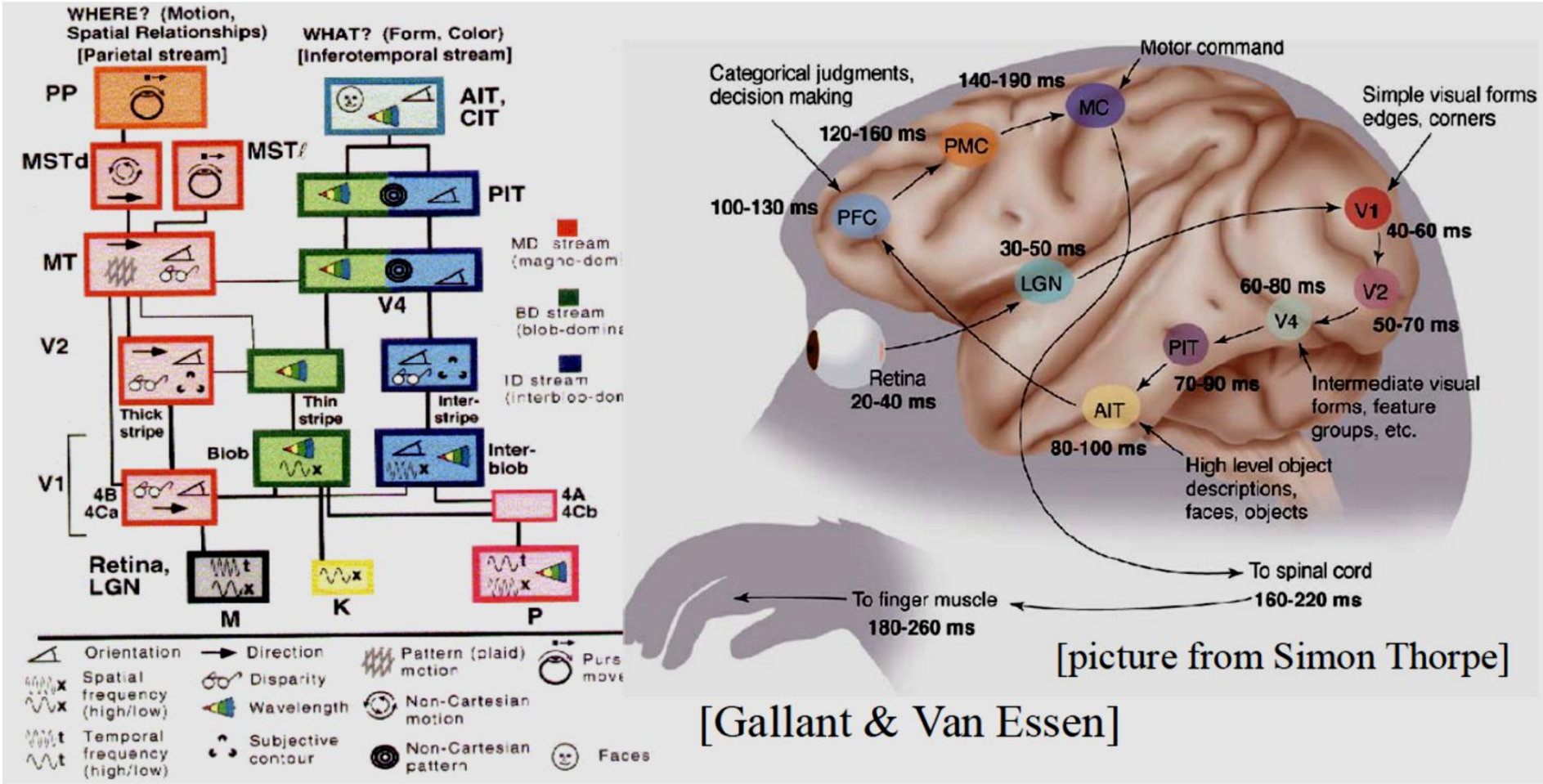
Deep learning addresses the problem of learning hierarchical representations with a single algorithm



Slide Credit: LeCun

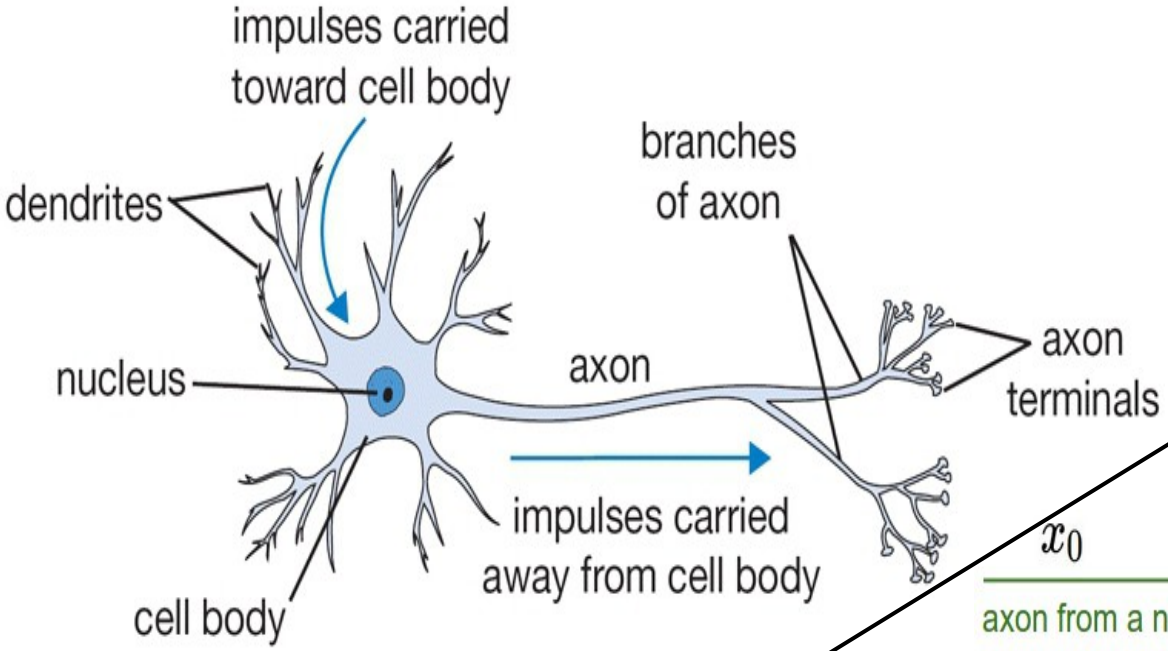
Inspiration

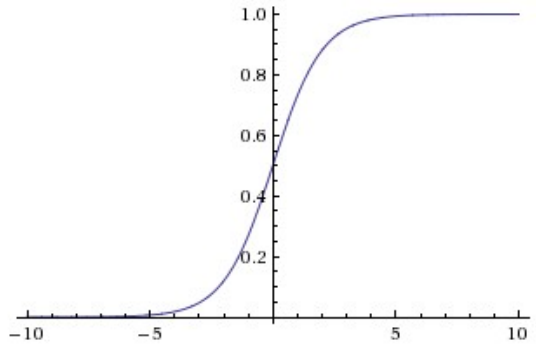
The ventral (recognition) pathway in the visual cortex has multiple stages



Slide Credit: LeCun

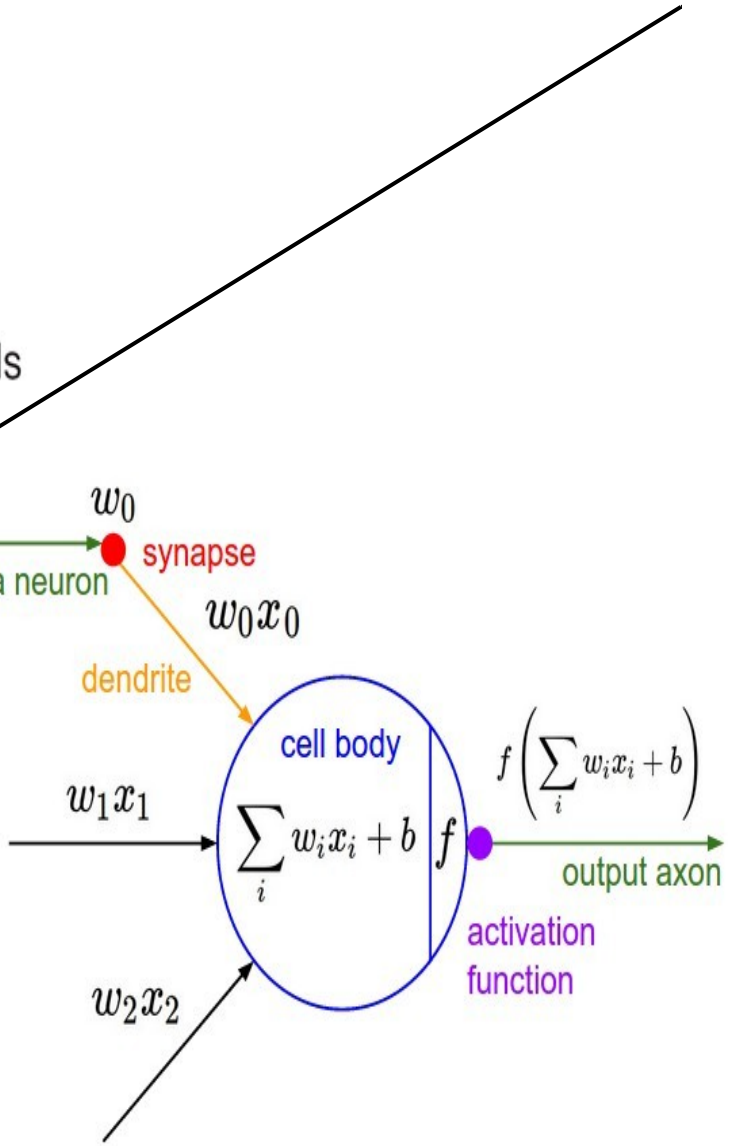
Inspiration





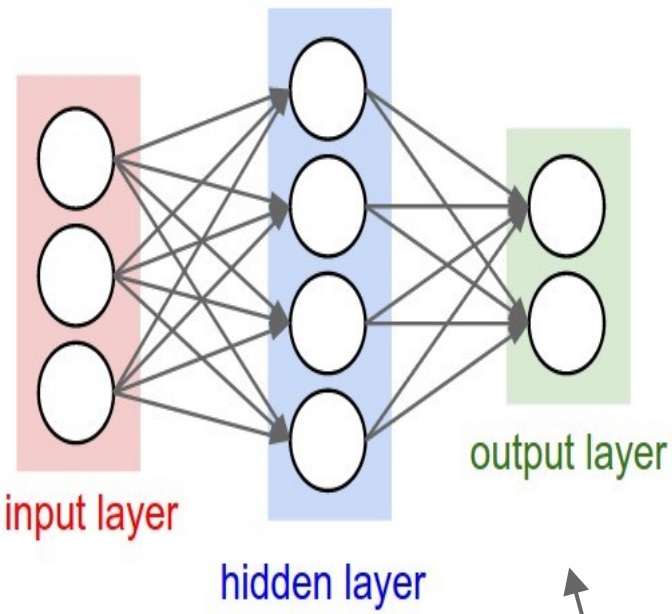
sigmoid activation function

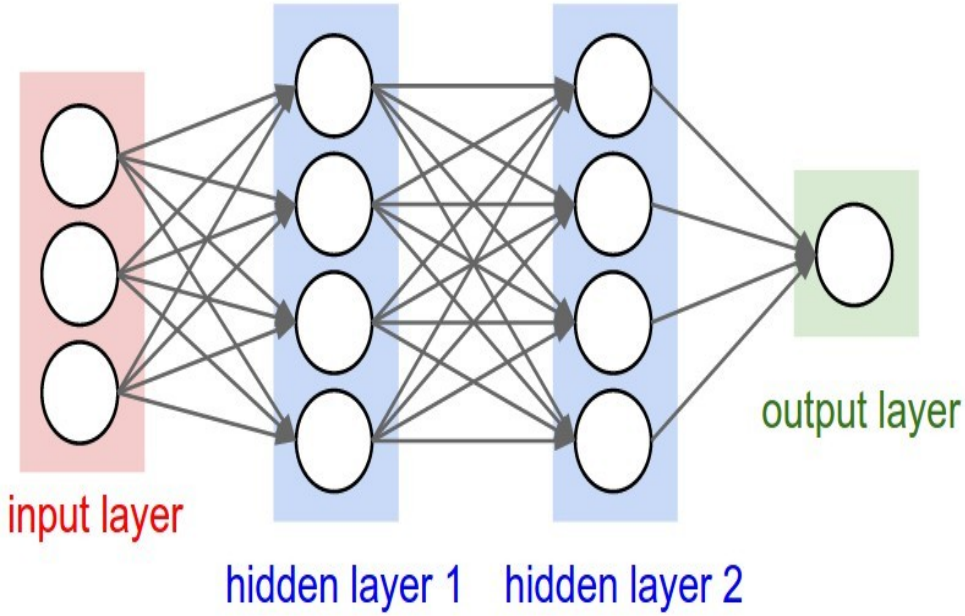
$$\frac{1}{1+e^{-x}}$$



Slide Credit: Li, Karpathy, Johnson

Neural Networks: Architectures





"2-layer Neural Net", or
"1-hidden-layer Neural Net"

"3-layer Neural Net", or
"2-hidden-layer Neural Net"

"Fully-connected" layers

Slide Credit: Li, Karpathy, Johnson

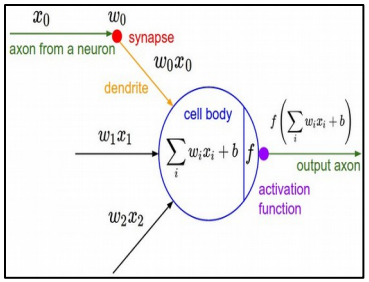
A bit of history

The **Mark I Perceptron** machine was the first implementation of the perceptron algorithm.

The machine was connected to a camera that used 20×20 cadmium sulfide photocells to produce a 400-pixel image.

recognized
letters of the alphabet

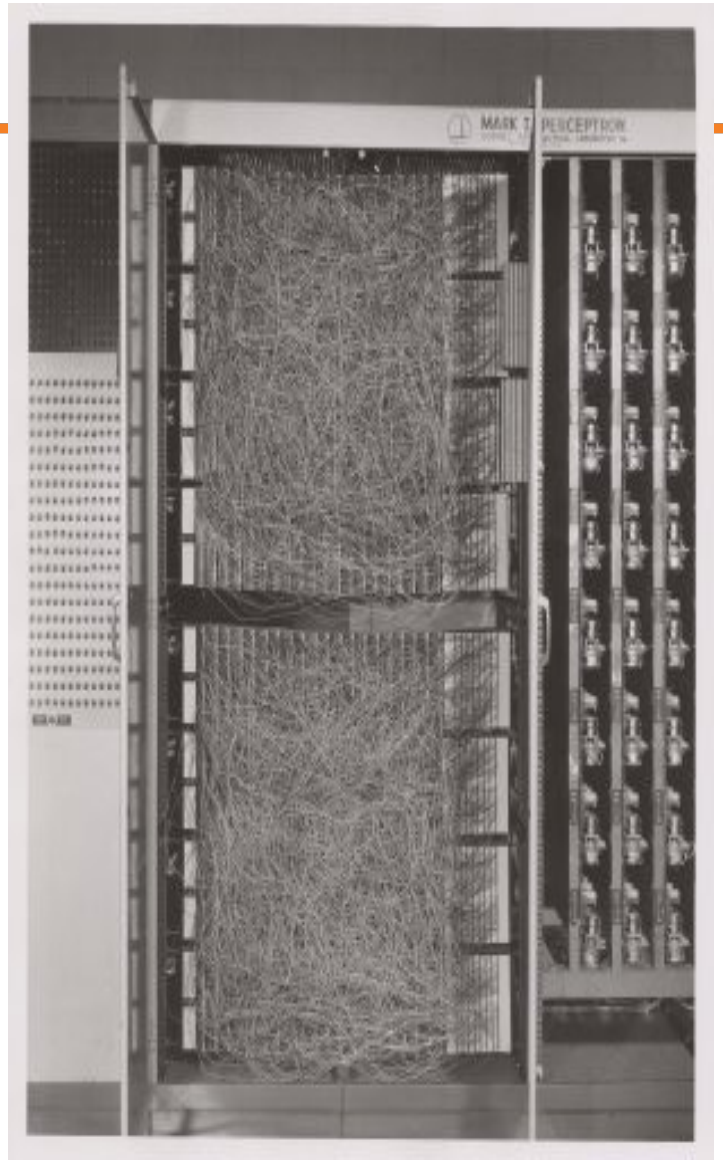
$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{otherwise} \end{cases}$$



update rule:

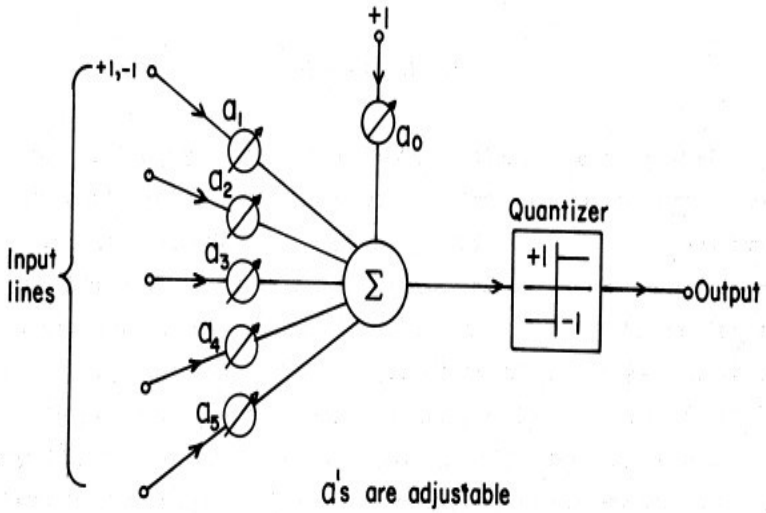
$$w_i(t+1) = w_i(t) + \alpha(d_j - y_j(t))x_{j,i},$$

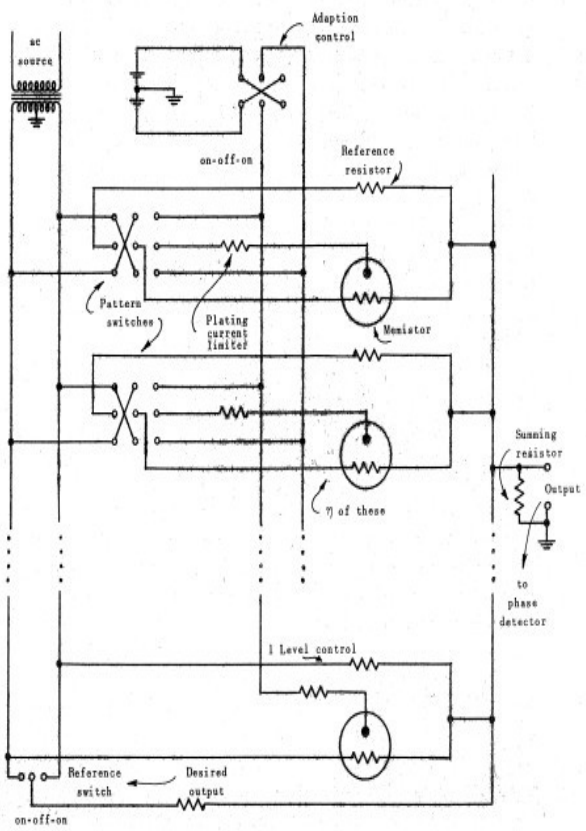
Frank Rosenblatt, ~1957: Perceptron



Slide Credit: Li, Karpathy, Johnson

A bit of history

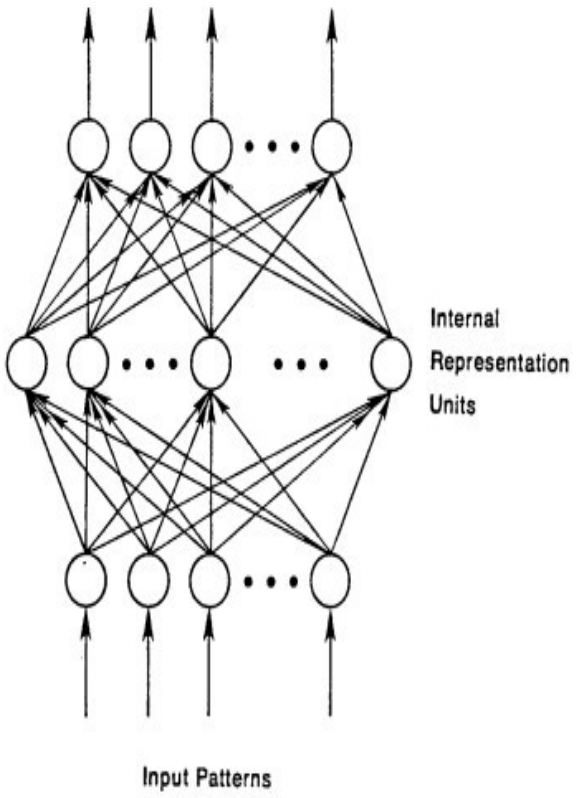




Widrow and Hoff, ~1960: Adaline/Madaline

Slide Credit: Li, Karpathy, Johnson

A bit of history



To be more specific, then, let

$$E_p = \frac{1}{2}\sum_j (t_{pj} - o_{pj})^2 \quad (2)$$

be our measure of the error on input/output pattern p and let $E = \sum E_p$ be our overall measure of the error. We wish to show that the delta rule implements a gradient descent in E when the units are linear. We will proceed by simply showing that

$$-\frac{\partial E_p}{\partial w_{ji}} = \delta_{pj} i_{pi},$$

which is proportional to $\Delta_p w_{ji}$ as prescribed by the delta rule. When there are no hidden units it is straightforward to compute the relevant derivative. For this purpose we use the chain rule to write the derivative as the product of two parts: the derivative of the error with respect to the output of the unit times the derivative of the output with respect to the weight.

$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial o_{pj}} \frac{\partial o_{pj}}{\partial w_{ji}}. \quad (3)$$

The first part tells how the error changes with the output of the jth unit and the second part tells how much changing w_{ji} changes that output. Now, the derivatives are easy to compute. First, from Equation 2

$$\frac{\partial E_p}{\partial o_{pj}} = -(t_{pj} - o_{pj}) = -\delta_{pj}. \quad (4)$$

Not surprisingly, the contribution of unit u_j to the error is simply proportional to δ_{pj}. Moreover, since we have linear units,

$$o_{pj} = \sum_i w_{ji} i_{pi}, \quad (5)$$

from which we conclude that

$$\frac{\partial o_{pj}}{\partial w_{ji}} = i_{pi}.$$

Thus, substituting back into Equation 3, we see that

$$-\frac{\partial E_p}{\partial w_{ji}} = \delta_{pj} i_i \quad (6)$$

recognizable maths

Rumelhart et al. 1986: First time back-propagation became popular

Slide Credit: Li, Karpathy, Johnson

A bit of history

Hubel & Wiesel,

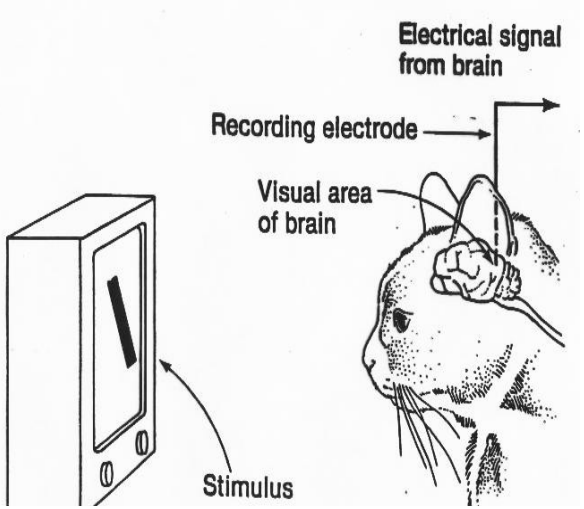
1959

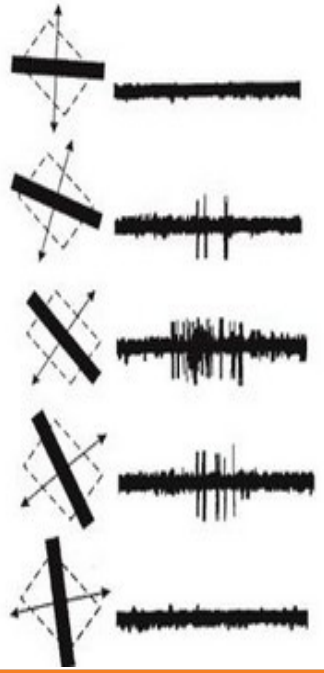
RECEPTIVE FIELDS OF SINGLE NEURONES IN
THE CAT'S STRIATE CORTEX

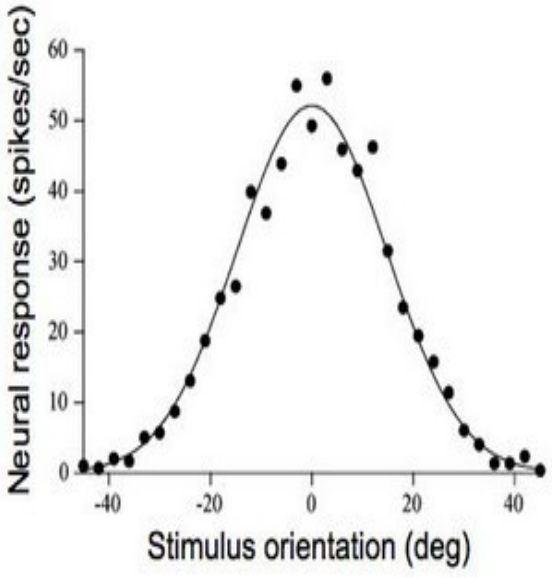
1962

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

1968...



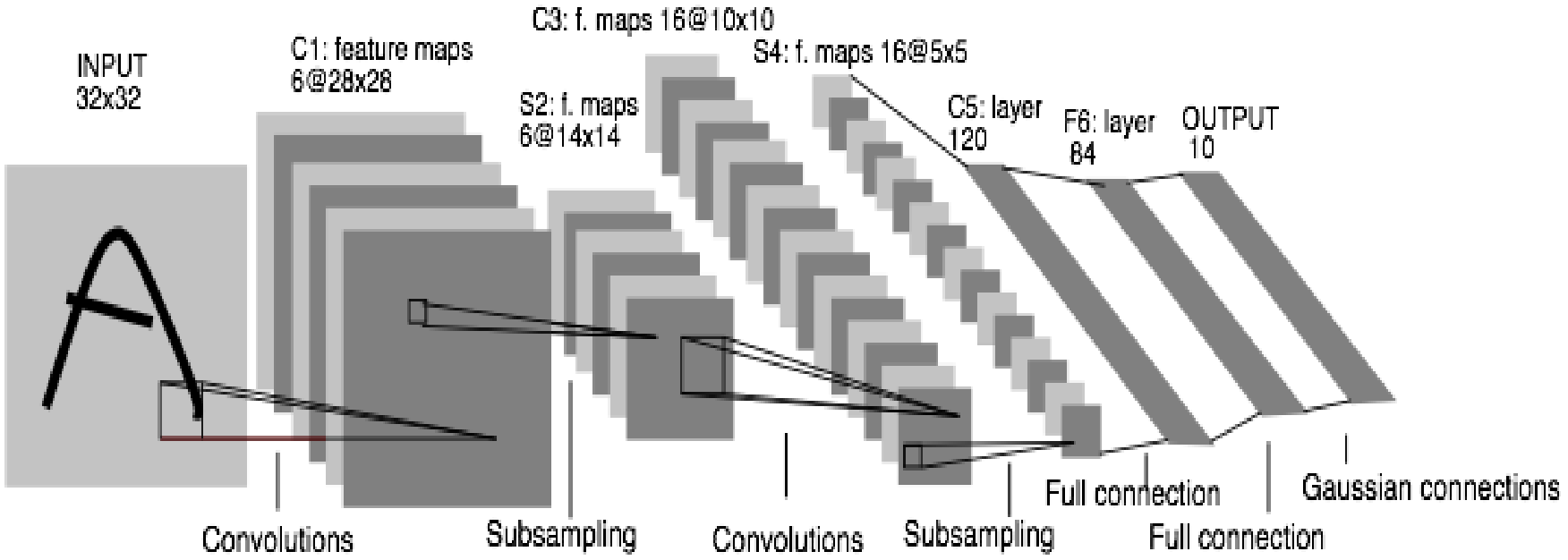




Slide Credit: Li, Karpathy, Johnson

A bit of history

LeCun, late '90s : Convolutional Neural Networks



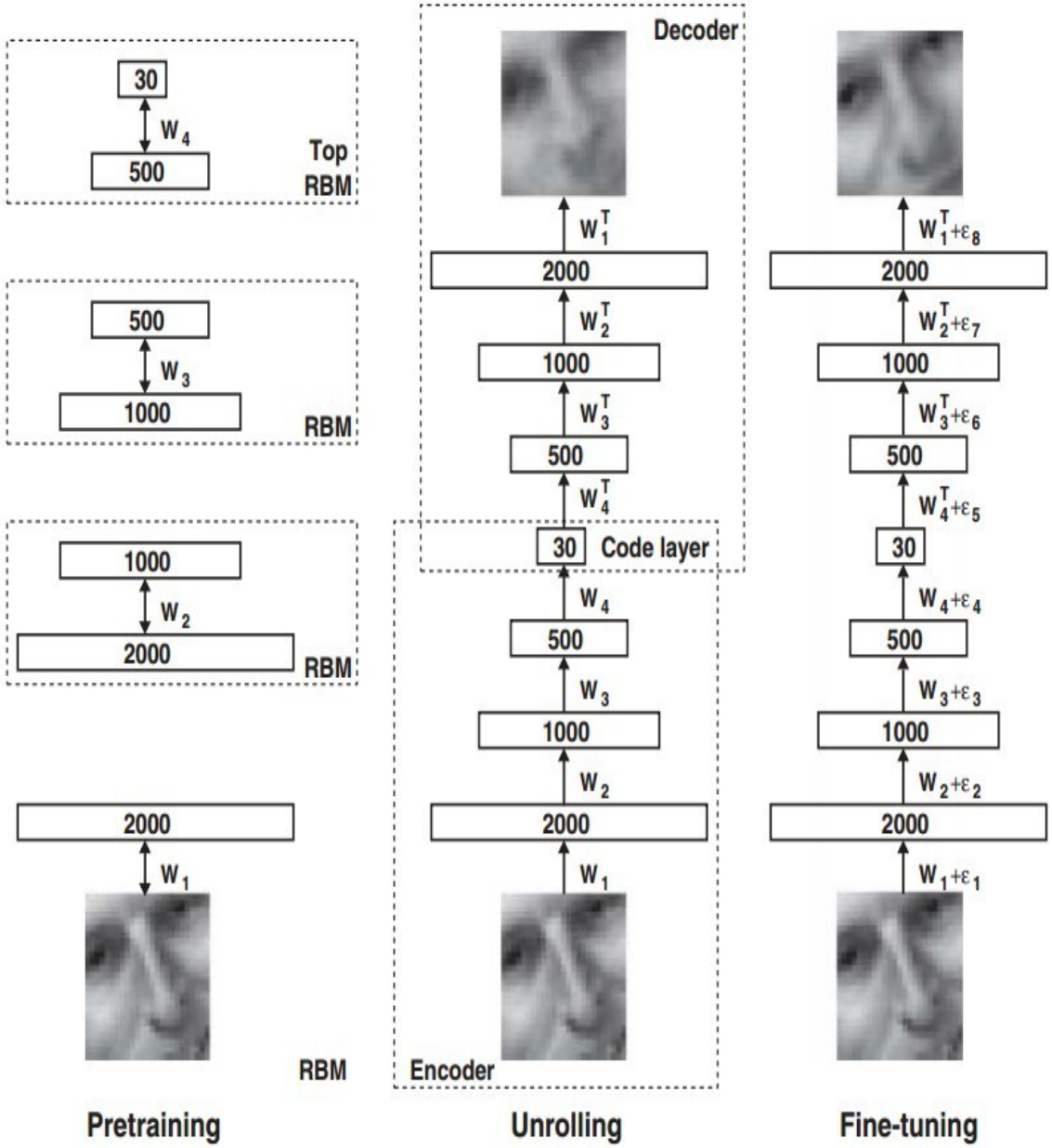
Gradient-based learning applied to document recognition
Y LeCun, L Bottou, Y Bengio, P Haffner, 1998

Slide Credit: LeCun

A bit of history

[Hinton and Salakhutdinov 2006]

Reinvigorated research in Deep Learning

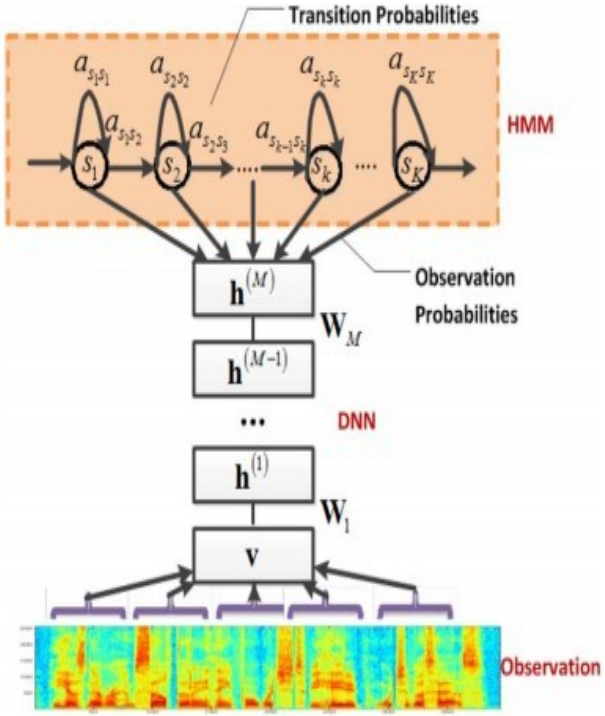


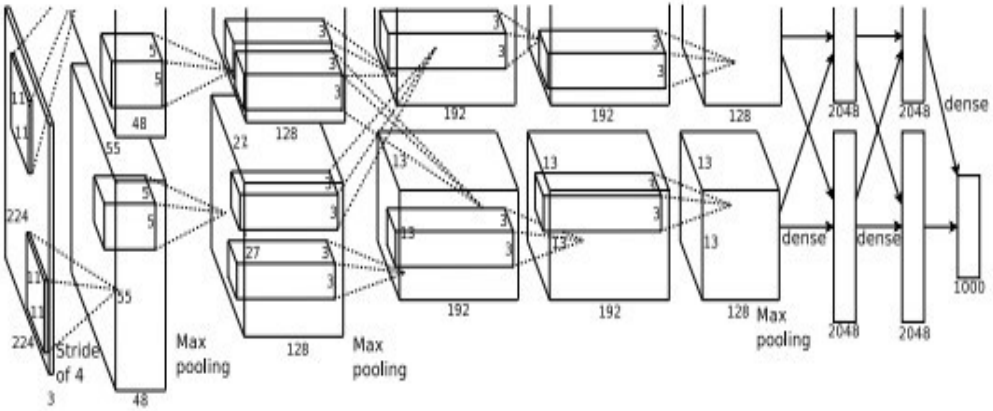
Slide Credit: Li, Karpathy, Johnson

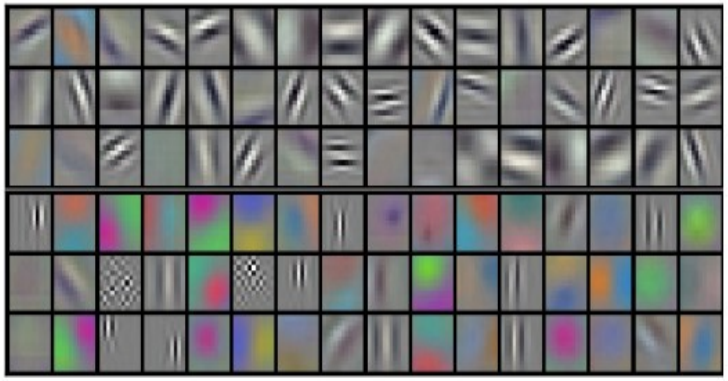
First strong modern results

Context-Dependent Pre-trained Deep Neural Networks for Large Vocabulary Speech Recognition
George Dahl, Dong Yu, Li Deng, Alex Acero, 2010

Imagenet classification with deep convolutional neural networks
Alex Krizhevsky, Ilya Sutskever, Geoffrey E Hinton, 2012

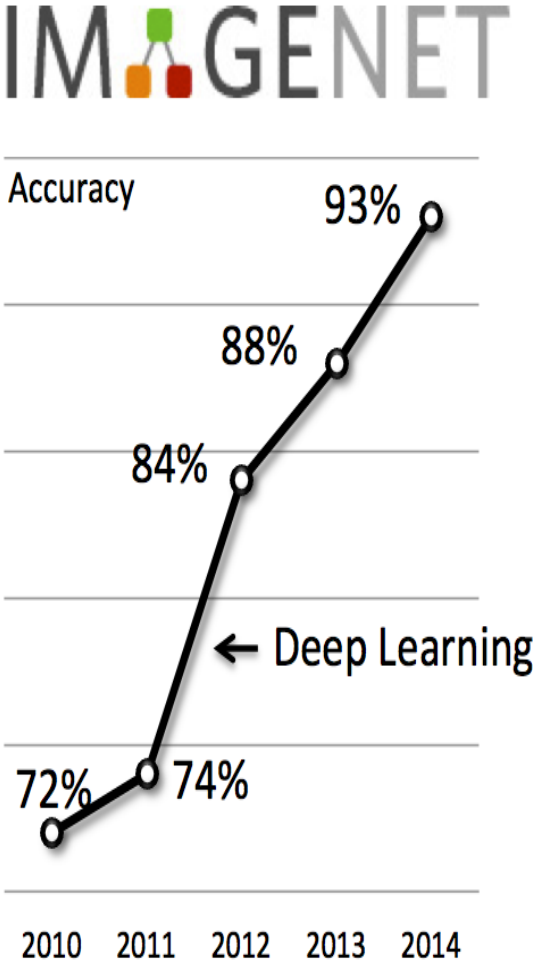






Slide Credit: Li, Karpathy, Johnson

Keeps getting better...



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

Microsoft 95.06%, Feb 06, 2015

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariant Shift

Google 95.18%, Feb 11, 2015

Deep Image: Scaling up Image Recognition

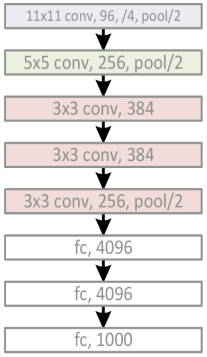
Baidu 百度 95.42%, May 11, 2015

Slide Credit:

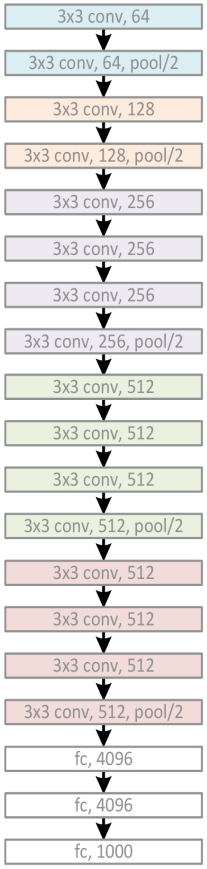
And deeper...

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



GoogleNet, 22 layers
(ILSVRC 2014)

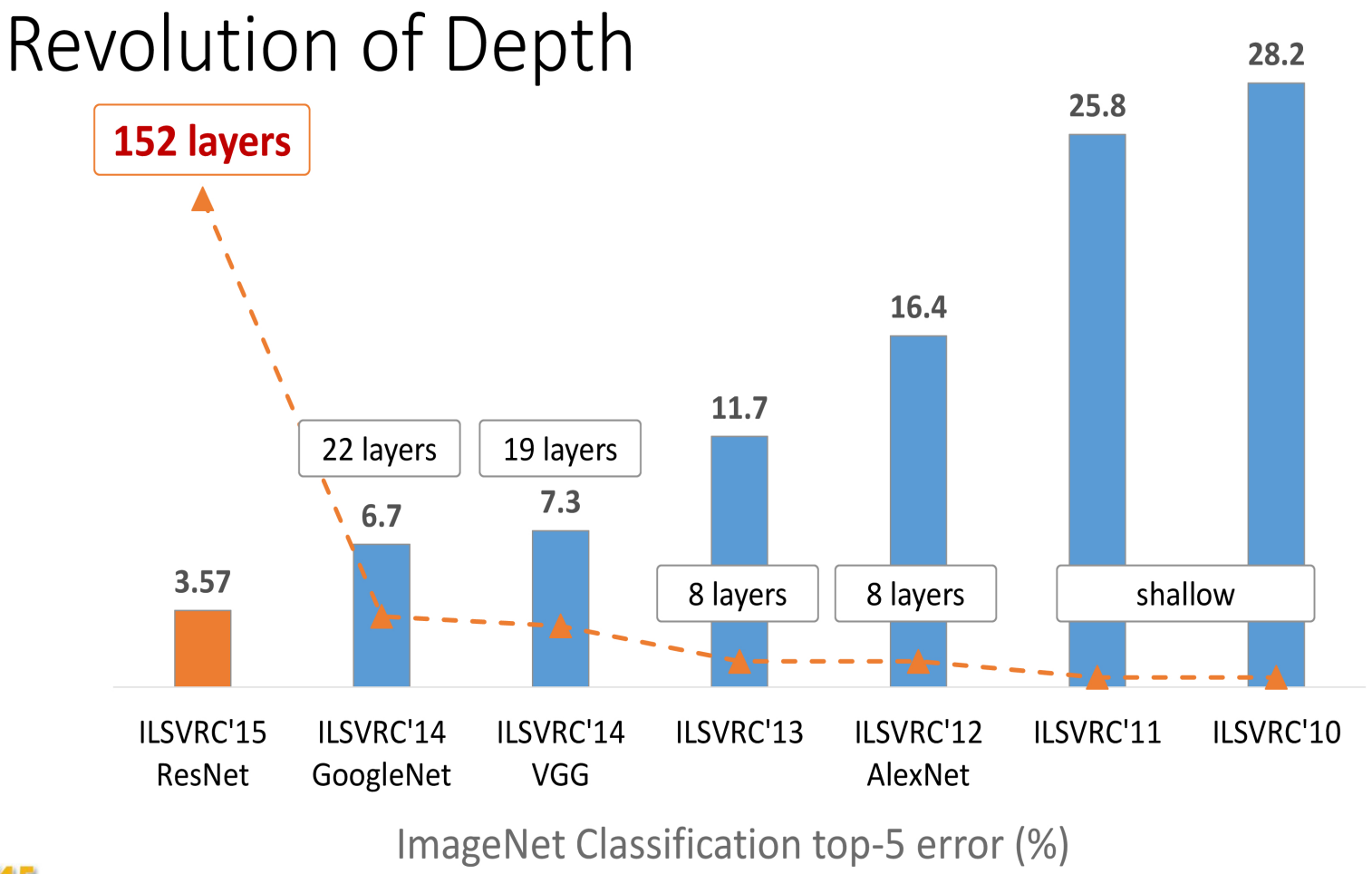
ICCV15
International Conference on Computer Vision

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

Slide Credit:

And deeper...

Microsoft Research



ICCV15 International Conference on Computer Vision

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

Slide Credit:

And deeper...

Microsoft Research

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)

VGG, 19 layers
(ILSVRC 2014)

ResNet, 152 layers
(ILSVRC 2015)

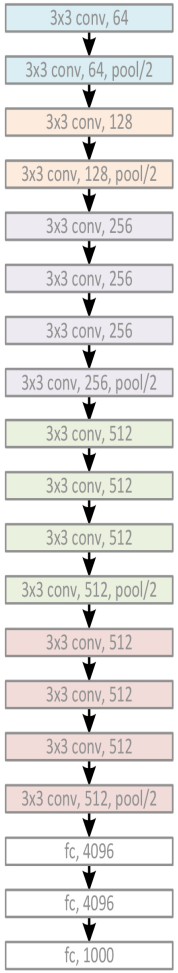
ICCV15 International Conference on Computer Vision

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

Slide Credit:

Network is a stack of components

rs
t)

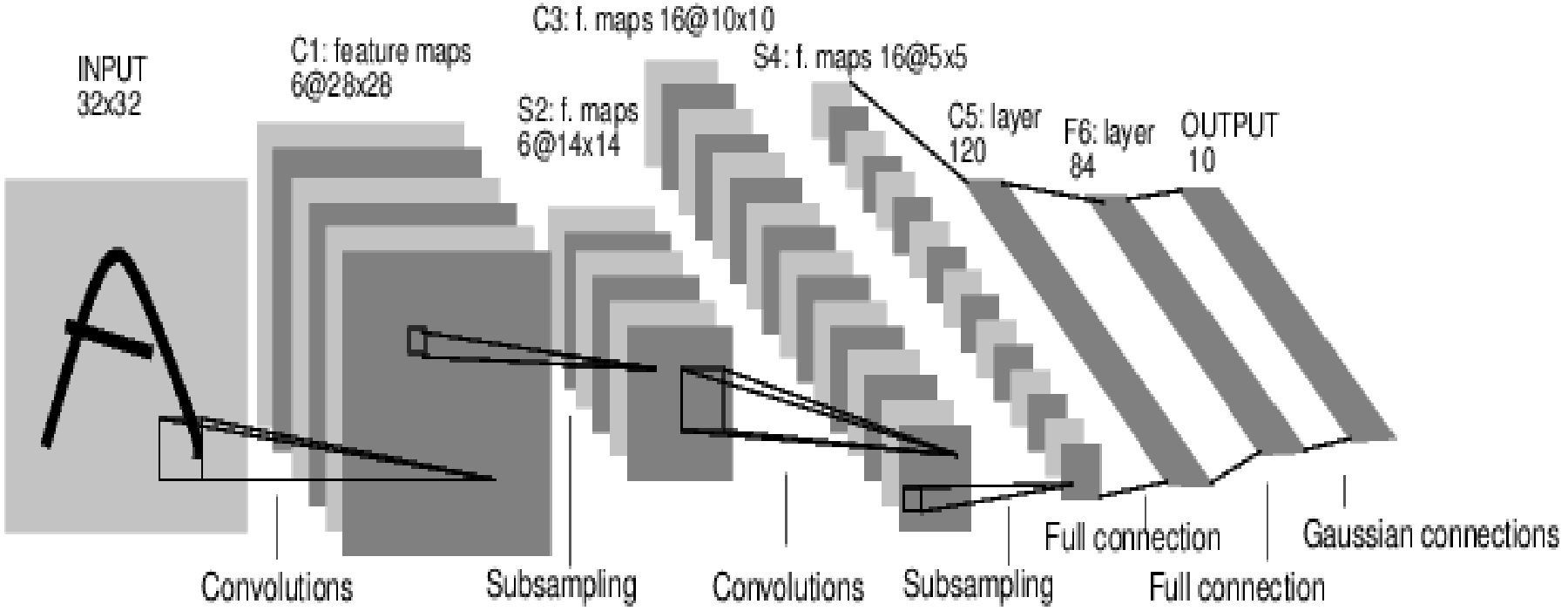


GoogleNet, 22 layers
(ILSVRC 2014)

ng, Shaoqing Ren, & Jian Sun, "Deep Residual Learning for Image Recognition", arXiv 2015

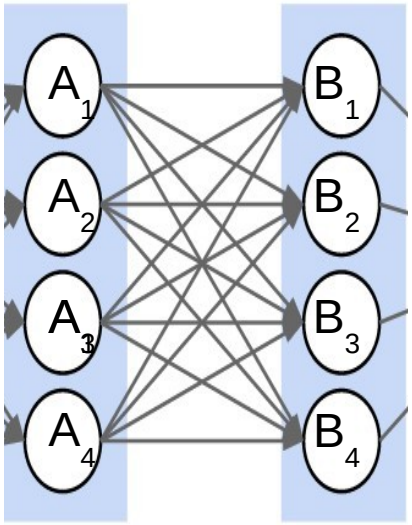
Slide Credit:

Components of a Convolutional Net



Slide Credit:

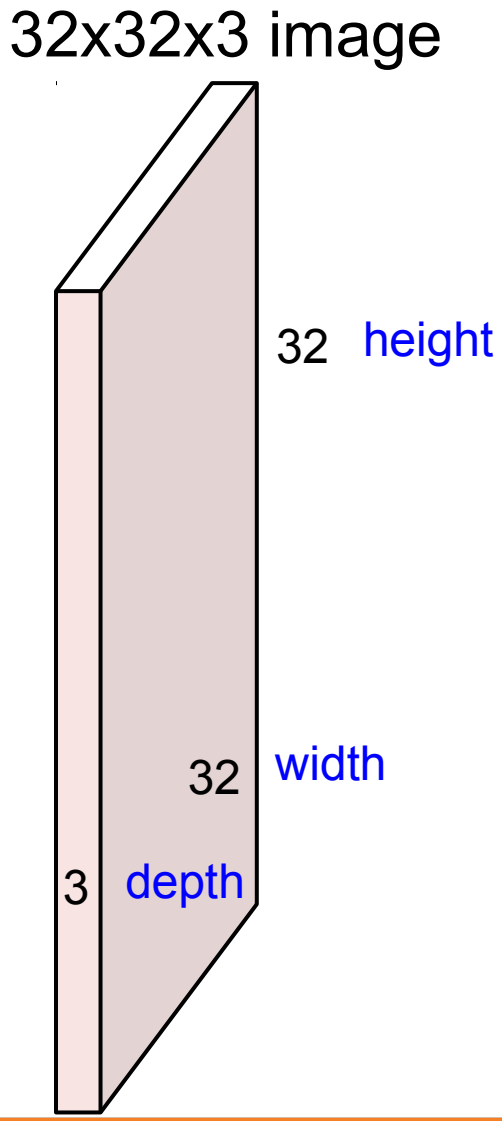
Fully Connected layer



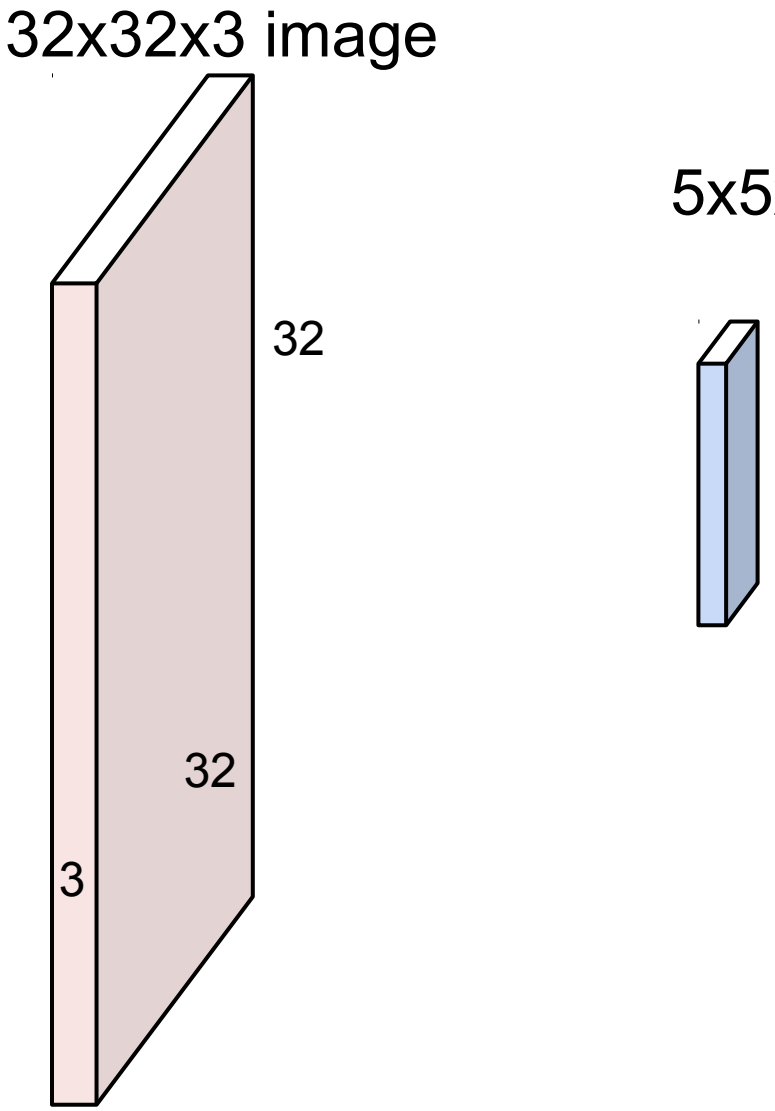
$$B_j = \sum_i \left(W_{ij} * A_i \right) + b_j$$

Slide Credit:

Convolution Layer



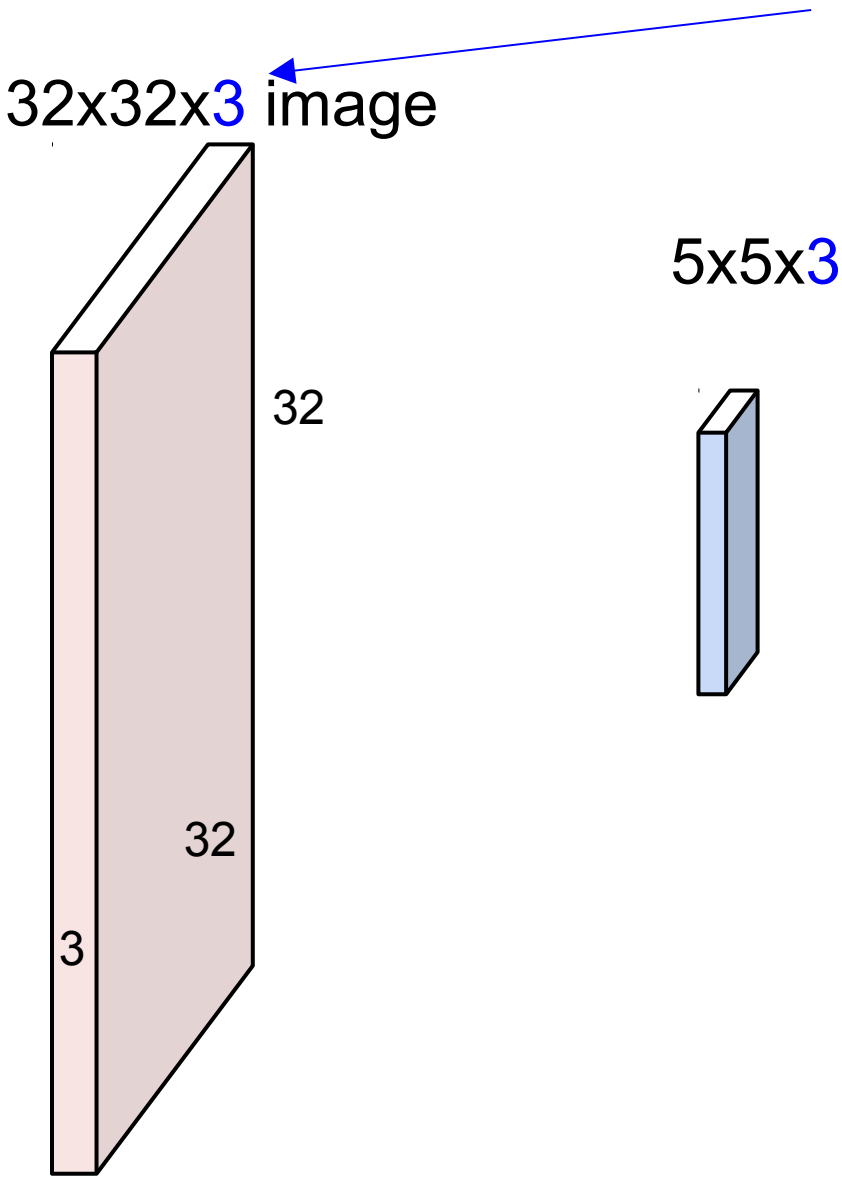
Convolution Layer



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

Slide Credit:

Convolution Layer



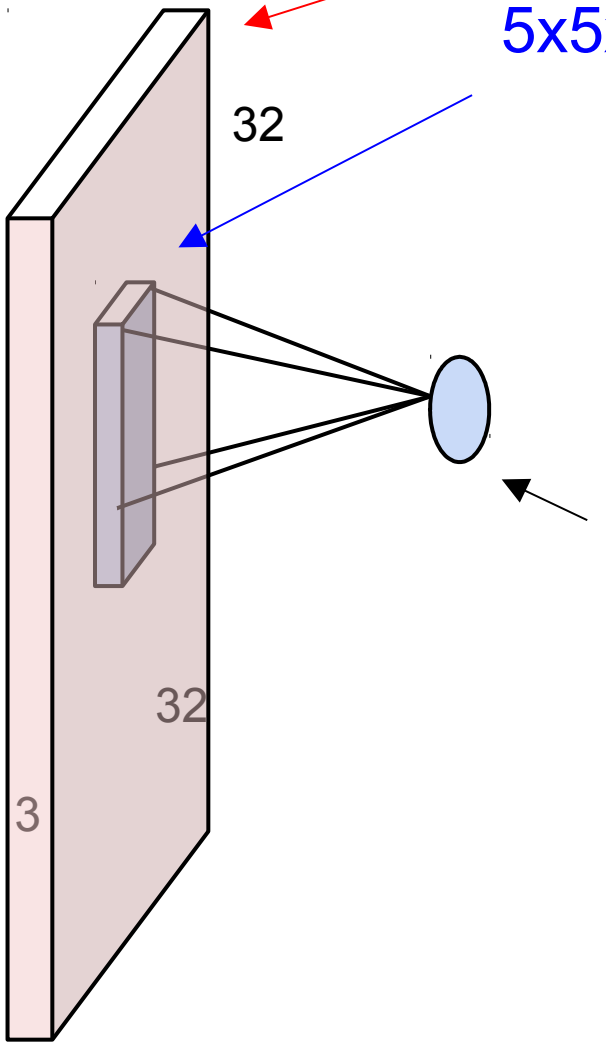
Filters always extend the full depth of the input volume

5x5x3 filter

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

Slide Credit:

Convolution Layer



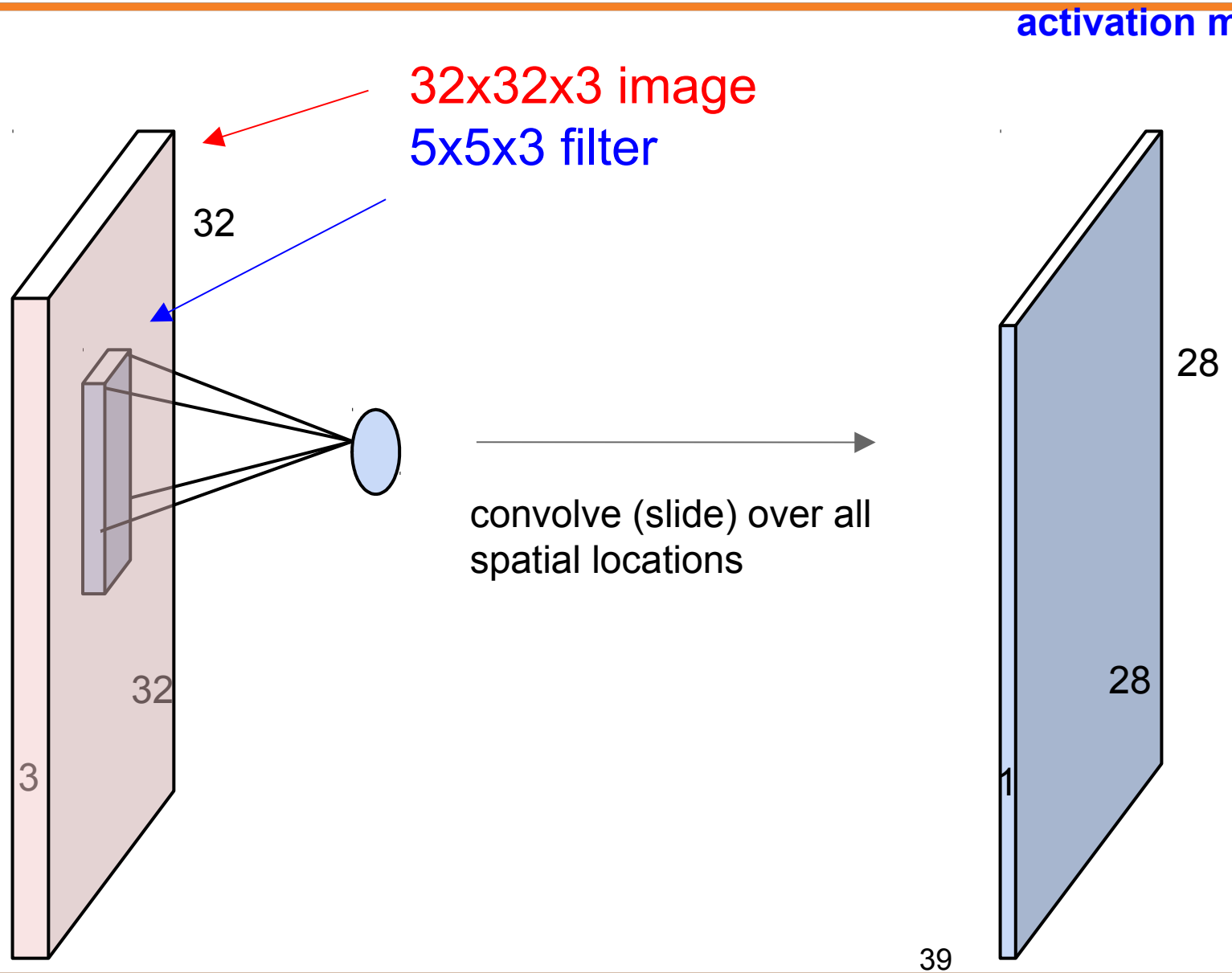
32x32x3 image

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)

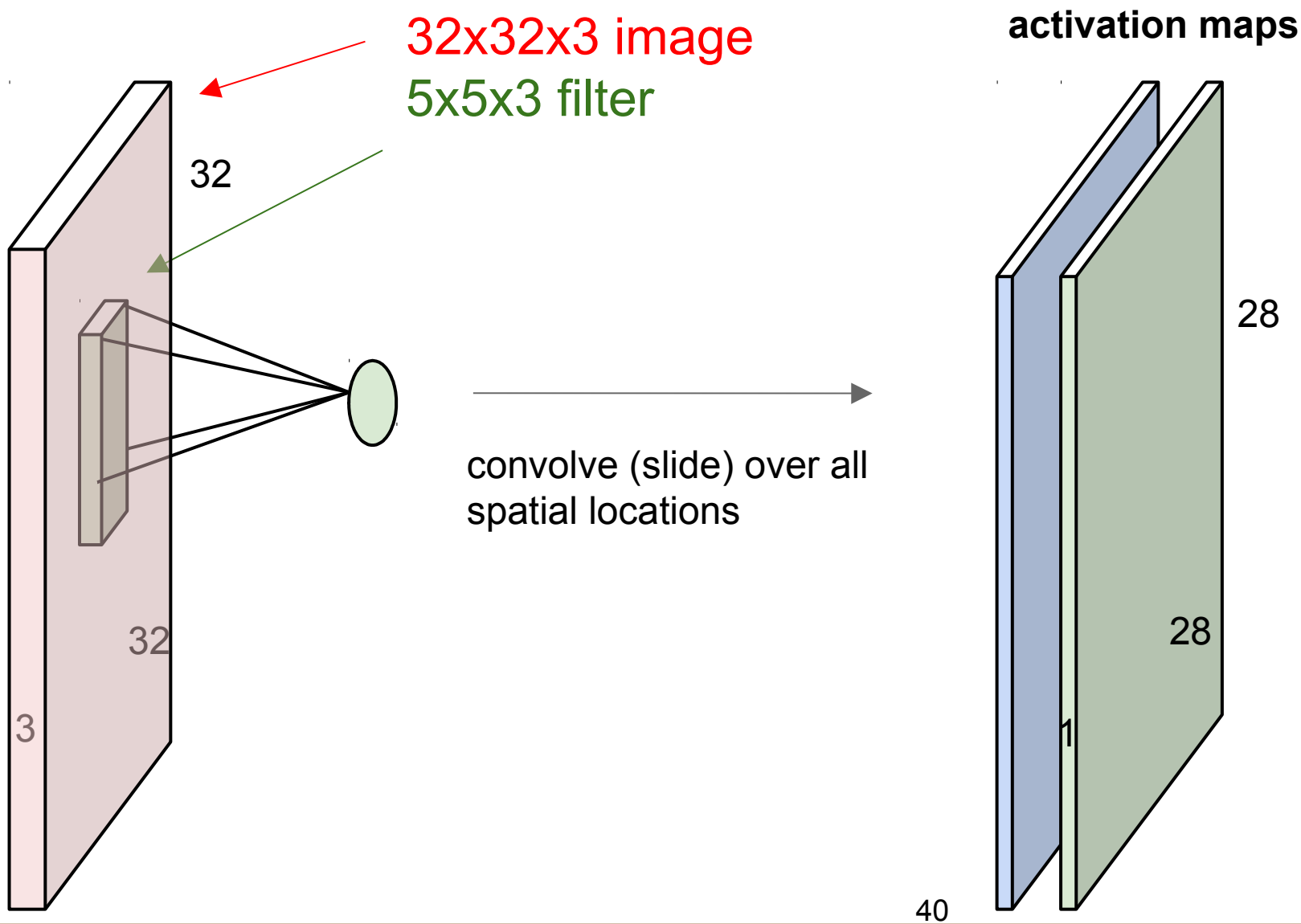
$$w^T x + b$$

Convolution Layer

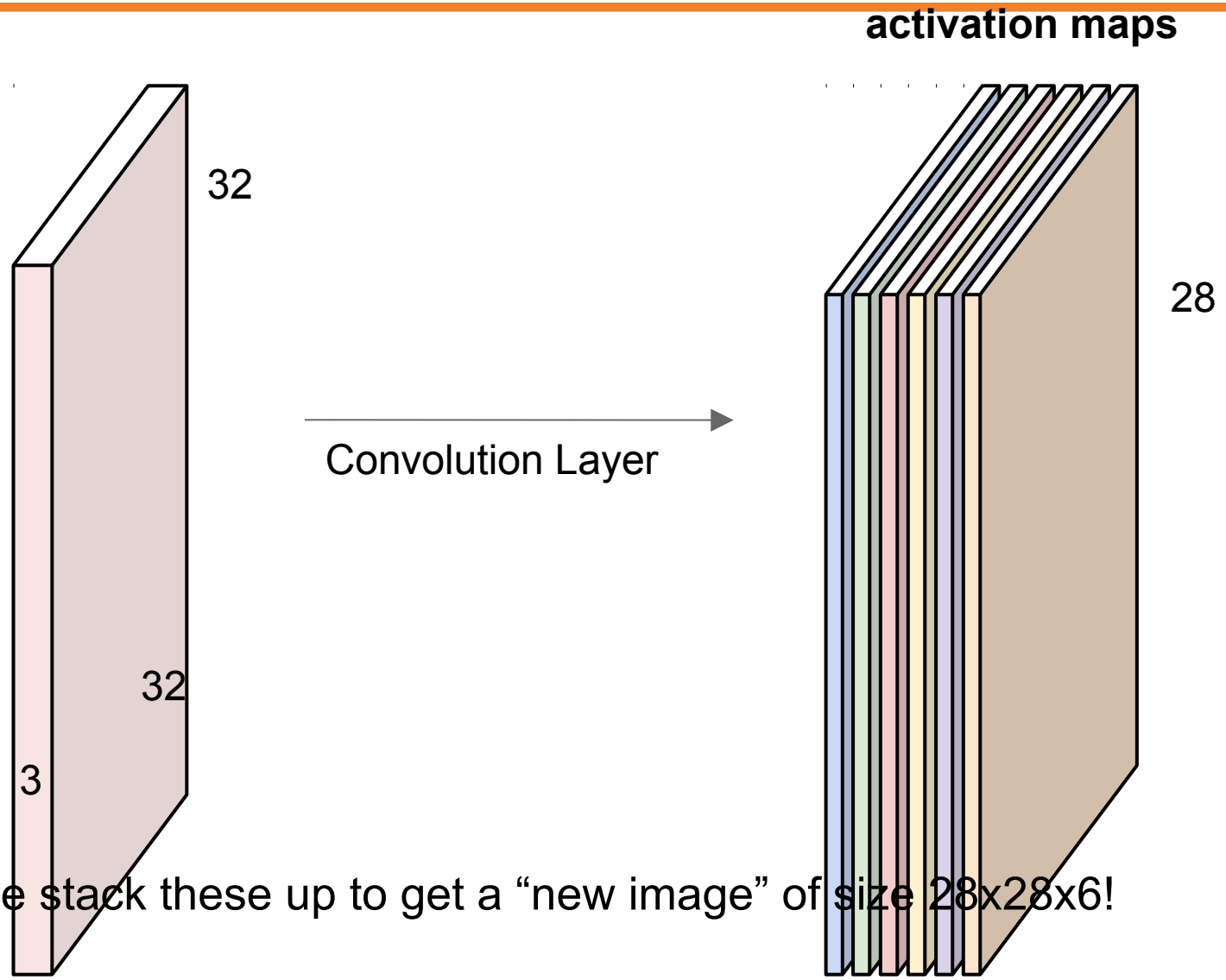


Convolution Layer

consider a second, green filter

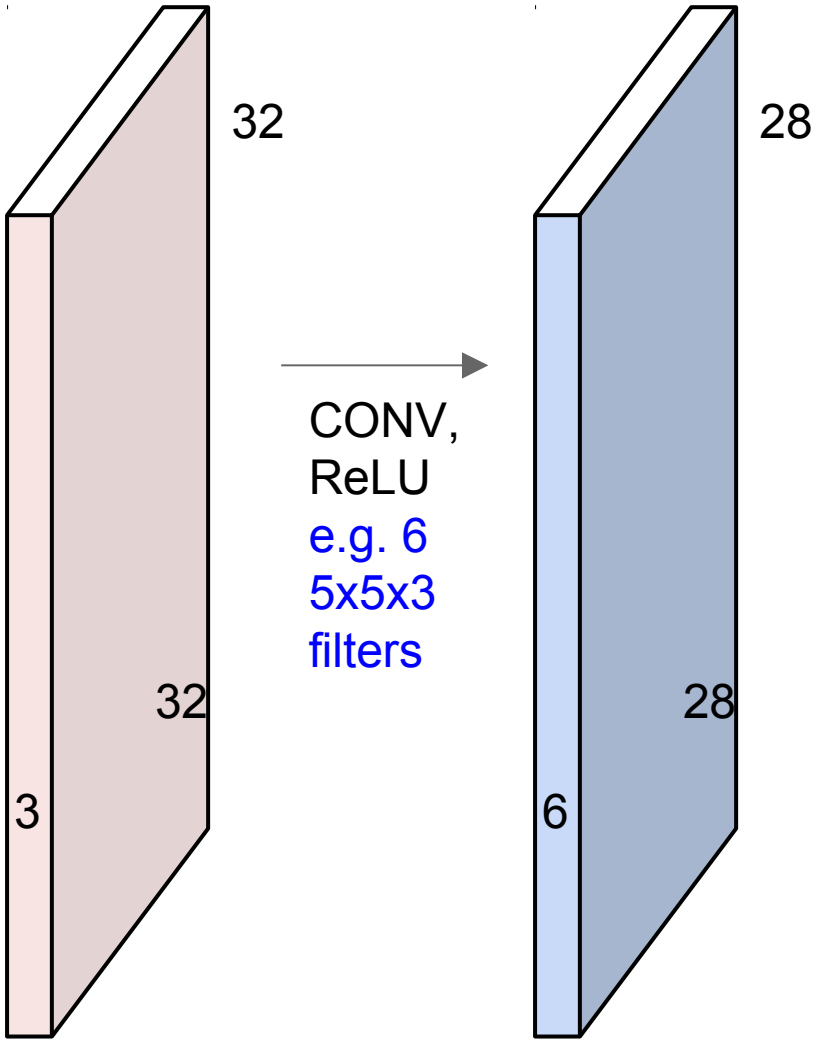


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

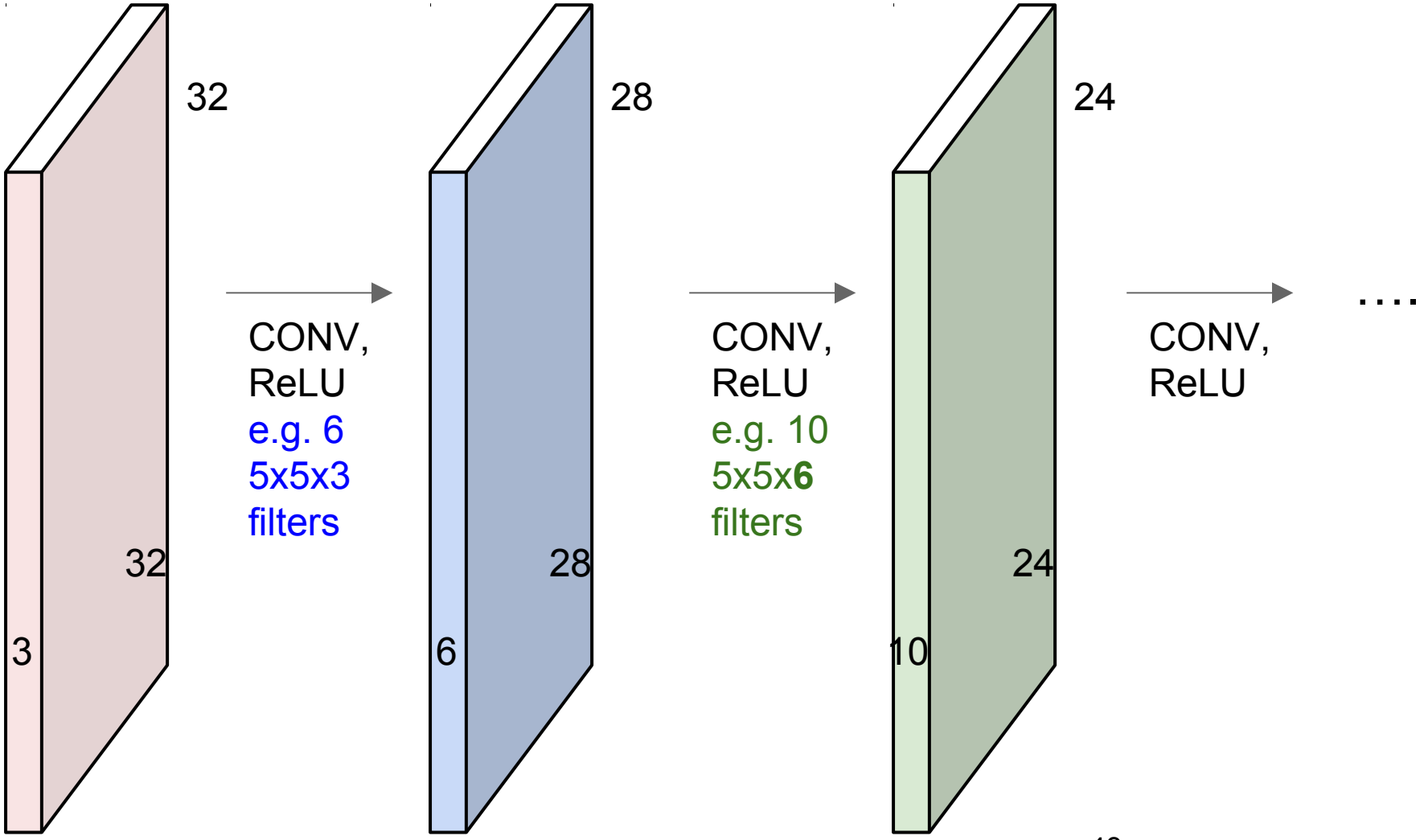


We stack these up to get a "new image" of size 28x28x6!

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



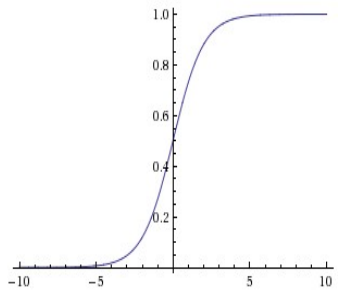
Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



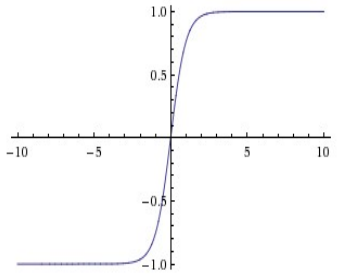
Activation Functions

Sigmoid

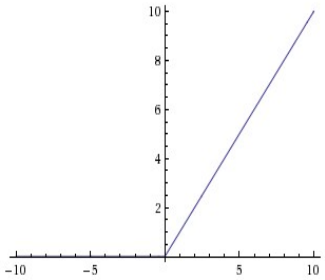
$$\sigma(x) = 1/(1+e^{-x})$$



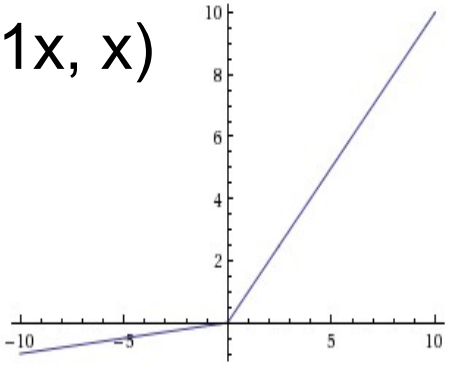
tanh tanh(x)



ReLU max(0,x)



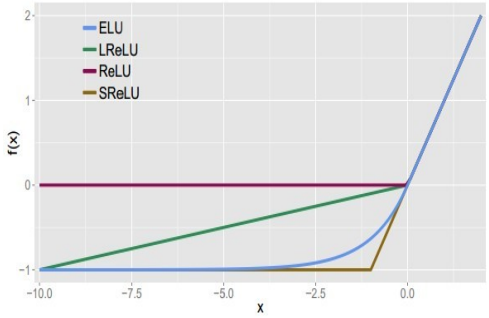
Leaky ReLU
max(0.1x, x)



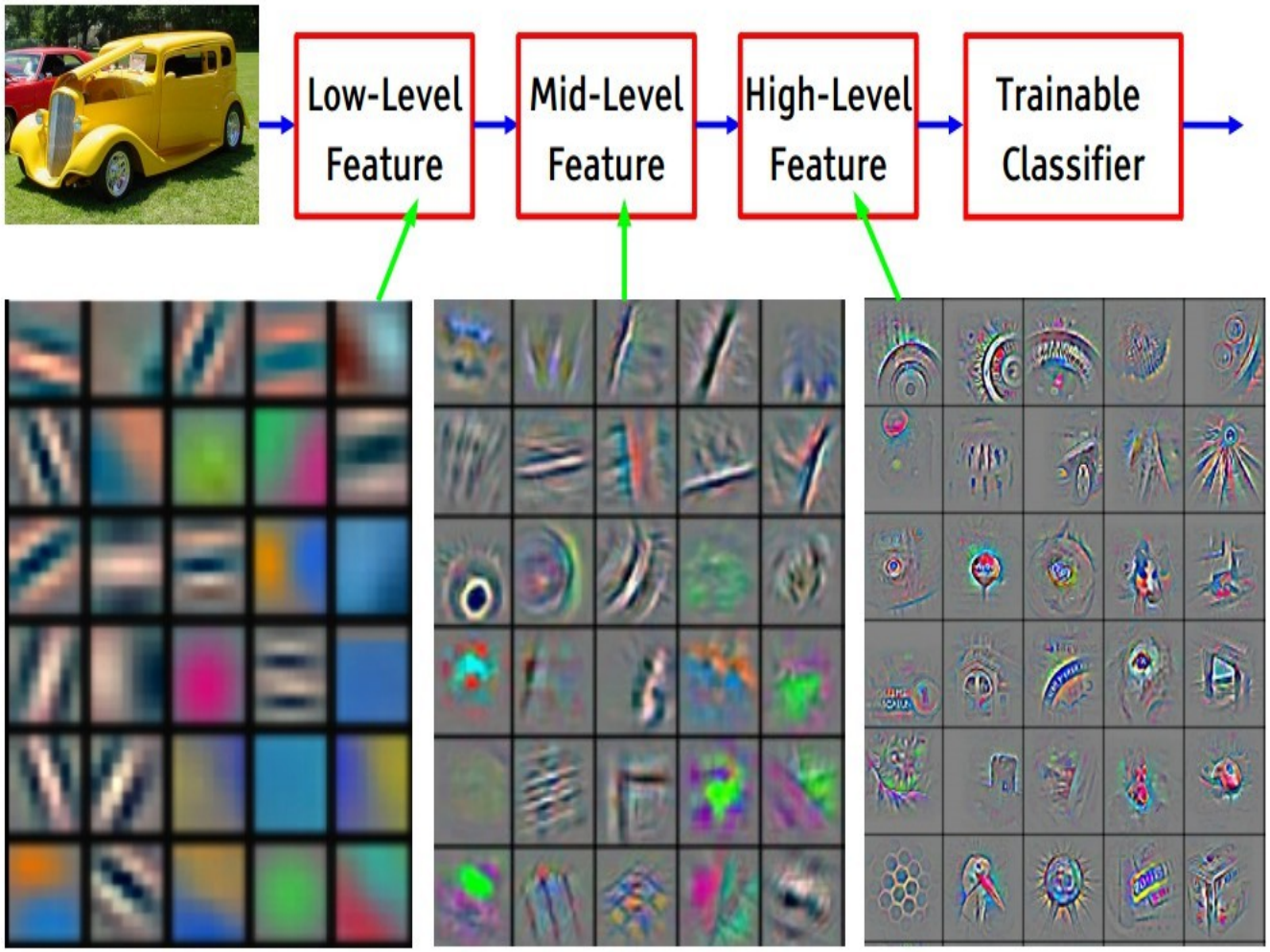
Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

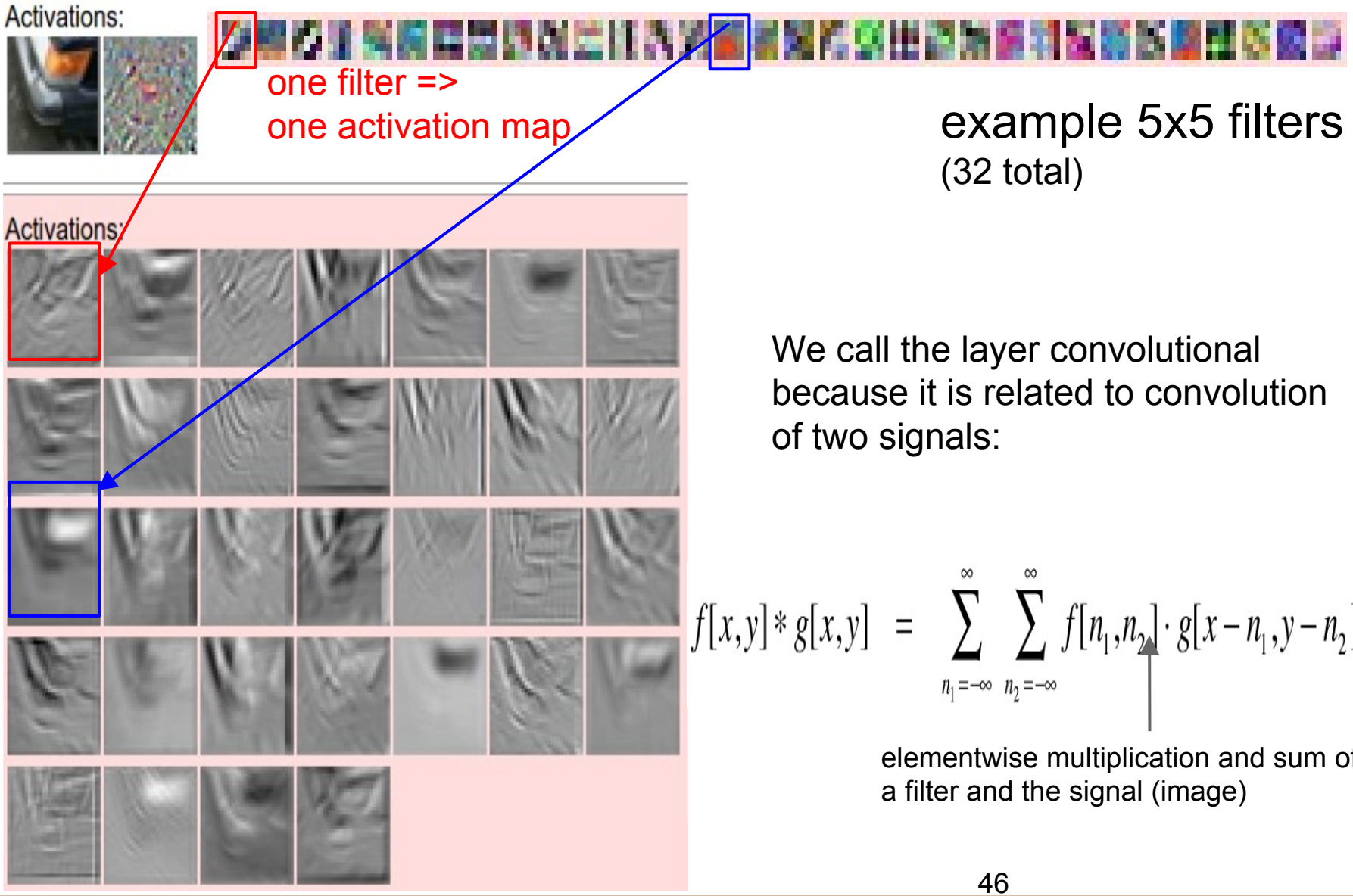
$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \leq 0 \end{cases}$$



Preview



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



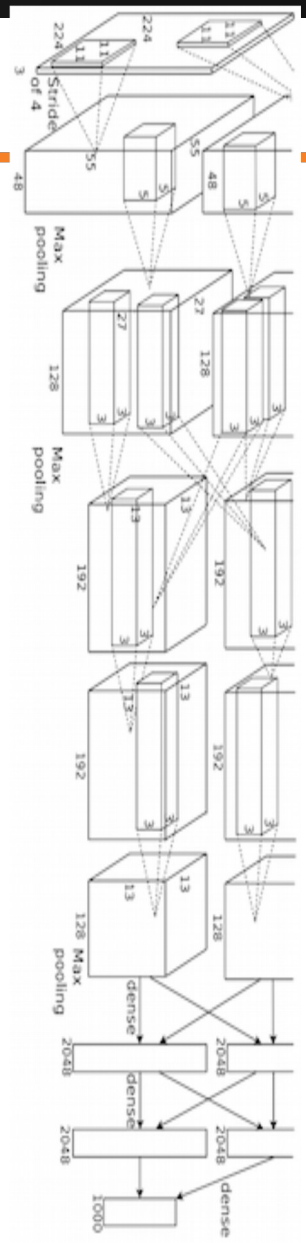
example 5x5 filters
(32 total)

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

$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

elementwise multiplication and sum of a filter and the signal (image)

Convolutional Network (AlexNet)



input image

weights

loss

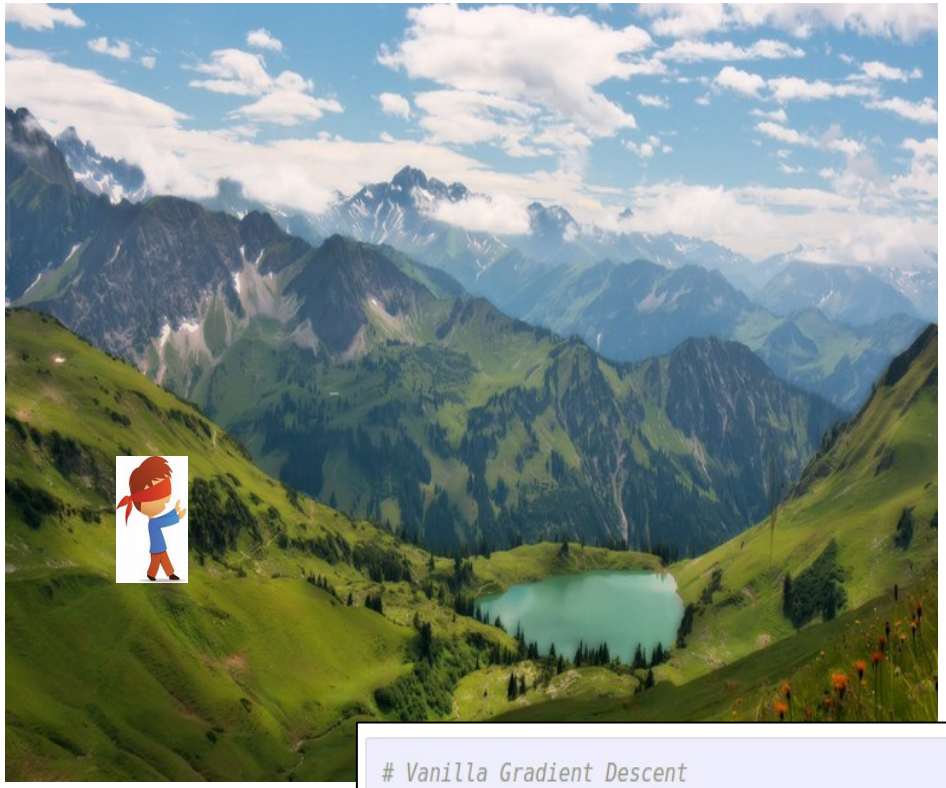
Loss function

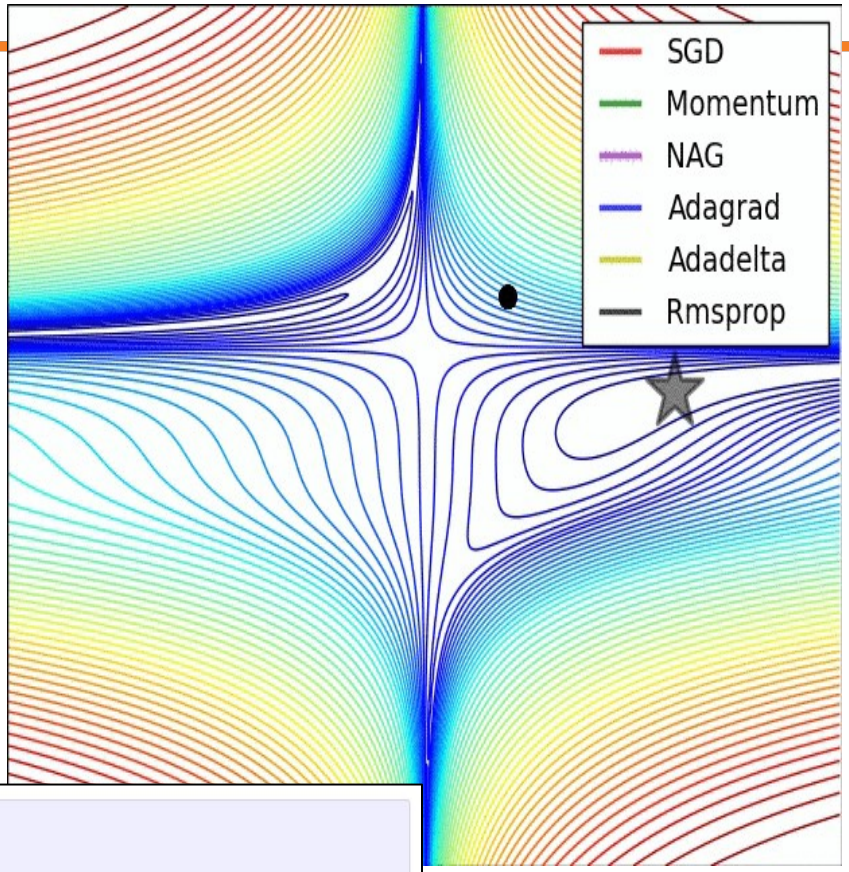
An example loss function (the hinge loss):

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

Slide Credit:

How to optimize?





(image credits to Alec Radford)

```
# Vanilla Gradient Descent

while True:
  weights_grad = evaluate_gradient(loss_fun, data, weights)
  weights += - step_size * weights_grad # perform parameter update
```

Follow the slope

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:	**W + h** (first dim):	**gradient dW:**
[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[0.34 + **0.0001**, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[?, ?, ?, ?, ?, ?, ?, ?, ?,…]
loss 1.25347	**loss 1.25322**	

current W:	**W + h** (first dim):	**gradient dW:**
[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[0.34 + **0.0001**, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[**-2.5**, ?, ?, ?, ?
loss 1.25347	**loss 1.25322**	

(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:	**W + h** (second dim)**:**	**gradient dW:**
[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[0.34, -1.11 + **0.0001**, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[-2.5, ?, ?, ?, ?, ?, ?, ?, ?,…]
loss 1.25347	**loss 1.25353**	

current W:	**W + h** (second dim):	**gradient dW:**
[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…] **loss 1.25347**	[0.34, -1.11 + **0.0001**, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…] **loss 1.25353**	[-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:	**W + h** (third dim)**:**	**gradient dW:**
[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[0.34, -1.11, 0.78 + **0.0001**, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…]	[-2.5, 0.6, ?, ?, ?, ?, ?, ?, ?,…]
loss 1.25347	**loss 1.25347**	

current W:	**W + h** (third dim)**:**	**gradient dW:**
[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…] **loss 1.25347**	[0.34, -1.11, 0.78 + **0.0001**, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,…] **loss 1.25347**	[-2.5, 0.6, **0**, ?, ?, ?,

(1.25347 - 1.25347)/0.0001
= 0

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

Evaluation the gradient numerically

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

```
def eval_numerical_gradient(f, x):
  """
  a naive implementation of numerical gradient of f at x
  - f should be a function that takes a single argument
  - x is the point (numpy array) to evaluate the gradient at
  """

  fx = f(x) # evaluate function value at original point
  grad = np.zeros(x.shape)
  h = 0.00001

  # iterate over all indexes in x
  it = np.nditer(x, flags=['multi_index'], op_flags=['readwrite'])
  while not it.finished:

    # evaluate function at x+h
    ix = it.multi_index
    old_value = x[ix]
    x[ix] = old_value + h # increment by h
    fxh = f(x) # evalute f(x + h)
    x[ix] = old_value # restore to previous value (very important!)

    # compute the partial derivative
    grad[ix] = (fxh - fx) / h # the slope
    it.iternext() # step to next dimension

  return grad
```

Evaluation the gradient numerically

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

- approximate
- very slow to evaluate

```
def eval_numerical_gradient(f, x):
  """
  a naive implementation of numerical gradient of f at x
  - f should be a function that takes a single argument
  - x is the point (numpy array) to evaluate the gradient at
  """

  fx = f(x) # evaluate function value at original point
  grad = np.zeros(x.shape)
  h = 0.00001

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    old_value = x[ix]
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    # compute the partial derivative
    grad[ix] = (fxh - fx) / h # the slope
    it.iternext() # step to next dimension

  return grad
```

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:

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

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

want $\nabla_W L$

Calculus

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

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

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

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

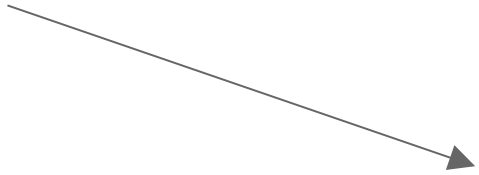
$$\nabla_W L = \ldots$$

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,…]

Slide Credit:

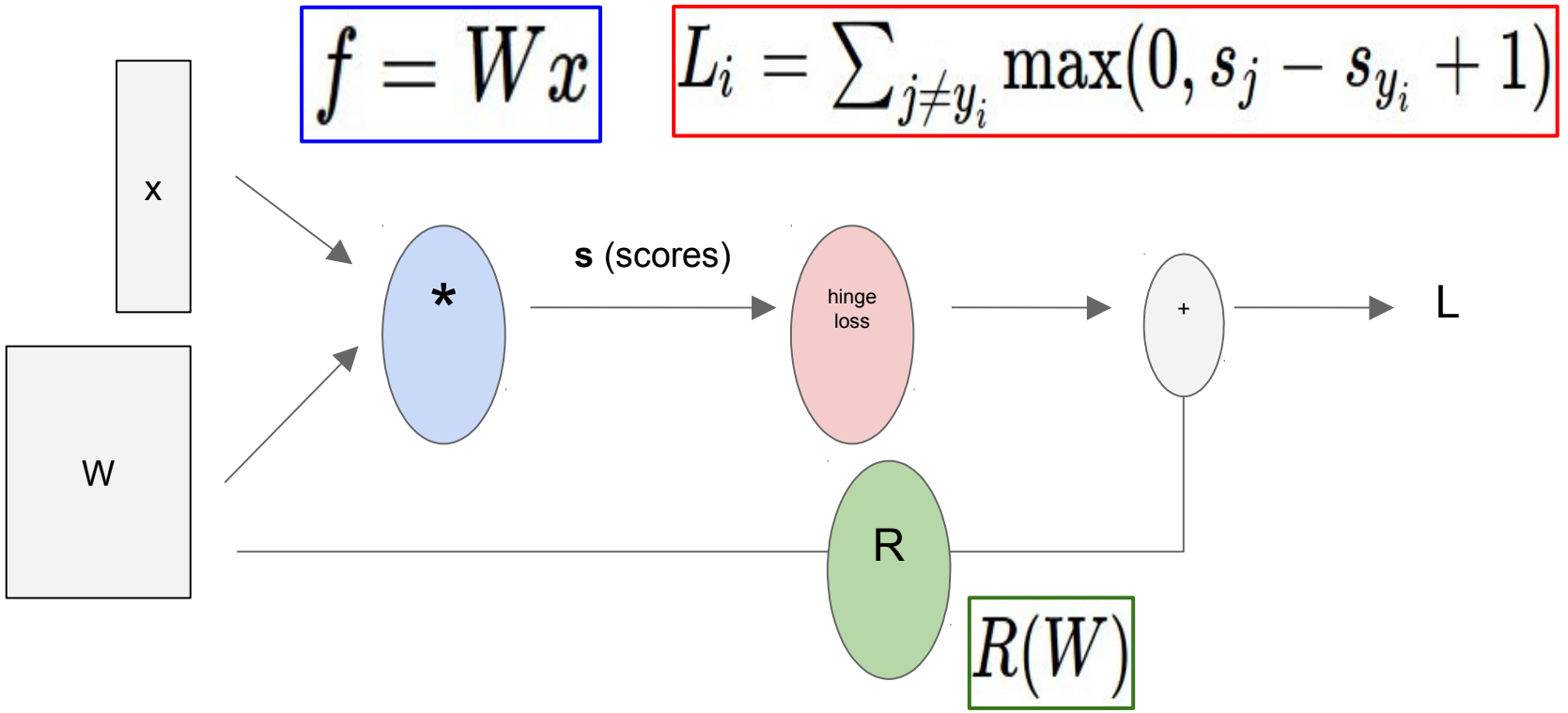
Gradient Descent

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

Numerical gradient: slow :(, approximate :(, easy to write :)
Analytic gradient: fast :), exact :), error-prone :(

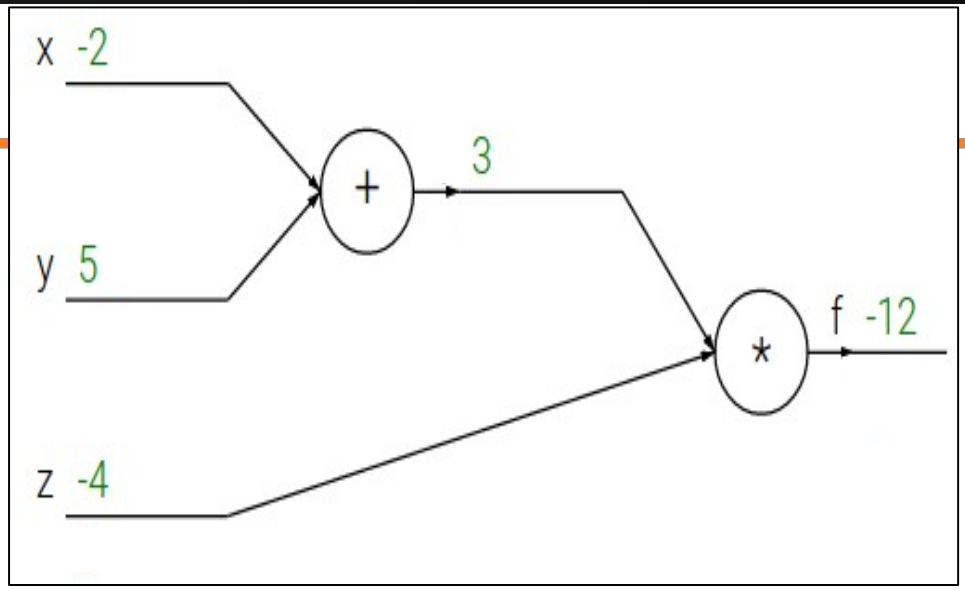
In practice: Derive analytic gradient, check your implementation with numerical gradient

Computational Graph



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

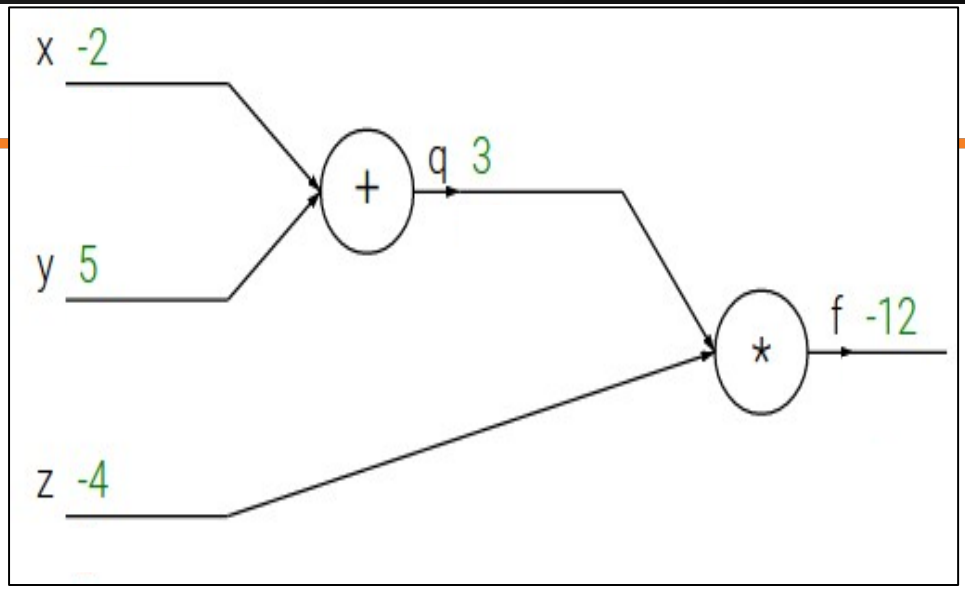
e.g. x = -2, y = 5, z = -4



Slide Credit:

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

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



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

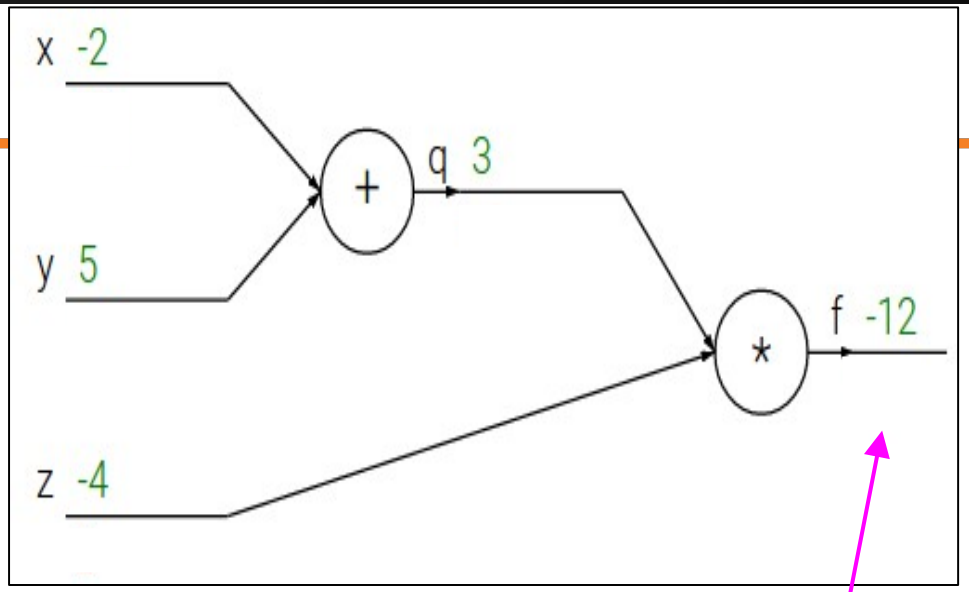
$$f = qz \qquad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

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

Slide Credit:

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

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



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

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

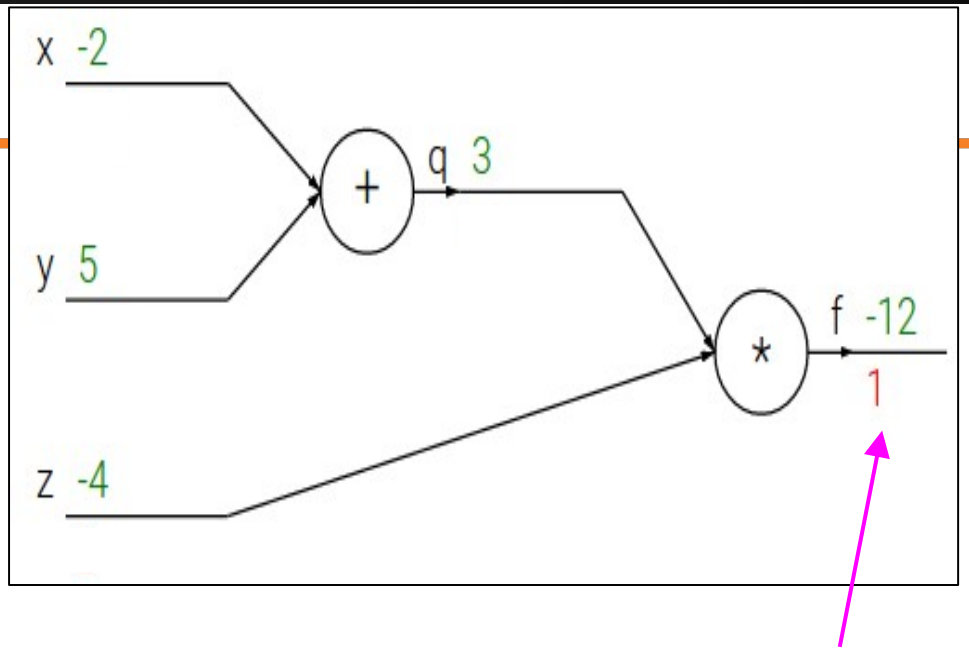
$$\frac{\partial f}{\partial f}$$

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

Slide Credit:

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

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



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

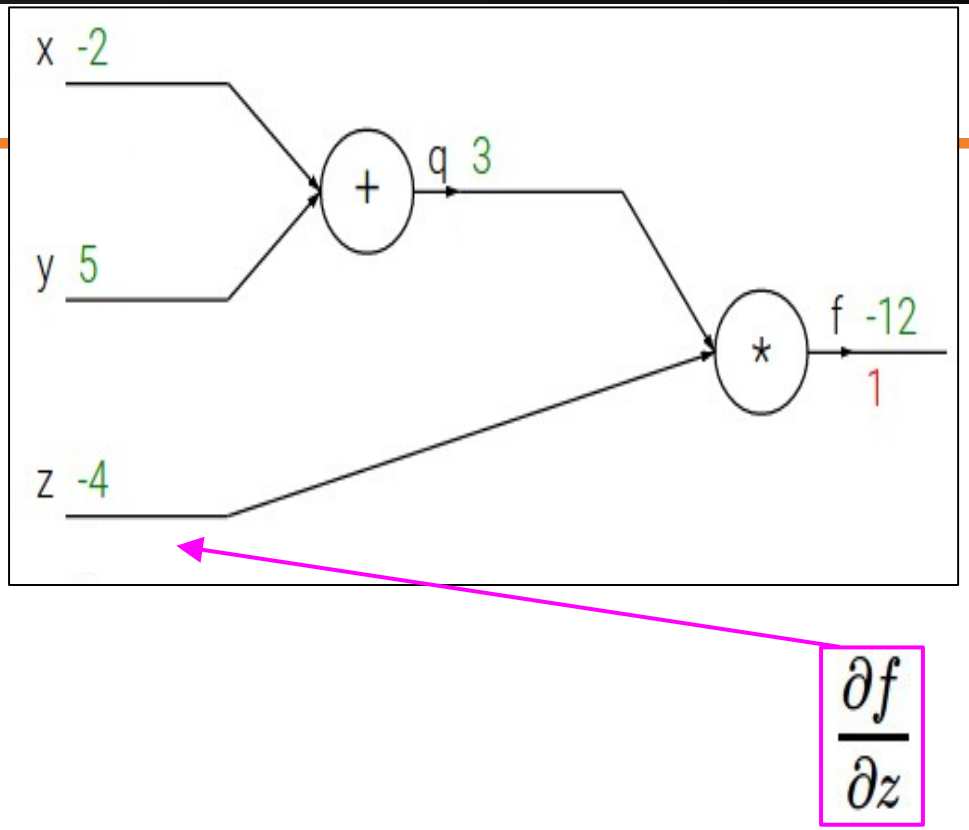
$$\frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

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

Slide Credit:

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

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



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

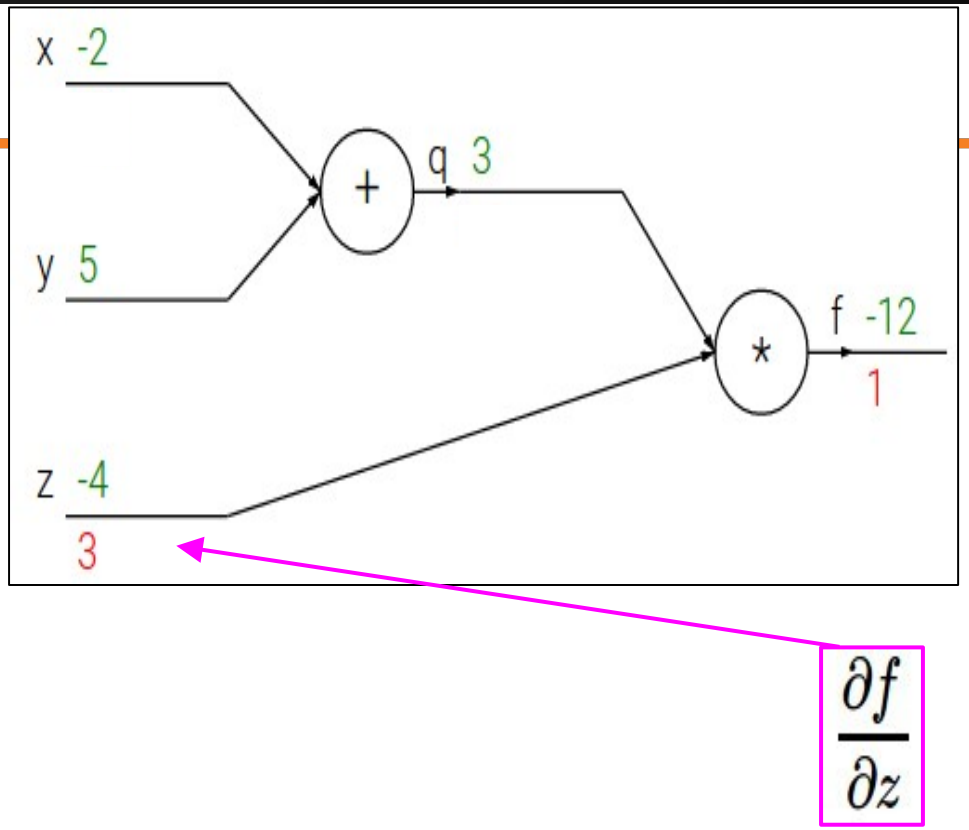
$$\frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

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

Slide Credit:

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

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



$$q = x + y$$

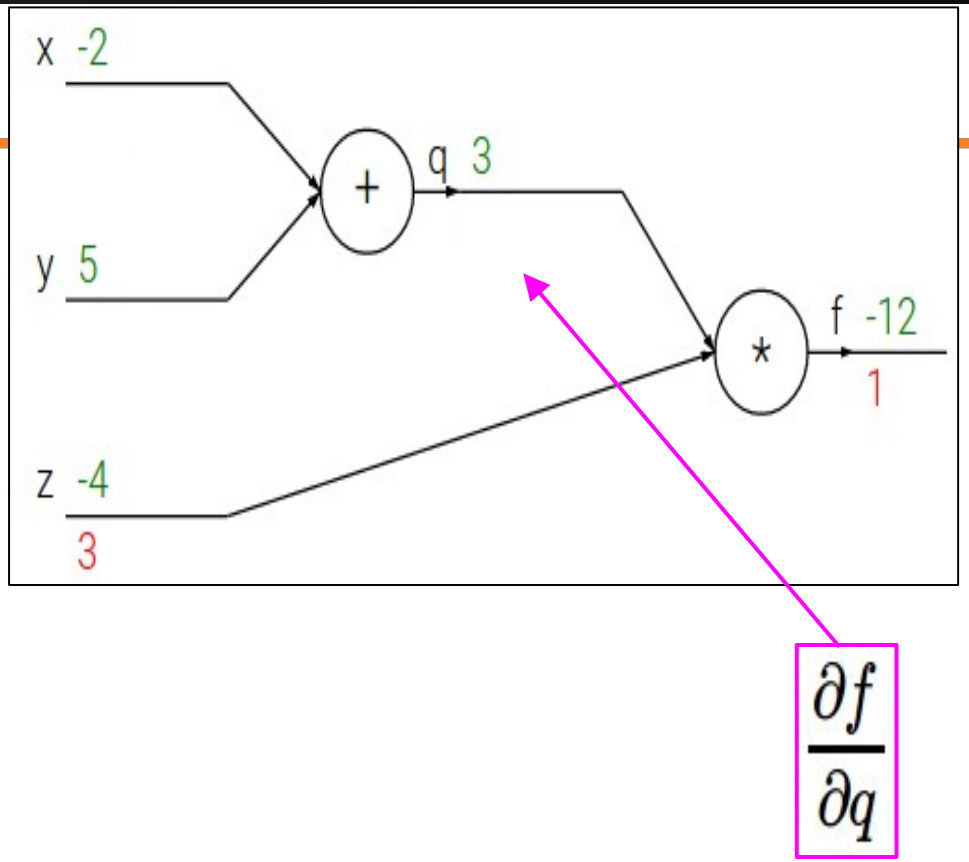
$$\frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

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

Slide Credit:

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

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



$$q = x + y$$

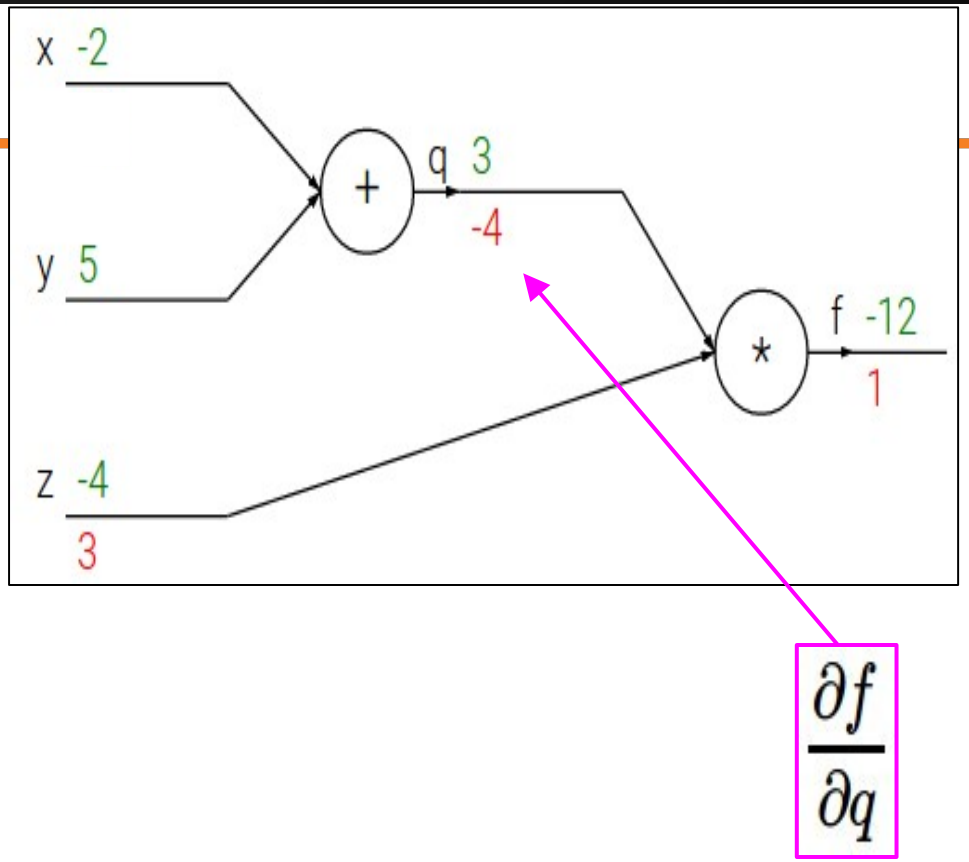
$$\frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

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

Slide Credit:

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

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



$$q = x + y$$

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

Slide Credit:

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

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

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

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

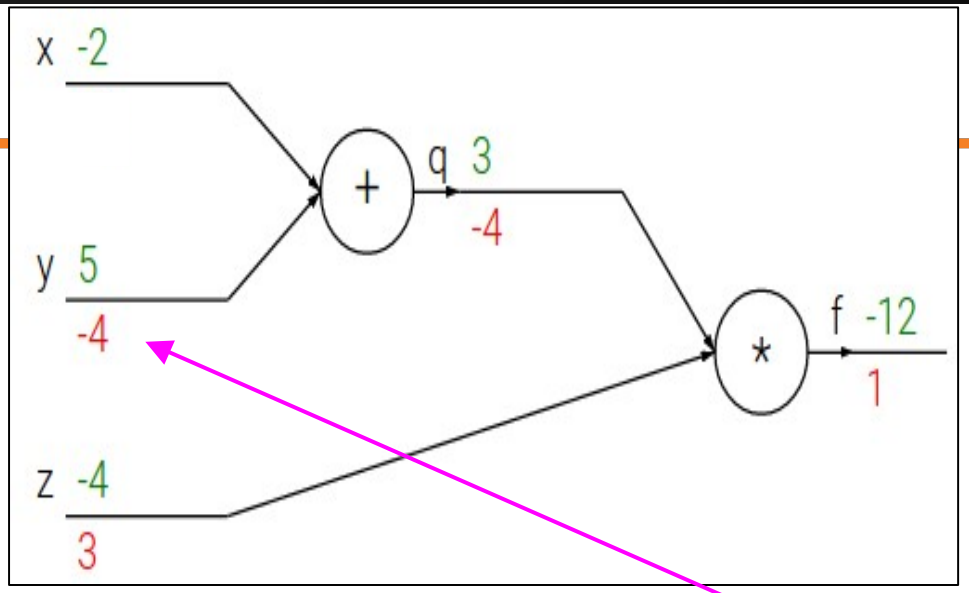
$$\frac{\partial f}{\partial y}$$

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

Slide Credit:

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

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



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

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

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

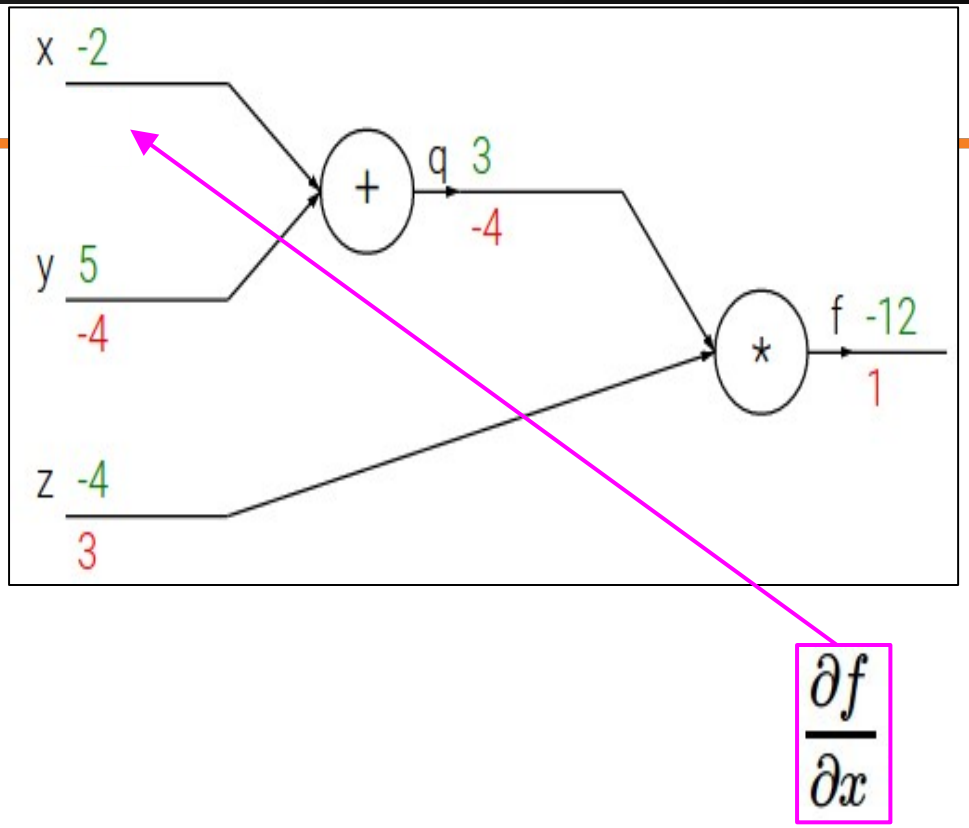
Chain rule:

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

Slide Credit:

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

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



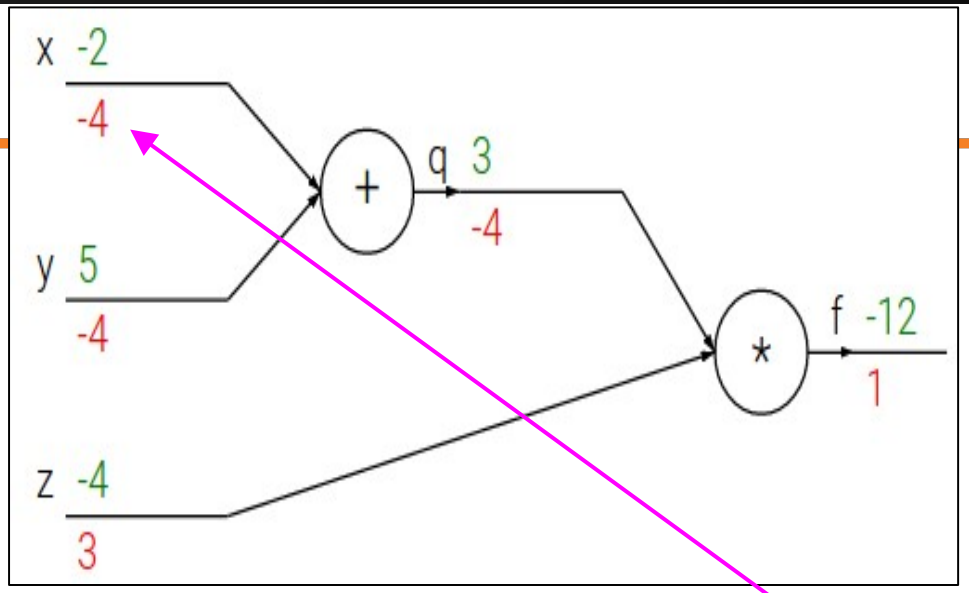
$$q = x + y$$

Want:

Slide Credit:

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

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



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

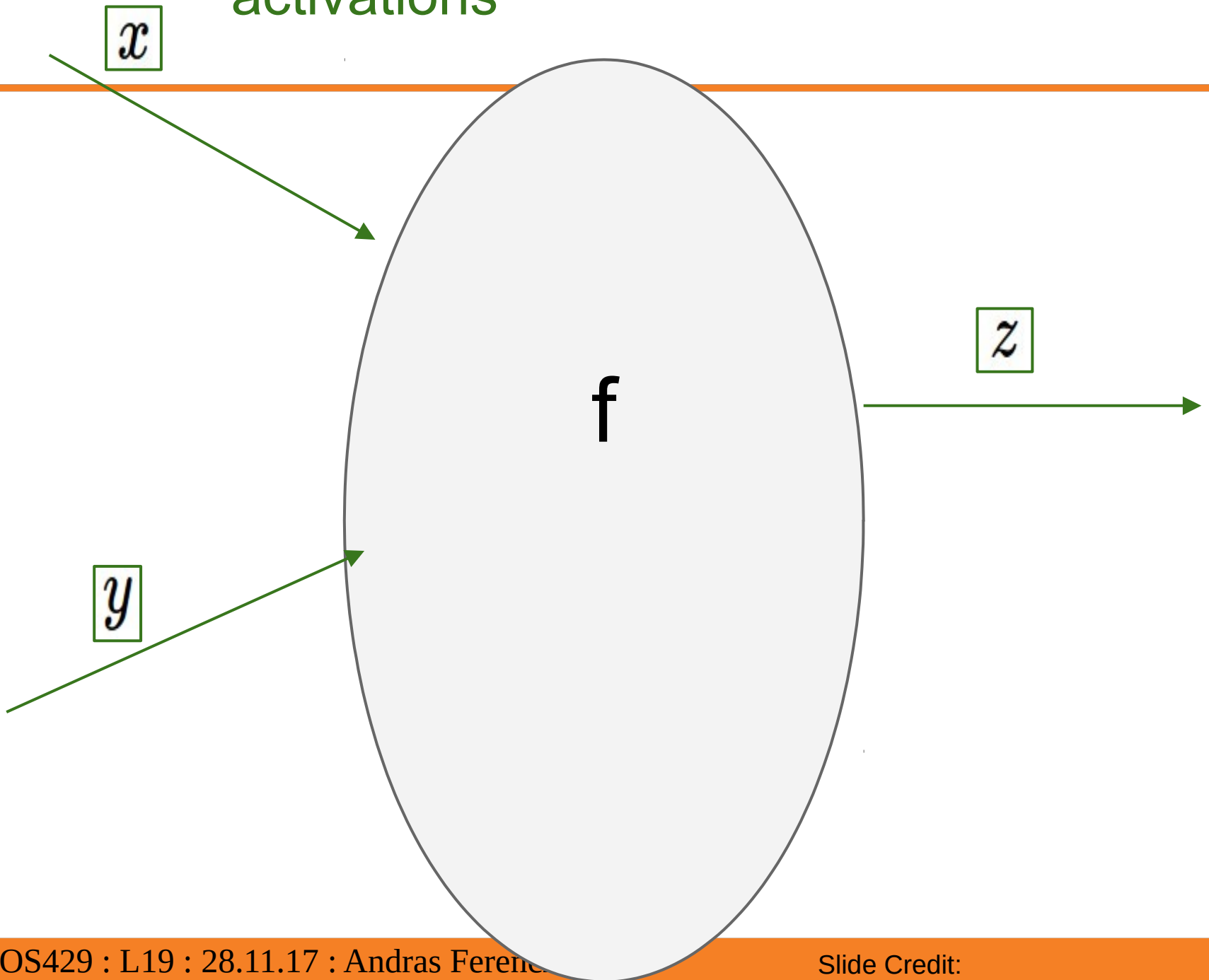
Chain rule:

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

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

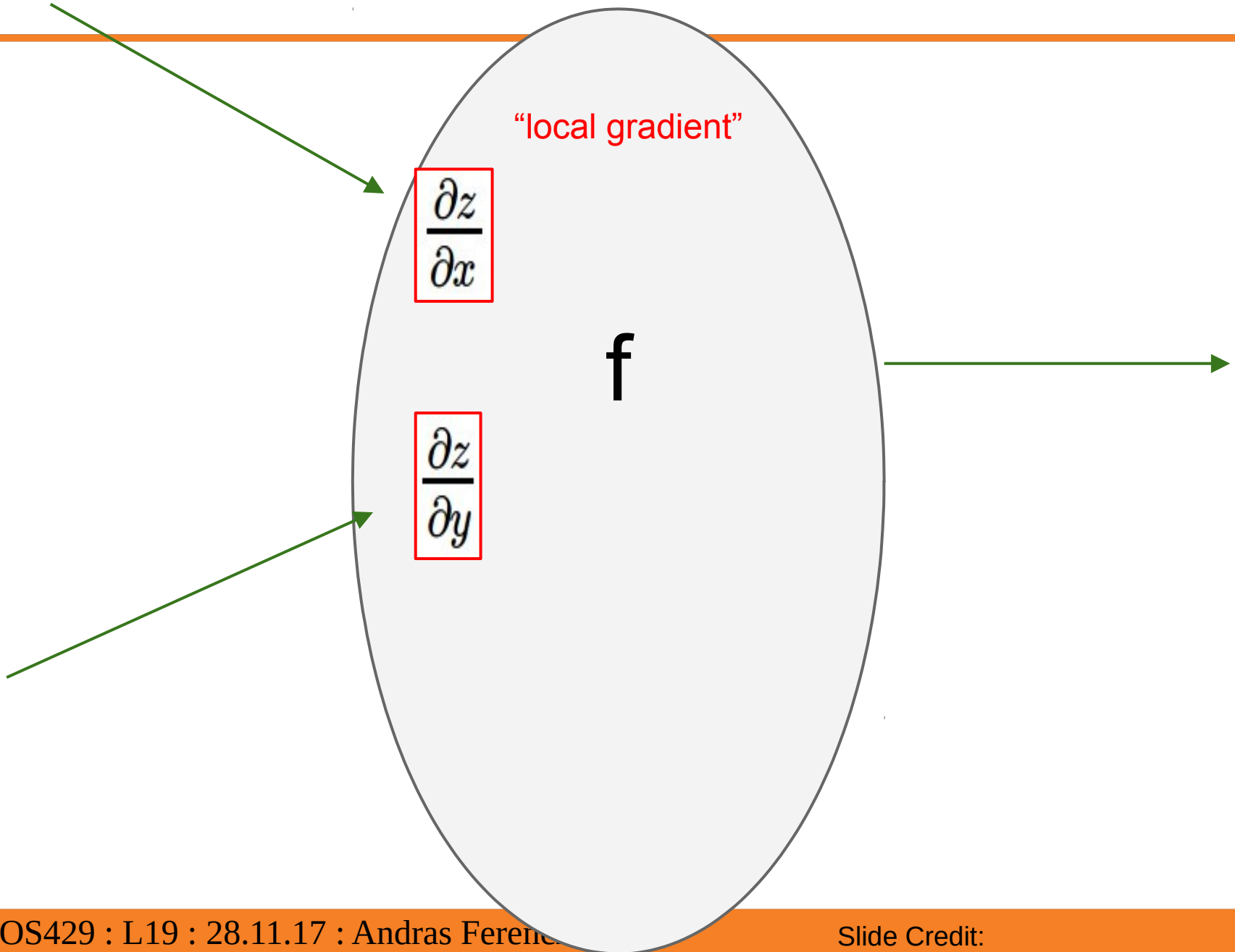
Slide Credit:

activations



Slide Credit:

activations



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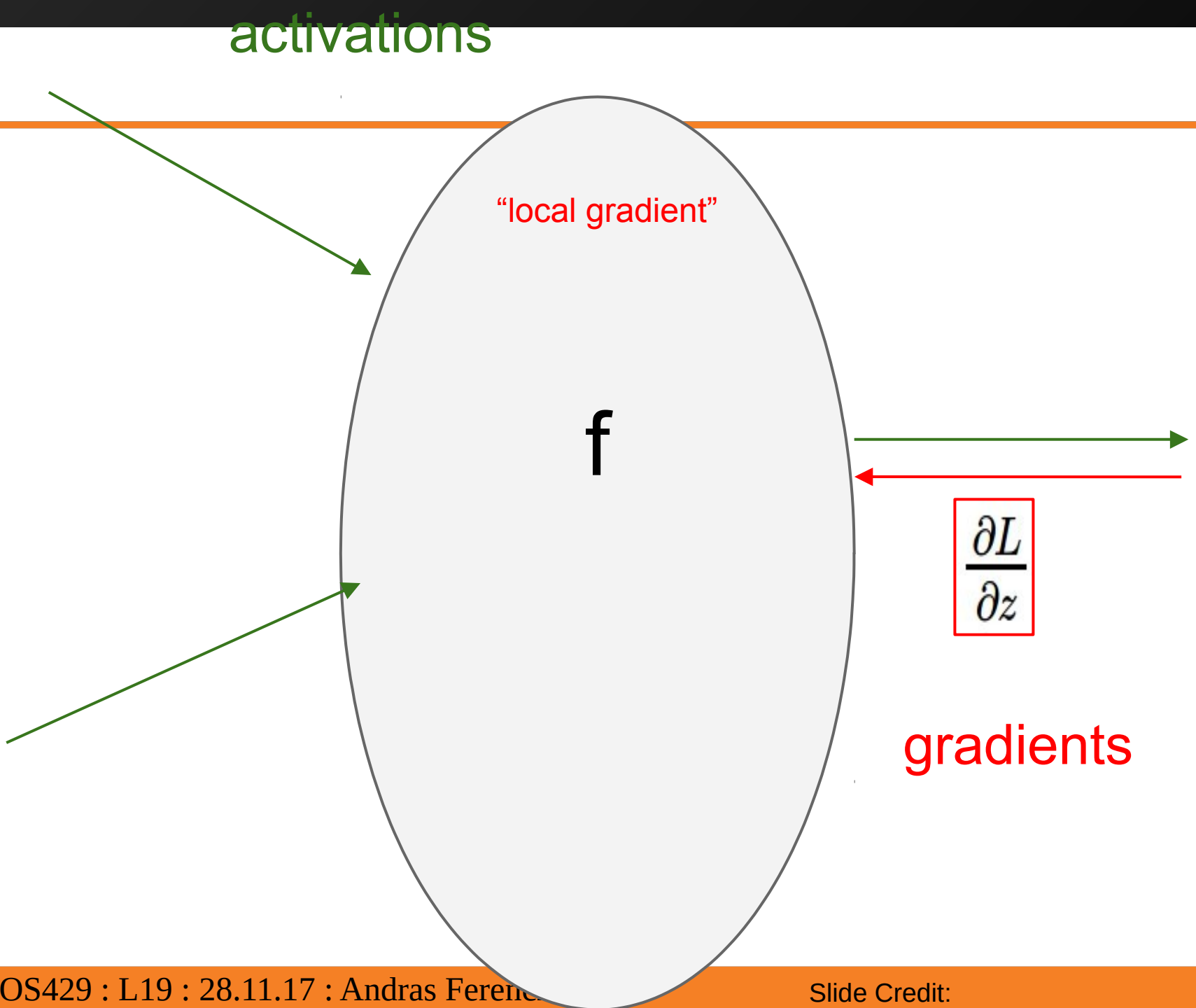

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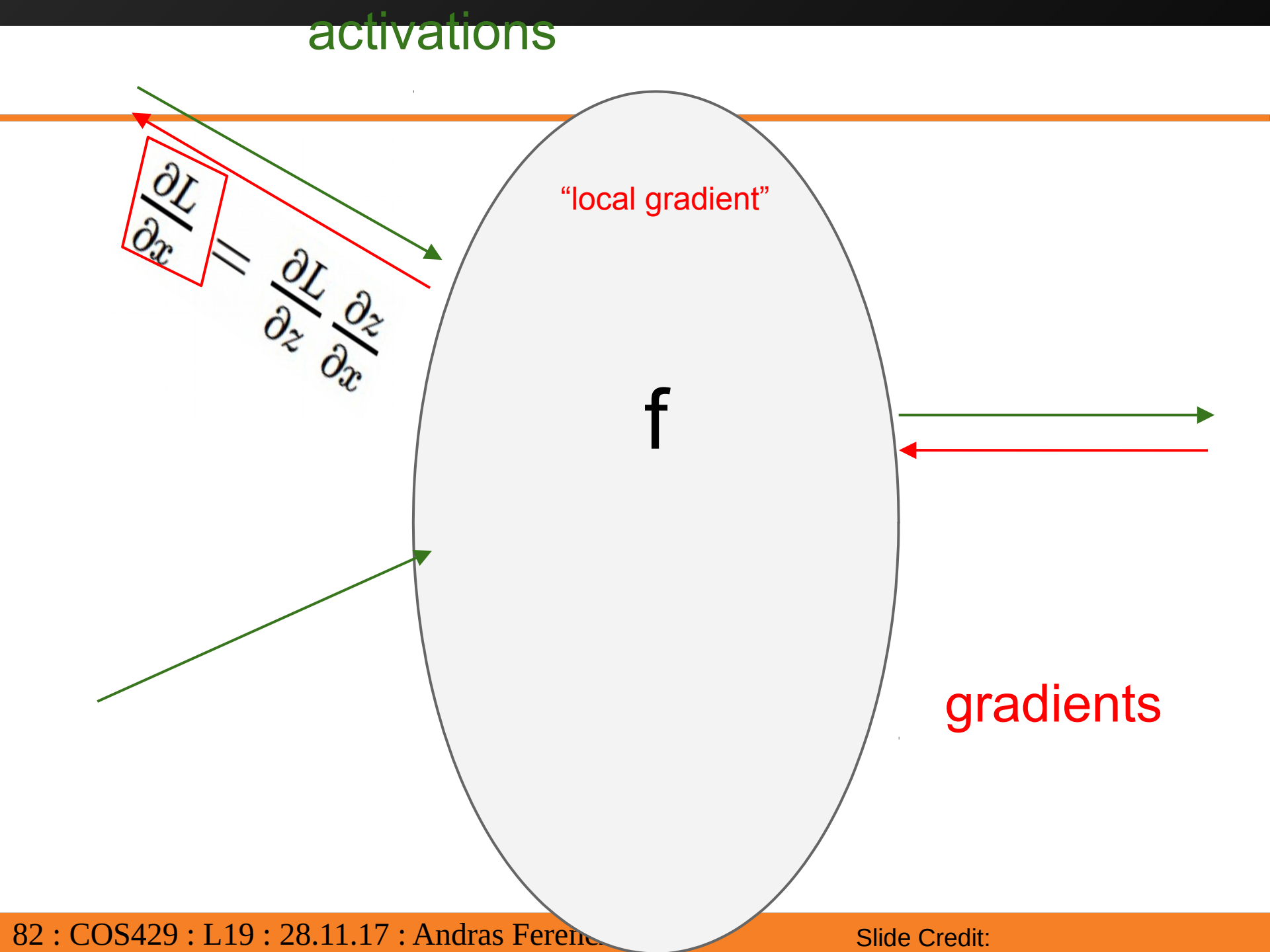

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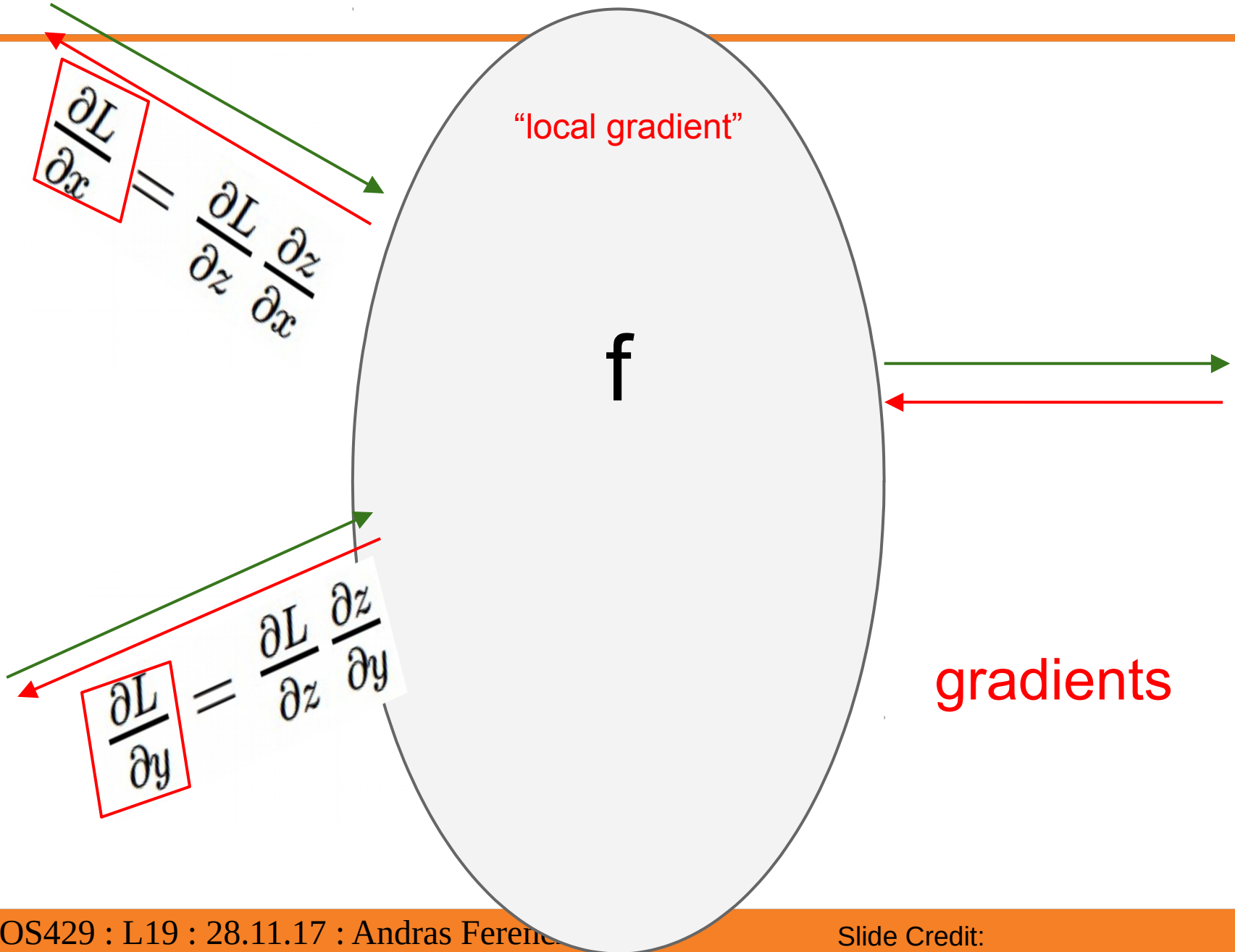
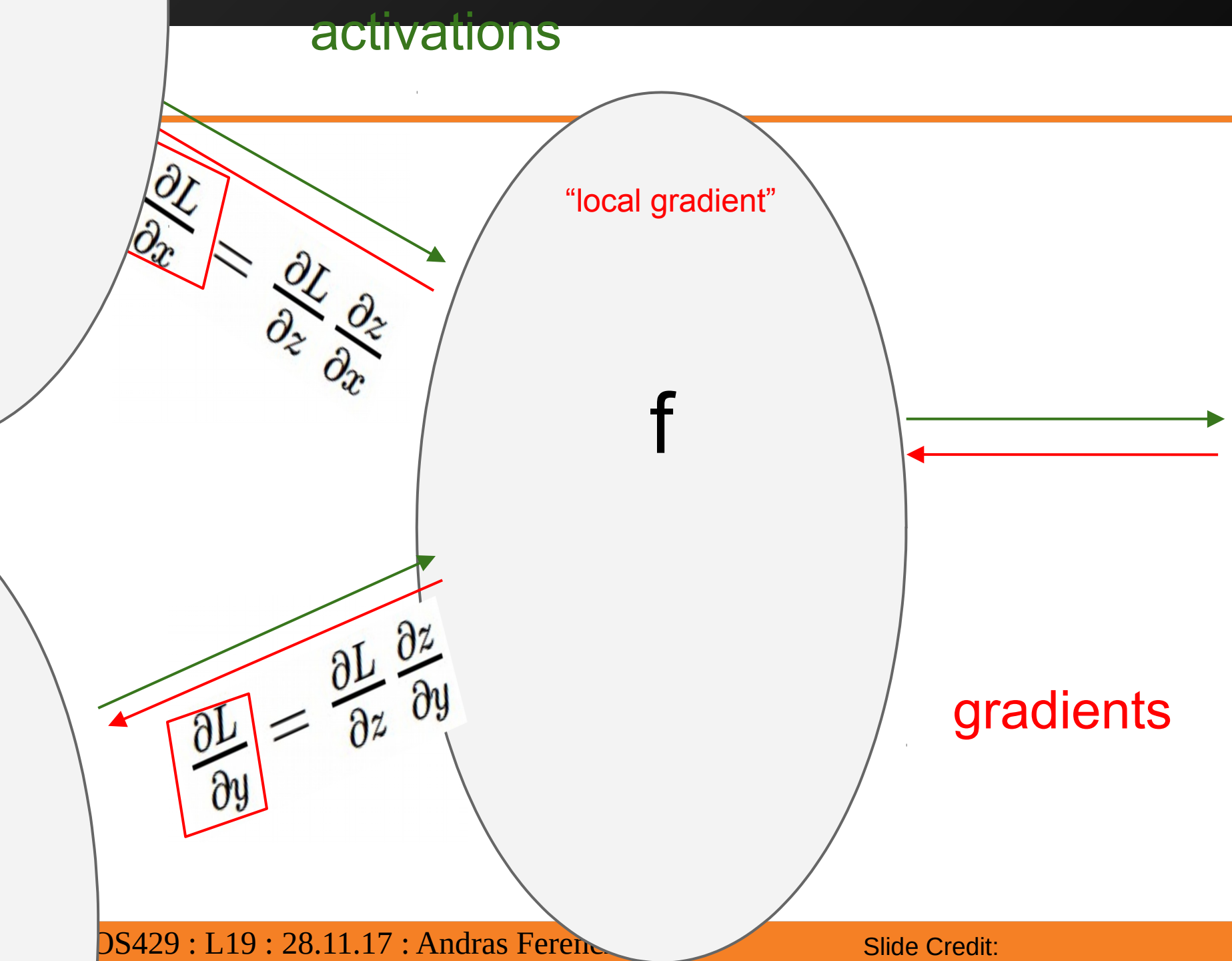
activations



Slide Credit:

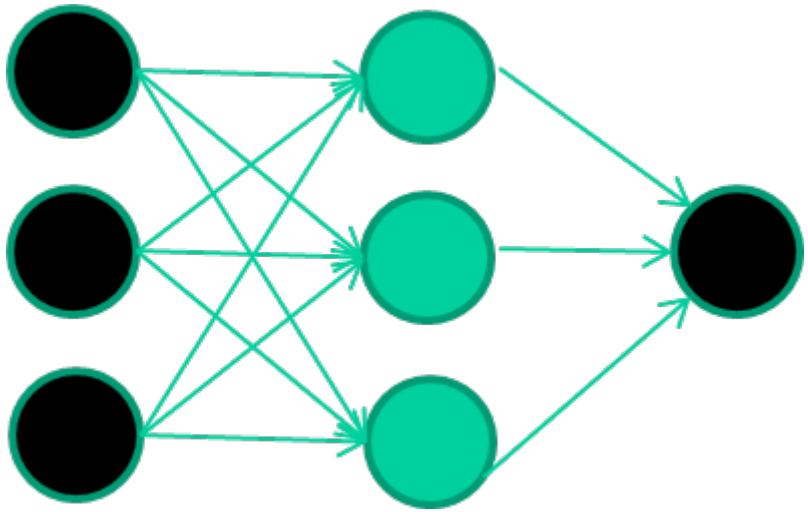
activations



Slide Credit:

A dataset

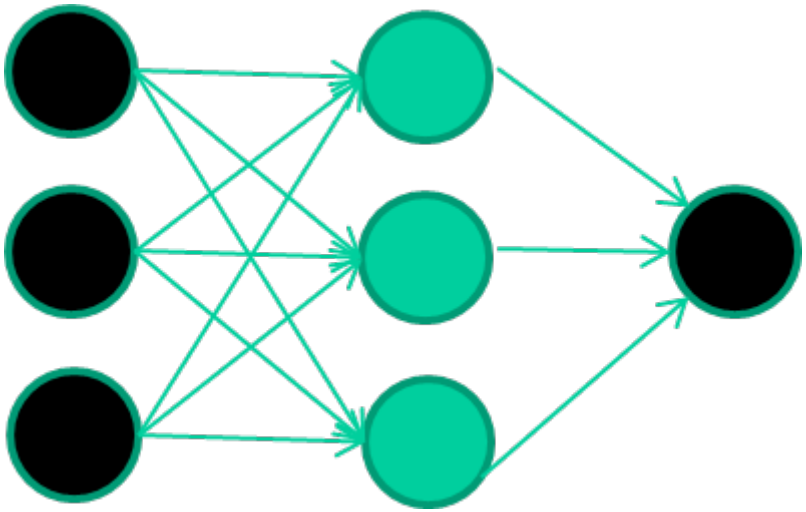
Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			



Slide Credit:

Training the neural network

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

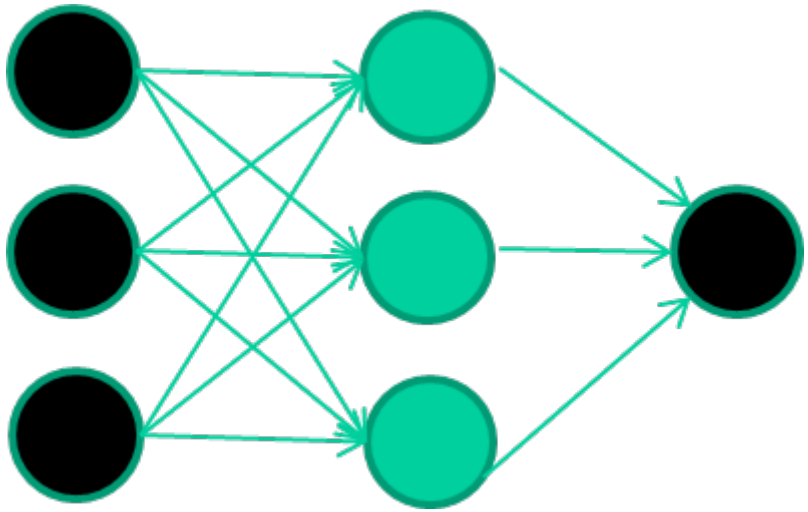


Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Initialise with random weights



Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Present a training pattern

1.4

2.7

1.9

Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Feed it through to get output

1.4

2.7

1.9

0.8

Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Compare with target output

1.4

2.7 **0.8**

0

1.9 *error* 0.8

Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Adjust weights based on erro

1.4

2.7

1.9

0.8

0

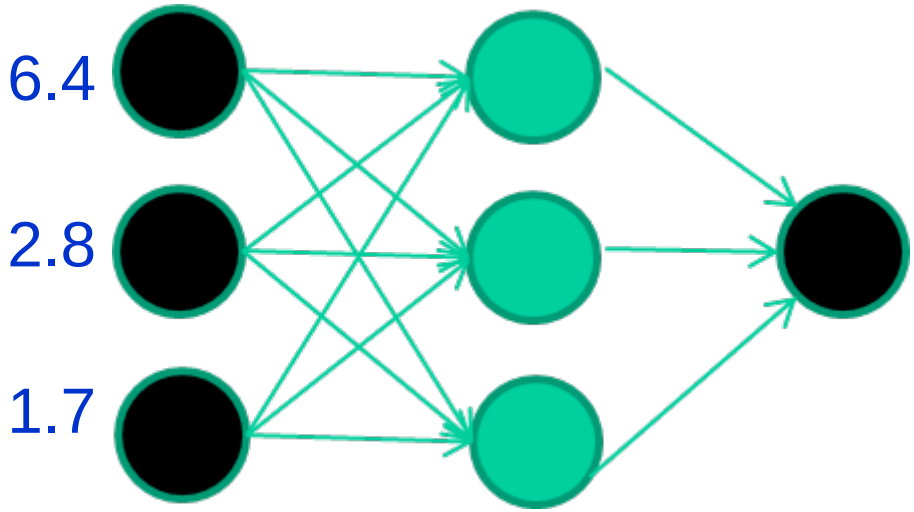
error 0.8

Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Present a training pattern

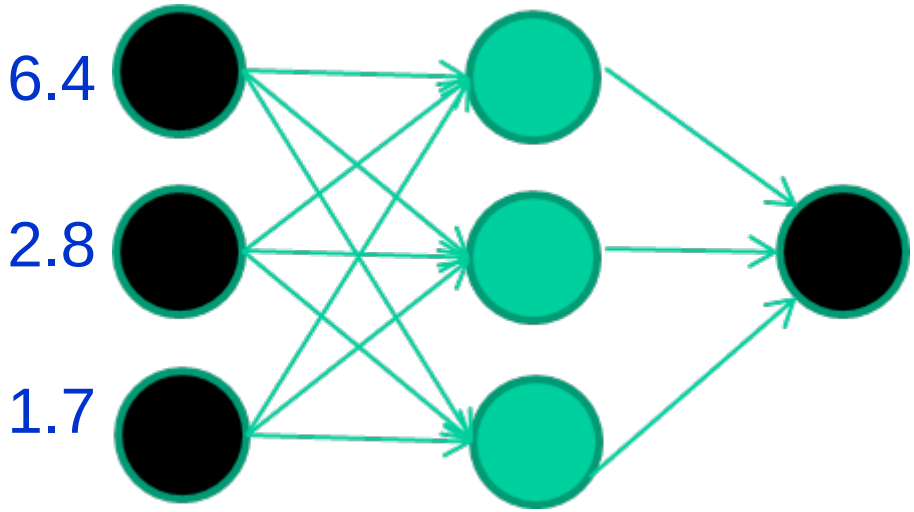


Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Feed it through to get output

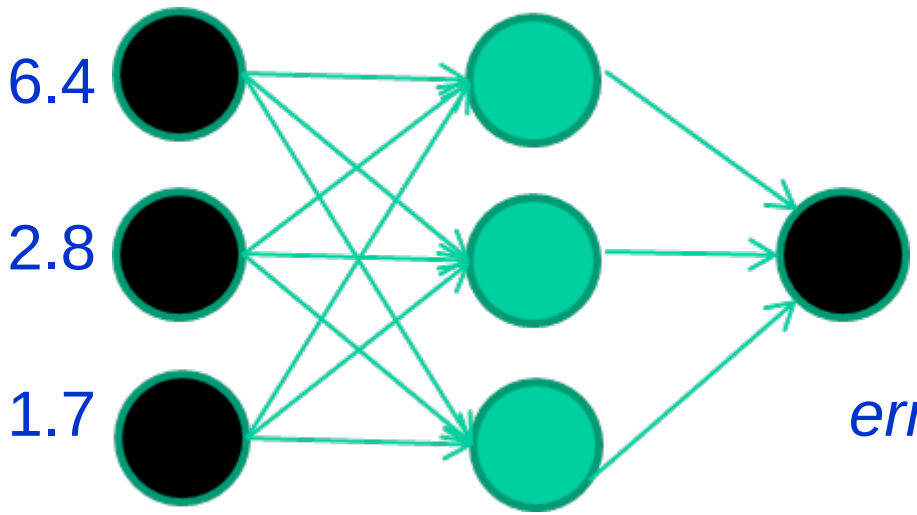


Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Compare with target output

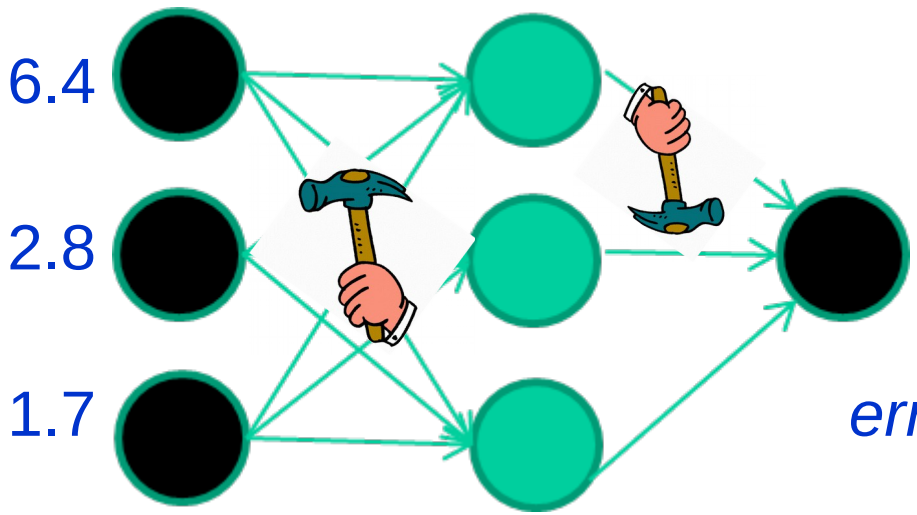


Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

Adjust weights based on erro

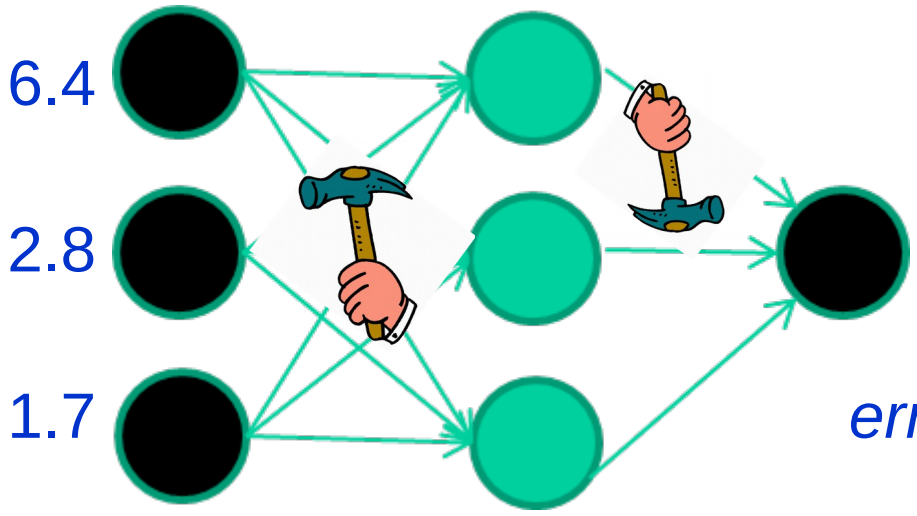


Slide Credit:

Training data

Fields			***class***
1.4	2.7	1.9	0
3.8	3.4	3.2	0
6.4	2.8	1.7	1
4.1	0.1	0.2	0
etc …			

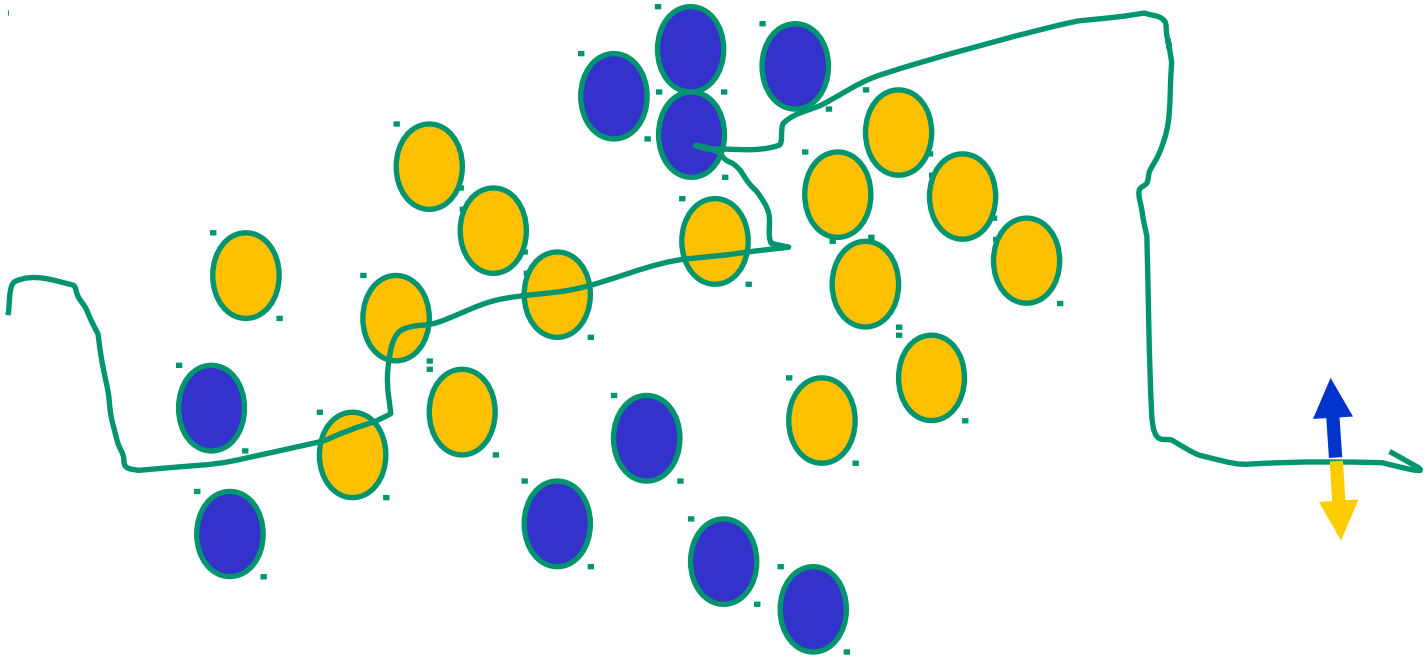
And so on ….



Slide Credit:

The decision boundary perspective...

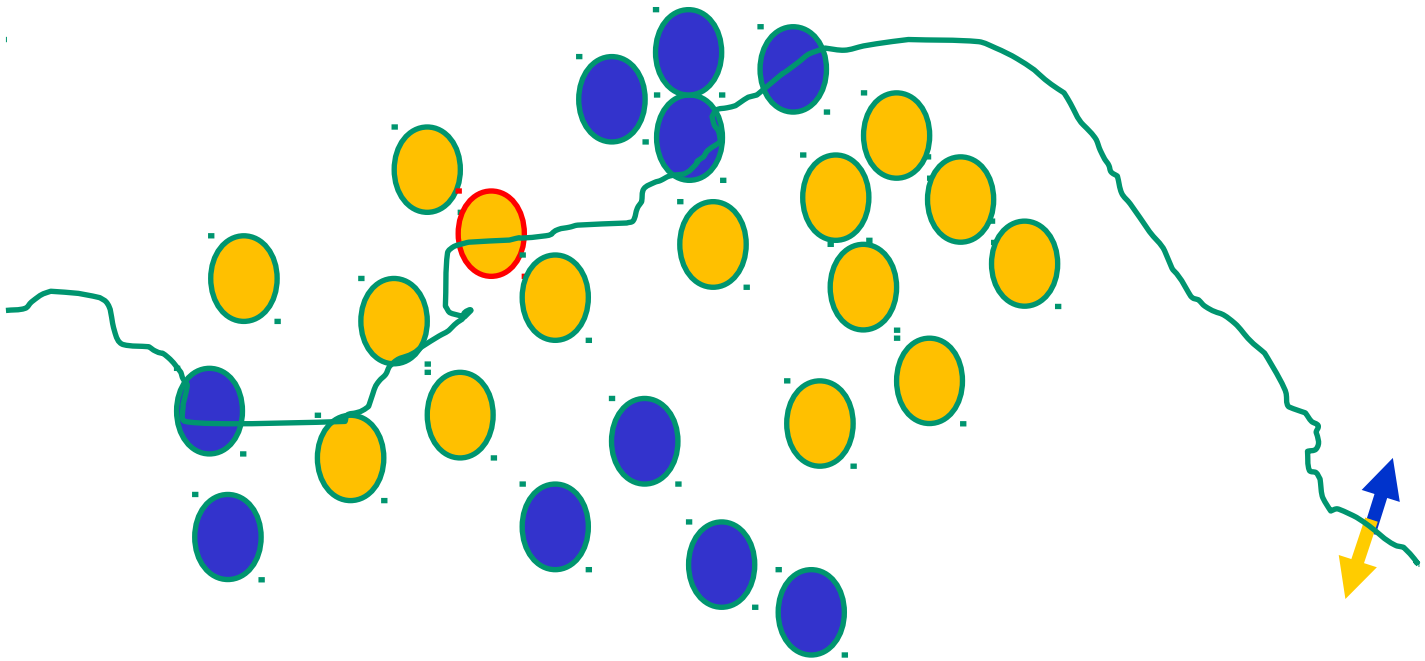
Initial random weights



Slide Credit:

The decision boundary perspective...

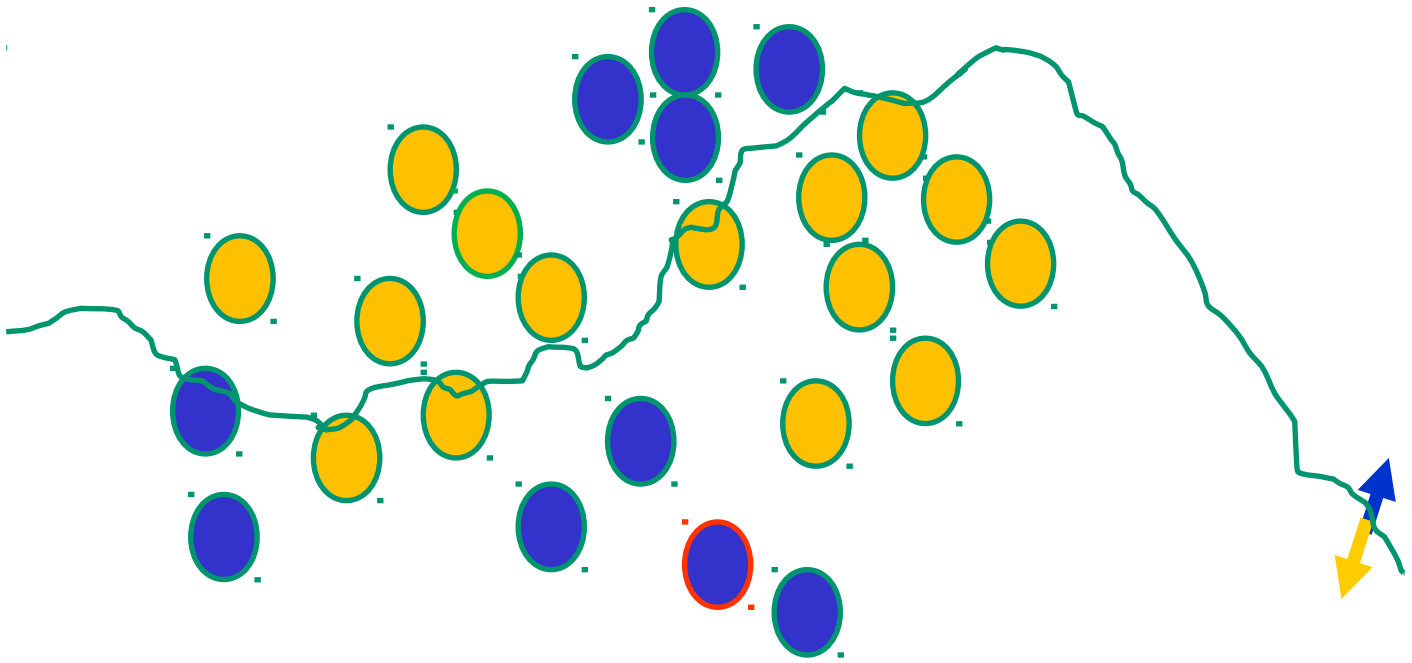
Present a training instance / adjust the weights



Slide Credit:

The decision boundary perspective...

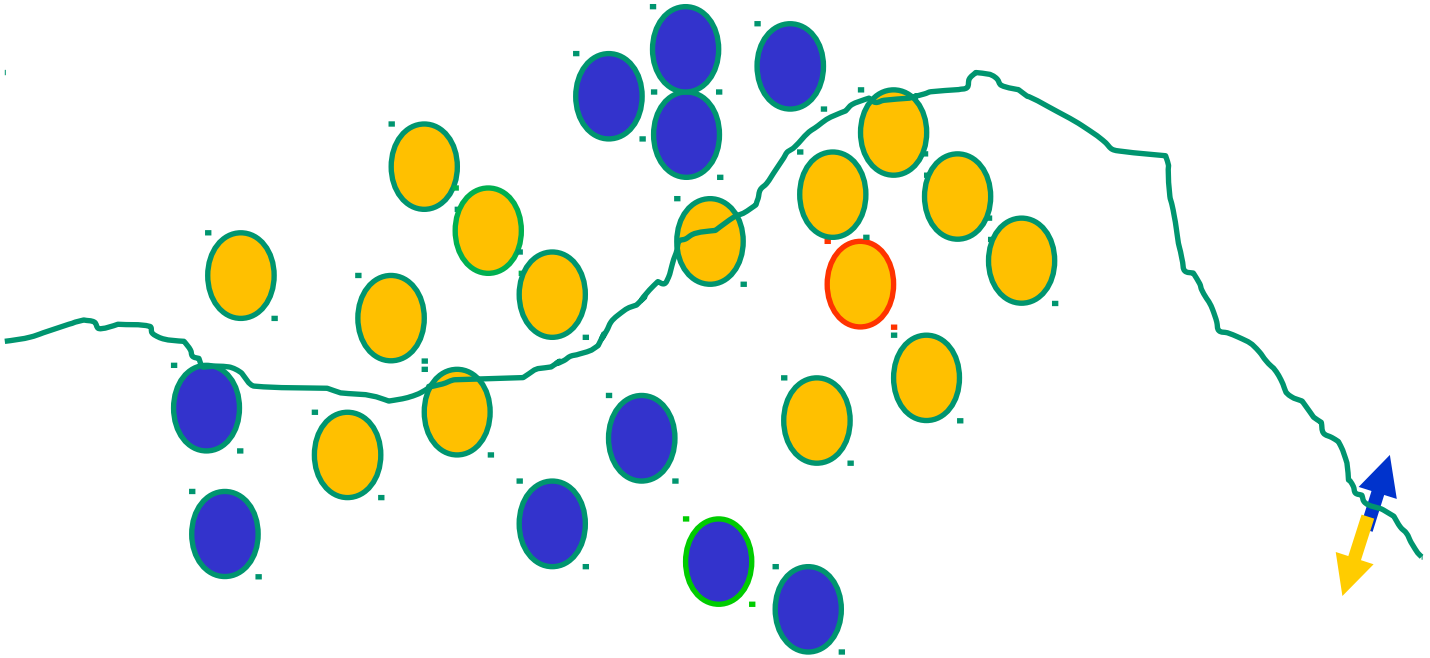
Present a training instance / adjust the weights



Slide Credit:

The decision boundary perspective...

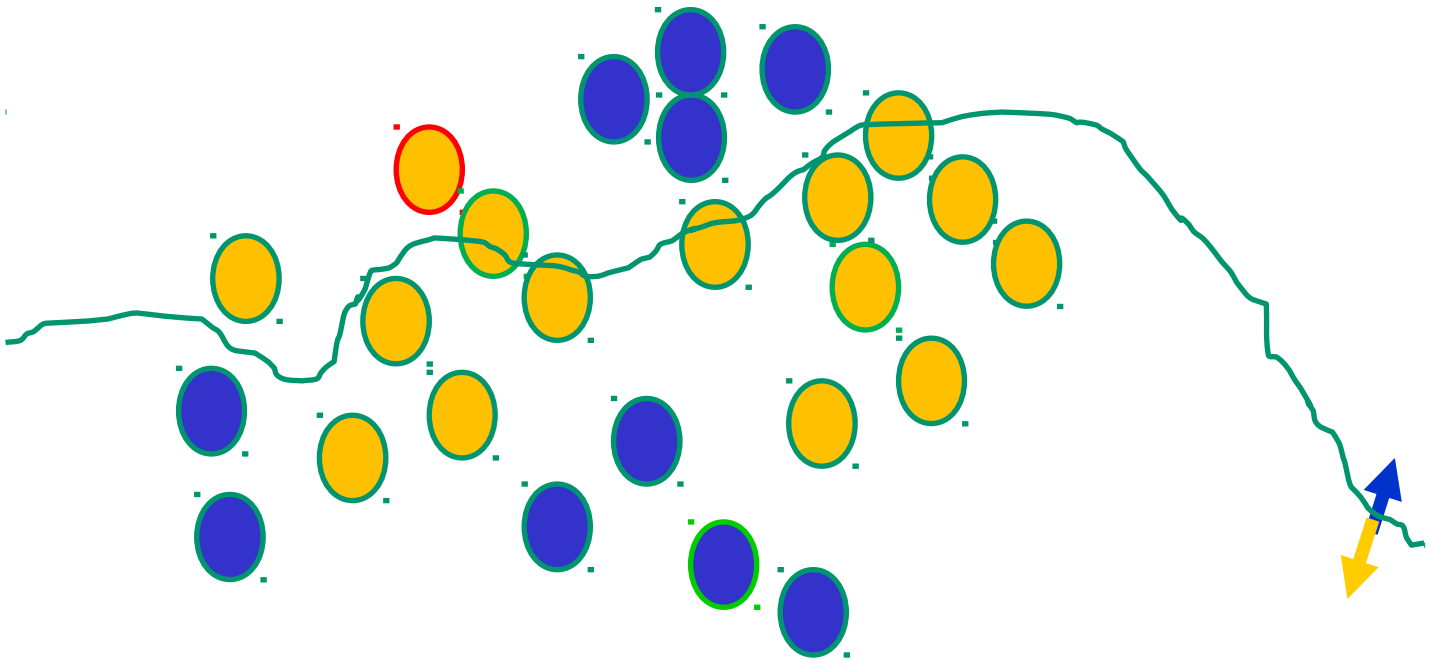
Present a training instance / adjust the weights



Slide Credit:

The decision boundary perspective...

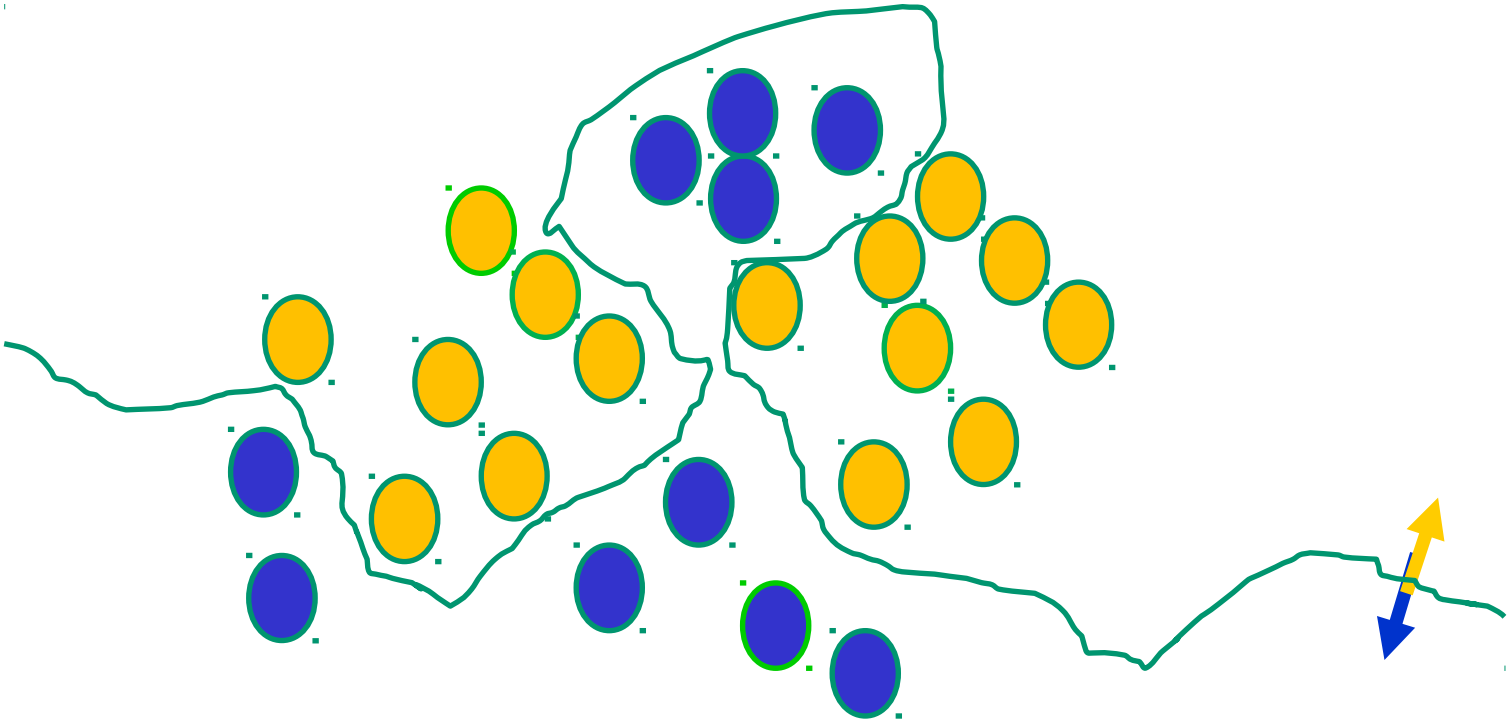
Present a training instance / adjust the weights



Slide Credit:

The decision boundary perspective...

Eventually ….



Slide Credit: